Using Residential Electric Loads for Fast Demand Response: The Potential Resource and Revenues, the Costs, and Policy Recommendations

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ABSTRACT

Energy storage devices, such as batteries, have been proposed as a solution to the need for additional power systems services caused by variability and uncertainty in system demand and renewable energy production. However, in many respects, buildings and appliances with thermal mass are equivalent or even superior to batteries for these purposes. In this paper, we examine the potential for residential thermostatically controlled loads (TCLs), such as air conditioners, electric water heaters, and refrigerators, to deliver power systems services and participate in short timescale energy markets. These loads operate within a hysteretic ON/OFF dead-band and therefore act much like energy storage devices, modulating power use around their baseline consumptions. Carefully designed demand response (DR) schemes allow us to both control aggregations of TCLs to track market or automatic generation control signals and ensure that they provide the service requested by the consumer. This paper estimates the size of the potential resource; potential revenue from participation in markets; and break-even costs associated with deploying DR-enabling technologies. We find that current residential TCL energy storage capacity in California is 8–11 GWh, with refrigerators contributing the most. Annual revenues from participation in regulation vary from \$10 to \$220 per appliance per year depending upon the type of appliance and climate zone, while load following and arbitrage revenues are more modest. We conclude with a number of policy recommendations including the design of new markets and communications/appliance standards that will make it easier to engage residential loads in fast timescale DR.

Introduction

To reduce greenhouse gas emissions many states have implemented renewable portfolio standards that require a certain percentage of electricity generation to come from renewable sources. Both wind and solar photovoltaics are expected to comprise a significant portion of new renewables; however, both technologies produce variable and uncertain power. As a result, system operators will need to procure more ancillary services such as regulation and load following (Makarov et al. 2009).

Rather than using existing and new generation units to provide the additional services needed, it may be more cost-effective and/or environmentally beneficial to provide these services with alternative technologies, namely energy storage devices (e.g., batteries, flywheels, compressed gas, and pumped hydro) and demand response (DR). We focus on DR for two reasons: First, it has significant potential for near-term deployment and impact. Second it has been identified as a crucial component of the portfolio of energy technologies needed to achieve massive de-carbonization of our energy supply system (CCST 2011).

One generally thinks of large industrial loads and commercial buildings as the best candidates for traditional DR programs because these customers consume large amounts of electricity and, subsequently, are able to curtail a substantial amount of power when a DR event is called. Moreover, it is simpler for the utility or aggregator to interact with a small number of large customers than a large number of small customers. However, there are several benefits to using aggregations of small residential loads to provide power system services. Specifically, these loads (1) can provide more reliable responses in aggregate than small numbers of large loads (Callaway 2011, Kirby 2003); (2) are spatially distributed; (3) employ simple local controls, which both facilitates faster responsiveness (Callaway 2011) and makes them easy to model for state estimation and control purposes (Koch, Mathieu, & Callaway 2011; Mathieu & Callaway 2012); and (4) display continuous, not discrete, control responses in aggregate as opposed to large loads which generally employ DR strategies such as stepping down industrial processes, HVAC loads, or lighting (Motegi et al. 2007).

Thermostatically controlled loads (TCLs), such as air conditioners, electric water heaters, electric heaters, and refrigerators, have perhaps the most potential of all types of residential loads. TCLs operate within a hysteretic ON/OFF temperature dead-band, which acts as a thermal energy storage reservoir, much like a battery's chemical energy storage reservoir. We can increase or decrease the power consumed by a population of TCLs by switching subsets of the population ON or OFF, but never forcing them outside of their dead-bands. A carefully designed load control scheme should allow us to control TCL power consumption to track a desired trajectory (e.g., market signal or automatic generation control signal) without a noticeable effect on end-use function (Callaway & Hiskens 2011).

In this paper, we use models of TCL populations to estimate the size of the TCL resource, possible financial rewards, and break-even costs associated with deploying DR-enabling infrastructure. We begin with a discussion of our methods, and then present results for our resource potential, revenue potential, and cost analyses. We conclude with a number of policy recommendations, which, if implemented, would allow loads to participate in energy and ancillary services markets more fully and effectively.

Methods

We use simple dynamic models along with publicly available data to quantify the TCL resource and revenue potentials. In this section, we briefly describe the model and the method we use to control the TCLs. We then describe our data sources. Finally, we describe how we derived the TCL model parameters. More details can be found in Mathieu (2012).

Model & Control Description

Each TCL is modeled with the following difference equation (Ihara & Schweppe 1981, Mortensen & Haggerty 1990, Uçak, C. & Çağlar R. 1998, Callaway 2009):

$$\theta_i(k+1) = a_i\theta_i(k) + (1-a_i)(\theta_{a,i}(k) - m_i(k)\theta_{g,i}) + \varepsilon_i(k) \tag{1}$$

where $\theta_i(k)$ is the internal temperature of TCL i at time step k, θ_a is the ambient temperature, and ε is Gaussian white noise. The dimensionless TCL parameter a_i is defined as $e^{-h/(C_iR_i)}$, where C is a TCL's thermal capacitance, R is its thermal resistance, and h is the simulation time step. θ_g, the temperature gain when a TCL is on, equals $R_iP_{trans,i}$, where $P_{trans,i}$ is a TCL's energy transfer rate, which according to our conventions is positive for cooling TCLs and negative for heating TCLs. The power consumed by TCL i when it is on, P_i, is defined as $|P_{trans,i}|/\text{COP}_i$, where COP is its coefficient of performance. The local control variable m is a dimensionless discrete variable equal to one when the TCL is on and zero when the TCL is off.

In each time step, we assume a TCL's temperature changes without regard to its temperature dead-band edges. Therefore, some TCLs may leave their dead-band within a time step. We assume that TCLs that leave their dead-band between k and $k+1$ are switched by their local controllers at $k+1$. Additionally, we assume that, through direct load control, we are able to switch TCLs on or off, except TCLs that are outside of their dead-band.

To model a population of N TCLs we use N individual TCL models. To control the system we use a proportional controller to determine the switch probability, η, intended for TCLs that are either off or on in a given time step. In each time step, a new switch probability is broadcast to all TCLs. If the value is negative, all TCLs that are on must switch off with probability $-\eta$, and if the value is positive, all TCLs that are off must switch on with probability η. Note that this control scheme does not honor minimum compressor on/off times; this is a subject for future research.

Data Sources

To calculate the DR resource potential of TCLs in California, we estimated the number of central air conditioners (ACs), refrigerators, central heat pump space heaters (referred to as simply 'heat pumps'), and electric resistance water heaters (referred to as simply 'water heaters') in five utility districts in the state: Pacific Gas and Electric (PG&E), Southern California Edison (SCE), San Diego Gas and Electric (SDG&E), Sacramento Municipal Utility District (SMUD), and Los Angeles Department of Water and Power (LADWP). Specifically, we used appliance saturation rate data from the 2010 California Residential Appliance Saturation Survey (Palmgren et al. 2010) and forecasts for the number of households in 2012, and extrapolated to 2020, from the California Energy Commission (CEC) (Marshall and Gorin 2007). For ACs and heat pumps, we used data by CEC forecasting climate zone (1-13), since power consumption varies as a function of outdoor air temperature. No saturation rate data is available for climate zone 6 (SMUD) so we used saturation rate data for climate zone 2 (PG&E Sacramento Area). We used typical meteorological year outdoor air temperature data from EnergyPlus (EERE 2012). Since the California Building (CB) climate zones used by EnergyPlus are different than the CEC forecasting climate zones, we mapped each CEC zone to a CB zone (Mathieu 2012). We also used interval locational marginal prices (LMPs) from the California Independent System Operator (CAISO 2012) and weather data from the National Oceanic and Atmospheric Administration (NOAA 2012) to compute energy cost savings through energy arbitrage.

TCL Model Parameters

TCL model parameters, given in Table 1, were derived or estimated from various sources (Mathieu 2012). To create a TCL population, we parameterize individual TCL models with the starred (*) parameters, which are randomly drawn from uniform distributions between the maximum and minimum shown in the table. The other parameters are computed from the starred parameters. We verified the TCL parameters by comparing the model-predicted mean annual energy consumption per appliance to actual California data (EIA 2005). To derive the model prediction for ACs and heat pumps, we used the appliance and temperature data described above to simulate TCL populations in each climate zone for one year. Also, though the power consumption of a compressor (i.e., AC, refrigerator, heat pump) changes as a function of ambient temperature (WECC 2007) and the COP of a TCL changes as a function of ambient temperature, we have not modeled these effects here. These are important topics for future research.

Table 1. TCL Parameter Assumptions & Mean Annual Energy Consumption

Parameter	ACs	Refrigerators	Heat Pumps	Water Heaters
Ambient temperature, θ_a (°C) *	variable	20	variable	20
Dead-band width, δ (°C) *	0.25 – 1.0	1 – 2	0.25 – 1.0	2 – 4
Temperature set point, θ_{set} (°C) *	18 – 27	1.7 – 3.3	15 – 24 [a]	43 – 54
Thermal resistance, R (°C/kW) *	1.5 – 2.5	80 – 100	1.5 – 2.5	100 – 140
Thermal capacitance, C (kWh/°C) *	1.5 – 2.5	0.4 – 0.8	1.5 – 2.5	0.2 – 0.6
Thermal time constant, RC (h)	2.25 – 6.25	32 – 80	2.25 – 6.25	20 – 84
Energy transfer rate, P_{trans} (kW) *	10 – 18	0.2 – 1.0	(−25.2) – (−14)	(−5) – (−4)
Coefficient of performance, *COP* (-) *	2.5	2	3.5	1
Power consumption, P (kW)	4 – 7.2	0.1 – 0.5	4 – 7.2	4 – 5
Model-predicted mean annual energy consumption per appliance, 2012 (kWh)	1,610	858	4,700	2,100
Actual California mean annual energy consumption per appliance, 2005 (kWh) (EIA 2005)	1,637	867	N/A	2,121

[a] We assume that homes do not turn on their heat pumps if the mean daily temperature is >15°C.

Resource Potential Analysis

We quantified the resource potential of residential appliances by using the TCL model described above to estimate the power capacity and the energy capacity of populations of TCLs. The power capacity is the maximum change in power available if all controllable TCLs (i.e., TCLs currently within their dead-band) are switched from on to off. The energy capacity is how much energy is stored within the controllable TCLs' dead-bands, i.e. the sum of energy required for each TCL to move from one edge of its dead-band to the other minus the TCL population's steady state energy consumption over the same time period. These values are a function of the number of TCLs in the population and the TCLs' parameters (Table 1), and determine the fast DR potential of a TCL population.

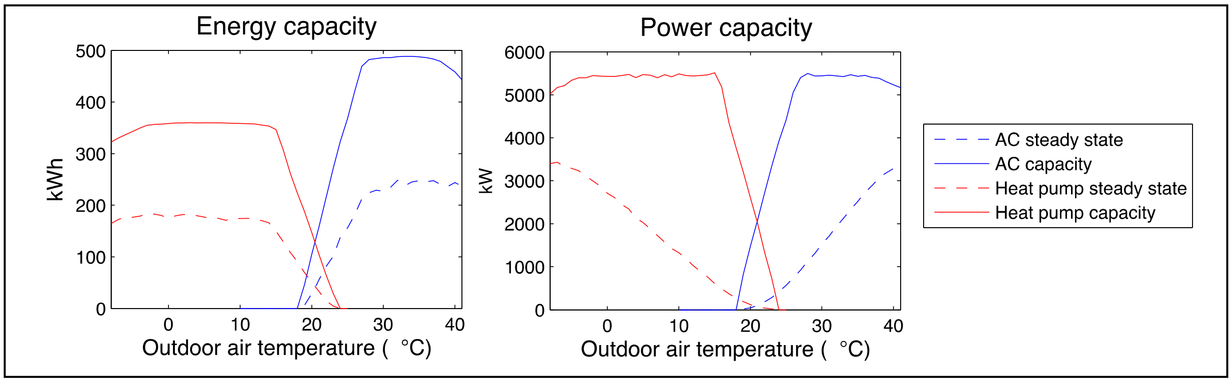
A TCL population's energy capacity is similar to a battery's energy capacity, but a TCL population's power capacity is not directly comparable to a battery's power capacity. While a battery can output the same power constantly until the battery is discharged, the power capacity of a TCL population changes if TCLs are outside of the dead-band and therefore uncontrollable. TCLs are more likely to be outside of the dead-band if the system is forced far from steady state.

In this section, we present the resource potential for populations of 1,000 TCLs, which are then used to calculate the total resource potential in the state of California.

Resource Potential of 1,000 TCLs

Power and energy capacities for ACs and heat pumps are a function of ambient temperature, as shown in Figure 1. Specifically, energy and power capacities are highest at moderately high/low temperatures, when all TCLs are cooling/heating. Capacities are small at ambient temperatures that are close to the TCL set points and also decrease at the highest and lowest temperatures when TCLs struggle to cool/heat the space.

Figure 1. Energy and Power Capacity of 1,000 Heterogeneous ACs or Heat Pumps



We report results for each type of TCL in Table 2. For ACs and heat pumps, we present the maximum and minimum capacities and the mean annual capacity in three representative climate zones. If a household has a combined AC and heat pump, their mean power/energy capacity is the sum of the mean values for ACs and heat pumps.

Table 2. Estimates of the Hourly Energy & Power Capacity for 1,000 Heterogeneous TCLs

	Aggregate Energy Capacity (kWh)	Aggregate Power Capacity (kW)
ACs		
Max	490	5,500
Mean of CEC Zone 5 (San Francisco)	30	380
Mean of CEC Zone 6 (Sacramento)	90	1,100
Mean of CEC Zone 10 (LA Basin Inland)	120	1,500
Min	0	0
Heat Pumps		
Max	360	5,500
Mean of CEC Zone 5 (San Francisco)	190	3,000
Mean of CEC Zone 6 (Sacramento)	170	2,600
Mean of CEC Zone 10 (LA Basin Inland)	120	1,800
Min	0	0
Water Heaters	1,200	4,300
Refrigerators	430	300

TCL Resource Potential in California

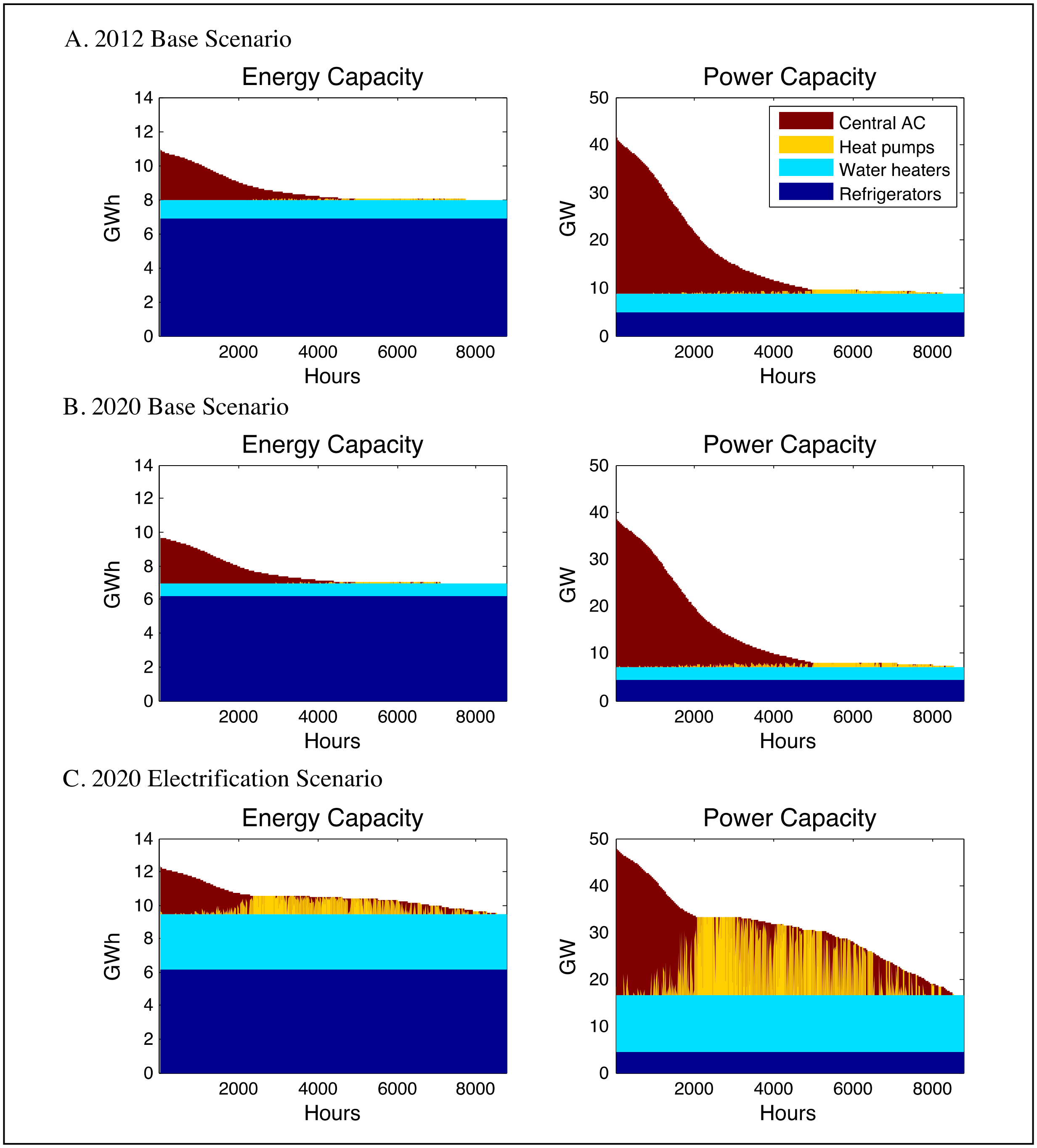
To understand the total TCL resource potential in California, we examined three scenarios: (A) 2012 base scenario; (B) 2020 base scenario, with increased numbers of households at the same appliance saturation rates as 2012 and increased COPs (by 0.5); and (C) 2020 electrification scenario, with increased saturation rates for heating (we assume 30% of gas water heaters and 30% of gas space heaters are electrified). For each scenario, we calculated the hourly TCL energy and power capacities, based on total appliance ownership and weather data by climate zone. Resource duration curves, similar to load duration curves, are shown in Figure 2. These graphs show the DR resource available in each hour of the year, sorted by hourly sum; thus, the y-axis shows the DR capacity that exists for at least the number of hours shown on the x-axis. For example, power capacity of all DR resources in Scenario A is at least ~9 GW for every hour of the year, and exceeds 20 GW for at least ~2,000 hours. Comparing Scenarios A and B, we can see that the effect of COP improvements outweighs the effect of additional appliances. In Scenario C, the assumed higher adoption of electric water heaters and heat pumps means that these appliances are a major component of the total DR resource potential. It is important to note that the water heater model does not include behavior-dependent water use profiles, which may impact hourly energy and power capacities, so we have less confidence in our results for water heaters than for other appliances.

Figure 2 shows that there is a significant DR resource potential inherent in current and projected future residential appliances in California. In fact, the power capacities are on the order of total state demand during peak hours in the summer. While these numbers may seem large, it is important to keep in mind the definition of power capacity. Specifically, at zero capacity all TCLs are completely off and at full capacity all TCLs are both available (plugged-in and switched on) and in the ON state (drawing power). Broken appliances and user behavior (e.g., people turning off their ACs on hot days when, based on their temperature set point and the outdoor air temperature, we would except them to be cooling) would decrease both energy and power capacities.

Revenue Potential Analysis

We have shown above that there is a large technical potential for DR from residential appliances in the state of California. In this section, we estimate how much money these appliances could earn in various electricity markets. TCL populations could profit from (1) participation in regulation, in which resources follow 4-second automatic generation control signals from the system operator; (2) participation in load following, in which resources are dispatched by the system operator on timescales of minutes; and (3) energy arbitrage in 5-minute energy markets. In each case, the amount of money they could make is a function of the power and energy capacities computed in the previous section. In this section, we use those results to quantify potential revenues from each of these revenue streams, for each class of TCL. An important caveat is that increasing participation of TCLs in any of these markets would lower the market clearing price decreasing the revenues that TCLs would earn. Thus, our analysis is only valid for small participation rates of TCLs, but is still suggestive of the rough magnitude of revenue potential and thus the potential cost-effectiveness of this resource.

Figure 2. Resource Duration Curves for Three Scenarios



Regulation and Load Following Revenues

Assuming TCL populations can be compared directly to energy storage devices, they could expect to earn \$785-2,010/kW by participating in regulation or \$600-1,000/kW by participating in load following over 10 years (Eyer and Corey 2010).[1] Though regulation is a

[1] These are present values, assuming 2.5% inflation and 10% discount rate, which imply a nominal rate of 12.75%.

more lucrative market, the potential is smaller; specifically, the 10-year maximum market potential in California is estimated to be 80 MW for regulation and 2,900 MW for load following (Eyer and Corey 2010).

Considering both power and energy constraints, we can compute a TCL population's 'regulation power capacity' and 'load following power capacity.' The revenues quoted above assume certain discharge durations (i.e. the amount of time to discharge at rated capacity before recharging): 15-30 minutes for regulation and 2-4 hours for load following. Therefore, we compute the regulation power capacity to be a TCL population's sustained 15-minute capacity and the load following power capacity to be a population's sustained 2-hour capacity. Assuming a TCL population must provide the same amount of up and down regulation or load following, the regulation power capacity is the minimum of (1) its energy capacity multiplied by 4, (2) the amount it can increase its power consumption from steady state, and (3) the amount it can decrease its power consumption from steady state. Similarly, the load following power capacity is the minimum of (1) its energy capacity divided by 2, (2) the amount it can increase its power consumption from steady state, and (3) the amount it can decrease its power consumption from steady state. Capacity and revenue results are reported in Table 3. For ACs and heat pumps, we use mean power and energy values computed over one year, and analyze the results for representative climate zones.

Table 3. Potential Revenues from Participation in Regulation and Load Following

	Regulation			Load Following		
	Power Capacity, 1,000 TCLs (kW)	Present Value of Revenue over 10 years, 1,000 TCLs	Mean Nominal Revenue ($/yr/TCL)	Power Capacity, 1,000 TCLs (kW)	Present Value of Revenue over 10 years, 1,000 TCLs	Mean Nominal Revenue ($/yr/TCL)
ACs						
Zone 5	37	$52,000	$9.40	15	$12,000	$2.20
Zone 6	220	$310,000	$57.00	45	$36,000	$6.60
Zone 10	310	$430,000	$79.00	60	$48,000	$8.80
Heat Pumps						
Zone 5	600	$840,000	$150.00	95	$76,000	$14.00
Zone 6	650	$910,000	$170.00	85	$68,000	$12.00
Zone 10	410	$570,000	$100.00	60	$48,000	$8.80
Combined ACs/Heat Pumps						
Zone 5	640	$890,000	$160.00	110	$88,000	$16.00
Zone 6	880	$1,200,000	$220.00	130	$100,000	$19.00
Zone 10	720	$1,000,000	$180.00	120	$96,000	$18.00
Water Heaters	240	$330,000	$61.00	240	$190,000	$35.00
Refrigerators	97	$140,000	$25.00	97	$78,000	$14.00

All values given to two significant figures. Revenues computed with values from (Eyer and Corey 2010).

Energy Arbitrage Revenues

In this section, we analyze the extent to which TCLs could save money by buying energy in CAISO's 5-minute energy market preferentially during low-price intervals and using the loads' storage capacity to avoid purchasing energy during high-priced intervals, i.e. energy arbitrage. The savings we calculate can best be thought to accrue to the load-serving entity (i.e. electric utility) that is purchasing the marginal energy on the spot market. New contracts between customers or aggregators and utilities would be required to distribute some or all of these savings to the owners of the appliances participating in arbitrage.

To compute the optimal power consumption over time, we relate the energy state (i.e. state of charge), e, of a TCL population in each time step, k, to past mean power usages, p:

$$(e(k+1) - e_{base}(k+1)) = (e(k) - e_{base}(k)) + (p(k) - p_{base}(k))\Delta T \tag{2}$$

where ΔT is the length of each time step (5 minutes), e_{base} is the energy state of the TCL population without external control, and p_{base} is the power usage of the TCL population without external control. e and p are positive and bounded by maximum capacities, which are time varying. Our goal is to find the optimal mean power usage in each time step that minimizes total energy costs over all time steps. We solve this problem as a linear program (LP). Once we determine the optimal trajectory for the whole year, $\boldsymbol{p^*}$, we use the proportional controller described above to track it. More details on this analysis can be found in Mathieu (2012).

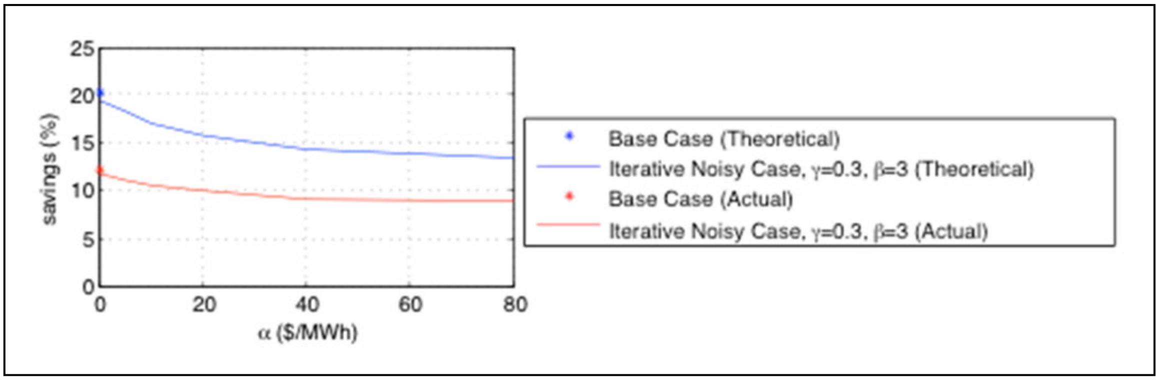
We used 2010 interval LMPs from MERCED_1_N001 (CAISO 2012), and temperature data from 'Merced 23 WSW' weather station (NOAA 2012) to compute savings through energy arbitrage. Merced revenue results are best compared to those for CEC climate zone 6 (Sacramento) in the previous section. We examined two cases: (A) a base case, in which we assume we have perfect temperature and price forecasts over 24 hours and so we use a 24-hour prediction horizon, and (B) an iterative noisy case, in which we assume we have noisy temperature and price forecasts over the next hour and so we use a 1-hour prediction horizon, and, at each interval, we run the LP to generate $\boldsymbol{p^*}$, though we implement only $p(1)$. In Case B, we model the temperature forecast error in the next hour as Gaussian white noise with standard deviation β, and we model the price forecast error, ω, with an autoregressive model of order one (i.e. AR(1)-process):

$$\omega(k+1) = \gamma\omega(k) + \alpha\varepsilon(k) \tag{3}$$

where ε is Gaussian white noise with standard deviation one, and $\omega(1) = 0$. Varying α, β, and γ, we can understand how performance changes with forecast error.

Figure 3 shows the effect of price forecast error on AC energy cost savings. As the price uncertainty standard deviation, α, increases, the savings decrease, but even for large values of α savings are possible. Similar analyses are possible for the price uncertainty autocorrelation, γ, and the temperature uncertainty standard deviation, β, though we do not expect β to be very large and we find that varying γ does not significantly affect the results. In Figure 3, we plot both the savings predicted by the LP (theoretical) and the savings computed after controlling the TCL population to follow the LP-generated control trajectory (actual). The difference results from the inability of the TCL population to track the control trajectory. Two issues cause poor tracking performance: (1) the LP algorithm does not take into account all dynamic temperature effects such as houses cooling during the night, which causes the ACs to turn on later in the day than expected based on the current outdoor air temperature alone; and (2) the proportional controller is unable to switch the correct number of TCLs in each time step, and this issue is further compounded by the fact that at each time interval some TCLs are outside of the dead-band and therefore uncontrollable. It is likely that a better control approach could lessen these issues causing the 'actual' to approach the 'theoretical.'

Figure 3. Effect of Price Forecast Error on AC Energy Cost Savings



In Table 4, we show the actual mean energy costs with no arbitrage and mean energy cost savings via arbitrage for each type of TCL. For Case 2, we set the price uncertainty standard deviation, α, to $40/MWh; the temperature uncertainty standard deviation, β, to 3°C for ACs and heat pumps and 0°C for water heaters and refrigerators; and the price uncertainty autocorrelation, γ, to 0.3.

Table 4. Wholesale Energy Cost Savings through Arbitrage (Merced)

	No Arbitrage Mean Energy Costs ($/yr/TCL)	Base Case Mean Energy Cost Savings		Iterative Noisy Case Mean Energy Cost Savings	
		($/yr/TCL)	(%)	($/yr/TCL)	(%)
ACs	$92.85	$11.33	12.2%	$8.39	9.0%
Heat Pumps	$266.94	$27.20	10.2%	$17.83	6.7%
Combined	$359.79	$38.53	10.7%	$26.22	7.3%
Water Heaters	$81.80	$33.57	41.0%	$13.39	16.4%
Refrigerators	$33.44	$9.05	27.1%	$4.52	13.6%

These savings, on the order of 10% of wholesale energy costs assuming noisy forecasts, are modest but not insignificant, and could be further improved by a refined control strategy that addresses some of the limitations of the approach discussed above. For water heaters and refrigerators, especially, refined control strategies could lead to much greater savings, given these appliances' large energy storage capacities. This is an area of continuing research.

In the next section, we compare the possible revenues estimated above to potential cost structures for enabling technologies to allow the TCLs to participate in electricity markets.

Cost Analysis

The cost of controlling loads to provide regulation, load following, or arbitrage is a function of the sensing and communications infrastructure required. In this section, we describe DR-enabling technologies, and then use the potential revenues derived in the previous section to compute per-TCL break-even capital and annual costs. These results help us understand how much money a firm or household could spend to enable DR and still be profitable.

DR-Enabling Technologies

In our work, we assume that, in each time step, the same control signal is broadcast to all loads, and each load acts upon the control signal based upon its current ON/OFF state. Therefore, the following components are required to enable TCL control:

- low latency broadcast communication system
- hardware/software that enables the loads to:
    - receive control signals
    - determine their current state i.e. whether they are currently ON or OFF
    - make decisions based on both the current control signal and their current state about whether or not they should switch ON or OFF
    - override the local control and switch (provided they are within their dead-band)

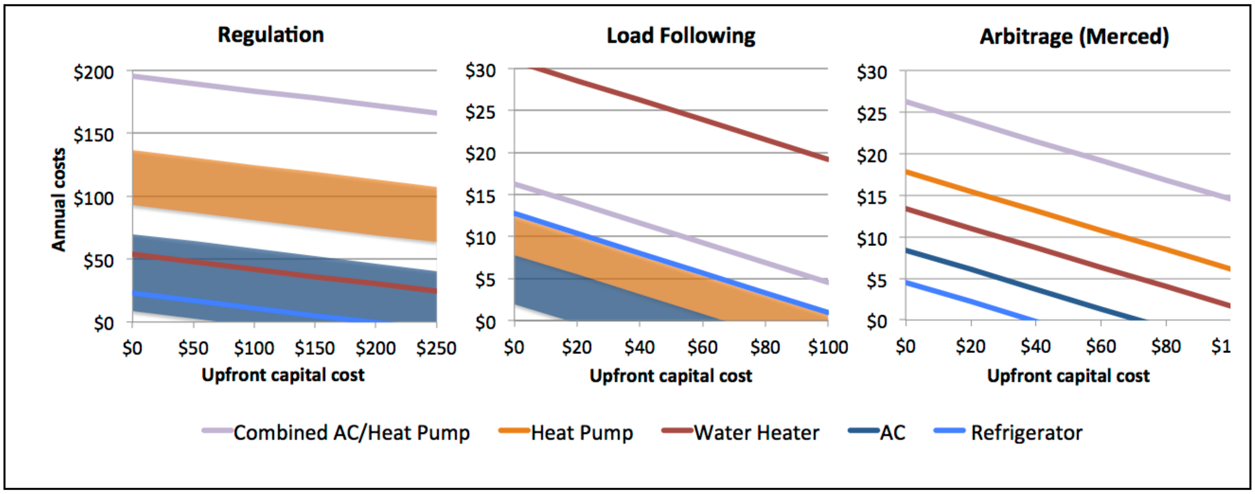
Additionally, equipment is required to provide the central controller with the following information at each time step: (1) the aggregate power consumption of the TCLs, (2) the number of devices available for control, and (3) the mean power consumption of the TCLs that are ON. While (2) and (3) can be estimated based on system models, (1) requires real-time data. In our previous work (Mathieu & Callaway 2012), we describe several ways to estimate the aggregate power consumption of the TCLs: with information from each of the loads, some of the loads, or the distribution substation. The method chosen is a tradeoff between the desired accuracy of the aggregate power measurement and the costs. For example, getting information from each of the loads results in a very accurate measurement of aggregate power, but requires low-latency data connections from each of the loads to the central controller. On the other hand, getting information from the distribution substation simply requires one low-latency data connection and a distribution substation power meter; however, we would need to estimate the aggregate power consumption of the TCLs, which make up a small fraction of the total substation load, using load forecasts, forecast noise models, TCL population models, and state estimation methods. Therefore, the choice of enabling technologies is a trade-off between costs, computing, and signal tracking accuracy.

Break-even Cost Points

We identify break-even cost points for DR by comparing regulation, load following, and arbitrage revenues to potential ranges of upfront capital costs and annual costs. Upfront costs include the cost of necessary equipment to enable control, described above, as well as hardware/software installation costs. Annual costs include reoccurring maintenance costs and financial compensation to residential customers participating in these programs. The goal of this analysis is to understand what cost points are required for profitable TCL participation in electricity markets.

For capital costs up to $250 per TCL, we calculated the annualized capital cost using a lifetime of 20 years and a real discount rate of 10%. Then, for each TCL and for each type of revenue stream (regulation, load following, and arbitrage), we calculated the maximum annual cost per TCL that would make total annual costs equal to the potential annual revenue. Results are presented in Figure 4. If the total installation and annual participant costs required to enable a TCL to participate in regulation, load following, or arbitrage fall below and to the left of the lines in Figure 4, then TCLs can potentially make money in these markets. For ACs and heat pumps providing regulation and load following, we present ranges bounded by values computed with the mean per-TCL earning potential from CEC Zone 10 (LA Basin Inland) and CEC Zone 5 (San Francisco). For combined ACs/heat pumps providing regulation and load following, we present values for CEC Zone 6 (Sacramento) since all three zones had very similar results. For arbitrage, we use values from the Merced analysis. Note that even the most cost-effective battery technologies being considered for grid regulation in a recent study (EPRI 2010) have upfront costs much higher than those shown in Figure 4.

Figure 4. Per-TCL Capital and Annual Costs Required to Break Even



The results in Figure 4 show that there is a wide range of cost structures for DR-enabling technologies that would allow TCLs to participate profitably in regulation, load following, or energy arbitrage. Refrigerators and water heaters are well-suited to the hour-scale requirements of providing load following, given their large energy storage capacities relative to their power capacities, while air conditioners and heat pumps are better-suited to the shorter-timescale regulation market. While the cost structures for enabling technologies and customer compensation are uncertain, the range of profitable cost structures shown in Figure 4 indicates that providing fast DR could potentially be accomplished cost-effectively with all four types of appliances in different climate zones.

Conclusions

We find that existing TCLs could provide a substantial portion of the fast timescale reserves required in power systems with high penetrations of intermittent renewables. Specific results depend upon the type of TCL and, for ACs and heat pumps, the climate that the TCL operates in. Comparing the arbitrage energy cost savings in Table 4 to the potential revenues from direct participation in energy markets in Table 3 (results for CEC Zone 6 are most relevant), we find that savings/revenues for arbitrage and load following are approximately the same for ACs and heat pumps while refrigerators and water heaters could earn more through load following. All TCLs could earn much more by participating in regulation, though as mentioned before, the regulation market is relatively small. In each case, savings/revenues are only valid if TCLs constitute a small portion of the market. As more TCLs participate, the marginal value of avoided procurement of ancillary services will likely decrease, and the revenues of TCL populations along with it. Further research is required to characterize the shape of ancillary service cost curves and thus the magnitude of TCL revenue reduction.

The key to inclusion of DR in energy markets is the resolution of a number of policy barriers. Based on our findings, we have several policy recommendations. First, we recommend the design of new energy and ancillary services market products suited to loads, which do not have the same characteristics and constraints as generators. For example, CAISO has proposed the Regulation Energy Management (REM) functionality that allows non-generator resources, which have strict energy constraints, to bid their 15-minute capacity into the regulation market (CAISO 2011). Other policies designed to facilitate the participation of loads in ancillary service markets should take into account the advantages of TCLs, which can provide much faster responses to control signals because they lack significant ramp rate constraints. FERC's proposed "pay-for-performance" standards for regulation compensation acknowledge this potential advantage of demand-side resources and would help TCLs cost-effectively provide regulation service (FERC 2011).

Our second policy recommendation is the design and adoption of communications and appliance standards that will make it easier to engage residential loads in DR. It is much less expensive to manufacture TCLs with necessary communications and control equipment than to retrofit existing TCLs (though that would also be a key component of large-scale DR deployment). Many companies, regulators, and research agencies are currently participating in the development of smart grid interoperability standards with the National Institute of Technology and Standards (NIST). Good communication standards should not only enable interoperability but also minimize privacy and security issues. Appliance standards, which historically have been very successful in California, should require smart grid connectivity, enabling low-cost appliance participation in new and existing markets for fast DR. Additionally, implementing standards for appliance factory settings could increase resource potentials. For example, increasing TCL dead-bands would proportionately increase energy storage capacities.

Acknowledgements

This work is funded in part by a PSERC Future Grid Initiative Grant.

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