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BY

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Integrating Renewable Energy with Time Varying Pricing

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Executive Summary

Hawaii has adopted a Renewable Portfolio Standard (RPS) that aims to achieve 70% of net sales of electricity through renewable sources by the year 2040 and 100% by 2045. With increasing adoption of intermittent sources of renewable energy, mainly wind and solar photovoltaic (PV), effective integration is paramount to fully realizing societal benefits. This study asks the question, how valuable is residential real-time pricing (RTP) in comparison to time-of-use (TOU) rates to absorb increasing sources of intermittent renewable energy? We couple a detailed power sector model with a residential electricity demand response model to estimate the system and consumer benefits of these two time-varying pricing mechanisms, where RTP is modeled on an hourly basis and TOU sets five rate blocks over the day. We investigate these impacts under two scenarios: 1) today's electricity generation system, assuming households' existing ability to adjust their demand; and 2) the 2040 electricity generation system consistent with the RPS, which assumes that wind energy capacity increases nearly five-fold and solar photovoltaic (PV) capacity doubles.

We find that in 2017 it takes a reasonably small amount of load-shifting under RTP – an approximately 5% increase in off-peak hour usage –to absorb 1.7 GWh or 90% of otherwise curtailed renewable energy. By 2040, this absorption could amount up to 560 GWh. Assuming this absorption offsets oil-fired generation, we estimate the additional integration of renewable energy to be valued at $27 million in GHG abatement. Unsurprisingly, we find that TOU rates are less beneficial to residential customers than RTP – on an order of between two and four times. TOU would result in customer benefits of $7 and $200/household in 2017 and 2040 (in our optimistic scenario), respectively, while RTP is between $34 and $335/household. Residential benefits from time varying rates can be quite substantial with high penetrations of intermittent renewable energy generation in comparison to current flat rates. While TOU provides customers with more certainty in rates, RTP offers clear benefits in best utilizing intermittent sources of renewable energy.

1. Introduction

Hawaii has adopted a Renewable Portfolio Standard (RPS) that aims to achieve 70% of net sales of electricity through renewable sources by the year 2040. With such high penetration of variable renewable energy sources, mainly wind and solar photovoltaic (PV), effective integration is paramount to fully realizing societal benefits. Flat rate pricing sets retail rates that attempt to account for the average wholesale cost of electricity production (Borenstein, 2005a). Under existing flat rate pricing, however, energy from renewable sources is already being curtailed (i.e. discarded) in Hawaii due to "oversupply" in some periods. Due to the variable nature of wind and solar resources, the true cost of electricity generation differs dramatically on a temporal basis and time varying pricing offers one opportunity to help limit waste of renewable energy and provide greater efficiency to the customer and electricity supplier. During periods of curtailment in which there is high renewable penetration, customers are paying much more than necessary for electricity because the marginal cost is essentially zero.[1]

Real-time-pricing (RTP) reflects the marginal cost of electricity generation with prices set at high frequency, where truly dynamic pricing happens instantaneously. Dynamic RTP is a theoretical first-best pricing solution that can substantially increase consumer efficiencies even with low price elasticities (Borenstein, 2005b; Borenstein and Holland, 2005); however, it can be difficult to implement (Borenstein, 2007, 2013).[2] Many programs, in practice, occur with day-ahead hourly pricing, which serves to provide customer certainty yet invites measurement error. Time-of-use (TOU) rates are pre-determined for specified blocks of time during the day. They can be thought of as average rates among similar hours.[3] Like flat rates, TOU rates give consumers price certainty and thus lead to more stable demand responses. As such, they are often easier to implement (Blonz, 2016), even though they still suffer from inefficiency. The magnitude of the difference between RTP and TOU in terms of efficiency loss will depend on the ways in which marginal cost fluctuates with available resources.

This study asks the question, how valuable is residential RTP in comparison to TOU to absorb increasing sources of variable renewable energy? We employ two models, one to estimate impacts to supply and the other to demand. A production cost model developed by GE Energy Consulting is used to develop a dataset on estimated hourly electricity generation costs under two scenarios. The first calibrates to Hawaii's current 2017 generation, where

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[1] Marginal cost is a measure of the incremental cost of producing the last unit. When energy is being curtailed, theoretically the incremental cost is zero. This does not take into account contracting arrangements.

[2] While RTP removes the cross-subsidization of customers who consume disproportionately more during times of high marginal cost under flat rate pricing, wealth transfers are required to make these customers no worse off under RTP (Borenstein, 2007).

[3] TOU prices set annually do not adjust for trends like seasonality, although certainly more granular TOU rates could be established.

wind and solar PV comprise 20%. The second assumes that these variable sources provide 50% of generation in the year 2040.[4] To simplify the analysis, the model assumes that no other changes are made to the system in terms of load, fuel price,[5] and thermal resource mix; thus it is the adoption of wind and solar PV that alone determines the differences between 2017 and 2040. The second model is of residential electricity demand and is used to estimate the magnitude of residential consumer response as a result of RTP and TOU. We use Hawaii-specific and literature-based estimates of residential consumer price responsiveness to electricity prices to assess how residents in Hawaii might change their behavior under RTP or TOU pricing schemes, primarily drawing on pilot programs for TOU and Critical Peak Pricing (CPP). CPP is another variant of RTP that refers to programs that focus on bringing down electricity demand during periods of higher than typical peak usage and cost. The new residential load profile is then provided as an input to the production cost model to estimate the impact of load-shifting on system costs. Altogether the study investigates: 1) the potential magnitude for residential load-shifting, 2) the gains to consumer welfare under RTP or TOU in comparison to current flat-rate pricing, 3) the relative difference in consumer welfare gains between TOU and RTP, 4) the impact of consumer load-shifting on system cost, and 5) the value of GHG emissions reductions achieved as a result of integration of otherwise curtailed renewable energy resources.

2. Prior Studies on Residential Demand Response: Substitution Elasticities

In a review of fifteen pilot TOU or CPP pricing experiments, Faruqui and Sergici (2010) conclude that price signals do indeed lead to residential electricity demand response, where higher prices lead to lower usage. The level of responsiveness, however, varies considerably depending on the level of prices, prevalence of air conditioning, and availability of enabling technologies. They find that within the TOU and CPP rate programs considered, there was a drop in peak usage from 3-6% and 13-20%, respectively, with traditional technologies. With enabling technology for CPP, like two-way programmable communicating thermostats and systems that allowed for remote control of appliances, this could go as high as 44% (Faruqui and Sergici, 2010). On the other hand, several studies have found no measurable substitution effect in response to implementation of time varying pricing. Jessoe and Rapson (2014) find that if consumers are not given sufficient advanced notice, they are more likely to conserve energy than shift usage to other periods. Jessoe et al. (2014) also found that customers who crossed a threshold of power usage, and were consequently switched to a mandatory TOU pricing, responded by reducing electricity usage even during times of lower rates. Allcott (2011) found an overall price elasticity of negative 0.1 for voluntary TOU customers in Chicago and attributed the modest response to energy conservation during peak periods rather than a shift in consumption to off-peak periods. Though energy conservation is a positive side effect from the point of view of reducing GHG emissions, inefficiencies that exist with respect to actual cost of electricity production for flat rate pricing will remain if

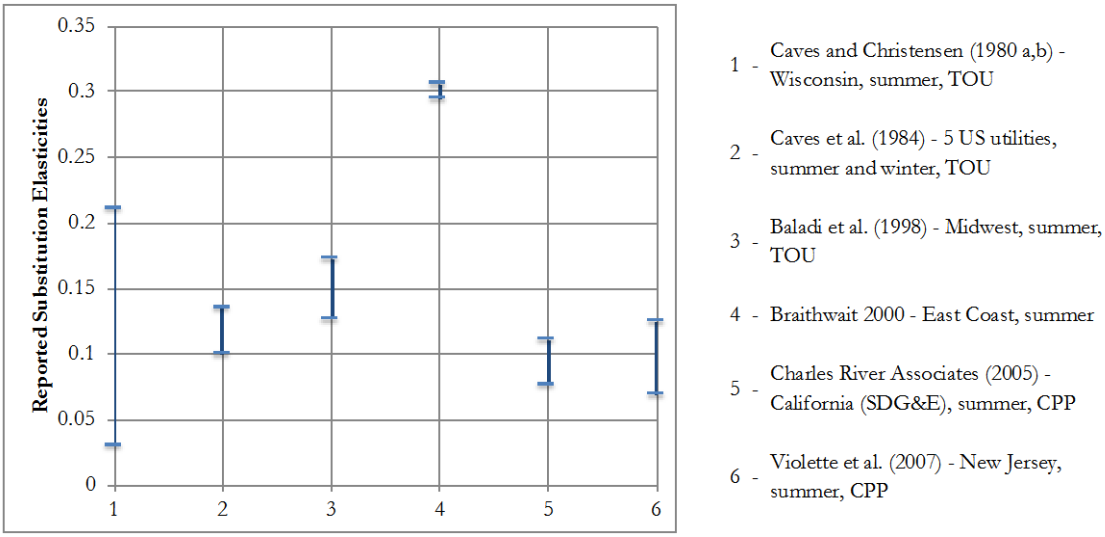
[4] The underlying data and assumptions are documented in the Oahu Distributed PV Grid Stability Study (HNEI, 2016).

[5] Assumed to be $60/barrel.

TOU pricing only results in energy conservation without any shifting of load (Orans et al., 2010). Lastly, a recent study supports the findings on the lower end of the spectrum within Faruqui and Sergici (2010).

Comparability among studies is quite difficult due to ranging methodologies and assumptions. As such, we focus our efforts on summarizing published estimates of *elasticity of substitution*, because we use a nested constant elasticity of substitution (CES) utility function within our demand response model.[6] Elasticity of substitution captures price sensitivity through the relative change in usage in time periods as a result of the relative change in prices. It is often reported as the negative of the change in the ratio of peak to off-peak usage given a change in the peak to off-peak price ratio. Five studies summarizing substitution elasticities in a CES framework for TOU and CPP regimes are shown below in Figure 1.[7,8]

Figure 1. Values of peak to off-peak substitution elasticity reported in the literature



The substitution elasticities reported within the studies are highly inelastic, ranging from 0.03 to 0.3.[9] Overall, studies suggest that differing values stem from variation in appliances and access to enabling technologies like automatic controls and in-home displays. Braithwait

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[6] Consumer response to time varying rates by load shifting is commonly measured through two parameters—*cross-price elasticity of demand* and *elasticity of substitution* (also called substitution elasticity).

[7] Faruqui and Sergici (2010) summarize recent studies (conducted from the late 1990's onward) of residential dynamic pricing experiments. Those that report substitution elasticities include Braithwait (2000), Charles River Associates (2005), and Violet et al. (2007).

[8] In a CES demand system, this is mathematically represented as $\ln\left(\frac{Q_p}{Q_o}\right) = \alpha + \beta \ln(\frac{P_p}{P_o})$ where the elasticity of substitution is equal to $-\beta$.

[9] An outlier not shown above, Filippini (1995), reports values of substitution elasticity as high as 2.9. However, Lijesen (2007) argued these values were a result of misspecification.

(2000) studied an East Coast TOU pilot conducted for two months in the summer of 1997. The author attributed the higher than average literature CES values to the use of programmable communication equipment for AC and other appliances. Studies of a CPP program were conducted in California with various pricing schemes from 2003-2004, where electricity customers were informed of days during the year when CPP would go into effect (Charles River Associates, 2005). In the scenario with enabling technology, customers who did not adopt enabling technology had a substitution elasticity of 0.09 and those that did adopt had a higher elasticity of 0.11. Violette et al. (2007) analyzed a CPP program in New Jersey, finding that households increased their substitution elasticity with programmable thermostats. Residents who were given a programmable thermostat for their central AC had an elasticity of 0.125, and those that did not have thermostat had an elasticity of 0.069. Those without central AC were found to have an elasticity of substitution of 0.063. Additional studies, including Alcott (2011), Jessoe and Rapson (2014), and Bollinger and Hartmann (2015), similarly point to the importance of automation and high frequency customer information in determining sensitivity to either prices.

3. Models, Data and Assumptions

3.1 Production Cost Model: Baseline Price Assumptions

To perform this analysis, a PLEXOS® based production cost model was developed for the Oahu power grid. The production cost model allows for a chronological simulation of the power grid at 10-minute intervals to accurately capture changes to system load and variability in wind and solar resources. The simulation develops a security-constrained commitment and dispatch schedule of each generator to minimize system cost in a similar fashion the grid operator (utility) determines which generators to run. The model also takes into account technical constraints on the system, including ramp rates, startup and shutdown times (and costs), minimum up and down times for generators, contingency and regulation reserve requirements, planned and forced outage events, and solar and wind forecast errors. This model has been routinely benchmarked and validated in prior analyses.[10]

To understand the role of TOU and RTP rates for renewable integration, two scenarios were analyzed representing the Oahu power grid. This included a 2017 Scenario, which simulated the power grid with existing renewable energy sources. The 2017 Scenario represents approximately 25% of annual renewable penetration as a percentage of load. The 2040 Scenario represents approximately 50% annual renewable penetration as a percentage of load. The future resource mix was developed to reflect HECO's April Power Supply Improvement Plan (PSIP) in the year 2040.[11] This includes 565 MW of wind capacity, 565 MW of utility-scale solar PV capacity, and 840 MW of distributed rooftop solar PV (DPV)

[10] For more information on previous analyses and documentation using production cost modeling in Hawaii, please visit: https://www.hnei.hawaii.edu/projects#GI

[11] The future resource mix assumed in this analysis used HECO's proposed plan as of April 2016, which does not align directly with more recent PUC filings (Post-April PSIP in December 2016), but is generally representative of current wind and solar growth proposals.

capacity. In addition, system load was increased to 8,450 GWh mostly due to increased electric vehicle penetration. All other system assumptions, including installed thermal capacity, load profiles, and operating conditions were maintained from current operations. The assumed oil price of $60/barrel is consistent between the two scenarios. An overview of the future 50% wind and solar system assumptions are provided in Table 1, which also includes the current power grid overview for reference.

Table 1. Overview of Current and Future Grid Scenario Assumptions

	2017 Power Grid: 20% Wind and Solar	Future "2040" Power Grid: 50% Wind and Solar
Peak Load (MW)	1,225	1,225
Annual Energy (GWh)	7,734	8,450
Electric Vehicles (GWh)	44	791
Wind & Solar Capacity (MW)	809	1965
Utility-Scale Wind	123	565
Utility-Scale Solar	148	565
Distributed PV	538	840
Available W&S (GWh)	1547	4225
Available W&S (% of Load)	20%	50%

Results of the production cost model provides baseline data on the marginal cost and quantity of generation (including curtailment), aggregated to an hourly basis. Marginal cost refers to the cost to produce the last unit of electricity produced, effectively the operating cost required to supply the next MW of load on the system. The varying marginal cost of electricity reflects the changing sources of generation on the system due to changes in system load, variable renewable energy profiles, and generator outages.

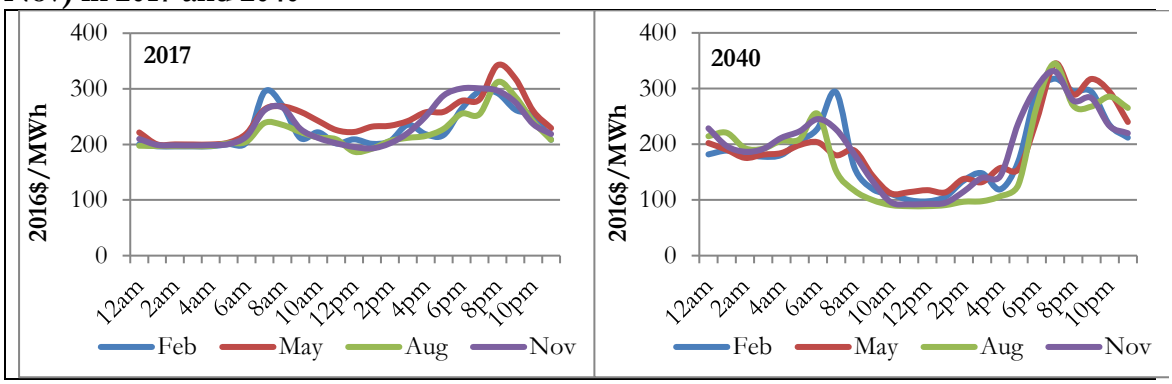
We assume that the wholesale price of electricity varies based on the hourly marginal cost. When curtailment exists, the marginal cost is treated as zero.[12] To address distribution, transmission, and other costs associated with the delivery of electricity, we add a markup of $90/MWh to arrive at prices faced by households (Hawaiian Electric Companies, 2016a).[13] Though we know it is unlikely for these costs to remain the same in the future, our point is to create similar conditions by which to test the role of generation-related marginal cost pricing. Figure 2 below shows the average hourly prices (including marginal and fixed cost) for the months of February, May, August, and November for 2017 and 2040. These months are selected to show fluctuations in available electricity supply by season. More solar PV in 2040—a total of 565 MW of utility-scale and 837 MW of distributed—puts downward pressure on marginal prices during the day. Prices reach a minimum of $90/MWh between

[12] Until the amount of curtailment is filled with new demand under RTP, at which point the price converts to that of a typical oil-fired unit.

[13] Retail prices are most often shown in cents/kWh. This would equate to 9 cents/kWh. We remain in MWh for consistency throughout the analysis.

11am -12pm, equivalent to the fixed costs of providing electricity. This is in contrast to 2017 where the lowest price is $187/MWh at 12pm with 148 MW of utility-scale and 538 MW of distributed solar PV. In addition, increased wind capacity in 2040 (totaling 563 MW) causes greater price volatility in the nighttime hours. Altogether, there is 809 MW of wind and solar PV capacity in 2017 (20% of annual load energy) compared to 1,965 MW in 2040 (50% of annual load energy). In both scenarios, thermal resources represent existing units.

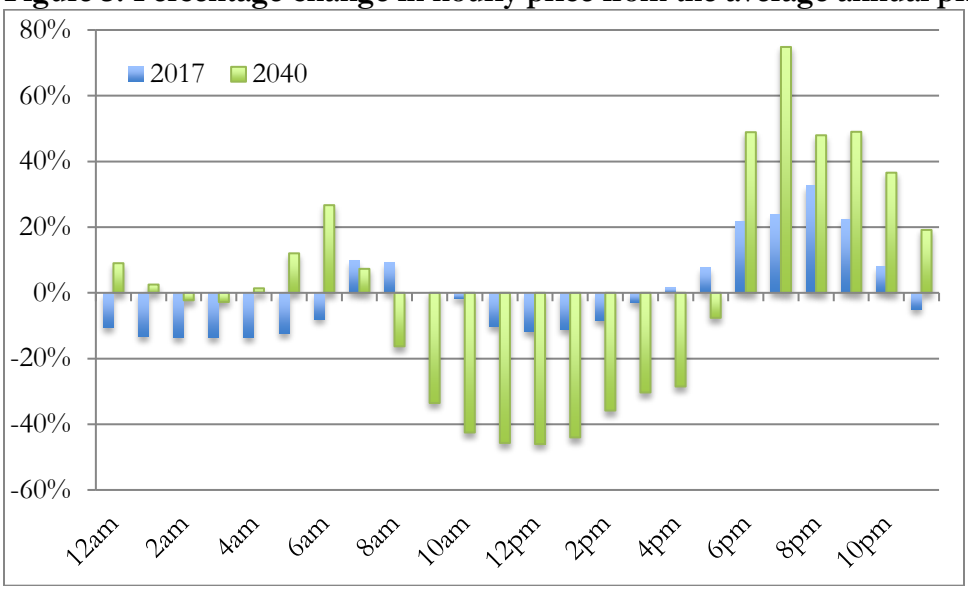
Figure 2. Average Hourly Retail Prices of representative months (Feb, May, Aug, Nov) in 2017 and 2040



Source: GE Energy Consulting, 2016.

For further illustration of the cost data and to provide insight into the creation of TOU blocks, Figure 3 below shows the percentage change in the average hourly price from the average annual price for 2017 and 2040. This illustrates that the lowest pricing occurs during high solar availability in the middle of the day and the highest pricing occurs during evening peak load hours.

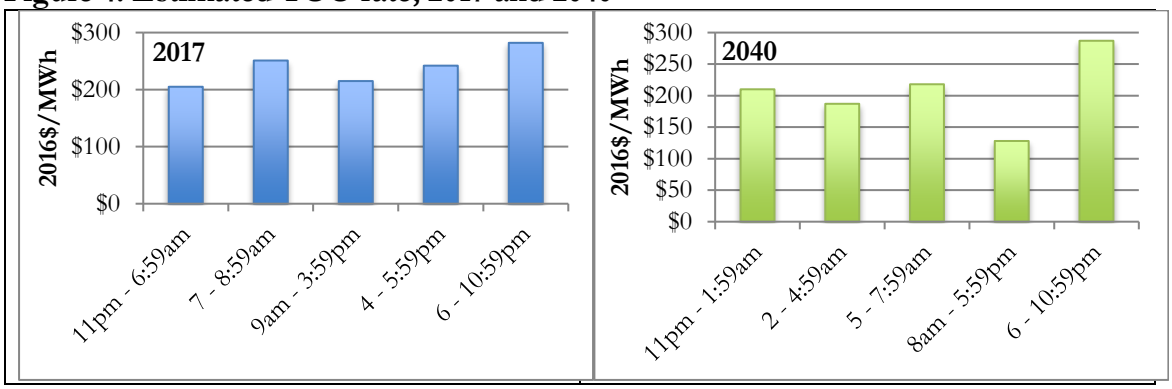
Figure 3. Percentage change in hourly price from the average annual price



Source: GE Energy Consulting, 2016.

Based on Figure 3, we grouped similar hours in each year to form five TOU periods.[14] For 2017 the blocks are: 11pm to 6:59am, 7 to 8:59am, 9am – 3:59pm, 4 to 5:59pm, and 6 to 10:59 pm. For 2040 the blocks are: 11pm to 1:59am, 2 to 4:59am, 5 to 7:59am, 8am to 5:59pm, and 6 to 10:59pm. Figure 4 shows the final set of TOU rates for 2017 and 2040. RTP rates for each hour are based on GE's marginal cost estimate for that hour plus the assumed fixed charge of $90/MWh.

Figure 4. Estimated TOU rate, 2017 and 2040



3.2 Residential Electricity Demand Response Model

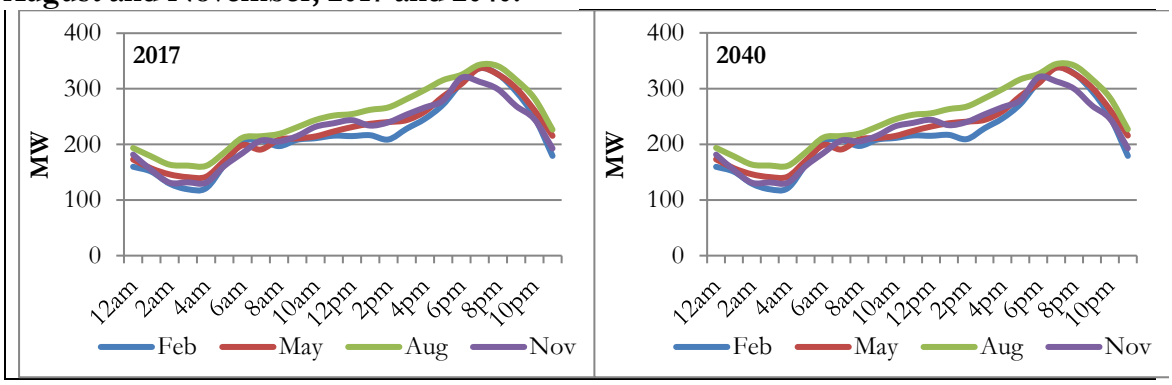
To estimate the magnitude of load-shifting opportunities as a result of RTP and TOU, we develop a model of residential consumer behavior based on the literature's estimates of households' demand sensitivity to changes in electricity prices. Baseline residential electricity demand is provided by a recent utility load study. [15] Navigant Consulting (2015) provides total electricity demand for Hawaiian Electric Company by major customer classes including residential for the four representative months of the year. From the total load across all sectors for each month, we calculate the percentage share of residential load for Oahu and apply it to the hourly generation profile to estimate the amount of gross residential load, as summarized in Figure 5.[16] The original gross load curve for each scenario was assumed to be approximately the same, adjusting for growth in electricity demand, but not a change to the underlying chronological pattern.

[14] This grouping differs from the utility's current grouping of three TOU periods.

[15] The Navigant Consulting (2015) report was filed by the electric utility within a regulatory proceeding. Only figures and not underlying data were provided. We used a software program, Graphclick, to estimate values from pictures of graphs out of the report. Therefore, values used in our analysis are subject to estimation error. However, the scenario analysis captures their overall shapes.

[16] The share of residential load for the representative months is applied to the entire 8,760 hours within the year. February is applied to the months January through March; May's share to April through June; August's share to July through September; and November's share to October through December.

Figure 5. Residential Electricity Demand for an Average Day within February, May, August and November, 2017 and 2040.



Source: Navigant Consulting, 2015; GE Consulting, 2016.

We construct a multi-level CES utility function where, in the first level, consumer well-being is derived from consuming electricity and all other goods (AOG) subject to a budget constraint. At the second level, consumers decide on how to use electricity during a twenty-four-hour period. The maximization problem is shown in Equation 1, and the grouping of hours within the day are shown in Figure 6.

Equation 1. Utility function and budget constraint

$$max\ U = \left[\alpha * \left(\sum_{p,o} \beta(p,o) * \left(\sum_{i} \theta(i,(p,o)) * \sum_{hr} \gamma(hr,i) * \left(\frac{Q(hr)}{Q_0(hr)} \right)^{\rho_{hr}} \right)^{\frac{\rho_{p,o}}{\rho_{hr}}} \right)^{\frac{\rho_{all}}{\rho_{p,o}}} + (1-\alpha) * \left(\frac{Q(AOG)}{Q_0(AOG)} \right)^{\rho_{all}} \right]^{\left(\frac{1}{\rho_{all}}\right)}$$

$$subject\ to \sum_{hr} \left(P(hr) * Q(hr) \right) + P\,(AOG) * Q(AOG) = I$$

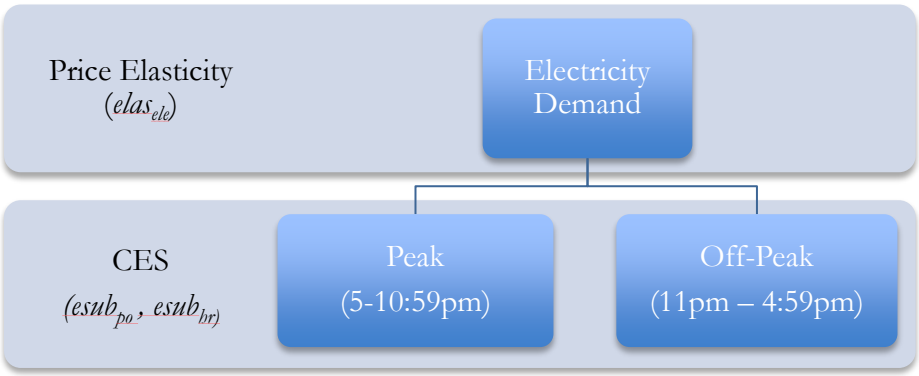
$$where: \rho_{all} = \frac{elas_{ele} - 1}{elas_{ele}}\ ;\ \rho_{p,o} = \frac{esub_{po} - 1}{esub_{p,o}}\ ;\ and\ \rho_{hr} = \frac{esub_{hr} - 1}{esub_{hr}}$$

α is the share of income spent on electricity purchases, 2.2% (DBEDT, 2016; ACS, 2016; UHERO, 2016); $\beta(p,o)$ is the share of expenditures of electricity spent in each period (peak and off-peak); $\gamma(hr,i)$ is the share of electricity expenditures spent on electricity for each hour within a block (see Figure 6); $elas_{ele}$ represents own-price elasticity, given as -0.07 in 2017 and -0.5 in 2040 (DBEDT, 2011);[17] $esub_{po}$ denotes the elasticity of substitution between the peak and off-peak period; $esub_{hr}$ is the elasticity of substitution between hours;

[17] Using annual per capita energy consumption and price (inflation-adjusted) data from 1970 to 2008 in a multi-variable log-log regression model, the Department of Business, Economic Development and Tourism (DBEDT) estimates that Hawaii residential price elasticity of demand for electricity is -0.07 in the short-run and -0.5 in the long-run.

$Q_0(hr)$ is the baseline consumption of electricity for each hour; $Q_0(AOG)$ is the baseline consumption of all other goods; and I represents the household budget following Oahu's average household income, $79,000 in 2017 and $85,000 in 2040 (ACS, 2016; UHERO, 2016).[18] $P(AOG)$, or the price (expenditure) of all other goods is taken to be exogenous. $P(hr)$, or the price of electricity in each hour, is also exogenous. For RTP it is based on the production cost modeling estimates for the cost of electricity provision in that hour, accounting for curtailment and fixed cost. TOU rates are shown in Figure 4. The model solves for $Q(hr)$, the quantity of electricity consumed in each hour under RTP or TOU rates, and $Q(AOG)$, the quantity of all other goods. The utility function models a representative household. To solve for the aggregate effect, we multiply by the number of residential customers, 269,000 for 2017 and 309,000 for 2040 (DBEDT, 2016; DBEDT 2012). Each model solve is done for the time period of one day, and the model loops through all 365 days of the year.

Figure 6. CES Daily Electricity Demand Function – Nesting Structure



The peak and off-peak hours are based on the residential electricity demand patterns exhibited in Figure 5. CES parameters are applied to peak and off-peak time periods, as well as between hours in the peak and off-peak (see *3.5 Scenarios*, below).

To estimate the welfare implications of RTP and TOU in comparison to flat-rate pricing, we apply a measure of Hicksian Equivalent Variation (EV), as shown in Equation 2.

Equation 2. Welfare Change

$$EV(p^{flat}, p^{RTP,TOU}, I) = e(p^{flat}, u^{RTP,TOU}) - e(p^{flat}, u^{flat}) = e(p^{flat}, u^{RTP,TOU}) - I$$

where p^{flat} is the initial flat-rate price vector; $p^{RTP,TOU}$ is the new RTP or TOU price vector; I represents income, which is a function of one's utility (u) and prices (p). The flat rate is computed such that consumers are no better or worse off under RTP and TOU given the same electricity usage pattern. Given business as usual electricity usage patterns, consumers' expenditures on electricity would be the same under the flat price, RTP prices, and TOU

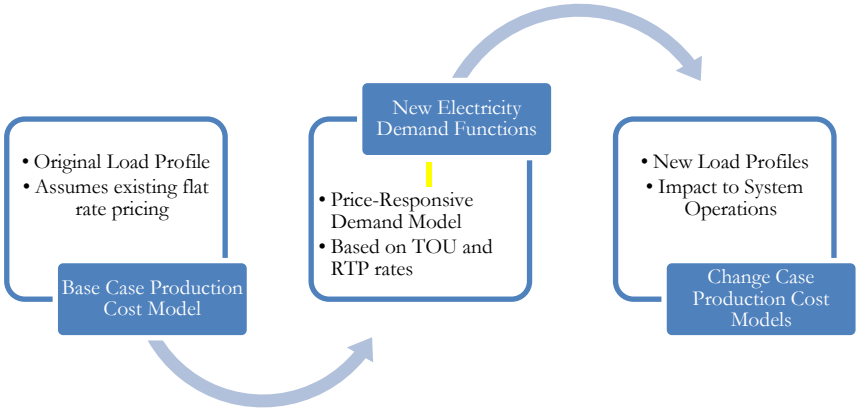
[18] We apply UHERO's real median family income year-on-year growth rate for Oahu to the American Community Survey's Oahu median household income in 2015 to obtain the median household income in 2017 and 2040.

prices. The flat rate is 24 cents/kWh and 19 cents/kWh in 2017 and 2040, respectively. Because we are not considering the cost of program implementation, such as the installation of smart meters or the cost of data collection and management, our estimates of welfare are solely of the benefits of time varying pricing to the consumer. The impact to the system is estimated by iteration with the production cost model.

3.3 Iteration

The results of the electricity demand functions created a new hourly residential demand profile for the year. The change to the underlying load forecast updated replaced the original load profile utilized in the production cost model. The production cost model was then simulated again to determine the least-cost commitment and dispatch of the power grid. This created a series of "change cases" that could be compared back to the Base Case which excluded the impact of TOU and RTP structures. Periods with increased loads required additional generation that could be served by curtailed renewable energy (if available) or conventional thermal generation if required. Periods with decreased loads required generators to either decrease output or turn offline. The new load profiles were still modeled exogenously to the production cost model, and therefore could not be adjusted in real-time given system conditions on the power grid.

Figure 7. Model Iteration



The system benefits of the new rate structures technologies were calculated by comparing the change to production cost when each new load profile was added to the grid (in isolation), relative to the Base Case without any change to the underlying load profile. Production costs included in the analysis include fuel costs, variable operations and maintenance cost (VO&M), and generator startup cost. It was assumed that all wind and solar generation was priced as a fixed take-or-pay power purchase agreement. Thus, any reduction in wind and solar curtailment was a direct savings to the system. Any changes to system operations and associated production costs can be directly attributed to the new rate structure.

3.4 GHG Impacts

To capture environmental impacts related to renewable energy integration, we use the EPA's "social cost of carbon" (EPA, 2015)[19] to estimate the value of GHG abatement. We assume that absorbed wind and solar PV curtailment displaces oil-fired generation, and the value of GHG abatement is shown in Equation 3 below. This does not account for any rebound effect in electricity demand, as it is unclear how that generation would be met.

Equation 3. Household GHG Savings

$$Household\ GHG\ Savings_t = \frac{reduced\ curtailment_t * social\ cost\ of\ carbon_t * fuel\ oil\ emission\ factor}{number\ of\ households_t}$$

where *social cost of carbon* = \$43/MTCO$_2$ in 2017 and \$72/MTCO$_2$ in 2040 (scaled to 2016 dollars), *fuel oil emission factor* = 0.67 MTCO$_2$/MWh (based on Oahu's 2015 generation profile and emission factors by fuel type) (EIA, 2016; EPA, 2014) and *number of households* = 269,000 in 2017 and 309,000 in 2040 (DBEDT, 2016; DBEDT, 2012).[20]

3.5 Scenarios

For the purposes of understanding the value of load-shifting under RTP and TOU with differing levels of intermittent renewable energy capacity, we adopt two scenarios for each 2017 and 2040 that address uncertainty in the availability and adoption of technologies to enable load shifting. For the 2017 scenario, we use DBEDT's (2011) estimate for short-run elasticity of demand for electricity in Hawaii, -0.07, and CES values for peak to off-peak electricity demand of 0.05 and 0.15 for the "moderate" and "optimistic" scenarios, respectively, which cover a range of literature estimates of recent pilot studies provided in Figure 1. We adopt 0.15 and 0.45 as elasticity values for substitution among hours within either the peak or off-peak blocks for the moderate and optimistic scenarios, respectively.[21] Since all CES values are non-zero, this means customers respond to prices both by shifting their electricity usage to different hours of the day as well as through increasing or reducing consumption.

For 2040, we assume that real income rises by 6% (see footnote 20). By adjusting for income growth, we ensure that there are no "income effects" between the 2017 and 2040 scenarios. We adopt DBEDT's (2011) estimate of -0.5 for the long-run price elasticity of demand. We

[19] For the social cost of carbon, we use values from the EPA's case that assumes a 3% discount rate. The social cost of carbon includes global environmental costs.

[20] We adopt the number of households in 2015 to reflect the number of households in 2017. The number of Oahu households in 2040 is derived from scaling DBEDT's resident population forecast by the average household size in 2010 (U.S. Census Bureau, 2011) and projected size in 2040 (DBEDT, 2012), and applying the growth rate to the number of households in 2015.

[21] The elasticity values at this level of inter-hour substitution for Hawaii are largely unknown, which is why we choose a reasonable range based on prior studies. Our intent is not to pin down a precise elasticity estimate, but rather to show a set of possible outcomes, with an emphasis on the differences between rate structures.

adopt CES values between peak and off-peak electricity of 0.2 and 0.4 for the "moderate" and "optimistic" scenarios, which covers the high-end of estimates provided in Figure 1. For the moderate scenario, we assume that hours are three times more flexible than the peak to off-peak and for the optimistic scenario we assume a factor of four. This gives CES values for between-hour substitution of 0.6 and 1.6. Table 2 summarizes the elasticity values used in each scenario.

Table 2. Scenario Summary

	Scenario			
	2017		2040	
	Moderate	Optimistic	Moderate	Optimistic
Price Elasticity	-0.07	-0.07	-0.5	-0.5
CES: Peak v Off-peak	0.05	0.15	0.2	0.4
CES: Between Hours	0.15	0.45	0.6	1.6

Due to the limited information on elasticity parameters, particularly under future technology, the range provided here are really meant to provide a wide that reflects development of future technology by which to test the sensitivity of rate design. Results are provided primarily to assess the value of RTP or TOU to consumers, estimated as an equivalent variation measure of welfare. Within each scenario, these results should be robust in terms of the comparison among rate structures. Results will also estimate the magnitude of load-shifting as a result of adopting residential RTP or TOU rates, the value of RTP or TOU to GHG abatement, and the impact of rate design to system costs; however, these estimates should be interpreted with caution because they will by definition be highly sensitive to elasticity. For tractability of presentation, we provide results for an average day for the months of February, May, August, and November.

4. Key Findings

We find that RTP benefits households substantially more than TOU, and the absolute benefits of each increase with higher penetration of intermittent sources of renewable energy. For 2040, RTP could increase household benefits by up to $335 annually relative to flat-rates while TOU provides benefits of $200 (optimistic scenario). However, in the near term, the relative benefits of either program to households are rather small – on the order of $34 and $7 annually per household for RTP and TOU (optimistic scenario). Because RTP clearly provides a better match between supply of intermittent sources of energy and hourly demand, we have similar findings for reduced curtailment and, subsequently, the value of GHG abatement.

4.1 Load-Shifting

Under RTP in 2017, as shown in Figures 7 and 8 (left panels), we estimate that residential load increases by roughly 2-6% during high sun hours (10am – 3pm), depending on the elasticity. In the late evening and early morning hours, load similarly increases to

accommodate, for example, wind energy. In contrast, during the evening hours from about 5-10pm, load falls by 2% to 10%. The period from 7-9am is challenging because residential electricity demand begins to ramp up, under flat rates, yet generation from solar PV is relatively small. Prices become more expensive in this time period and usage relatively declines by up to 10% in the optimistic scenario. This effect is most pronounced in the winter months, shown by November and February. In addition, a similar pattern occurs when solar begins to wane at the end of the high sun hours. In this case, during 3-4pm, usage remains similar to patterns seen under flat rates. Because there are fewer renewable resources in the near-term, the overall relatively small change in electricity usage patterns results in enormous absorption of curtailment on a percentage basis – an estimated 90% and 98% of the 1.9 GWh's of otherwise curtailed energy in the moderate and optimistic scenarios.

In comparison, under TOU rates in 2017 (Figures 8 and 9, right panels), loads experience similar patterns of movement, though the magnitude is smaller because these rates provide a much less perfect connection between available supply and demand. Load during the high sun hours increases by 0.5-2%, and the late evening and early morning hours (11pm – 7am), by 1-4%. Load similarly increases during the 4-6pm block despite the slight increase in prices. This is because there is a shift in usage away from the other peak hours (i.e., 6pm-11pm) in which the price of electricity increases far more than in the 4-6pm block. Note also that there is nearly no variation in hourly electricity demand between months because TOU rates are fixed for the entire year. Because TOU rates are more blunt than RTP, only 18% and 44% of otherwise curtailed energy is absorbed in the moderate and optimistic scenarios.

A more long-run perspective on customer ability to shift load via behavioral changes and technology adoption, are shown in Figures 10 and 11 for the 2040 "moderate" and "optimistic" scenarios.

Figure 8. 2017 "Moderate"
Percentage Change in Residential Electricity Demand from Baseline by Month[22]

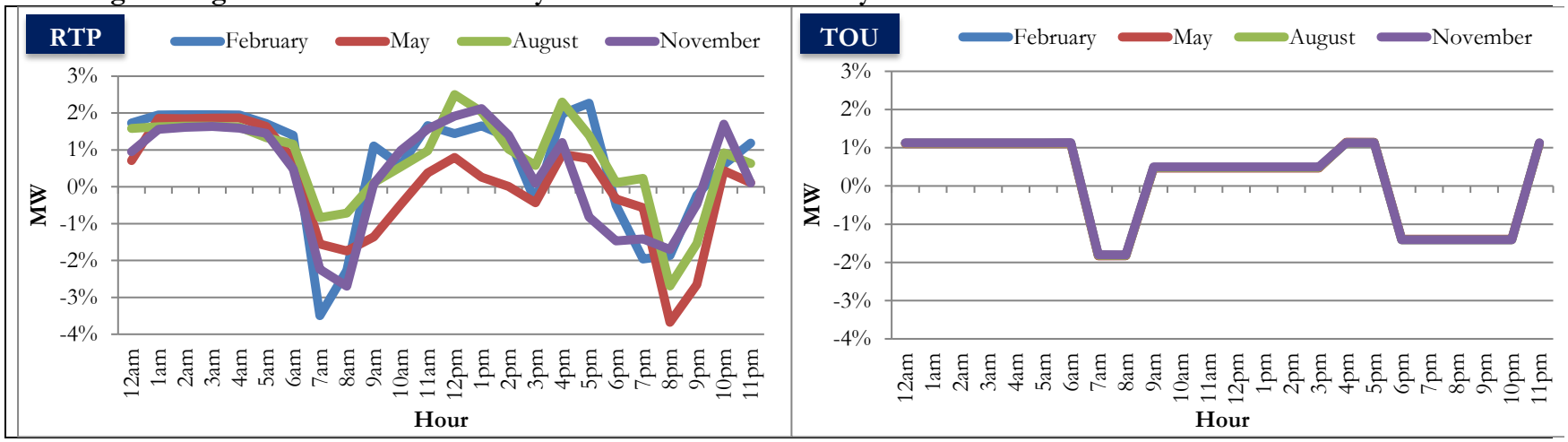
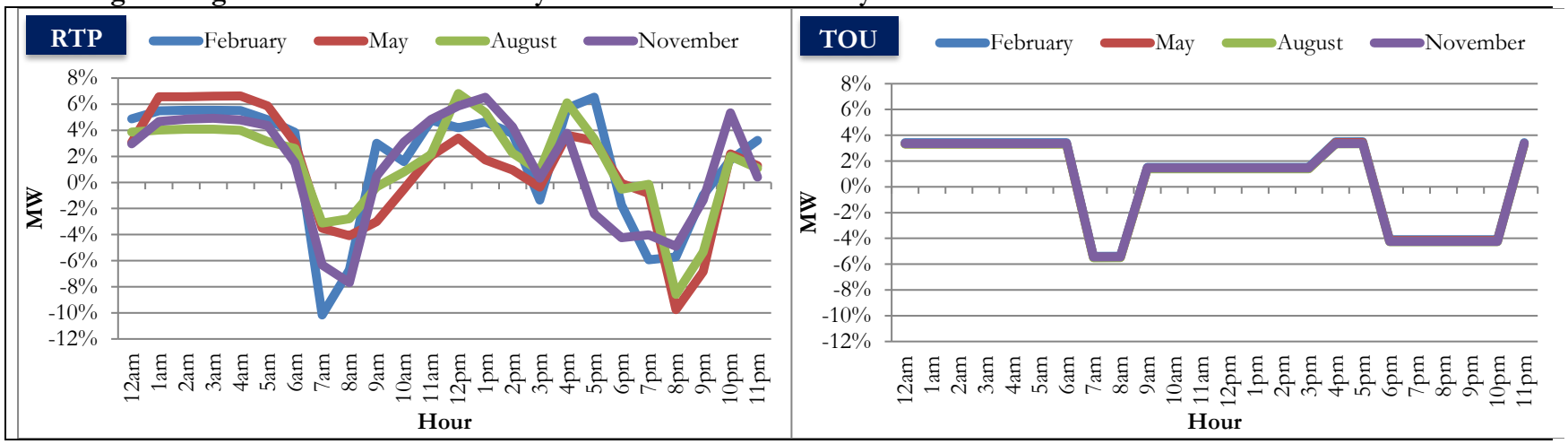


Figure 9. 2017 "Optimistic"
Percentage Change in Residential Electricity Demand from Baseline by Month



[22] Technically the slopes in this figure as well as Figures 8 thru 10 should be vertical since results are reported on an hourly basis.

Figure 10. 2040 "Moderate"
Percentage Change in Residential Electricity Demand from Baseline by Month

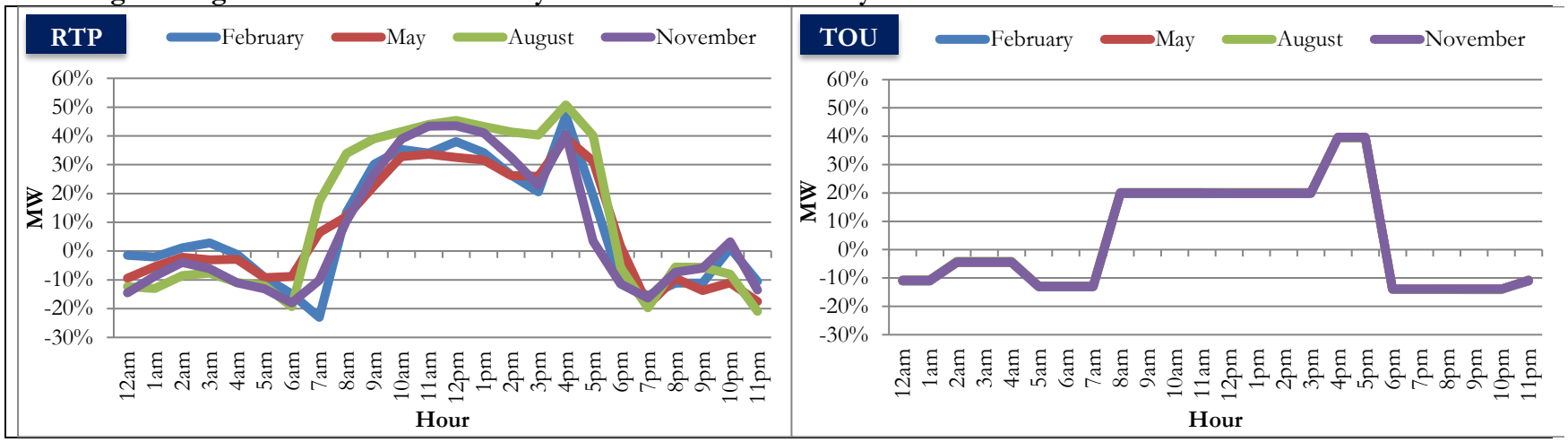
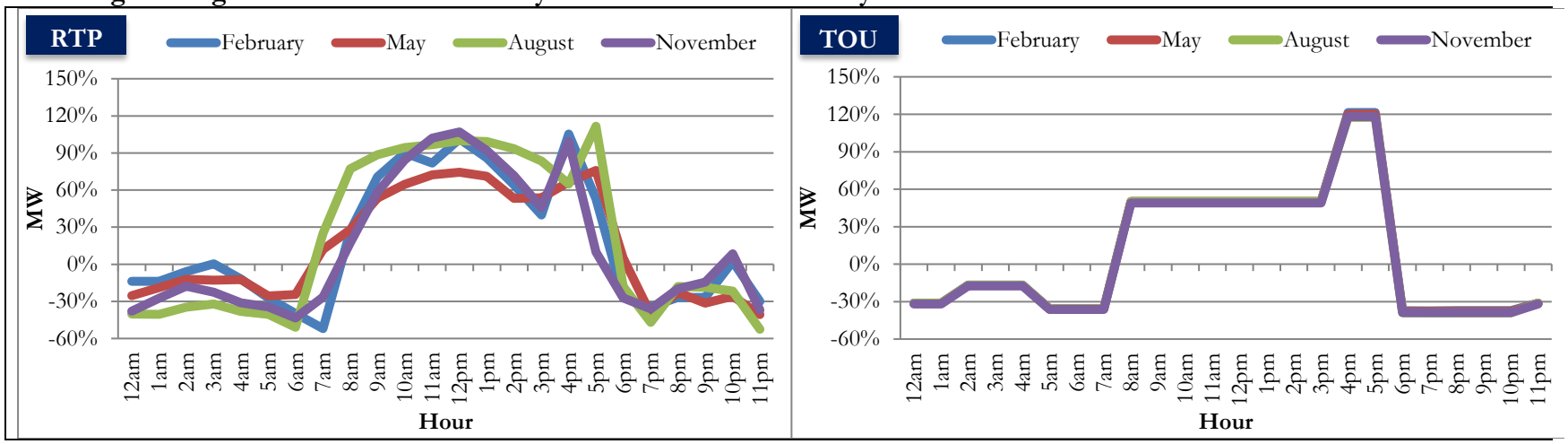


Figure 11. 2040 "Optimistic"
Percentage Change in Residential Electricity Demand from Baseline by Month



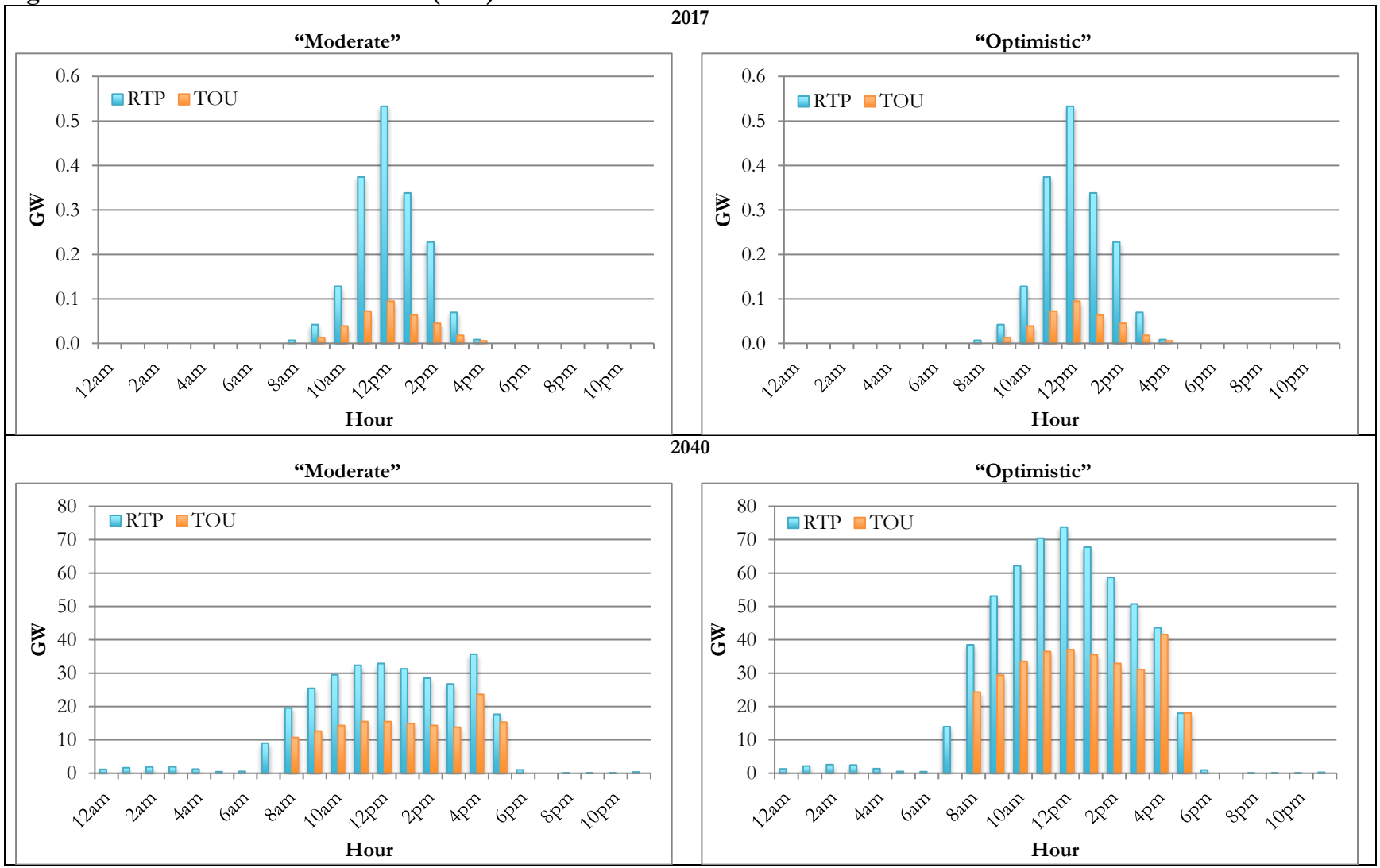
The 2040 scenario introduces considerable amounts of solar-based energy and our results reflect shifts of the load profile to high sun hours. The "moderate" scenario finds that under RTP there is an up to 50% increase in usage during high sun hours, when prices are nearly 50% lower. Usage declines during all other hours. Overall electricity demand increases by about 9% as a result of lower cost electricity. Though there is a similar "rebound" effect in the 2017 scenario, it is less than 0.4%. Under TOU rates, electricity demand follows a similar shape. However, the magnitude of load-shifting to the daytime hours is less than half that under RTP; between 8am-4pm, loads increase by 20%. Though 4-6pm are peak hours, loads are higher by 40% because its TOU price is far below that of the 6-11pm block. Therefore as with the near-term results, load shifts from the highest price peak hours to the much less costly hours in the peak period; electricity prices are more than twice as great in the 6-11pm period than in the 4-6pm period. The rebound effect under TOU in 2040 is approximately 4% (where it is negligible in 2017).

The "optimistic" scenario leads to an even larger amount of load shifting, to over 100% increase during daytime hours under RTP. There is a similarly large rebound effect of 18% because households can lower their electricity bills by shifting their load thus leaving them with additional money to spend on electricity and all other goods. The optimistic scenario assumes tremendous flexibility across hours within blocks of time; thus there is a significant movement among hours within a block, and not just across blocks of time. Similarly, increases in demand under TOU rates are largely concentrated in daytime hours (due to solar PV and the resulting 9 cents/kWh to 15 cents/kWh difference between the 8 – 6pm period and adjacent periods), increasing by roughly 50% compared to the baseline between 8-4pm, and by 120% between 4-6pm. Total electricity demand increases by 10% as a result of consumers being able to reduce their electricity bill for the same level of electricity demand. Lastly, due to the more than two-fold increase in renewable capacity in 2040, curtailed renewable energy increases from 1.9 GWh to 970 GWh under flat rates. Replacing flat rates with RTP or TOU lead to the absorption of 58% and 33%, respectively, of this otherwise curtailed energy in the optimistic scenario.

4.2 Avoided Curtailment

In the absence of time varying pricing, the majority of excess renewable energy occurs during high sun hours. The main curtailment occurs between 9am and 4pm. However, in 2040, baseline curtailment also extends outside of daytime hours due to the 350% or 440 MW growth in wind capacity. While under TOU rates there is no benefit (i.e. change in one's electricity bill) to switching among hours within a TOU block, the flexibility of RTP means there is incentive to substitute demand within a block of hours. Hence the amount of avoided curtailment is larger under RTP than TOU. Figure 12 illustrates the sum of annual avoided curtailment by hour as a result of RTP and TOU in all four scenarios.

Figure 12. Annual Avoided Curtailment (MW)



4.3 Consumer and Environmental Welfare

The introduction of time varying pricing allows for efficiencies within the power system, with benefits to consumers as well as reductions in GHG emissions. Using the metric of Hicksian Equivalent Variation, Figure 13 summarizes findings for the increase in annual household welfare (measured in 2016$/household) as a result of RTP and TOU in comparison to today's flat-rate pricing scheme. This computation is solely a measure of direct benefit to households because neither the costs of program deployment nor the benefits of reducing GHG emissions are included (see Section 5 for further discussion). Under RTP, there is a household benefit of $13 to $34 in 2017 and, in 2040, up to $335. This result seems qualitatively comparable to Alcott's (2011) estimates that find within the pilot RTP program in Chicago, consumer surplus increased by $10/household, though Oahu and Chicago clearly have different electricity rates and electricity consumption needs (heating versus cooling). The cumulative benefit to Oahu residents amounts to as much as $9 million in 2017 and $103 million in 2040. Under TOU there is a per household benefit of $2 to $7 in 2017 and up to $200 in 2040; the total benefit to Oahu residents is up to $2 million in 2017 and $60 million in 2040.

Figure 13. Change in Household Benefit (2016$/household)

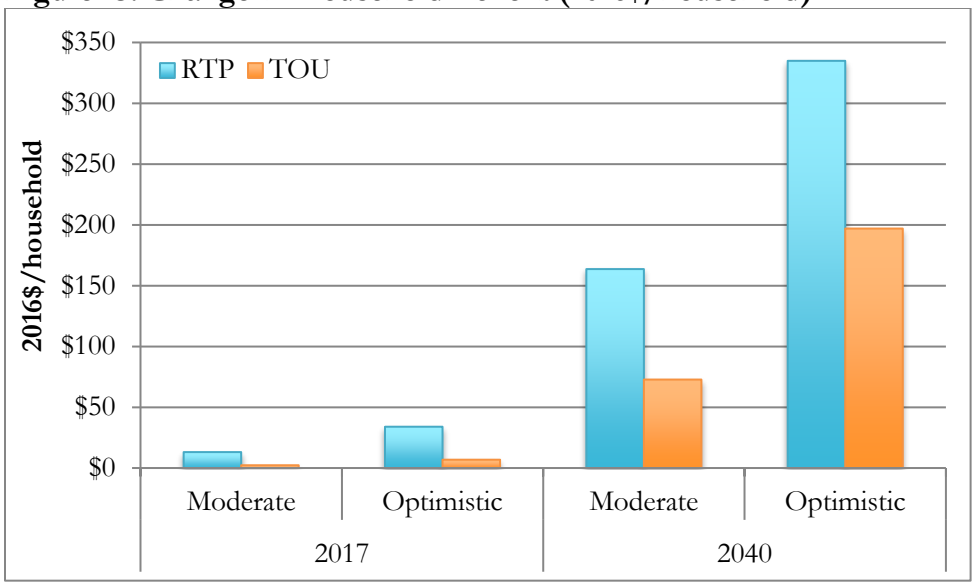


Table 3 below shows our estimates for the value of GHG abatement. For comparison to the welfare calculation, we estimate global GHG abatement value, scaled per household. These are global benefits as GHGs are a global pollutant and reducing GHGs in one location has benefits throughout the world. Since the social cost of carbon measures global benefits, our estimated benefits are global in scale.

Table 3. Value of GHG Abatement

	GHG Savings (2016$/household)			
	2017		2040	
	Moderate	Optimistic	Moderate	Optimistic
RTP	$0.19	$0.20	$47	$88
TOU	$0.04	$0.09	$24	$50

We estimate there is a $0.09 to $0.20 benefit in terms of GHG abatement per household in the year 2017 for TOU and RTP, respectively. In level terms, this amounts up to $24,000 under TOU and $54,000 under RTP. Because there is much more expected curtailment under flat rate pricing in 2040, the value of TOU or RTP as a GHG abatement strategy rises substantially. Under TOU rates in 2040, we estimate a range of $14 to $50 per household for the moderate and optimistic scenarios, totaling $7 to $15 million in global benefits. With RTP, GHG savings amount to $47 to $88 per household, translating to $14 to $27 million.

5. Power System Impacts

5.1 Production Cost Savings

Flexible loads, either through TOU or RTP rates allows the power system to be run more efficiently. Rather than rely solely on changes to generation from the utility's power plants, rate design can incent consumers to decrease consumption during times traditionally served by expensive peaking units, and to increase consumption during times of surplus or lower marginal cost of generation. This leads to a reduction in annual production cost, which predominately includes fuel costs, but is also composed of variable operations and maintenance costs, and startup and shutdown costs associated with generating electricity.

These savings, referred to as avoided costs, are attributed to several changes to power system operations with flexible loads. In this example, TOU and RTP rates better align the grid's hourly load profile with wind and solar resource availability. At high renewable penetration levels, this can shift energy to time periods of surplus renewable generation and can reduce the amount of curtailment on the grid that could not be utilized previously due to insufficient demand or other grid constraints. Because wind and solar generators are zero marginal cost resources (i.e. no fuel costs), the reduced curtailment saves considerable money because it offsets the fuel consumption of oil-fired generation.[23] Load is also shifted away from peak load periods traditionally served by less fuel efficient and thus expensive peaking generation.

In addition, the changing load pattern also smooth's and flattens the daily *net load* (load minus renewable energy) profile that must be served by the utility's resources. The flatter load profile minimizes the number of times generators must shutdown during low load periods and turn back online during high load periods. This decreased cycling reduces the start costs associated with turning a generator on and reduces maintenance costs and equipment degradation. In addition, a

[23] From the production side, we assume that all wind and solar costs are based on take-or-pay contracts where the utility must pay for the generation regardless of whether the grid can accept it.

flatter net load profile allows fewer units to be online for ramping requirements. This allows the remaining online generators to operate at higher, more fuel efficient generating points.

Table 4 provides a summary of the annual production costs and savings for each scenario, along with the total resource curtailment. From this table it can be observed that in the 2017 scenario, TOU and RTP rates have a relatively small impact on the grid's generation cost relative to the 2040 scenario. This is because the Baseline scenario in 2017 has minimal curtailment, and thus there is little opportunity to shift load previously served by oil-fired generation to zero marginal cost wind and solar resources. In addition, because most of the conventional thermal generators in Oahu are oil-fired, there is limited price differential between the generating fleet. As a result, the benefits of shifting generation from one plant to another is relatively limited.

Table 4. Changes to Power System Operations

	Baseline	TOU Moderate	TOU Optimistic	RTP Moderate	RTP Optimistic
	Value	*% Change*			
		2017			
Generation (GWh)	7,699	0.0%	0.0%	0.1%	0.3%
Curtailment (GWh)	2.0	1.3%	0.9%	-12.7%	-26.4%
Total Production Cost ($000)	$554,302	0.03%	-0.03%	0.2%	0.2%
Average Production Cost ($/MWh)	$72	0.03%	-0.03%	0.1%	-0.03%
		2040			
Generation (GWh)	7,709	1.05%	2.6%	2. 5%	4.6%
Curtailment (GWh)	971	-13.7%	-31.1%	-27.1%	-50.3%
Total Production Cost ($000)	$402,270	-1.5%	-1.3%	-2.4%	-3.3%
Average Production Cost ($/MWh)	$52	-2.5%	-3.8%	-4.8%	-7.5%

Table 4 also shows that TOU rates in the 2017 scenario increases annual production costs on the system. This is because the TOU rates are not able to differentiate between high renewable resource days and low renewable resource days, and instead follows a seasonal average. Therefore, in a lower overall renewable penetration scenario, a shift of additional loads to mid-day may actually increase the cost of generation on low solar days. A similar phenomenon is seen in the RTP scenarios. This is likely due to a saturation effect, where the arbitrage opportunity seen in the Baseline scenario collapses quickly when load is moved from a high price hour to a low-price hour because there is no surplus renewable energy to serve the shifted load.

The largest benefits are seen in in the 2040 scenario because the renewable penetration is highest (50% of available energy) and load is shifted from peak load hours to periods of surplus renewable energy. In this case, the benefits of the RTP scenario outweigh the TOU scenario because the load shift can more accurately follow the renewable resource availability (based on a zero marginal cost price signal associated with renewable energy) rather than seasonal averages.

6. Discussion and Conclusion

This study uses a detailed dataset of expected electricity generation costs aggregated up to hourly intervals for the year 2017 and 2040 to test the effectiveness of two time varying pricing mechanisms in terms of consumer benefit, grid management (measured in terms of changes in curtailed energy), and GHG emissions reductions. This dataset accounts for Hawaii's forecasted transition toward high levels of adoption of renewable energy by 2040. We use these data as the primary input into a household electricity demand model that represents the ability of residential customers to respond to either hourly RTP or block-based TOU electricity price changes – both overall and from one hour of the day to another. The model employs a nested CES utility function and is run for every day of the year. We report results for an average day in four representative months of the year: February, May, August, and November. Overall we find that RTP rates are between two to three times more beneficial to residential customers than TOU rates. Whereas RTP in the year 2040 could increase household welfare by up to $335 annually, TOU's comparable increase is on the order of magnitude of $200. In addition, whereas RTP could reduce curtailed renewable energy that appears under flat rates by up to 560 GWh, TOU could achieve only 57% of this reduction. Though the magnitude of GHG emissions abatement value is small in the near-term, with higher levels of renewable energy uptake by 2040, it becomes quite meaningful by the year 2040 – estimated at $27 million under the optimistic RTP scenario.

TOU and RTP rates also impact operations and efficiency of the bulk power system. Production cost savings increase significantly with increased renewable penetration because new load profiles are able to align better with underlying renewable resources, reduce curtailment, and offset generation from oil-fired plants. The benefits of the RTP scenario outweigh the TOU scenario because the load shift can more accurately follow the renewable resource availability rather than seasonal averages

5.1 Study Limitations and Future Work

We define RTP on an hourly basis and TOU rates set within five blocks of time for a day over the period of a year. Though this is a common means of setting TOU rates, additional efficiencies could be fairly straightforwardly gained by setting TOU rates by season, by day of the week (i.e., weekday versus weekend day), or adopting a variant of TOU plus CPP. These mechanisms would move TOU closer to our RTP estimates. However, because TOU rates inherently do not account for uncertainty within supply costs, even seasonally adjusted TOU rates could expose utilities to supply cost risks or result in costly load-management programs (Faruqui and George, 2002). Though Herter and Wayland (2010) find that residential CPP in California was a promising demand response mechanism even without technology or automation, absorption of intermittent renewable energy in many ways requires "critical low pricing." Future research could empirically assess whether consumer responses are symmetrical between high and low prices.

Moreover, our analysis provides a partial equilibrium perspective on the absorption of curtailment and its impact on prices. Within our study this is likely to be sufficient because there is such a large amount of curtailment and the residential sector is only a quarter of total load. Moving forward to study the broader commercial sector, however, may require better feedback mechanisms through a general equilibrium or iterative approach that captures the changes in electricity prices and potential saturation of the price arbitrage opportunities.

Our analysis assumes that either RTP or TOU rate mechanisms are adopted by all consumers, likely through mandatory pricing requirements. While our per household results might capture a range of possible behavioral and technological responses to time varying pricing, the aggregation of effects ultimately depends on the level of adoption related to voluntary programs. For opt-in programs, participants can often be a small subset of the total electricity customers. As of 2014 at least one utility in each state (with the exception of Rhode Island) offers time varying pricing, yet only 4% of residential customers are enrolled in programs (Sherwood et al., 2016). Because our analysis only identifies the average, or representative household, it cannot provide insight into load shifting behaviors or welfare implications of non-typical households that might voluntarily choose to opt in or out of time varying rate mechanisms. For example, considering demographics can be an important component in establishing time varying pricing programs. Often concern is cast regarding people who might be most vulnerable to rate changes, especially low-income households that might be least likely to participate in a voluntary program. Opponents of dynamic pricing often argue that electricity customers would be exposed to too much volatility (Alexander, 2010), while others contest the fairness of today's system of flat-rates (Faruqui, 2010). Wood and Faruqui (2010) found that low-income households tend to have flatter load curves than the average household and therefore are likely to benefit proportionately more from TOU rates, even without peak reduction. Borenstein (2013) presents an opt-in dynamic pricing program that provides options to minimize volatility and has no cross-subsidization between customer types.

Lastly, we do not consider the cost of implementing and maintaining time varying rate programs. Nor do we account for the potential benefits to the electricity grid and reduction in needed generation capacity or storage that would come about by households shifting their electricity load profiles. To ensure reliability, the grid is designed and sized to serve load at all times, and the required amount of generating capacity is based on the expected peak load, plus a planning reserve margin to account for uncertainty. Currently, the grid's peak load may only occur for dozens of hours out of the entire year. To the extent that TOU and RTP can reduce loads during those time periods, less capacity is required and the grid operator can defer new investments in expensive generating resources. Depending on the level of control and speed of response of loads enrolled in RTP rates there may be additional benefits associated with providing ancillary services. For example, if loads are able to respond within a few seconds of a utility's request, either via pricing or direct load control, it can be counted on as a regulating reserve resource which are used to balance the grid's short-term fluctuations in load and variable renewable generation. This decreases the need to utilize traditional generation for these purposes and leads to additional production cost savings. Future research could include a representation of capacity benefits associated with various pricing mechanisms that take into account the deferred cost of new generating capacity for reliability needs. In addition, as direct load control becomes more prevalent, the use of flexible loads for grid services like fast-frequency response, regulation reserves, and other ancillary service needs.

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