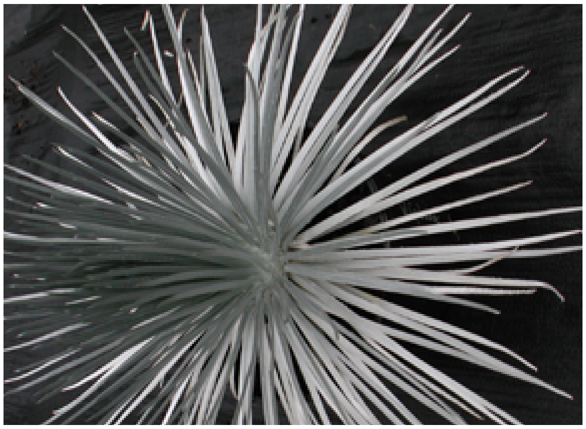

UHERO
THE ECONOMIC RESEARCH ORGANIZATION
AT THE UNIVERSITY OF HAWAIʻI

ENERGY POLICY & PLANNING GROUP

Estimating the Opportunity for Load-Shifting in Hawaii:
An Analysis of Proposed Residential Time-of-Use Rates

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EXECUTIVE SUMMARY

Hawaii's largest electric utility, Hawaiian Electric Company (HECO) and its subsidiaries recently proposed a Time of Use (TOU) pricing scheme for residential rates. The TOU scheme has three tiers of prices: daytime, on-peak, and nighttime. The proposed rates have the highest cost during the on-peak period from 5pm to 10pm. For Oahu, the lowest cost is at nighttime, from 10pm to 9am. The difference between high and low rates is $0.33/kWh. For Maui and Hawaii Island, the lowest cost is during the daytime, 9am to 5pm. The difference between high and low rates are $0.35/kWh and $0.50/kWh, respectively. It is not stated whether the rates will be implemented as an opt-in, opt-out or mandatory program. This report summarizes literature on time varying pricing for residential rates to inform Hawaii's electricity stakeholders, including ratepayers and policy-makers, of the potential impacts and considerations regarding the potential for TOU pricing in Hawaii.

Using a simulation model of consumer electricity demand coupled with historic residential electricity load data, we estimate the magnitude of load-shifting potential as a result of proposed residential TOU rates. Using estimates from the literature as well as a more bottom-up approach to characterizing typical household appliance usage, we develop three scenarios to characterize consumer responsiveness to HECO's proposed TOU rates. Our results assume that all residential customers follow the new rate schedule, and thus serve as an upper-bound for actual impacts. We find in our scenario based on the most common literature estimates that the proposed TOU rates could lead to a 10% reduction for on-peak electricity usage by participating residential consumers, and increase daytime and nighttime consumption by 9% and 8%, respectively. The reduction in daytime and nighttime rates results in an overall net increase in electricity demand, by about 3%. Because residential electricity demand is about a quarter of overall electricity usage in Hawaii, we find there is a 1.7 and 2.4% increase in nighttime and daytime demand, respectively, and a slightly larger decline of 2.8% in on-peak loads.

This study has several limitations. First, estimating the probability of opting in or out of such a program is outside the scope. However, experience with similar voluntary programs on the U.S. mainland suggests that the actual response rate is low – with fewer than 4% of residential customers. The magnitude of opportunity for gain from such a program in Hawaii is larger, however, because electricity rates as well as the proposed difference between daytime/nighttime and on-peak rates are higher than in the continental U.S. Second, we are not accounting for existing solar photovoltaic (PV) customers who would be highly unlikely to sign up for TOU rates. Third, we do not account for the effect of declining battery system costs on load-shifting potential.

The learning opportunity from this kind of TOU program, particularly if operationalized in an experimental fashion with variation in household technology and information, may be important in understanding adoption of real-time-pricing (RTP). While TOU pricing may be a first step to matching times with high levels of renewable energy supplies and consumer demand in the aggregate, it is RTP for all customer classes that provides part of the solution to system stability with high penetration of intermittent renewable energy. This is an area of future inquiry.

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I. INTRODUCTION

Most electricity companies offer electricity at a set retail price that attempts to account for the average wholesale cost of electricity production that can fluctuate on an hourly, daily, and seasonal basis (Borenstein, 2005a). Time-of use (TOU) pricing, critical peak pricing (CPP), and real time pricing (RTP) are all time varying pricing schemes that set prices based on the timing of electricity usage. Time varying pricing attempts to gain efficiencies by moving electricity prices away from average pricing and closer to marginal pricing. Doing so encourages users to shift their energy consumption to times when costs to generate are relatively low (Boiteux, 1960; Borenstein, 2005b). The difference between average and marginal pricing is increasingly relevant with high levels of intermittent renewable energy adoption. Ideally, these pricing schemes provide incentive for electricity users to shift their load to times of day when generation costs are lower, which often coincides with times when more renewable resources are available. Depending on the pricing scheme, this can help provide a better match of demand to available renewable supplies in the aggregate or even on a minute-to-minute basis.

TOU pricing is a general term that establishes different rates for specified blocks of time during the day. CPP is a variant of TOU pricing, which most commonly refers to programs that focus on bringing down electricity demand during peak usage, usually in the evening for residential customers. RTP more closely follows the actual cost of electricity generation with prices set on an hourly basis or at greater frequency. This comes closest to a "dynamic" pricing scheme. Opponents of dynamic pricing often argue that electricity customers would be exposed to too much volatility (Alexander, 2010). However, "the presumption of unfairness in dynamic pricing rests on an assumption of fairness in today's tariffs" (Faruqui, 2010). RTP is the only pricing scheme that aims to address the problem of incremental cost volatility as a result of integrating intermittent resources. The price feedback between the utility and the customer provided by RTP helps send signals to the utility to bring additional generation online during periods of rapid rises in consumption or take them offline during periods of potential curtailment. It helps send signals to customers to incent electricity usage when costs to generate are low and dissuade electricity usage when costs to generate are high.[1]

Hawaii's largest electric utility, Hawaiian Electric Company (HECO) and its subsidiaries recently proposed a TOU pricing scheme for residential rates. The TOU rates were submitted in response to a request by Hawaii's Public Utilities Commission (PUC). This scheme has three tiers of prices: daytime, on-peak, and nighttime. The proposed pricing during the on-peak is akin to CPP, coupled with very low pricing during the daytime and nighttime periods. This report summarizes literature related to time varying pricing for residential rates with the purpose of informing Hawaii's electricity stakeholders, including ratepayers and policy-makers, of the potential impacts and considerations regarding TOU pricing in Hawaii. Using a simulation model of consumer behavior coupled with historic residential electricity load data, we estimate the magnitude of load-shifting potential as a result of these proposed residential TOU rates.

We organize this paper as follows. In Section II, we discuss the framework and goals of Hawaii's proposed

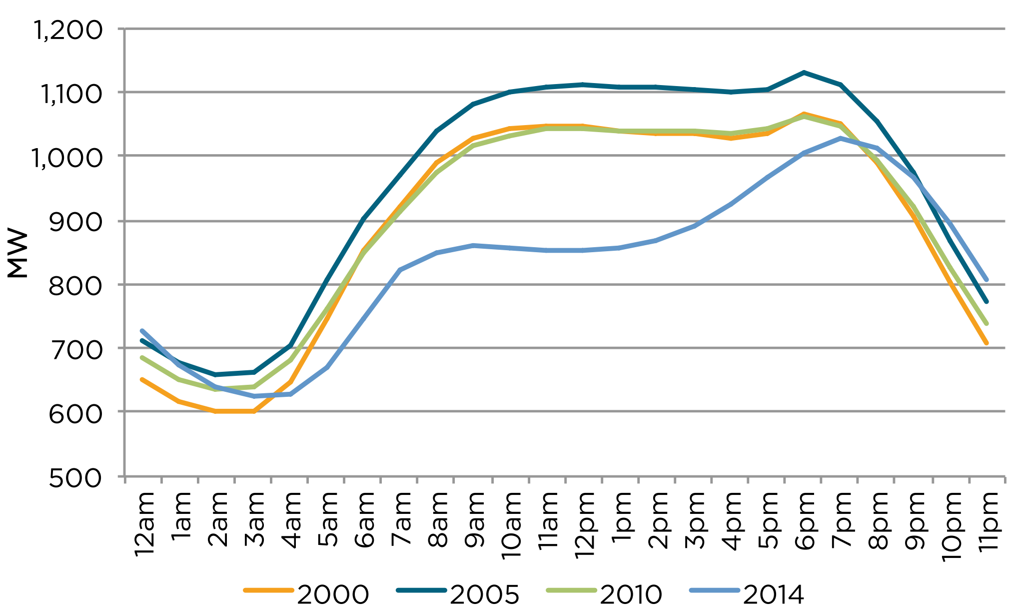
1 This is a rather simplified statement of the interaction of loads and intermittent energy. Clearly there is a more complicated relationship based on issues of spinning reserves or other storage technologies.

TOU rates. In Section III, we take a broad view of other studies that analyze households' propensity to consume electricity when prices change. We further examine residential consumer's motivation to shift load under a TOU pricing scheme. In Section IV, we present a simple consumer model for residential electricity demand and describe our three scenarios of consumer electricity price sensitivity. In Section V, we report key findings from our analysis. Lastly, in Sections VI and VII, we provide discussion and concluding remarks, respectively, focusing on additional considerations and impacts regarding TOU pricing.

II. HAWAII'S TIME-OF-USE PRICING PROPOSAL

As Hawaii progresses towards its renewable energy goals, electric utilities face the challenge of integrating large amounts of intermittent renewable energy resources. Hawaii has a tremendous amount of solar photovoltaic (PV), which has served to bring down the mid-day load in terms of utility service requirements (Figure 1). It has also created this so-called "duck shaped" load curve, where the on-peak requires fast ramp up to meet the spiking load as generation from solar PV declines. Figure 1 below shows the change in the aggregate average daily load from 2000 to 2014. While there are many factors affecting overall demand, and potentially load shape, it is clear that the mid-day load has dramatically declined over the last decade. As mid-day load decreases with increased solar PV penetration, meeting evening load requires greater ramping up of utility electricity supply, as exemplified in the 2014 load curve for Oahu.

Figure 1. Oahu Hourly Net Load Data



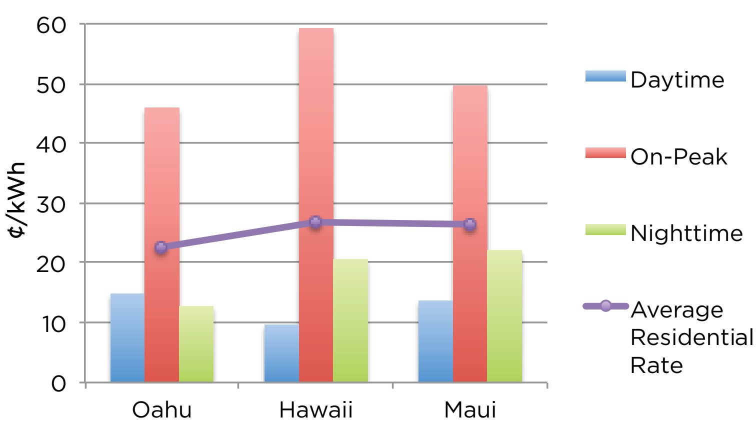
Source: FERC, 2015.

To encourage shifting residential demand away from evening hours, HECO and its subsidiaries proposed TOU rates in November 2015 for its service area: Oahu, Hawaii Island, and Maui. The rate proposal is currently up for review by the PUC. If approved, the rates would include a rate schedule for residential customers with a three-tiered price scheme. It is unclear, however, how TOU rates might be implemented. In theory they can be mandatory or have an opt-in or opt-out provision.

In the most recent proposal submitted to the PUC in April 2016 (Hawaiian Electric Companies, 2016a),[2] the rates generally adjust from lowest cost for electricity usage during the daytime period from 9am to 5pm, the highest cost during the on-peak period from 5pm to 10pm, and a middle cost during the nighttime period from 10pm to 9am—with the exception of Oahu (Figure 2).[3] The daytime/nighttime rates are set according to the projected marginal cost of generation in 2017. Oahu's nighttime rate is set two cents lower than its daytime rate, likely due to its primary reliance on inexpensive coal-fired generation. On-peak rates are adjusted to compensate for fixed costs.

Hawaii's TOU proposal aims to move loads away from the on-peak hours. The differences between high and low TOU rates are \$0.33/kWh on Oahu, \$0.35/kWh on Maui, and \$0.50/kWh on Hawaii Island.

Figure 2. Residential TOU Electricity Rates Compared With Flat Rate[4]



Source: Hawaiian Electric Companies, 2016a

2 This proposal follows an earlier request submitted by Hawaiian Electric Companies in March 2016 (Hawaiian Electric Companies, 2016b), both of which are in response to the PUC's request to update and provide alternative rates designs. We select one of the rate schedules ("PUC-HECO-IR-20-a-i") that is based on allocating fixed costs in the on-peak period and holds the daytime rate constant.

3 These identified time periods do not necessarily coincide to times of low and high demand, though this varies with season and weather.

4 To eliminate an additional income effect, the flat rate is calculated such that an average household's electricity bill would be the same if they did not change their usage. While our calculated flat rate for Oahu is nearly identical with that reported under Schedule R in "PUC-HECO-IR-20-a-i", Hawaii's rate is lower by nearly \$0.02, and Maui's by \$0.07. See Section IV (Methodology and Scenarios) for further details. Also, the rates for Maui reflect that of Maui Island; for modeling purposes, the rest of Maui County is omitted from the analysis since their electricity demand makes up less than X% of the statewide total.

III. RESIDENTIAL PRICE ELASTICITY RESPONSES: A REVIEW OF EXISTING STUDIES

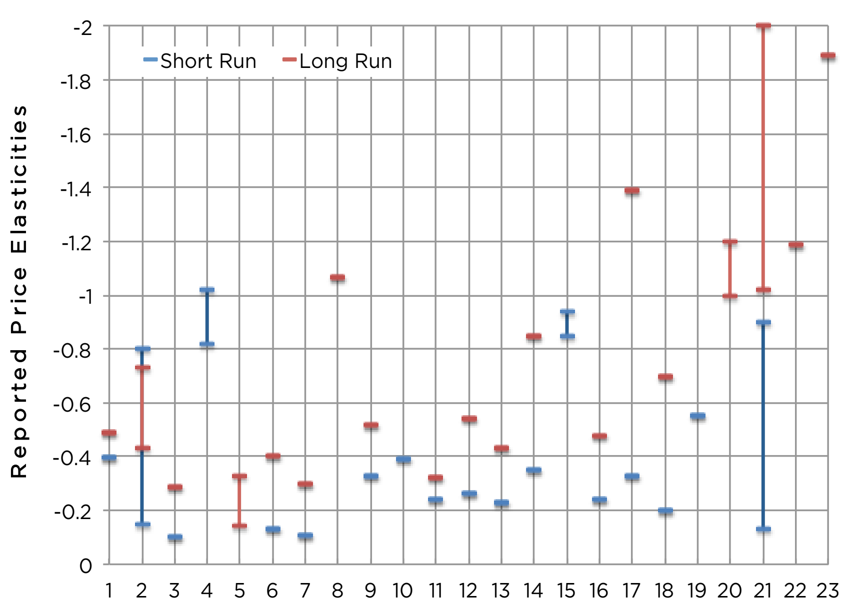
Time varying pricing has been tested and used by select utility companies in the U.S. and abroad for decades. The first major effort in the U.S. to study time varying pricing schemes began in 1975 driven by the U.S. Department of Energy (DOE). These early studies brought to light the difficulty in determining a generalizable estimate of how consumers respond to electricity price changes. Within the field of economics, the parameter that is used to measure consumer sensitivity to prices is called *price elasticity of demand*. In shorthand, this is often referred to as "demand elasticity," and is calculated as the ratio of the percentage change in quantity demanded to the percentage change in price.

Consumer Price Responsiveness: Short-Run and Long-Run

Estimating demand elasticity is important to understanding expected aggregate consumer response to price changes. When electricity prices first shift, consumer response tends to be limited, with only minor changes in demand. Over time, however, consumers exhibit greater responsiveness on the whole, and in some cases show major changes in electricity consumption. This greater responsiveness over time may be due to opportunities for technology adoption, such as investing in more efficient appliances.

Differences between short- and long-run demand elasticities, as found in twenty-three studies for the U.S. and other developed economies, are shown below in Figure 3. Short-run elasticities are reported in blue and long-run in red. The markers indicate either the single value reported by the study or the bounds of the range of values.

Figure 3. Short- and long-run price elasticity of demand, as reported in identified studies



1 - Okajima and Okajima (2013) - Japan
2 - Alberini and Filippini (2011) - US
3 - EPRI (2010) - US (regional)
4 - Fell et al. (2010) - US (4 Census tracts)
5 - Nakajima and Hamori (2010) - US (48 states)
6 - Paul et al. (2009) - US (regional)
7 - Metcalf (2008) - US (4 Census regions)
8 - Dergiades and Tsoulfidis (2008) - US
9 - Halicioglu (2007) - Turkey
10 - Reiss and White (2005) - US (California)
11 - Bernstein and Griffin (2005) - US (regional)
12 - Narayan and Smyth (2005) - Australia
13 - Dahl and Roman (2004) - US
14 - Epsey and Epsey (2004) - US (48 states)
15 - Kamerschen and Porter (2004) - US
16 - Silk and Joutz (1997) - US
17 - Chang and Hsing (1991) - US
18 - Bohi and Zimmerman (1984)
19 - Barnes et al. (1981) - US
20 - Halvorsen (1975) - US (48 states)
21 - Taylor (1975) - US and UK
22 - Houthakker et al. (1974) - US
23 - Houthakker and Taylor (1970) - US

Elasticity estimates less than one (in absolute value) are considered "inelastic," meaning there is less than a one percent change in the quantity of electricity demanded for every one percent change in the price of electricity. Elasticities greater than one (in absolute value) are considered "elastic," meaning there is more than a one percent change in quantity demanded for every one percent change in price. Within the studies surveyed, all short-run demand elasticities for electricity are found to be inelastic. The median value is about -0.3, though there is variation. In the long-run, most studies found demand elasticities to remain inelastic, with the median value around -0.5. There are a few studies that found quite a large magnitude of sensitivity to price, ranging up to almost -2. These tend to be older studies that do not rely on more contemporary econometric estimation techniques. More recent studies suggest demand for electricity is inelastic, even in the long-run.

The studies represented in Figure 3 are for changes in flat rate electricity pricing schemes. As might be expected, similar results were found in a study of short- and long-run elasticities looking specifically at TOU pricing. Depending on geography and demographics, own-price elasticity of demand for peak electricity usage ranges from -0.2 to -0.8 (Aigner, 1985). In other words, a 10% increase in electricity rates during peak times results in a 2% to 8% decline in usage during the peak.

Consumer Substitution with Time Varying Rates

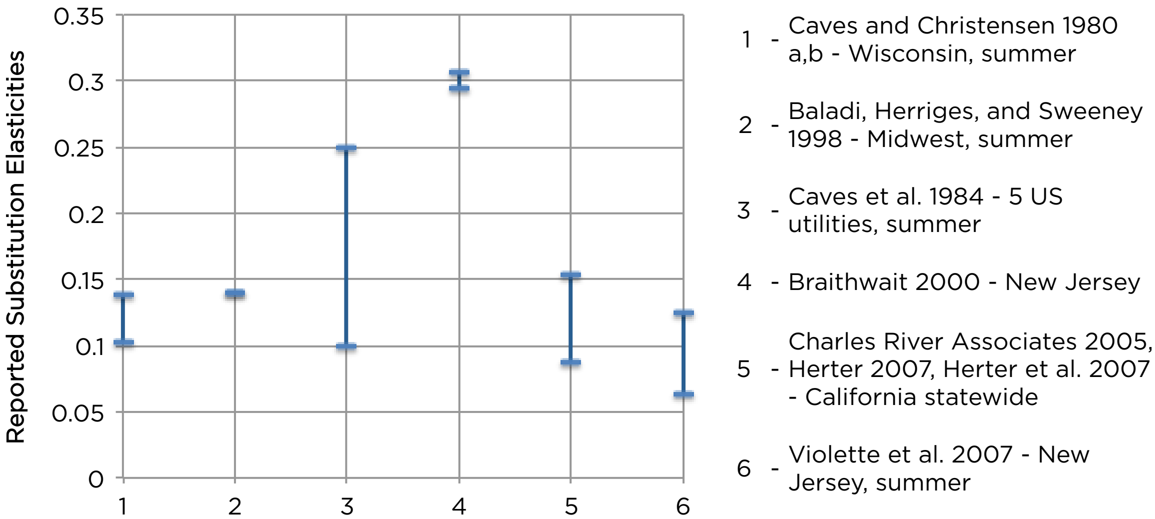
There is additional literature focusing on measuring consumers' ability to adjust their timing of demand as a result of time varying rates. These studies examine how much consumers respond to prices in one time period by shifting their electricity demand to other time periods, often from peak to off-peak times. This effect is crucial to the overall efficacy of time varying rates (Taylor, 2005).

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). While both parameters reflect the ability and preference of consumers to change their electricity usage across periods of time, they are different calculations for evaluating response to price changes between periods. Cross-price elasticity measures the change in demand in one period in response to a change in price in another period.[5] Substitution elasticity captures price sensitivity through the relative change in usage in time periods as a result of the relative change in prices. For model calibration, we focus on substitution elasticity.[6] Substitution elasticities are typically positive, meaning that time periods are substitutes for one another, where higher values indicate more substitutability between periods. Six studies summarizing substitution elasticities for CPP regimes are shown below in Figure 4.

5 Where a negative value indicates electricity consumed in the two periods are complements, and substitutes when cross-price elasticity takes on a positive value.

6 This is due to our use of a nested constant elasticity of substitution utility function model.

Figure 4. Values of peak to off-peak substitution elasticity reported in the literature



The substitution elasticities reported within the studies are highly inelastic, ranging from around 0.1 to 0.3 (though most are below 0.2). An outlier, Filippini (1995), reports values of substitution elasticity as high as 2.9, however Lijesen (2007) argued these values were a result of misspecification. Many of the studies reporting substitution elasticity explored various underlying reasons why values might differ. An extensive study of factors that may contribute to load shifting with TOU implementation in Wisconsin over the summers of 1976 and 1977 analyzed customer shifts in both duration and appliance use. Of a 6-, 9-, and 12-hour peak, the 6-hour peak shows the greatest evidence of shifting (Caves and Christensen, 1980a, 1980b). They also found that ownership of major appliances leads to larger values for substitution elasticities in Wisconsin and the Midwest (Baladi et al., 1998). Appliances, especially air conditioning, played an important role in the ability to shift load, in particular on hot summer days (with a substitution elasticity of 0.21 for households with air conditioning compared with 0.10 for those without) (Caves et al., 1984).

Furthermore, technologies that enable consumers to adjust their electricity usage automatically to prices (i.e., enabling technologies) play a critical role in increasing substitution elasticity values. Braithwait (2000) reported that overall substitution elasticity values tightly clustered around 0.3 from a New Jersey TOU Pilot study conducted for two months in 1997. The users in this pilot were given communication equipment that allowed them to program usage patterns in response to pricing. Studies of a CPP program were conducted in California with various pricing schemes from 2004-2005, where electricity customers were informed of days during the year when CPP would go into effect. The research estimated that customers who did not adopt enabling technology had a substitution elasticity of 0.087 and those that did adopt had an elasticity almost twice as large. Violette et al. (2007) analyzed a TOU program in New Jersey conducted during a summer timeframe, finding that households increased their substitution elasticity with programmable thermostats. The study found that 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. In addition, those without central AC were found to have an elasticity of substitution of 0.063.

Other studies have found no measurable substitution effect in response to implementation of TOU pricing. Namely, consumers show a tendency to conserve energy rather than shift usage to other periods (Alcott, 2011; Jessoe and Rapson, 2014). Allcott (2011) despite substantial hourly variation in the wholesale market price. This paper evaluates the first program to expose residential consumers to hourly RTP found overall price elasticities of -0.1 for voluntary TOU customers in Chicago, but attributed the modest response to energy conservation during peak periods rather than a shift to off-peak periods. Jessoe et al. (2014) 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. Energy conservation could be a positive side effect from the point of view of reducing greenhouse gas emissions. However, TOU pricing does not necessarily provide a cost-effective means for energy conservation. Inefficiencies that exist with respect to actual cost of electricity production for flat-rate pricing will remain if TOU pricing only results in energy conservation without any shifting in load (Orans et al., 2010). Load shifting, therefore, is a critical objective of TOU pricing and lack of evidence of load shifting may reflect a need for enabling technologies such as smart meters or smart appliances.

IV. CONSUMER ELECTRICITY DEMAND MODEL: METHODOLOGY AND SCENARIOS

To estimate the magnitude of load-shifting opportunities as a result of HECO's proposed TOU rates, we use a simple model of consumer demand based on the literature's estimates of households' demand sensitivity to changes in electricity prices. Specifically, we construct a multi-level utility function. In the first level, consumer well-being is derived from consuming electricity and all other goods subject to a budget constraint. At the second level, consumers use electricity during a twenty-four hour period, where the hours are grouped in three tiers as proposed by the TOU blocks. We adopt a nested constant elasticity of substitution (CES) utility function. The combined maximization problem is represented in Equation 1.

Equation 1. Utility function and budget constraint.

$$\max U = \sum_j \left[\left(\alpha(j) * \left(\sum_i \beta(t,j) * \left(\frac{Q(t,j)}{Q_{ele}(t,j)} \right) \right)^{(\rho_{all}/\rho_{ele})} \right) + (1-\alpha(j)) * \left(\frac{Q(AOG,j)}{Q(AOG_0,j)} \right)^{\rho_{all}} \right]^{\left(\frac{1}{\rho_{all}}\right)}$$

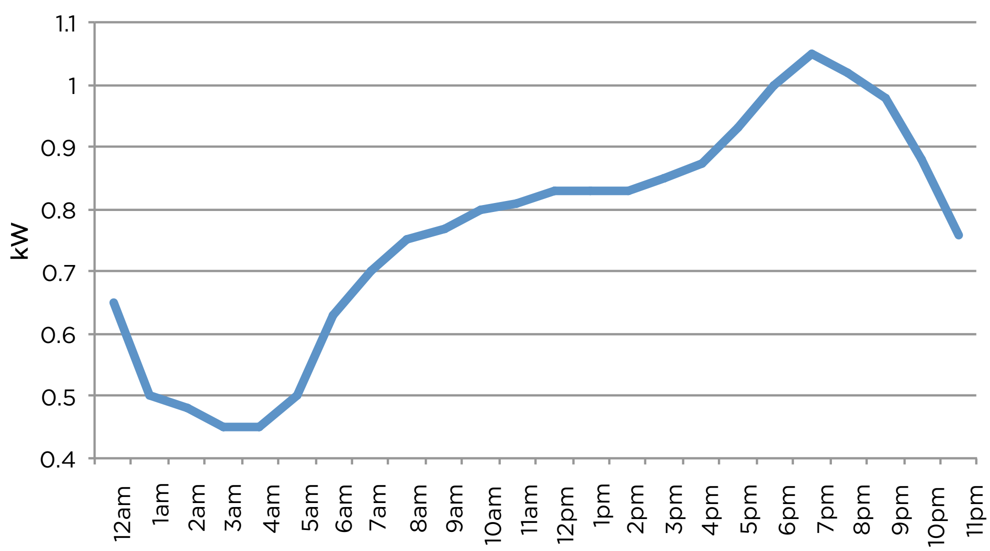
$$\text{subject to } \sum_i (P(t,j) * Q(t,j)) + P(AOG,p) * Q(AOG,j) = I \text{ for all } j$$

$$\text{where: } \rho_{all} = \frac{elas_{ele} - 1}{elas_{ele}} \; and \; \rho_{ele} = \frac{esub_{ele} - 1}{esub_{ele}} \text{, and}$$

a is the value share of income spent on electricity purchases; *β* is the value share of income spent on each tier of electricity; *t* denotes the three time periods corresponding to the TOU rates; *j* denotes the three island systems controlled by HECO and its subsidiaries; $elas_{ele}$ represents own-price elasticity; $esub_{ele}$ denotes the elasticity of substitution among the three time periods; and *l* represents the household budget following each county's average household income (DBEDT, 2015). *P(AOG)*, or the price of all other goods on each of the islands *j*, is taken to be exogenous. $P(t, j)$, or the price of electricity in the TOU time period *t*, is also exogenous and is based on the proposed TOU rate schedule. The model solves for $Q(t, j)$, the quantity of electricity consumed in each TOU time period *t*, and $Q(AOG, j)$, the quantity of all other goods, given these prices.

To distribute the total annual electricity consumption in 2015 over time (as given in DBEDT, 2016), we use a residential load curve for the non-PV customer as shown in Figure 5.[7] The load profile is a daily average from 2,280 non-PV smart meters installed in the areas represented by the zip codes 96815 and 96816 from June 2014 to May 2015 on a 15-minute interval basis. By using a non-PV residential customer load curve, due to data limitations, we overestimate the impact of TOU rates. Existing Net Energy Metering (NEM) customers have little to no incentive to participate in a TOU program. However, non-PV customers comprise the majority of residential load.[8]

Figure 5. Daily Average Residential Load Curve (non-PV customer)



Source: Hawaii Energy, 2015.

To isolate the price effect of changing from flat rates to TOU rates in motivating changes in consumer demand for electricity, we assume if usage remained the same under the TOU rates, then there would be no change in the

7 The load curve was estimated from a graphic provided by Hawaii Energy. Clearly better data would provide opportunity for more detailed analysis, including exploring issues of seasonality and heterogeneity between customers.

8 As of May 2016, approximately 15% of Oahu households have solar PV (City and County of Honolulu, 2016; U.S. Census, 2007-2014).

total amount paid for electricity as a result of signing up for the TOU program. Therefore the baseline rates are calculated so that the average household's electricity bill under the flat rate is the same as under the TOU rates assuming the same electricity usage pattern. This removes what would otherwise cause an "income effect," meaning that a customer would use more energy if, for example, they happened to save on electricity costs even using the same amount of energy.

Scenarios

To account for the variation in measured demand response across studies, we select three alternative scenarios with a focus on varying substitution elasticity parameters. We label these scenarios: Appliance, Literature, and Restrictive. All scenarios are modeled with an own-price elasticity of -0.4, which is the average of the median of the short- and long-run elasticities as reported in Figure 3, and assume full customer participation in the TOU program.

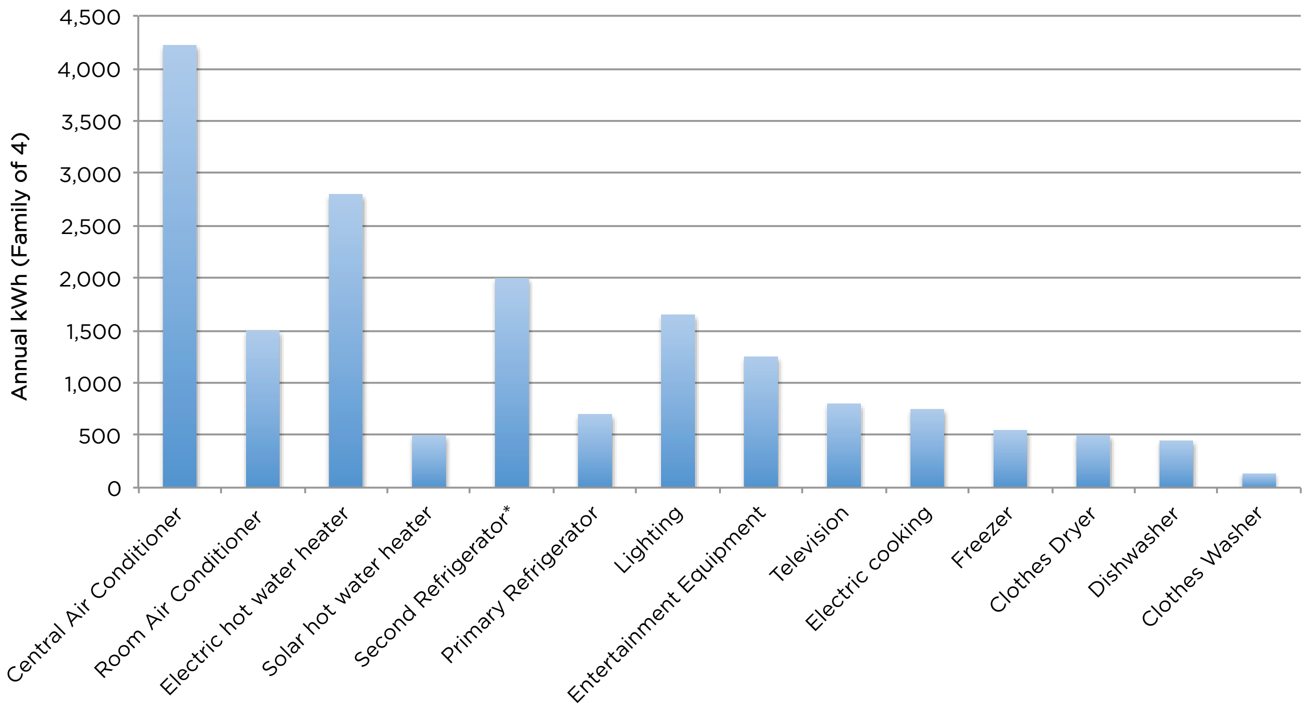
Appliance Scenario

The Appliance Scenario serves as an upper-bound estimate of the opportunities for load shifting from peak to off-peak hours given current technologies. We account for a typical household's appliances to estimate the maximum amount of flexible generation. We adopt appliance load shapes from Levy and Kilicotte (2013)[9] and Pratt et al. (1989),[10] which provide average annual hourly consumption by appliance. These individual appliance load shapes are then scaled using annual energy use estimates by appliance for a household of four in Hawaii (HECO, 2013) as shown in Figure 6.

9 The demand response roadmap provides the load profile for residential water heating on an October peak day in 2011.

10 Metered data were collected from 499 residences in the Pacific Northwest over four years as part of the End-Use Load and Consumer Assessment Program. The appliance load shapes from Pratt et al. (1989) are also used in a more recent U.S. Department of Energy study (Sastry et al., 2010).

Figure 6. Hawaii Annual Energy Consumption By Appliance (kWh)



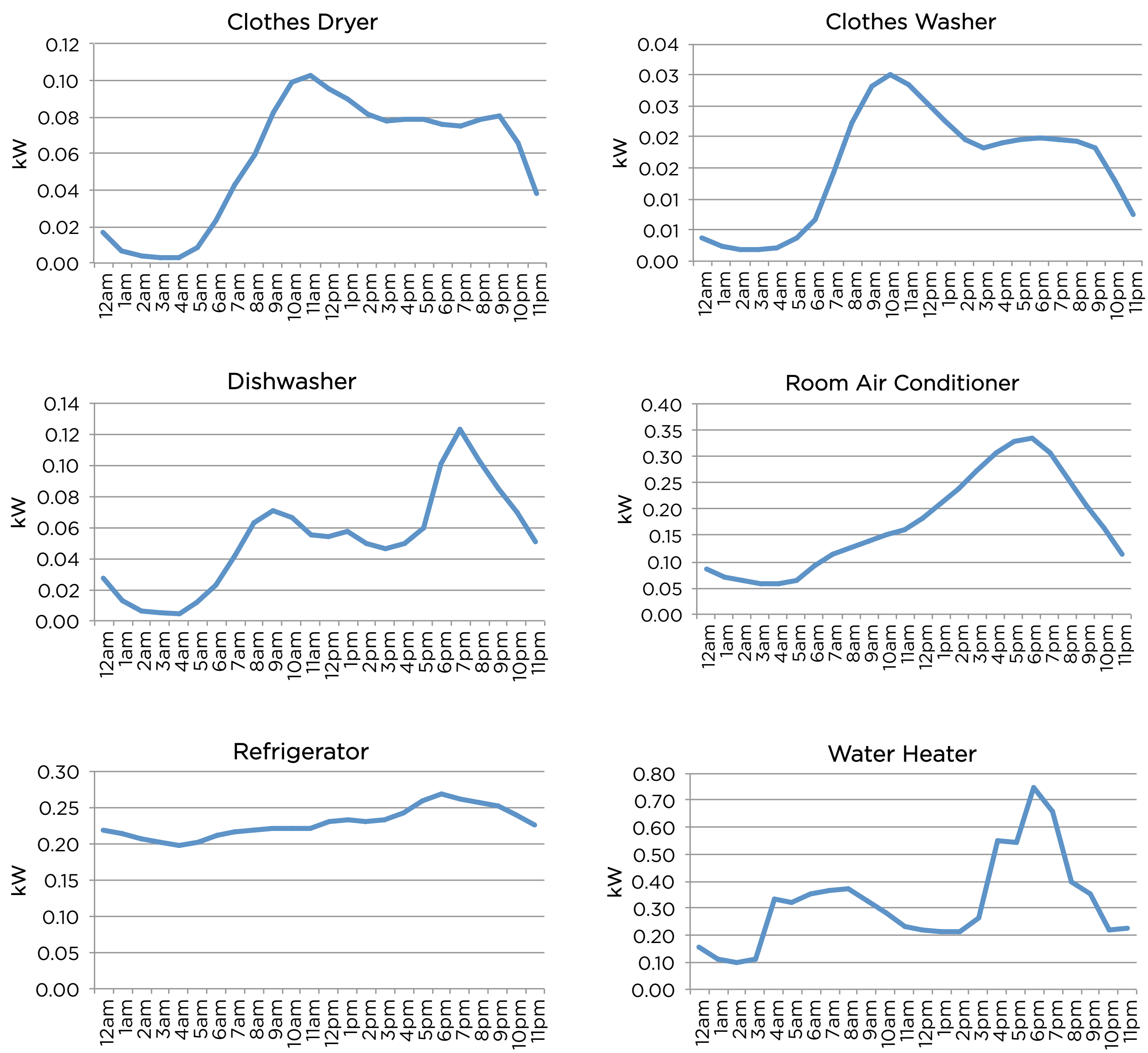
*Second refigerator is assumed to be less energy-efficient.

Source: Hawaiian Electric Companies, 2013.

We identify air conditioners, electric hot water heaters, second refrigerators, clothes dryers, clothes washers, and dishwashers as appliances theoretically capable of shifting away from on-peak consumption with relative less inconvenience to consumers. These loads are illustrated on an hourly basis in Figure 7.[11]

11 The load curves were estimated from graphics provided in Sastry et al. (2010) and Pratt et al. (1989).

Figure 7. Daily Appliance Load Curves



Source: Pratt et al., 1989; Levy and Kiliccote, 2013; Hawaiian Electric Companies, 2013.

We heroically assume households can shift their entire on-peak electricity usage for the above appliances to other hours.[12] To determine flexible on-peak electricity consumption by appliance for all households in Hawaii, we multiply the annual electricity or energy use[13] by the share of "shiftable" load and the average U.S. household penetration rate per appliance[14] (EIA, 2013), scaled by the number of Hawaii households and the average number of persons per household (U.S. Census, 2015). This results in an estimate for on-peak electricity consumption for loads identified as "shiftable." Based on total residential electricity consumption of roughly 2.5 TWh in 2015 (DBEDT, 2016), the total share of flexible generation during the on-peak (5-10pm) in the residential sector is estimated to be 18%.[15]

With an own-price elasticity of -0.4, the Appliance Scenario is run with a substitution elasticity among the three tiers of 3. This means that electricity consumption among time periods is highly substitutable and non-binding. Rather, our estimated maximum share of flexible load (18%) acts as the primary constraint. This scenario serves as an upper-bound for the potential of residential load shifting given today's typical appliance usage.

Literature Scenario

For the Literature Scenario, we choose a substitution elasticity parameter of 0.15, as it is within the range commonly found in most studies (excluding New Jersey General Public Utility, GPU, which is much higher at 0.3). We apply this elasticity parameter to the opportunity for load-switching among all price tiers. This scenario serves as our most representative of experiences in other places.

Restrictive Scenario

Whereas the Appliance Scenario gives an upper bound on load switching opportunities with current technologies, the Restrictive Scenario looks at a very low substitution elasticity of 0.05. This value reflects the findings of Alcott (2011) and Jessoe and Rapson (2014), with little to no evidence of load-shifting. This scenario serves to provide insight into the magnitude of price-induced changes in consumption within each time period, with limited load shifting.

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12 Except for air conditioners which only shift the first three hours of their on-peak consumption to the mid-day period to pre-cool homes.

13 We assume households either have room AC or central air AC, and take the average energy use of central AC and two room AC to derive the flexible generation for AC.

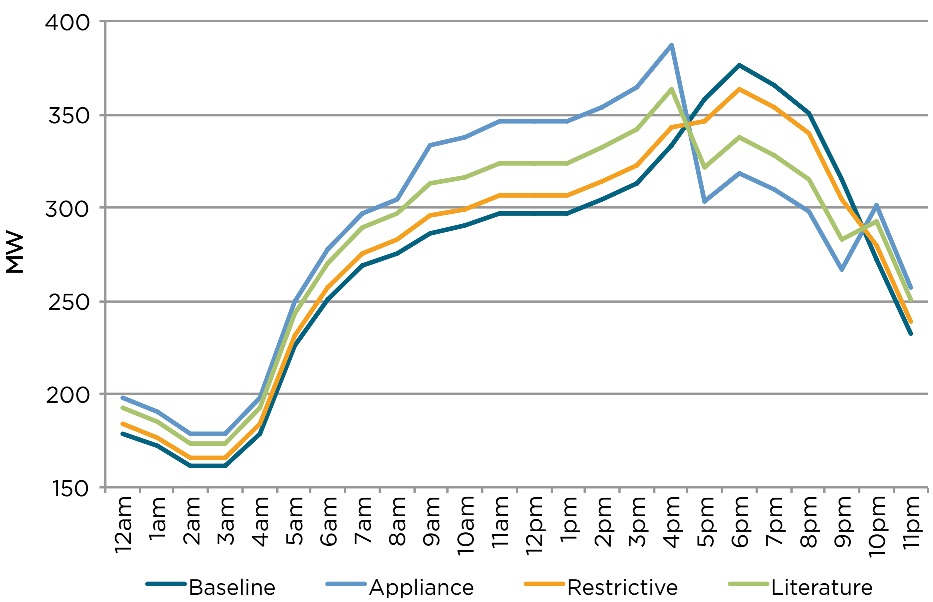
14 87% of U.S. households have air conditioning equipment; 41% of households have an electric hot water heater; 23% own a secondary refrigerator; 30% have a freezer; 80% have a clothes dryer; 59% have a dishwasher; and 82%, a clothes washer.

15 This translates to 32% of daily electricity consumption based on an average of 18.3 kWh consumed by a non-PV household (Hawaii Energy, 2015).

V. KEY FINDINGS

We find that if all residential customers adopt TOU rates as proposed, there could be about a 10% reduction in on-peak residential electricity demand – both as a result of price-induced conservation and load shifting. Overall we find that there will be incentive to increase total electricity demand. Though there is load-shifting into day and nighttime hours for all three islands, there is more load-shifting to the night on Oahu because of relative rates. And the dramatic difference in rates on Hawaii Island leads to the largest relative shift in loads. Figure 8 below plots our estimated change in the annual hourly load profile for the sum of Oahu, Hawaii Island, and Maui County demand, under the baseline (no TOU pricing) and three alternative scenarios. Note that the uniform "shift" up or down during the three tiers is purely illustrative. The bordering hours of the on-peak period may be more substitutable, though this is not accounted for within our consumer model. Customers who are able to change their consumption behavior may be shifting their load near the bounds of the period rather than throughout.

Figure 8. Estimated Hourly Residential Load Profile



Total of Oahu, Hawaii Island, and Maui

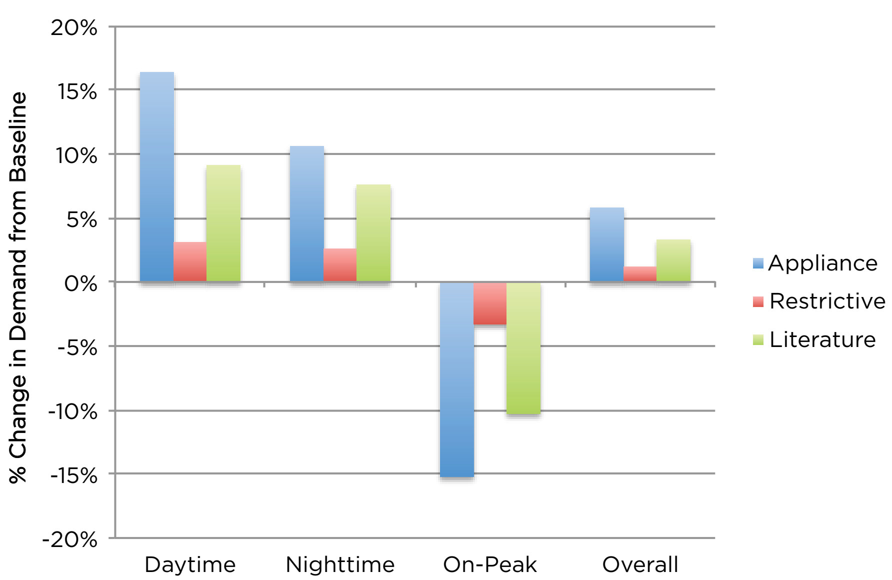
The Appliance Scenario, which assumes that up to 18% of on-peak consumption can be moved easily (i.e., high elasticity of substitution among tiers) to off-peak periods, unsurprisingly exhibits the greatest decline in usage during the on-peak period. The daytime period (9am – 5pm) reaches the highest level of usage throughout, when rates are typically lowest. We find that daytime period demand could increase by up to 16%, nighttime demand could increase by about 10%, and on-peak period demand could decline by as much as 15%. During the on-peak, this amounts to a decline by 54 MWh compared to the baseline.[16]

The Literature Scenario traces the load profile of the Appliance Scenario on a smaller scale. Electricity consumption in the daytime increases by 9%, in the nighttime by 8%, while demand in the on-peak period is lower by 10% (amounting to 36 MWh compared to the baseline). Given this scenario most closely follows the examples reported in the literature (though studies are limited and varied), it gives our best estimate for load-shifting possibilities as a result of the proposed TOU rates.

The Restrictive Scenario, which assumes a substitution elasticity close to zero, shows only a slight deviation upwards during the daytime and nighttime periods and downwards during the on-peak period. Consumption increases by 3% during the daytime period, 2% during the nighttime period, and a 3% decline during the on-peak period (amounting to 12 MWh compared to the baseline). Most of this response is due to adopting dramatically different prices within those time periods. This scenario serves to showcase the magnitude of change in consumption that may be coming simply from changing prices rather than load shifting.

The impact of TOU rates on electricity demand in each period as well as overall is summarized in Figure 9.

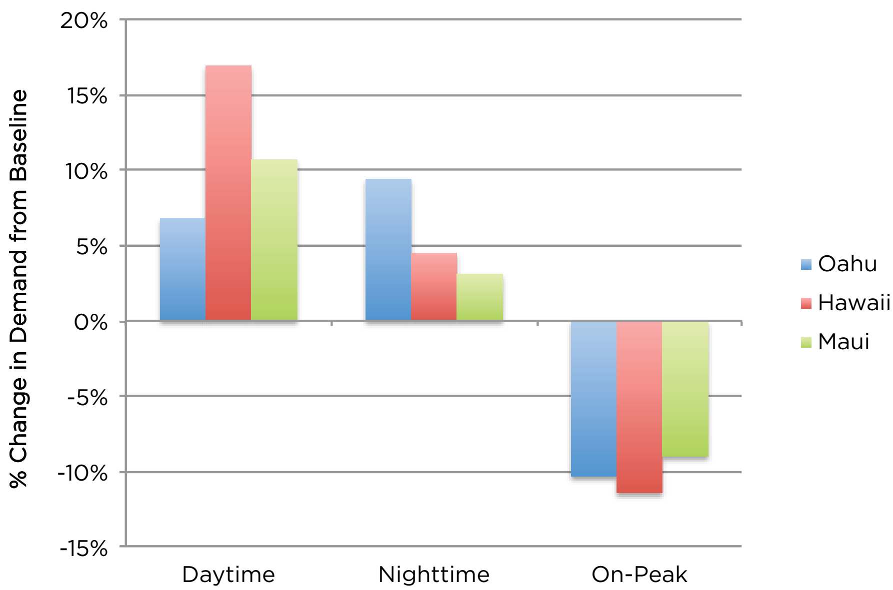
Figure 9. Change in Electricity Demand from the Baseline (%)



16 This result is largely driven by the Oahu's lowest rate occurring in the nighttime and Oahu's load comprising 68% of residential load among the three islands. The impacts of load-shifting from TOU rates were also modeled using a candidate schedule ("PUC-HECO-IR-17") from the March 2016 filing. This candidate schedule's rates were also calculated by allocating the fixed costs to the on-peak period. However, Oahu's daytime rate was the lowest of all three periods, following that of Maui Island and Hawaii Island. Therefore, the increase in consumption during the daytime period exceeded that of the decline during the on-peak period by roughly 3,700 MWh.

Overall, we find that adoption of the rates proposed under the TOU program leads to an increase in residential electricity demand of 1% to 6%. Low pricing during daytime and nighttime hours cause this result. Figure 10 below focuses on the Literature Scenario and shows results for Oahu, Maui and Hawaii Island.

Figure 10. Literature Scenario, Change in Electricity Demand from Baseline (%)



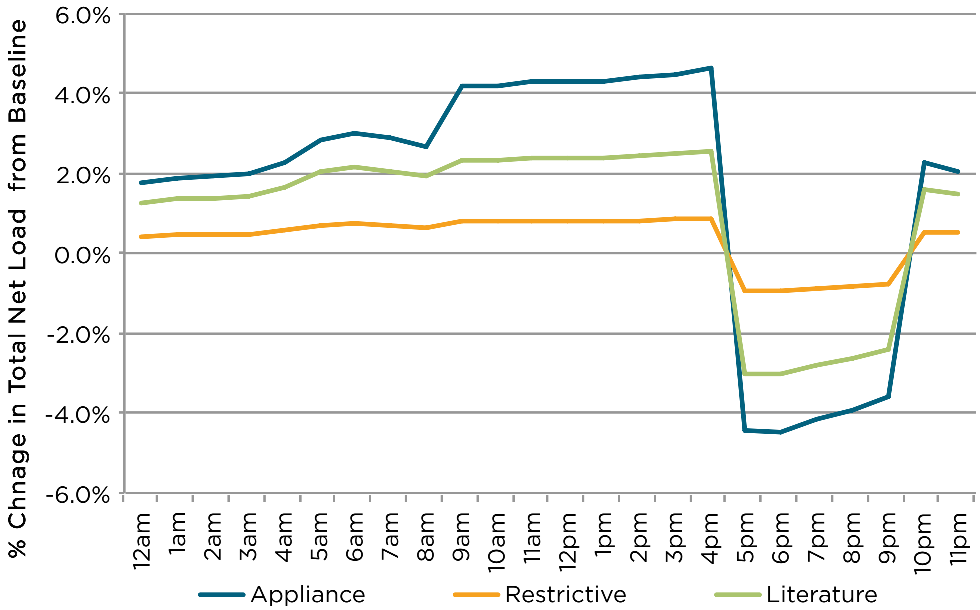
For Oahu, Hawaii Island, and Maui

Because Oahu's proposed TOU rates have the lowest rates during the nighttime period there is relatively more load shifting toward nighttime hours than daytime. For Hawaii Island, the dramatic $0.50/kWh difference in rates between on-peak and daytime hours causes the most relative shifting. There is an 11% reduction in on-peak electricity demand, a nearly 17% increase in daytime demand, and a 4% increase in nighttime demand. Maui experiences a nearly 10% reduction in on-peak demand, an 11% increase in daytime demand, and a 3% increase in nighttime demand.

Although TOU rates can have considerable impact on the residential load and residential customers account for 86% of total customers, the residential sector makes up less than 26% of total demand (DBEDT, 2016). Figure 11 illustrates our estimates for the change in total electricity demand from the baseline.[17]

17 The change in total electricity demand is calculated based on the 2014 net load curve (FERC, 2015) as shown in Figure 11 for Oahu (and scaled according to total demand for the other two islands). To obtain the non-residential load, the residential load in the baseline scenario is subtracted from the total net load. The residential load in each of the three scenarios is then added to the non-residential load.

Figure 11. Change in Total Electricity Demand from the Baseline



By re-scaling our results to the overall electricity load, we can see that the magnitude of load shifting as a result of residential adoption of TOU rates (meaning all residential customers) is limited. Even in the scenario with the greatest switching, the Appliance Scenario, adopting TOU rates results in a 4.3% increase in daytime loads, a 2.3% increase in nighttime loads, and a 4.1% reduction from the on-peak. The more likely Literature Scenario leads to a 2.4% increase in daytime loads, a 1.7% increase in nighttime loads, and a 2.8% reduction in the on-peak. Once accounting for voluntary participation, system impacts would be likely nearly imperceptible.

VI. DISCUSSION

While these results might capture the range of behavioral response of the average consumer who adopts TOU pricing, the overall effectiveness of the program is contingent on actual customer participation. 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 TOU pricing, yet only 4% of residential customers are enrolled in TOU programs (Sherwood et al., 2016). In a test of TOU rates in the Midwest, a total of 2,400 out of 60,000 random households contacted chose to participate in TOU pricing (Baladi et al., 1998). A statewide California study found that of 8,679 enrollment packages sent out, 1,759 customers elected to participate in the CPP program, with an appreciation payment of $175 offered, and 4% opted out after a few months (Charles River Associates, 2005). A New Jersey study found that even with an offered payment incentive for participation, there was a 4% response rate (Violette et al., 2007).

There are many considerations in regards to optional participation in a TOU program, including whether rates are set such that they benefit the individual customer. Given the large proposed spread in rates, the opportunity for gain in Hawaii may be larger than in other U.S. locations. On the other hand, Hawaii has a high penetration of solar PV customers. Customers who are in the NEM program would have little to no incentive to enroll in TOU rates because they likely net generate during the daytime hours so adopting the TOU rates would lead to these PV customers receiving far less money for the electricity that they generate. PV customers on the more recent grid-supply option already experience a block-pricing schedule akin to TOU rates.

For many customers, the key to increasing household participation and response to voluntary time-variable pricing programs may lie in information access and appliance technology. To make the decision to participate in a TOU program, information from the utility company should be accessible and provide sufficient information for users. A review of literature shows the possibility that quick, clear, and meaningful feedback about energy usage has the potential to reduce electricity consumption by 5-20% (Vine et al., 2013). A study of Southern California households found that consumers exhibit greater response to average price rather than to pricing schemes such as TOU (Ito, 2014). The author offers reasons that monthly bills are often complex and hard to understand and it is difficult for electricity customers to monitor their consumption without an in-home display (IHD). Additional studies found that customers with more knowledge and information about electricity rates and usage find more ways to respond to pricing (Jessoe and Rapson, 2014).

Potential for cost-savings extends into the utility side with peak demand reduction from full customer participation. In the European Union, for example, several countries have extensive smart meter installation in households. It is estimated that smart meters coupled with time-variant pricing in Europe could result in significant cost savings for utility companies given a reduction in the need for peaking infrastructure, with savings tied directly to the amount of customers shifting load (Faruqui et al., 2010a). With TOU pricing, it is therefore beneficial to the utility company to promote technology, such as IHDs, which enables customers to shift their energy load.

Consideration of lifestyle and demographics is also an important component in establishing TOU programs. Lifestyle of households may explain some variation between consumers' load-shifting abilities. Sanquist et al. (2012) found that household lifestyle patterns accounted for 42% of the variance in electricity consumption from major appliances. Often, concern is cast on people who might be most vulnerable to rate changes, especially low-income households that might be least likely to participate in a voluntary program. On the other hand, studies have shown that TOU pricing can have benefit to low-income households. In a study conducted in Australia, Simshauser et al. (2014) found that 64% of households are better off with TOU pricing compared with flat-rate pricing, with the greatest improvement amongst low-income groups. Wood and Faruqui (2010) found similar benefits to low-income households under a TOU program and attributed the gains to the tendency for such households to have flatter load curves than average, and therefore would relatively benefit even without peak reduction. All things considered, Martiskainen and Ellis (2011) argue that energy policy should take an interdisciplinary approach between economics, socio-psychology, and technology.

VII. CONCLUSION

In this study, we develop three scenarios to characterize consumer responsiveness to varying electricity rates during the daytime, on-peak, and nighttime periods assuming full customer participation: an Appliance Scenario that assumes the highest degree of substitutability between periods, a Literature Scenario that assumes a shiftable load within the median range found empirically in many studies of TOU pricing, and a Restrictive Scenario that assumes very little electricity substitution between periods. To maximize the success and benefits of implementing a TOU program, our study underscores two critical considerations. The first is the importance of enabling technologies providing for greater potential load shifting, both in regards to information and automation, and the second is the importance of customer participation in achieving efficiency goals in electricity generation.

From our modeling, we find that HECO's proposed TOU rates could lead to a 10% reduction in on-peak electricity usage by participating residential consumers, and increase daytime consumption by 9% and nighttime consumption by 8% (Literature Scenario). We find there is a resulting positive increase in overall electricity consumption, largely as a result of consumer price responsiveness to off-peak prices being about half of today's current electricity rates hours. This effect would be even greater accounting for an income effect[18] as a result of overall lower electricity costs. Furthermore, the model results point to the importance of appliances in a residential household's decision to shift load. The difference in percentage change during TOU periods between the Appliance and Literature Scenarios suggest that although a certain amount of appliance load is potentially switchable, residents are unlikely to switch that amount of their appliance load, especially without enabling technologies. Moreover, expectations for overall load-shifting should be quite modest. This is due to both residential electricity demand being about a quarter of total load and, if the program is voluntary, uptake is likely to be low based on experience with other programs in the U.S. and the high penetration of PV. That said, the learning opportunity from this kind of TOU program, particularly if operationalized in an experimental fashion with variation in household technology and information, may be important in understanding adoption of other variable pricing mechanisms, like RTP. While TOU pricing certainly helps to better match available renewable energy supplies with consumer demand, fixed block rates only capture a fraction of the efficiency gains in comparison to RTP (Borenstein, 2005b).

Future work will look at the possibilities for RTP in Hawaii. This work will include analysis of non-residential rates, as commercial and industrial customers account for about two-thirds of electricity loads (Hawaiian Electric Companies, 2015). The magnitude of commercial and industry electricity suggests that there is greater possibility for load shifting within these sectors, however, empirical evidence shows a dramatic range of outcomes[19].

18 Due to increased disposable income brought about by lower priced goods and services because of lower production costs as a result of lower electricity prices.

19 Among 43 surveyed utilities in the U.S., Wang and Li (2015) found switching from a flat to a TOU rate resulted in a large range of change in the electricity costs of -72% to +83%, where businesses with shorter workdays would save the most from switching.

Study Limitations

Our estimates for the potential for load-shifting away from on-peak hours are biased upward not only by our assumption that all residents participate in the program but also because, due to data limitations, we use a non-PV customer load curve that is scaled to all resident demand. In reality, existing PV NEM customers would have little to no incentive to participate in a TOU program. It is outside of our study scope to estimate the probability of customers opting into a TOU program as proposed. It should be noted, however, that declining battery technology costs could also be a tremendous mechanism for storage and load shifting. Incorporating battery technology is an additional area for future research.

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