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Demand Response as a Real-Time, Physical Hedge for Retail Electricity Providers: The Electric Reliability Council of Texas Market Case Study

Andrew Blohm [1,*], Jaden Crawford [2] and Steven A. Gabriel [3,4]

1 Resideo Technologies, 901 E 6th St, Austin, TX 78702, USA
2 Leap, 1700 Montgomery Street, Suite 200, San Francisco, CA 94102, USA; jaden@leap.energy
3 Department of Mechanical Engineering, College of Engineering, University of Maryland, College Park, MD 20742, USA; sgabriel@umd.edu
4 Department of Industrial Economics and Technology Management, Faculty of Economics and Management, Norwegian University of Science and Technology, 7491 Trondheim, Norway
* Correspondence: andrew.blohm@resideo.com

Abstract: Residential demand response (DR) programs are generally administered through an electricity distribution utility, or an electric grid operator. These programs typically reduce electricity consumption by inducing behavioral changes in the occupants of participating households. We propose implementing a wholesale-price-sensitive residential DR program through the retail electricity provider (REP), who has more naturally aligned incentives to avoid high wholesale electricity prices and maintain customer satisfaction, as compared to distribution utilities, grid operators, and the average residential consumer. Retail electricity providers who serve residential consumers are exposed to substantial price risk as they generally have a portion of their portfolio exposed to variable real-time wholesale electricity prices, despite charging their residential customers a fixed retail electricity price. Using Monte Carlo simulations, we demonstrate that demand response, executed through internet-connected thermostats, to shift real-time residential HVAC load in response to real-time prices, can be used as an effective physical hedge, which is both less costly and more effective than relying solely on financial hedging mechanisms. We find that on average a REP can avoid USD 62.07 annually per household using a load-shifting program. Given that REPs operate in a low margin industry, an annual avoided cost of this magnitude is not trivial.

Keywords: demand response; residential load; load shifting; economic dispatch; REP; real-time; IoT; energy hedge; physical hedge; HVAC

Citation: Blohm, A.; Crawford, J.; Gabriel, S.A. Demand Response as a Real-Time, Physical Hedge for Retail Electricity Providers: The Electric Reliability Council of Texas Market Case Study. *Energies* **2021**, *14*, 808. https://doi.org/10.3390/en14040808

Academic Editor: Benedetto Nastasi
Received: 23 November 2020
Accepted: 29 January 2021
Published: 3 February 2021

1. Introduction

Demand response (DR) refers to deliberate actions taken by or on behalf of electricity consumers to change the amount of grid electricity that they would otherwise have consumed over a specific period of time in response to wholesale market prices or dispatch signals from the DR program administrator. DR is regaining popularity in the literature [1], as it is seen as a relatively low-cost means to achieve economic and sustainability goals. For example, DR can be used as a means of inducing bulk changes in consumer electricity consumption in order to reduce electricity prices, assist in the integration of variable generating sources [2], lower system balancing costs [2], avoid investment in generation capacity (in particular avoided peak generation cost) [3,4], shave peak demand [5–7], save on customer electricity bills, and improve environmental sustainability [8] to name a few areas.

Broadly speaking, there are two categories of DR: (1) incentive-based programs and, (2) time-based rates. Time-based rates include interruptible service rates, which require the ratepayer to curtail usage on short notice, or in specific intervals, in exchange for a lower rate, and time-of-use (TOU) rates, which vary electricity prices as a function of time, usually for periods more likely to have higher demand, more grid stress, or higher prices [9].

Incentive-based programs usually provide end-users participation incentives separate from the retail electricity rate and can include such programs as emergency demand response programs, capacity market programs, and system peak shaving programs.

Given the significant, positive benefits that DR programs deliver; we would expect to see such programs used in system planning across deregulated electricity markets. But residential customers do not tend to register for, or respond to, DR programs and developing strategies to attract customers is a topic that needs more research [1]. Further, there is a perception that DR programs do not meet their load commitments, which can be problematic for system operators and resource planners [5].

Research on optimal demand response programs tends to assume away the challenges of customer participation. In the literature, customers are often assumed to participate solely based on savings. For example, the constraint function often includes some measure of consumer benefit, often the minimization of households' bill payments [10–14]. These studies find bill savings of more than 25% [12,13] and 5% [15].

Additional studies using pseudodata have found that an optimized deployment of DR at the household level could save consumers between 8 and 22% during a typical summer day [16,17]. Other studies have estimated the magnitude of these impacts at between EUR 18 per month in winter and EUR 26 per month in the summer [18,19]. Ref. [20] found expected cost savings of a TOU program to be in the EUR 50 to 150 per year; not considering the investment costs to enable participation, such as costs for smart meters, connected devices, etc.

But, if residential customers are only being reimbursed for their efforts through their avoided costs then most of the benefits of such a program are accruing to other actors. Furthermore, bill savings are small given that most residential consumers pay a flat rate which is fixed for the term of the contract regardless of the quantity demanded or the wholesale price in any given interval, and TOU rates are fixed rates for specified blocks of time (on-peak and off-peak, for example) that do not vary based on actual wholesale prices or system conditions in any given interval, thereby only exposing consumers to a small fraction of the wholesale market variability. The bill savings are particularly small when compared to the services provided and consumers' effort to provide them. As a result, from a savings perspective, these consumers have little natural incentive to moderate electricity consumption in any interval smaller than an entire billing cycle.

Furthermore, the participation requirements of the programs proposed in the literature are cumbersome. For example, [21] requires an hourly estimation of hot water consumption and temperature preferences; [22] requires customer risk priorities, as well as thermal comfort vs. savings preferences; [23] requires for each consumer appliance, the kW sizes, consumption preferences for the appliance (restricted or open, which is admittedly likely to change over the course of a day), and, consumer bid prices (i.e., their strike price); [12] assumes the ability to publish meaningful real-time prices a few hours in advance such that households can make consumption decisions; [12] requires for each planning horizon, an hourly energy consumption schedule for each appliance, as well as the maximum and minimum power levels by appliance; [24], while admittedly providing a significant incentive still assumes the micro-grid operator knows for each customer the outage cost function and the daily interruptible energy limit, which might limit participation.

Within the literature, the issue of residential customer participation in DR programs, is largely viewed through an information-deficit lens, identifying a lack of information by the residential end-user as a significant barrier to successful residential DR program implementation [8,25]. Many of the existing approaches assume that residential end-users are capable of becoming good DR program participants if outdated metering technologies are replaced and real-time load and pricing information are provided to the household [8].

Ref. [25,26] find that electricity consumption is largely 'invisible' and that consumers don't have a good awareness about their consumption. Given that the primary use of electricity for most households is space conditioning, it can be said that households don't really demand electricity but instead demand a certain level of comfort. And in general, there is a lack of understanding of the relationship between additional kWh and perceived comfort. The theory suggests that if a household has a better understanding of its energy consumption via actual consumption data and appliance specific consumption (presented in real-time) [26], then we might expect an uptick in the responsiveness of residential consumers to DR programs.

However, in deregulated markets, experiences to date suggest that electricity is a low-involvement product for a majority of consumers regardless of the information provided to them. In these deregulated markets consumers have a choice in determining their electricity provider. And in general, there are low barriers to switching energy providers with high amounts of information available (usually mailers, websites, etc.), and, significant savings if a new provider is selected. Historical data suggests that consumer switching behavior is well below expectations, reinforcing the idea that electricity is a low-involvement product, with routines and inertia being the dominant factors in determining customer behavior [27].

This does not mean that residential electricity consumers are uninterested in reducing electricity consumption generally, or that consumption cannot be reduced in response to high prices: It simply means that residential consumers require incentives that ensure the customers' demand for comfort is met within acceptable margins, information requirements are not onerous, and the consumer is not required to change their behavior, themselves, in response to market or grid signals.

We believe many of the problems surrounding DR programs, stem not from consumers' lack of information, but from the structure of the programs: The incentives for the DR program administrator and the consumer are not aligned in ways that are meaningful enough to consumers for them to initiate the required load-reducing behavior at the time the load reduction is needed. In other words, even if we paid residential customers the true market value of their services [24], residential consumer behavior is an unreliable mechanism for reliable demand response load reduction. Instead, a more natural partnership exists between aggregators, acting on the behalf of consumers, and Retail Electricity Providers (REPs).

Under our proposed DR model, using aggregators acting on behalf of consumers and REPs, the incentives of all involved parties are aligned by the already existing deregulated electricity market through the real-time pricing mechanism.

REPs often give WiFi-enabled thermostats to residential customers as part of their customer recruitment and retention efforts. Customers like these devices because of their ability help to reduce their energy spend and/or their contributions to carbon emissions. We propose and provide results for a program in which a REP provides WiFi-enabled smart thermostats, and potentially slightly lower rates, to a portfolio of residential electricity consumers. In return, the consumers allow the REP, via an aggregator, to automatically and temporarily adjust their thermostats from time to time, which will further reduce their electricity consumption while maintaining a reasonable level of comfort.

The focus of the remainder of the paper is on a hypothetical REP operating in Electric Reliability Council of Texas (ERCOT), where Resideo and Leap are presently implementing hedging programs utilizing end-use customer load curtailment. We show that a REP operating a real-time price avoidance program could achieve significant savings from avoided costs.

2. Results

Using historical weather and wholesale pricing data for Load zone Houston, in combination with the coefficients from the regression model, we determine the optimal strategy over the period of analysis. We demonstrate the REP's avoided cost using historical data for Load zone Houston over the period 1 January 2011 to 1 September 2020. We use settlement point prices and day-ahead prices for Load Zone Houston from 1 January 2011 through 1 September 2020 because ERCOT underwent significant market changes between 2010 and 2011. For the purpose of this analysis we assume that the REP only uses the real-time market (i.e., no other contracting mechanisms used). This assumption does not consider the significant role of the day-ahead market or power purchase agreements in a REP's portfolio. However, the results of this analysis in the short term still inform how a REP might reduce costs in the exposed portions of their portfolio; and in the longer term might serve to influence buying behavior in the PPA marketplace. The customers whose load is being shifted represent a subset of the REPs total portfolio of customers at a given settlement point, and this subset of customers is being used to mitigate price risk associated with all of the REP's customer load at that settlement point. So, as long as the REP has total portfolio load exposure in the real-time markets equal to, or greater than, the amount of shiftable load from the smaller, demand response subset of the portfolio, the PPAs will not impact the profit differential from the REP's load-shifting activities.

The value of the load-shifting program is significant with an average annual avoided cost of USD 62.07 per residence, as well as significant ability to reduce exposure during years with excessively high prices. Given that REPs operate in a low-margin industry, an annual avoided cost of this magnitude is not trivial. Further, real opportunities exist to leverage a real-time physical hedge as a part of broader changes to the forward strategies for purchasing electricity, potentially saving even more. Once a REP has a sufficiently large portfolio of IoT devices capable of acting as a physical hedge, other hedging alternatives such as financial options become less necessary.

In Tables 1 and 2 we show the results of our analysis for Load zone Houston at USD 150 and USD 300 strike prices. Strike prices are determined by the REP and indicate a real-time LMP at or above which the REP wants the aggregator to initiate a demand-response event. The tables include the expected avoided cost per residence; the total days of the year (DOY) in which a demand-response event would have occurred (DOY w/Event); the total number of dispatch hours for each year (Total Hours); the total number of distinct events for each year (Events); and a breakdown of the number of 1-hr, 2-hr, 3-hr, and 4-hr demand-response events. As the tables indicate, even when doubling the strike price from USD 150 to USD 300, the REP would still realize 90% of the average avoided cost value, while reducing the average number of demand-response events by 53%. This is not surprising as the majority of the avoided-cost value is derived from avoiding exposure to prices well in excess of either strike price. It also indicates that a REP has ample ability to optimize meaningful savings and customer comfort by adjusting strike prices.

Load Zone Houston

The results of a load-shifting program for 2011–2020 are presented below. Note that 2020 includes 1 January 2020 through 1 September 2020.

Table 1. Annual avoided cost of a load-shifting program deployed in ERCOT assuming a USD 150 per MWh strike price.

Market Analysis: Strike Price USD 150 per MWh									
ERCOT Load Zone	**Year**	**Avoided Cost**	**DOY w/Event**	**Total Hours**	**Events**	**1-h**	**2-h**	**3-h**	**4-h**
LZ Houston	2011	USD 136.00	86	147	101	72	15	11	3
LZ Houston	2012	USD 19.30	38	63	43	30	7	5	1
LZ Houston	2013	USD 28.80	60	87	69	57	7	4	1
LZ Houston	2014	USD 19.0	55	117	70	41	14	12	3
LZ Houston	2015	USD 23.30	51	94	56	35	10	5	6
LZ Houston	2016	USD 35.50	74	145	91	57	19	10	5
LZ Houston	2017	USD 63.20	87	159	106	75	15	10	6
LZ Houston	2018	USD 66.80	83	207	113	63	16	24	10
LZ Houston	2019	USD 193.10	113	242	143	81	33	21	8
LZ Houston	2020	USD 35.70	52	106	58	28	14	14	2
LZ Houston	Average	USD 62.07	70	137	85	54	15	12	2

Table 2. Annual avoided cost of a load-shifting program deployed in ERCOT assuming a USD 300 per MWh strike price.

Market Analysis: Strike Price USD 300 per MWh									
ERCOT Load Zone	**Year**	**Avoided Cost**	**DOY w/Event**	**Total Hours**	**Events**	**1-h**	**2-h**	**3-h**	**4-h**
LZ Houston	2011	USD 128.00	60	101	71	51	11	8	1
LZ Houston	2012	USD 16.30	24	37	28	22	4	1	1
LZ Houston	2013	USD 24.40	38	56	44	36	4	4	0
LZ Houston	2014	USD 14.40	28	48	36	27	7	1	1
LZ Houston	2015	USD 19.10	27	54	30	19	3	3	5
LZ Houston	2016	USD 28.20	57	101	63	39	14	6	4
LZ Houston	2017	USD 55.30	65	109	79	60	11	5	3
LZ Houston	2018	USD 58.60	47	115	66	37	14	10	5
LZ Houston	2019	USD 182.00	74	151	93	55	23	10	5
LZ Houston	2020	USD 31.10	31	60	33	15	9	9	0
LZ Houston	Average	USD 55.74	45	83	54	36	10	6	3

Given that ERCOT is a summer-peaking system, it is not surprising that the highest prices and thus, the most value of a load-shifting program, tend to occur during the hottest months. What might be surprising is that non-trivial avoided costs from cooling load can be realized during winter and shoulder months, as shown in Figure 1. It is important to remember that this analysis only addresses avoided costs from cooling load. Avoided costs in January, February, and December would be higher with the incorporation of electric heating. It is also important to note that the high 2019 prices are are not anomalous, but the result of thermal generation retirements decreasing ERCOT's reserve margins, resulting in increasingly volatile prices. Absent the impacts of COVID-19 on ERCOT system load, we would have expected 2020 to look similar to 2019.

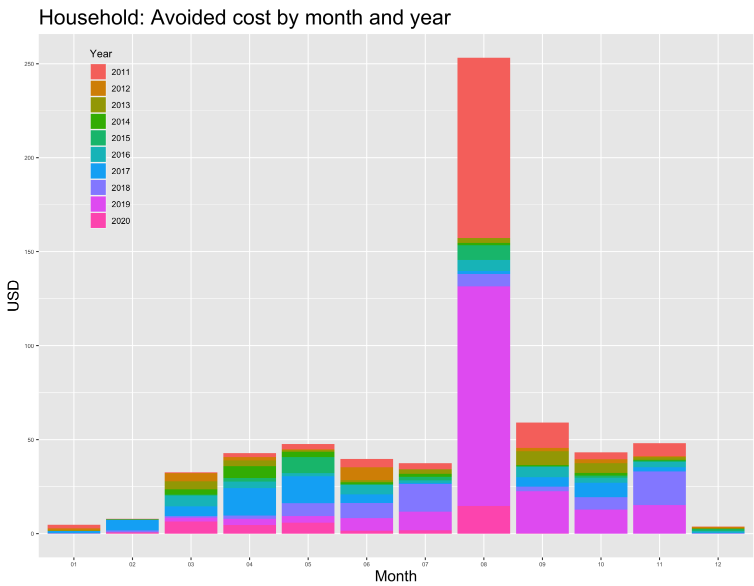

Figure 1. Avoided cost by month and year at USD 150 strike price.

It is also important to recognize that even though the majority of the value of a load-shifting program tends to occur during the hottest months (See Figure 1), the number of events outside of those months can be even more significant than the savings derived in them, as shown in Figure 2. We do not expect meaningful disruption to customer comfort since these demand-response events utilize small thermostat setbacks, and since the majority of the demand-response events are initiated during hours when the majority of residential occupants are not home. In Figure 3 we show the number of events over the period 2011 to 2020 by start-time hour, at a USD 150 strike price. Given average event length and event start time most events will have little overlap with hours in which occupancy rates are high. Even still, since the majority of the value is derived from the hottest months, if a REP is particularly sensitive to customer comfort, it can utilize higher strike prices in lower-value months to ensure that it avoids both very high prices and frequent demand-response events.

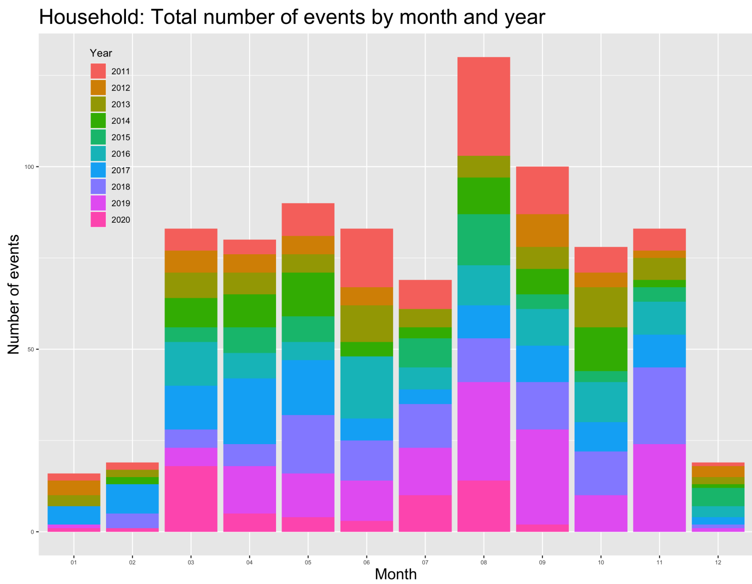

Figure 2. Number of events by month and year per household at USD 150 strike price.

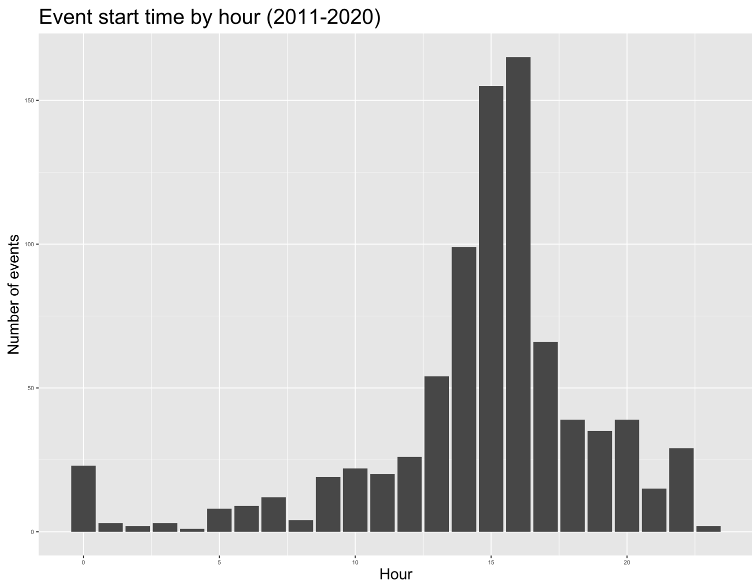

Figure 3. Number of events by hour over the period 2011–2020.

3. Discussion

Residential demand-response programs are typically designed to reduce customer load by inducing changes in customer behavior. Mechanisms for reduction often include charging households different prices at different times of the day, providing information about real-time load or wholesale market prices, or similar information-based methods. Another popular method is to incentivize household investment in energy-efficiency improvements through energy-efficiency programs. These programs tend to deliver relatively small load reductions to the program provider. One reason for this is that the incentives of the program provider and the household are not aligned: The value to the household of engaging in the program is outweighed by costs in time, financial investment, or both.

By contrast, a REP (or aggregator acting on their behalf), controlling customer load using IoT devices in real-time, in response to wholesale market prices, has more naturally aligned incentives since, by coordinating the resources' consumption, it can lower its entire portfolio's exposure to volatile wholesale market prices, subsequently reducing the cost to serve its end-users. REPs must supply the electricity demanded by their customers in all intervals, regardless of their contract positions or exposure to high real-time prices, despite having fixed-priced contracts with those customers. However, REPs have the ability to deploy internet-connected devices to their customers, or to incentivize them to allow the REP to utilize IoT devices that the customers have already installed in their homes. In fact, many REPs already give IoT devices to residential end-users as a means of customer acquisition and retention. Access to these devices gives a REP the capability to directly control a meaningful portion of their customers' load, ensuring that they sufficiently respond to wholesale electricity market prices. Thus, they are in an optimal position to manage and benefit from such a load-shifting program.

Several important caveats exist to the results of this analysis. First, settlement intervals for load in ERCOT are 15-min in length with sub-interval pricing available every 5-min, since generators settle in 5-min intervals. Given that price spikes can occur at any sub interval of the 15-min settlement period and that price forecasting is imperfect, an aggregator is unlikely to achieve the entirety of the value proposed here. There are also constraints in regards to the time required to transmit a signal to each thermostat in the portfolio, which can take a few minutes. Second, the hourly abstraction artificially lowers the number of events while also increasing the average event length. For example, short price spikes, which are quite common, are missed by this approach if the average hourly price in which they occur falls below the strike price. However, it should be noted that the results proposed here are consistent with our experiences running a load-shifting program in ERCOT. Third, the regression analysis generates a load-removed estimate for an entire event based on event duration and weather; which is then applied equally to each event interval to determine the avoided cost. However, this is an oversimplification, as the largest load-removed values occur early in the event, since most, if not all, HVAC systems are off given the temperature setback applied. As units cycle back online (once the new set point temperature threshold is triggered) the load-removed value for the interval decreases. Aggregators that are skillful at matching the highest load-removed values with the highest prices should be able to secure even higher avoided costs.

Finally, managing customer comfort is an important, if not the most important aspect, of a load-shifting program that uses IoT devices controlling the HVAC system to achieve load reductions. Customer opt outs (i.e., leaving an event early because of actions taken by an aggregator) are a challenge however, the REP and household have a common goal. REPs, having invested in IoT devices, do not want to see a customer leave and thus, will choose the strike price and deployment strategy carefully, so as to not stress the household. Meanwhile, customers are interested in participating in enough events so that they can keep their cheaper electricity rates.

In a typical year, the demands on the household of a load-shifting program are minimal. In Figures 4 and 5, we show that in an average year there are six events per month with an average duration of 1.5 hours. It is important to remember that an aggregator can reduce customer fatigue by adjusting both the setpoint delta, and the REP can reduce customer fatigue by adjusting the strike price. For example, while the analysis below reflects a USD 150 per MWh strike price, increasing the strike can significantly lower the number of events per year and as a result the total household time spent in events.

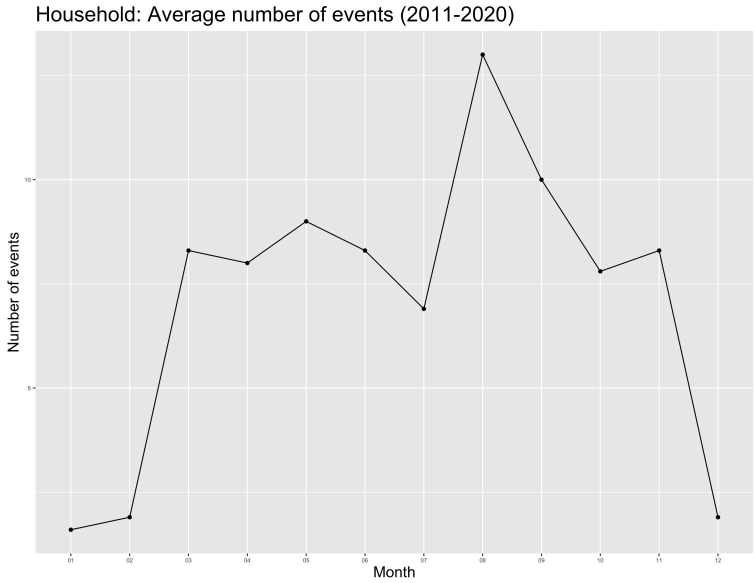

Figure 4. Average number of events by month over the period 2011–2020.

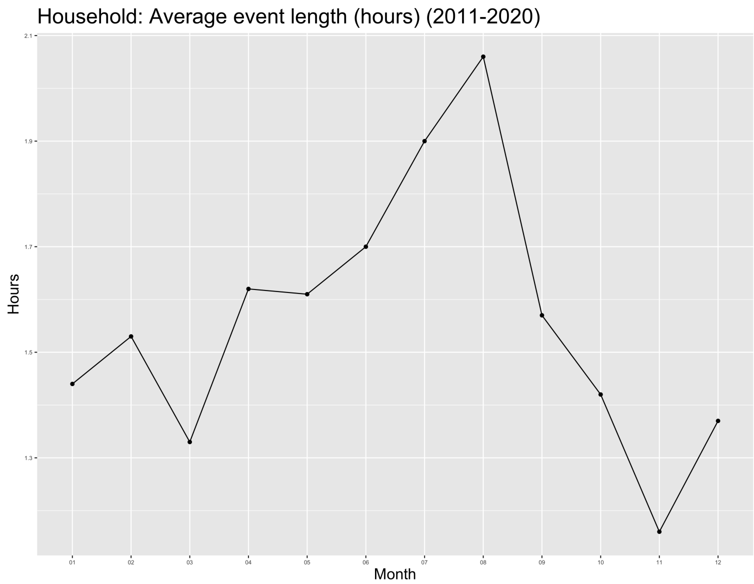

Figure 5. Average event length by month over the period 2011–2020.

Finally, as was discussed in Figure 3, given the average event length and event start time most events will have little overlap with hours in which occupancy rates are high.

Important research remains in determining the customer response to our proposed interventions at scale; refining the available household resource; and, designing optimal control policies. Resideo is presently running a residential demand response program through REPs in ERCOT, utilizing automated control of participating customers' WiFi-connected thermostats. And, results from Resideo's existing LoadFlex program in Texas suggests that such an arrangement can be profitable for REP, aggregator, and customer alike. Given our experiences, we find that the performance of this type of automated residential demand response portfolio is predictable in a way that individual household behavioral response is not. As such, we expect the portfolio to outperform other DR resources in terms of availability, dependability, and average kW response per household.

4. Materials and Methods

4.1. Materials

4.1.1. Historical Wholesale Electricity Price Data

We use publicly available, historical wholesale price data for load zone Houston, in the ERCOT ISO, which covers much of Texas. The data are available online at http://www.ercot.com/mktinfo/prices. Wholesale price data are available for every 15-minute settlement period over the period of analysis (i.e., 1 January 2011–1 September 2020).

4.1.2. Historical Temperature Data

For the same period we use a gridded weather data product produced using Earth Networks weather station data and Global Weather Corporation models [28]. The gridded data product has two advantages over publicly available data: (1) there are fewer missing data, and (2) the weather variables are calcluated using weather stations co-located with population centers, whereas the best quality public weather stations tend to be at airports, which tend to be far from the population centers they serve. The gridded data product allowed us to create a population weighted temperature variable using household location.

4.2. Methodology

To estimate the value of real-time price avoidance using internet-of-things (IoT) devices to move residential load in real-time we break the problem into three separate sub-problems. First, we determine all of the possible interventions that could have taken place. Then, we determine the value of the sets of actions. Finally, we determine an optimal path through all of the available options to create a daily deployment strategy.

4.2.1. Enumeration of the Permissible Strategies

To determine the value of the DR program we enumerate all permissible strategies and evaluate each over the historical period (i.e,. 1 January 2011 to 1 September 2020). A strategy is a set of instructions on how to deploy the resource (i.e., when and for how long); whereby the optimal pathway is the strategy with the highest reward. However, without some constraints the size of the problem is prohibitive in terms of the number of combinations to evaluate. Instead of looking for one optimal path across the entire period of analysis, we look for the optimal daily path and stitch those together to form the optimal path for the entire period. Now the problem is to define a daily set of instructions (i.e., hourly information on whether to begin a DR and for how long), for each hour of a 24-h period (i.e., midnight to midnight) that maximizes the reward. Given the number of possible strategies in a 24-h period, we imposed this constraint to limit the size of the problem.

We further reduce the size of the problem by considering a smaller set of event durations. Given the workings of the wholesale market, event durations could range from as little as 15 min to many hours. However, as a first approximation, we consider 5 different event durations: 0-h (no event), 1-h, 2-h, 3-h, or 4-h long events.

Additional reasonable and illustrative constraints include:

1. Events must start and stop on the same day (prevent double-counting).
2. A household cannot be in more than one DR event at a time.
3. Each household is allowed a one-hour load-recovery period after an event, such that the house can reaclimate to the previously defined thermostat setpoint.

We use Monte Carlo simulation methods to iterate all of the set of permissible daily strategies that satisfy the constraints. One approach would be to determine all the possible permutations of the set of event durations over a 24-h period and then whittle those down to only those that satisfy our constraints. However, this approach is not practical given existing computational limits. The number of permutations of a set of event lengths 0, 1, 2, 3, and 4-h in a 24-h period is 5^{24}, since there are five options available for each hour of a 24-h period. Instead, we implemented a Monte Carlo simulation approach that simultaneously incorporated the constraints, enabling the algorithm to only produce permissible strategies. We determined the appropriate stopping point, the maximal number of permissible strategies given the set of constraints, using a combinatorial approach. We found that there are 5,976,577 daily strategies that satisfy the set of constraints. Next, we determined the value of each daily strategy as described below.

4.2.2. Reward Function

The value of a load-shifting event is a function of the amount of load that can be removed, the amount of load-recovered, which is the increased energy consumption after an event to return a household to its previously scheduled setpoint, and the electricity prices at those times. The optimal path through the data will properly balance those periods in which a load-shift should be implemented and when a business-as-usual approach is sufficient.

A simple way to think about the business-as-usual profit, i.e., $\text{Profit}_{\text{BAU}}$ is that it represents a REP's behavior in a world without demand response events. Then $\text{Profit}_{\text{BAU}}$ is the average price paid by the consumer minus the price paid in each interval multiplied by the load for that interval; and then, summed across all intervals ($\sum_{t=1}^{T}(\bar{P}_C - P_t) \cdot L_t$). This calculation requires that assumptions be made of the average customer load profile (L_t for each interval t), as well as the percentage of the portfolio exposed to real-time electricity prices. We expand this simplified version to include the percentage bought day-ahead in Equation (1).

$$\text{Profit}_{\text{BAU}} = \sum_{t=1}^{T+1}\Big((P_C - DA_t) \cdot K \cdot L_t + (P_C - P_t) \cdot (1-K) \cdot L_t\Big) \tag{1}$$

The BAU profit is a function of wholesale market prices, day-ahead market positions taken by the REP, as well as the prices paid by the consumer and quantities demanded in time period t.

To model the profit of a REP with a load-shifting option we need two pieces of additional information; (1) the predicted load-removed and (2) the load-recovered, which are themselves functions of temperature and the duration of the event. We derived a reward function equation that varies the amount of load purchased in the day-ahead and real-time markets. In Equation (2), we expand the $\text{Profit}_{\text{BAU}}$ to include load-shifting. The primary difference between $\text{Profit}_{\text{BAU}}$ and $\text{Profit}_{\text{DR}}$ is the inclusion of the $\bar{L}_{\text{RM}}$ and L_{RC} terms, which reflects the ability to move load from a time period in the event of high prices.

$$\begin{aligned}\text{Profit}_{\text{DR}} = \textstyle\sum_{t=1}^{T}\Big(&(L_t - \bar{L}_{RM}) \cdot P_C - K \cdot DA_t \cdot L_t - (1-K) \cdot P_t \cdot L_t + (P_t - DA_t) \cdot K \cdot \bar{L}_{RM} + \\ &+ (1-K) \cdot P_t \cdot \bar{L}_{RM}\Big) + (P_C - DA_{T+1}) \cdot K \cdot L_{T+1} + (P_C - P_{T+1}) \cdot (1-K) \cdot L_{T+1} + \\ &+ (P_C - P_{T+1}) \cdot L_{RC}\end{aligned} \tag{2}$$

where

P_C is the price consumers pay for electricity minus the transportation charges (i.e., TDSP)
P_t is the real-time price of electricity at time t
DA_t is the day-ahead price of electricity at time t
L_t is the customer load at time t
$DART_{DR}$ is the day-ahead, real-time spread (i.e., $P_t - DA_t$)
$\bar{L}_{RM}$ is the average load-removed per hour across the DR event
L_{RC} is the load-recovered at time $T+1$ as a result of a DR event
T is the length of the demand response event
K is the percentage of the consumer load in time period t purchased in the day-ahead market

One approach to evaluating each of the daily strategies would be to calculate the $\text{Profit}_{\text{BAU}}$ and $\text{Profit}_{\text{DR}}$ for an average customer. Instead, we simplify the problem by identifying opportunities where the REP's profit can be improved by load-shifting (i.e.,

$\text{Profit}_{\text{DR}} - \text{Profit}_{\text{BAU}} \geq 0$). Differencing the two equations above, we arrive at the following reward function (Equation 3).

$$\text{Profit}_{\text{DIFF}} = (\bar{P}_{DR} - P_C) \cdot L_{RM} - K \cdot \overline{DA}_{DR} \cdot L_{RM} + (P_C - P_{T+1}) \cdot L_{RC} \quad (3)$$

where

$\bar{P}_{DR}$ is the average price of electricity during the DR event

If the profit difference is positive then the event is an event that could improve the reward. In the next section, we discuss the method to determine the load-removed and load recovered.

4.2.3. Estimating Load-Removed and Recovered

The load-removed is an estimate of how much HVAC load can be shifted from an interval; while load-recovered is the increased load in the intervals following an event as HVAC setpoints are allowed to return to the pre-event levels.

We estimate the load-removed and load-recovery for each event using pseudodata generated from [29]. The load-removed and load-recovered values from [29] are consistent with the load-removed and load-recovered values that we have experienced running this type of program in ERCOT. The authors of [29] developed a building energy model that simulates heating and cooling load as a function of average building parameters. The model uses a grey-box approach, which entails fitting heat transfer equation parameters using econometric and optimization methods instead of determining the parameters for each household individually. We use the model to estimate estimate load-removed and load-recovery given outdoor air temperature and event duration for 76 hypothetical households.

Using the generated data, we estimate Equation (4) using a panel fixed effect regression model with clustered standard errors (clustered at the household level). We use the plm package in R to estimate the model. We also explored interaction terms but they were not found to be statistically significant. To calculate the degree day hours we use a break point of 65°F. In this analysis we focus on the value of a summer time load-shifting program given the higher wholesale market prices and forward contract costs REP's face during this period. Though it should be noted there aren't any restriction to running a load-shifting program during the winter months, though the prevalence of electric heating varies widely across Texas.

Load-removed and load-recovery are modeled using Equation (4), whereby the dependent variable is load-removed (MWh) and load-recovered (MWh) for each event, respectively.

$$y_{it} = \mu_i + \lambda \cdot CDDHr_{it} + \gamma \cdot CDDHr_{it}^2 + \beta \cdot Duration_{it} + \alpha \cdot Duration_{it}^2 + \epsilon_{it} \quad (4)$$

where

i is the household index
t is the event index
y_{it} is the estimated load-recovered (MWh) for household i and event t
μ_i is the household fixed effect for household i
$CDDHr_{it}$ is the cooling degree hours for event t for household i
$Duration_{it}$ is the length of event t for household i
ϵ_{it} is the error term

Table 3 shows the development and results of our analysis of the load-removed data. Here too, we fit a model including interaction terms but found them not to be statistically significant.

Table 4 shows the development and results of our analysis of the load-recovery data. As noted above, we also fit a model including interaction terms but found them not to be statistically significant.

Using the historical weather data, in addition to the coefficients above, we determine the load-removed and load-recovered for each possible event over the period 1 January 2011 to 1 September 2020.

Table 3. Load-removed–panel fixed effects with clustered standard errors (household).

	Dependent Variable: Load Removed (MWh)			
	(1)	**(2)**	**(3)**	**(4)**
cddHr	0.00003310 ***	0.00006690 ***	0.00004090 ***	0.00001940 ***
	(0.00000133)	(0.00000308)	(0.00000519)	(0.00000117)
$cddHr^2$		−0.00000024 ***	−0.00000014 ***	−0.00000001
		(0.00000002)	(0.00000003)	(0.00000001)
duration			0.00043100 ***	0.00158000 ***
			(0.00005660)	(0.00020200)
$duration^2$				−0.00020700 ***
				(0.00004420)

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 4. Load-recovered–panel fixed effects with clustered standard errors (household).

	Dependent Variable: Load Removed (MWh)			
	(1)	**(2)**	**(3)**	**(4)**
cddHr	0.00002550 ***	0.00005020 ***	0.00002930 ***	0.00001500 ***
	(0.00000122)	(0.00000246)	(0.00000409)	(0.00000096)
$cddHr^2$		−0.00000017 ***	−0.00000010 ***	−0.00000001*
		(0.00000002)	(0.00000003)	(0.00000001)
duration			0.00034500 ***	0.00111000 ***
			(0.00004740)	(0.00015900)
$duration^2$				−0.00013800 ***
				(0.00003500)

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5. Conclusions

In Texas' deregulated electricity markets, REPs act as intermediaries between electricity producers and end-use electricity consumers. Since REPs are not allowed to own or operate generation assets, Per TX Senate Bill 7, they buy wholesale electricity through bilateral contracts, such as power purchase agreements (PPA), and through ERCOT (Electric Reliability Council of Texas) day-ahead and real-time energy markets, which they resell to their retail customers. REPs make better program administrators for price-responsive DR programs than distribution utilities or grid operators because REPs have a more direct incentive to avoid real-time exposure to high wholesale market prices, compared to distribution utilities and grid operators, who use prices/pricing as a proxy for other grid conditions (such as peak load). REPs have access to household load profiles, necessary for estimating DR performance and anticipated household value, as well as the household interval-level meter data for post event performance evaluation. In addition, aggregators have the infrastructure necessary to automate home IoT device operations at scale; while also having access to historical telemetry data (i.e., runtime, setpoints, etc.) from the IoT devices they control (i.e., thermostats, water heaters, pool pumps, etc.) to augment the REPs' household load profiles, which addresses much of the necessary household data.

Since residential customers' load is both variable and stochastic, it is unknown to the REP prior to the interval in which the demand occurs. Indeed, it is even unknown to the REP in real-time since residential billing meters do not send real-time telemetry, and ex-post interval meter data is often not available until days after the operating day. This load stochasticity creates demand uncertainty for the REP that cannot be managed by carrying inventory, as a retailer of a different commodity would, given the non-storable nature of bulk electricity [30]. Since bulk electricity cannot be kept in inventory, it is necessary for real-time supply to always equal real-time demand.

One of the tools that an REP can use to mitigate price risk is shifting the load of their customers from one time period to another time period. This type of demand response is relatively common among large commercial and industrial (C&I) power consumers, but is still quite uncommon among residential power consumers. This discrepancy is the result of some key differences between the way C&I customers and residential customers buy electricity. Many C&I customers procure electric power via contracts or rates that expose some of their demand to short-term wholesale electricity market prices. In addition, the demand charges that C&I customers pay are directly based on their demand, coincident to bulk electric system peak demand. Thus, C&I customers have natural incentives to shift load, and although short-term wholesale market prices are unknown in advance, their relatively stable load profiles, as compared to residential customers, enables them to consistently and predictably do so.

Unlike C&I customers, residential customers are generally charged a flat, fixed rate for electricity, regardless of the wholesale price of electricity at the time of consumption. Also unlike C&I customers, residential customers' demand charges tend to be disconnected from their individual demand, coincident to system peaks. Rather, residential customers' demand charges are generally set based on the average coincident peak demand of all customers in a given rate class within a given topographical boundary. For these reasons, and the fact that residential load tends to be relatively volatile, residential customers do not have the same natural incentive as C&I customers to shift load.

It has been demonstrated in [30] that a retailer cannot reproduce the risk-reducing benefits of physical hedging by pure contractual hedging. This benefit gap, between pure contractual hedging and physical hedging, can widen significantly when near-term market conditions, such as unexpected large-scale generation capacity retirements, cause significant increases in power purchase agreement and energy futures prices, indicating significant potential for extreme price volatility in spot/imbalance market prices over the term of those agreements. When these conditions exist, REPs' margins are reduced as a result of the higher PPA costs because they are unable to increase rates for their existing, contracted customers.

Properly shifting load away from higher-priced hours can have two benefits: (1) increased profit resulting from the load-shift, by reducing load during high price periods while allowing for load-recovery in more profitable periods and, (2) the ability to shift load serves as a risk-mitigation tool that allows REPs to reduce their exposure to price risk and their cost to mitigate it. The ability to control a residential consumers load should enable the REP to lower residential rates, or to increase prices less than their competitors when increases are unavoidable, and thereby pass along significant savings to their customers. The average Texas household consumed 14,112 kWh in 2018 [31], which means that for every USD 0.01 reduction in the retail rate (per kWh) the household would save approximately USD 140.00 per year.

In the end, REPs could use a load shifting-program to offer residential customers a lower electricity rate commensurate with their risk. For the customer, such a program is advantageous since they receive a lower rate across all hours (instead of just savings during those hours in which the program is running) and the requirements for their participation are minimal (i.e., don't override the thermostat setpoint change thereby exiting a price event early). The benefits to REPs are clear since they benefit from a lower-risk portfolio and if the portfolio large enough, lower hedging costs. They also have the ability adjust how much power they buy day-ahead vs. real-time in order take advantage of favorable day-ahead/real-time spreads. Further, managing such a program is straightforward, as the REP or aggregator could easily monitor customer compliance and potentially withhold lower electricity rates from those customers not participating above a certain threshold.

We are not the first to argue that electricity retailers are logical drivers/market participants for DR [32–34]. Ref. [35] identified the reduction in the variance of REP expenditures, as well as an overall flattening of maximum hourly expenditure to be significant positive factors for the REP associated with DR programs. However, to our knowledge we are the first to estimate the benefits of such a program for a REP, as well as implement one in the ERCOT market.

Our estimated ten-year average annual savings of USD 62.07 per household assuming a USD 150/MWh strike price, and USD 55.74 assuming a USD 300/MWh Strike price, are significant. This is especially so given that a REP's residential customers do not need to be exposed to the real-time wholesale electricity price in order for the retailer to realize the avoided-cost savings from a residential hedging program. Since REPs do not buy wholesale power separately for residential, commercial, and industrial customers, a demand response program comprised of residential customers can be used as a flexible real-time hedge to mitigate wholesale price exposure for the REP's entire portfolio within a given load zone.

Author Contributions: Conceptualization, A.B., J.C. and S.A.G.; methodology, A.B., J.C. and S.A.G.; software, A.B.; validation, A.B. and J.C.; formal analysis, A.B.; investigation, A.B., J.C. and S.A.G.; data curation, A.B.; writing—original draft preparation, A.B., J.C. and S.A.G.; writing—review and editing, A.B., J.C. and S.A.G.; visualization, A.B.; supervision, A.B.; project administration, A.B. and S.A.G.; funding acquisition, J.C. and S.A.G. All authors have read and agreed to the published version of the manuscript.

Funding: The work in this paper was partially funded by a grant from the State of Maryland as well as Whisker Labs and Earth Networks under the Maryland Industrial Partnership Program [Contract No. 5905.21].

Conflicts of Interest: During the completion of this work, Andrew Blohm worked for Whisker Labs, Germantown, MD, and owned stock options in Whisker Labs. During that time, Whisker Labs ran the load-shifting program described below. Subsequently, Whisker Labs was purchased by Resideo Technologies, which continues to run the load-shifting program. Andrew Blohm owns stock options in Resideo Technologies. Jaden Crawford worked for Whisker Labs when this study was performed, and currently works for Leap. Leap is running a hedge program that utilizes commercial, industrial, and residential load shifting.

Abbreviations

The following abbreviations are used in this manuscript:

AMI	Automated metering infrastructure
C&I	Commercial and Industrial
CDD	Cooling degree day
DOY	Days of Year
DR	Demand response
ERCOT	The Electric Reliability Council of Texas
EUR	Euro
HVAC	Heating, ventilating, and air conditioning
IoT	Internet of things
ISO	Independent system operator
kW	Kilowatt
kWh	Kilowatt-hour
MWh	Megawatt-hour
PPA	Power purchase agreement
REP	Retail electricity provider
RTO	Regional transmission organization
TOU	Time-of-use

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