

Article

Nontargeted vs. Targeted vs. Smart Load Shifting Using Heat Pump Water Heaters

Manasseh Obi ^{1,*}, Cheryn Metzger ², Ebony Mayhorn ², Travis Ashley ² and Walter Hunt ²¹ Portland General Electric, Portland, OR 97204, USA² Pacific Northwest National Laboratory, Richland, WA 99354, USA; cheryn.metzger@pnnl.gov (C.M.); ebony.mayhorn@pnnl.gov (E.M.); travis.ashley@pnnl.gov (T.A.); walter.hunt@pnnl.gov (W.H.)

* Correspondence: smartwh@pgn.com

Abstract: Deployment of CTA-2045-enabled devices is increasing in the U.S. market. These devices allow utilities or third-party aggregators to control appliance energy use in homes, and could also be applied to end uses in small commercial buildings. This study focuses on a field study using CTA-2045-enabled water heaters to shift electric load off the peak and toward periods when renewable resources are more prevalent (e.g., near noon for solar resources and near midnight for wind resources). The following load shifting strategies were compared to understand effects on the aggregate load-shifting capabilities of Heat Pump Water Heaters (HPWHs) and on consumer hot water supply: non-targeted (traditional), targeted (grouped, with different shifting schedules) and “smart” (adaptive control commands). The results of this study show that targeted and smart control strategies yield significantly more load-shifting potential from a population of water heaters than the non-targeted approach without sacrificing hot water supply to occupants. However, as control commands become more aggressive, aggregators may face challenges in meeting consumer hot water demand. The findings and lessons learned can benefit electric utilities and inform updates to manufacturer controls and communications standards. The data collected may also be useful for developing and validating HPWH models.

Keywords: building services; demand response; demand side management; energy management; energy efficiency; energy storage; renewable energy; water heaters; direct load control



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1. Introduction

Many initiatives have been launched to enable the power grid to operate with unprecedented levels of renewable energy generation (e.g., solar and wind). For example, Oregon and California have passed legislation mandating 50% of energy generation is sourced from renewable sources by 2040 and 60% by 2030 [1], respectively. Renewable energy generation is intermittent, and poses significant challenges for balancing generation and load demand, as required to maintain a reliable supply of electricity. To support power grid modernization to integrate more renewable energy, research funds have been directed toward understanding how demand-side resources (e.g., electric water heaters, air conditioners, electric vehicles and other appliance end uses) may be equipped with controls and communication interfaces that enable them to provide flexible grid services while meeting consumer expectations.

For decades, utilities have leveraged large energy consuming end-use devices (e.g., water heaters) in Demand-Side Management (DSM) programs through Direct Load Control (DLC). For DLC, professionals are contracted to retrofit end-use devices with load control switches that enable power to be cut or cycled remotely via one-way communication by a utility. This approach is limited, as DSM aggregators do not have information on the equipment status to proactively mitigate effects on consumer amenities. After customers experience inadequate end-use device performance, they may submit complaints and decide to opt out of programs, which restricts the potential for large-scale adoption. To

address scaling issues of traditional DSM DLC approaches, a standard for a modular communication interface was introduced by the Consumer Technology Association (CTA) in January of 2013. This standard was designed to facilitate interoperability with any smart grid device and any communications network. It defines common Demand-Response (DR) commands and behavior, as well as two-way communication protocols for energy-related communication with residential devices. Currently, the standard is referred to as CTA-2045-A [2]. As described in [3], this standard enables otherwise disconnected devices to be connected under the following conditions:

- The original appliance manufacturer must provide the standard CTA-2045 port.
- Any stakeholder (e.g., utilities) can provide the external, additional “connected” hardware (referred to as a Universal Communications Module [UCM]) required to turn an unconnected, CTA-2045-ready appliance into a connected appliance.
- The modular interface must support all developed communication methods at the physical layer (e.g., Wi-Fi, 4G LTE, etc.) and at the command layer (e.g., Smart Energy Profile [SEP], OpenADR, etc.).
- A third party can manufacture the connected hardware.

In the US, water heaters make up 14% of annual household electricity consumption [4] and they have relatively large energy storage capacities. Therefore, electric water heaters are prime candidates for shifting loads to provide cost-effective grid services that help maintain the generation-load balance required for reliable grid operations. Heat Pump Water Heaters (HPWHs) save 60% of annual energy consumption compared to conventional Electric-Resistance Water Heaters (ERWHs). HPWHs are equipped with back-up electric resistance elements, which can be used to load up and recover in load shifting strategies. This means that the large-scale adoption of HPWHs could provide substantial peak load reductions and low-cost, flexible grid services to support renewable integration for utilities. However, the load shifting performance and consumer acceptance of CTA-2045 enabled HPWHs has not been demonstrated for all regions in the U.S.

Several published model-based and laboratory experimental studies have assessed load shifting capabilities of electric water heaters [5–9] and investigated effects of different aggregation strategies, control commands and tank temperatures, as well as the provision of different grid services (e.g., peak management and ancillary services). A field validation study on an ERWH in one household was also conducted to examine the performance of a DSM approach designed to optimize DR based on day-ahead prices [10]. DLC programs that can implement dynamic pricing, on average yielding larger load reductions than those without [11,12]. A study in the United Kingdom applied a cross-case comparison of two domestic DR trials, using secondary qualitative analysis to compare two very different approaches to delivering DR, with each resulting into KW reduction that differed from one another by an order of magnitude [13]. The authors found that in the design of effective DR programs, flexibility of participants, load control methodology, occupant disruption tolerance and engagement should be considered. To gauge the acceptability of a range of DR tariffs and explore factors affecting it, the authors in [14] compared different tariff structures to the level of perceived control given to participants. A direct load control tariff with tightly defined hours and an override option was found to be more acceptable than time of use tariffs, as the former provided a general sense of control. The experience of utilities in New Zealand with DR is detailed in [15], where a market price responsive DLC approach known as ‘ripple control’ is used to switch water heaters. According to the authors, with ripple control, a reduction in network peak demand of up to 30% is typically achieved. A study in Brazil concluded that load management using DR is a very efficient technique for energy conservation [16]. In Pakistan, as a solution to the electricity capacity shortfall, it was demonstrated that peak load reduction solved the capacity shortfall while significantly reducing peak demand levels during hot summer months [17]. A peak demand management trial was conducted in western Australia, which relied on a Network Interface Card (NIC), located within participating customers Advanced Metering Infrastructure’s (AMI) Smart Meter running the Zigbee Smart Energy

Profile (SEP) [18]. The author demonstrated the use of technology to perform DLC; this work focused on the control air conditioners, not water heaters. Furthermore, the author concluded that retrofitting of demand response enabling devices are expensive. A case study in Japan explored residential energy use and energy saving among older adults [19]. Using statistical data, the authors examined the energy usage patterns and found that heating (HVAC, water heaters, etc.) is the primary source of improving energy conservation. This study was limited, however, in that it focused only on older adults in the sample size considered. Additionally, it did not discuss load shifting strategies nor considered energy-poor households. A discrete choice experiment on a sample of 556 respondents residing in Switzerland studied consumer preferences in the design of DLC programs, and found that customers are influenced largely by trust in the utility running the DLC program, consumer knowledge of the program offering and the availability and ease of overriding options [20]. Another study analyzed data from an experiment where residential water heaters were automatically disconnected during peak periods of the day in Norway, and concluded that DLC can be an effective tool for decreasing peak-load consumption [21]. Current literature considers DLC by using integrated controls, which can sometimes be cost-prohibitive to install and integrate, and in most cases will require the retrofitting of existing appliances. In light of the increasing penetration of smart devices, the internet of things and the concept of “smart homes”, devices that are able to communicate smartly and seamlessly over secure networks have become more promising than ever before, and judging by the current literature, there is a need for more research work to be done in this space. This work builds on previous work from [22,23], which focused on comparing the difference in reactions between ERWHs and HPWHs to load-curtailement events where the results from obtained showed that a seven-days-per-week (24×7) load shifting control paradigm can be maintained to align with renewable generation with minimal customer impact (about 3% participant opt out per week). Another objective of phase 1 was to determine the reduction potential (on-peak) of a “smart” heat pump water heater compared to a resistance water heater in watts. It was discovered that Heat pump water heaters would be a valuable addition to any demand response program, as they offer about one- to two-thirds the peak load reduction capability of electric resistance water heaters, providing utilities with a flatter water heater use and recovery profile.

This paper investigates the impact of several aggregated load curtailment strategies and CTA-2045 demand-response commands using real world data for ~150 HPWHs. The primary research questions here are:

- Can a targeted shed command strategy yield more total energy shifted for a population of water heaters than a non-targeted strategy with extended event periods?
- Can greater energy shifting be attained by employing a smart learning algorithm and different CTA-2045 control commands (e.g., shed, critical peak and grid emergency) without homeowners noticing?

By comparing results from three different strategies, namely, the targeted, non-targeted and smart DLC methodology, this paper adds to the body of knowledge by providing researchers an insight into designing DR strategies in the 21st century using the newer CTA-2045 communications protocol.

2. Materials and Method

Households were recruited from ten different utilities in the Pacific Northwest by sending multiple communications to nearly all customers with electric water heating. Approximately ~150 households signed up with an average of 2.9 persons per household, which is consistent with the national average of 2.7 per household according to the Energy Information Administration Residential Energy Consumption Survey (EIA RECS) conducted in 2015. A HPWH with a CTA-2045 port was installed in each home. The water heaters were provided by two manufacturers (manufacturers A and B) with their own internal proprietary algorithms for using the heat pump, electric resistance elements or both to heat water. The amount of power that is drawn from HPWHs varies greatly with

operating mode, so individual HPWH reactions to various demand-response signals may also be different. This work analyzes the aggregate and per-unit impacts of HPWHs used for load shifting.

A Universal Communication Module (UCM) was provided and plugged into each water heater to allow telemetry and command signals to be exchanged between a demand-response aggregator and water heater via the network of choice (Wi-Fi, radio frequency, cellular, etc.), radio frequency in this case. The following three different load shifting strategies were tested: non-targeted, targeted and “smart” strategies (Table 1). Non-targeted, in this context, means that the same load curtailment signal is sent to the entire population of water heaters included in the study. In the targeted approach, water heaters were grouped into different categories (e.g., low and high morning and afternoon users), and each group is sent different curtailment schedules. The proprietary third-party “smart” strategy is an individualized control that uses the two-way communication to incorporate feedback, enabling it to proactively adapt control commands and mitigate hot water shortages.

Table 1. Project Phase Highlights.

| High-Level Control Strategy | Approximate Count of Controlled Water Heaters | Study Period |
|--|---|---------------------------|
| Non-targeted Flip-Flop Groups | ~150 HPWHs | January–mid-February 2019 |
| a.m./p.m. Target Groups | ~150 HPWHs | mid-February–March 2019 |
| Third-Party “Smart” Proprietary Individual Control | ~60 HPWHs | February–March 2020 |

The CTA-2045 specification provides three curtailment commands with different levels of aggressiveness: shed, critical peak and grid emergency. Each command was tested on the population using the third-party “smart” control strategy to investigate consumers’ tolerance with 24×7 load shifting. Each curtailment strategy was imposed on the population of water heaters. Before any curtailment event, a one-hour load up command was sent to allow the water heaters to store sufficient hot water to ride through curtailment events.

2.1. Representative Control and Event Weeks

To analyze the load-shifting and shaving performance, representative control and event weeks were compared. Representative control weeks served as a baseline, while the representative event weeks include aggregated responses of all water heaters undergoing events during the various test periods. Two baselines were computed, since the number of participants dropped significantly after the non-targeted and targeted strategies were tested. In addition, testing periods for the smart strategy occurred in a different calendar year from the other two strategies. Control week data collected from 7 January–11 February 2019 were used to compute the baseline for the non-targeted and targeted strategies; this is referred to as “2019 winter baseline” herein. The average outdoor temperature during the 2019 winter baseline period was 41 °F. For the smart curtailment strategy, data collected from 1 November 2019–13 January 2020 without curtailment events were used to compute the baseline; this is referred to as “2020 winter baseline” herein. The average outdoor temperature during this period was 44.6 °F.

Representative control weeks were computed by averaging power consumption of each water heater over each hour (e.g., all the Mondays at 1 a.m.) across all non-event weeks included in the specified baseline periods (1). Representative event weeks were

calculated similarly, by averaging power consumption of all event groups that responded to the same curtailment strategy in each test period.

$$P_{Ai} = \frac{1}{N + M} \sum_{j=1}^M \sum_{k=1}^N \bar{P}_i[j][k], \quad i = 1, 2, \dots, T \quad (1)$$

where;

P_{Ai} = total aggregated average power consumption for representative week hour i

$\bar{P}_i[j][k]$ = average power of HPWH — j during week hour i of week k

M = number of online water heaters during the study period

N = number of weeks included in study period

T = number of hours in a week

2.2. Metrics

A few metrics were selected to evaluate the aggregated response to different load-curtailment strategies. The load shaved because of each strategy was assessed based on the average power reduction attained over an event period. The average power reduction was computed by averaging the difference between the representative control week hour and the event week hour during each event period (2). Total energy shifted during an event is used to indicate how much energy is delayed for consumption at later time. The total energy shifted per event is calculated by summing the differences in the representative control and event week hour results (3).

$$\overline{\Delta P}_l = \frac{1}{T_2 - T_1} \sum_{i=T_1}^{T_2} (\bar{P}_{Ai,C} - \bar{P}_{Ai,E}), \quad l = 1, 2, \dots, L \quad (2)$$

$$\Delta P_{Al} = \sum_{i=T_1}^{T_2} (\bar{P}_{Ai,C} - \bar{P}_{Ai,E}), \quad l = 1, 2, \dots, L \quad (3)$$

where;

$\overline{\Delta P}_l$ = average power reduction over event period l

ΔP_{Al} = total aggregated power reduction over event period l

T_1 = starting hour of event period l

T_2 = ending hour of event period l

2.3. Non-Targeted Strategy

For the non-targeted the population of water heaters was divided into two equal groups, balanced by five key criteria, including:

- total energy use for the week (kWh)
- minutes above 1000 W for the week (a surrogate for minutes in electric resistance mode)
- maximum energy usage (kWh, any day of the week) between 5 a.m. and 9 a.m. This helped to gauge the magnitude of the morning water heating peaks for each home
- maximum energy usage (kWh, any day of the week) between 5 p.m. and 9 p.m. This helped to gauge the magnitude of evening water heating peaks for each home
- minutes opted out of the demand-response events.

For each week of the six-week study, the two groups were flip-flopped, with one acting as the control group with no events imposed and the other having two regularly scheduled events imposed on it daily. A variety of morning, afternoon and evening shed-period time blocks were attempted (Table 2) to determine the range of energy shifting benefit throughout the day. Table 2 also provides the average outdoor temperature for each week of the study. Three-hour curtailment events were chosen at the recommendation of the utility partner to achieve a significant energy reduction without participants noticing.

Table 2. Non-targeted Strategy Schedule.

| Week Start Date | Event Group Name | Morning Event Times | Afternoon Event Times | Average Outdoor Temp (°F) | Average Outdoor Temp (°C) |
|------------------|------------------|---------------------|-----------------------|---------------------------|---------------------------|
| 7 January 2019 | Group 1 | 7–10 a.m. | 10 p.m.–1 a.m. | 43.8 | 6.6 |
| 14 January 2019 | Group 2 | 7–10 a.m. | 10 p.m.–1 a.m. | 42.6 | 5.9 |
| 21 January 2019 | Group 1 | 6–9 a.m. | 6–9 p.m. | 45.6 | 7.6 |
| 28 January 2019 | Group 2 | 6–9 a.m. | 6–9 p.m. | 42.1 | 5.6 |
| 4 February 2019 | Group 1 | 8–11 a.m. | 10 p.m.–1 a.m. | 32.0 | 0.0 |
| 11 February 2019 | Group 2 | 8–11 a.m. | 10 p.m.–1 a.m. | 40.6 | 4.8 |

2.4. Targeted Strategy

The targeted strategy was designed to achieve greater load shifting than the non-targeted strategy without participants noticing by sending three-hour curtailment signals to high hot water users and longer five-hour curtailment events to low users. To set up the targeted strategy, each water heater was assigned as either a low or high hot water user during both morning and evening after observing average non-event energy over ten weeks of data taken during the winter season of 2018. This resulted in four different groups: low a.m., high a.m., low p.m. and high p.m. The a.m. peak period was assumed to be 6–9 a.m. on weekdays. The water heaters were ordered from lowest to highest a.m. peak energy. Since the population of water heaters followed similar energy use patterns, a line was drawn halfway between the extreme values, and all water heaters above that line were considered “high a.m. peakers,” and all below that line were considered “low a.m. peakers.” The same activity was done for the p.m. peak period, which was designated to be from 6–9 p.m. on weekdays.

When the water heaters were organized from lowest to highest p.m. peak energy use, the group of water heaters was again divided in half. Those in the upper half were considered “high p.m. peakers,” and those in the lower half were “low p.m. peakers.” The experiments with the high and low, a.m. and p.m. peakers were scheduled to run in two-week increments (see intended experimental schedule in Table 3 along with average outdoor temperatures for each week). The first experiment had an error for the first three days, so it spanned only a week and a half. The first set of two-week experiments included only a.m. events. The second set of two-week experiments included only p.m. events. The third set of two-week events included both a.m. and p.m. events. The goal of the third set of two-week events was to understand whether there was a significant effect on the results if multiple events were conducted in the same day.

2.5. Smart Strategy

The third-party “smart” learning algorithm was designed to optimize behavior of individual participants in responding to day-ahead, real-time variations (e.g., hourly) in energy prices while maintaining hot water availability as usual in households. The “smart” algorithm sends individualized curtailment commands to each water heater and receives feedback about the status of hot water stored. If the remaining hot water storage is detected to be too low during a curtailment event, the algorithm will adjust the control command to either begin heating (load up) or return the water heater to normal operation.

With this strategy, each CTA-2045 curtailment command was tested over a two-week period, as summarized in Table 4. Table 4 also includes the average outdoor temperature for each week curtailment events were scheduled. In addition, the smart strategy was attempted with an ISO New England hourly price schedule and shed commands in the last week of the study.

Table 3. More Aggressive, Targeted Strategy Schedule.

| Week Start Date | Event Group Name | Shed Event Times | Average Outdoor Temp (°F) | Average Outdoor Temp (°C) |
|------------------|-------------------|------------------|---------------------------|---------------------------|
| 18 February 2019 | Low a.m. Peakers | 6–11 a.m. | 38.5 | 3.6 |
| | High a.m. Peakers | 7–10 a.m. | | |
| 25 February 2019 | Low a.m. Peakers | 6–11 a.m. | 35.4 | 1.9 |
| | High a.m. Peakers | 7–10 a.m. | | |
| 4 March 2019 | Low p.m. Peakers | 5–10 p.m. | 35.7 | 2.1 |
| | High p.m. Peakers | 7–10 p.m. | | |
| 11 March 2019 | Low p.m. Peakers | 5–10 p.m. | 45.0 | 7.2 |
| | High p.m. Peakers | 7–10 p.m. | | |
| 18 March 2019 | Low a.m. Peakers | 6–11 a.m. | 55.6 | 13.1 |
| | High a.m. Peakers | 7–10 a.m. | | |
| | Low p.m. Peakers | 5–10 p.m. | | |
| | High p.m. Peakers | 7–10 p.m. | | |
| 25 March 2019 | Low a.m. Peakers | 6–11 a.m. | 48.7 | 9.3 |
| | High a.m. Peakers | 7–10 a.m. | | |
| | Low p.m. Peakers | 5–10 p.m. | | |
| | High p.m. Peakers | 7–10 p.m. | | |

Table 4. “Smart” Strategy Schedule.

| Week Start Date | Curtailment Command | Morning Event Times | Afternoon Event Times | Average Outdoor Temp (°F) | Average Outdoor Temp (°C) |
|------------------|---------------------|--------------------------------|-----------------------|---------------------------|---------------------------|
| 3 February 2020 | Shed | 6–11 a.m. | 5–10 p.m. | 45.0 | 7.2 |
| 10 February 2020 | Critical Peak | 6–11 a.m. | 5–10 p.m. | 41.8 | 5.4 |
| 17 February 2020 | Critical Peak | 6–11 a.m. | 5–10 p.m. | 42.9 | 6.1 |
| 24 February 2020 | Grid Emergency | 6–11 a.m. | 5–10 p.m. | 44.1 | 6.7 |
| 2 March 2020 | Grid Emergency | 6–11 a.m. | 5–10 p.m. | 48.3 | 9.1 |
| 9 March 2020 | Shed | 6–11 a.m. | 5–10 p.m. | 43.3 | 6.3 |
| 23 March 2020 | Shed | Hourly variable price schedule | | 45.0 | 7.2 |

3. Data Analysis

3.1. Data Collection

Data was downloaded from the e-Radio website through a web Application Programming Interface (API). The data collection process is described in Figure 1 in which a CTA-2045 module is used by e-Radio to send signals to the water heater and then retrieve the data. The CTA-2045 port that is built into the water heater tank provided an array of data that could be used to monitor water heater and communications network status as well as observe individual water heater behavior as needed. The following data were retrieved at one-minute intervals for analysis:

- curtail type (none, shed, grid emergency, start autonomous cycling, request power level, load up, CTA-2045 error, customer override (opt-out), end shed, terminate autonomous cycling)
- instantaneous power (Watts)
- present energy storage capacity (Watts-hour): current energy required to restore tank to desired temperature.

In addition, the customer complaints (submitted manually) were obtained from an online customer web portal.

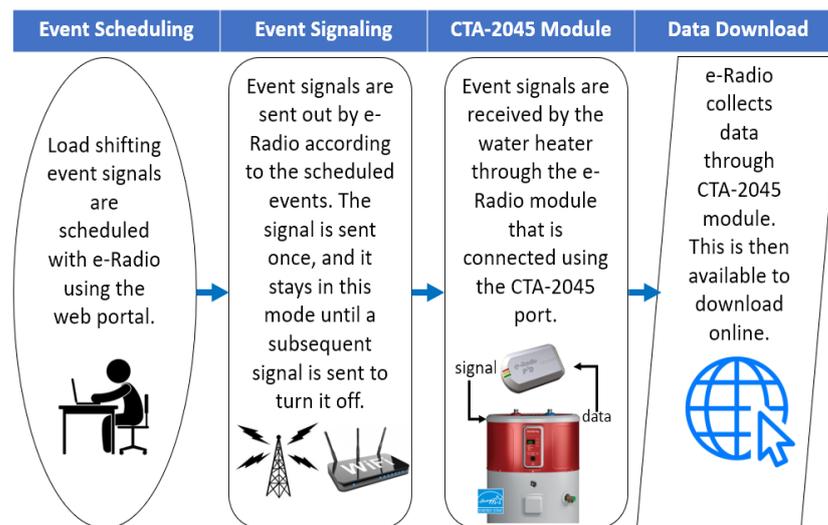


Figure 1. Wireless communication enabled through CTA-2045 module.

3.2. Data Adjustments

Data were collected and data adjustments were made to ensure any one water heater was not having a relatively strong influence on the average (e.g., if it was always off or always in electric resistance mode). If a water heater read zero watts for an entire week, that water heater was excluded from the analysis for that week.

A subset of approximately 40 participants were sub-metered to compare the CTA-2045 reported values to the actual power draws observed. Results indicated that one HPWH manufacturer, accounting for 80% of the HPWHs included in this study, reported power data accurately. The other manufacturer reported preprogrammed values based on the HPWH mode, which were significantly higher than the power reported through the UCM. Therefore, correction factors were applied to the CTA-2045 power data from this manufacturer based on the monitored values observed.

4. Results

4.1. Consumer Acceptance

Over the course of the pilot study, the participants could communicate dissatisfaction if hot water was unavailable on demand in several ways. They could opt out remotely via the web portal or physically through the UCM, or submit a formal complaint through the web portal. Remote opt-outs do not always indicate dissatisfaction. For example, a participant could choose to opt out temporarily if they planned to have visitors and do not want to risk a hot water shortage. There is also no definitive way to tell when the UCM is offline because it was unplugged, or the password/router/ISP was changed. Therefore, to assess customer satisfaction, the following factors were considered: opt-outs that occur during or within an hour after a load-curtailement event; and complaints that reported cold-water experiences.

Table 5 summarizes consumer dissatisfaction because of different strategies and commands tested. Specifically, one column reports the opt-outs that occurred during or within an hour after an event compared to the total number of events successfully communicated to all participating water heaters over the study period (weeks) for each strategy. Another column provides the number of complaints of hot water being unavailable when demanded. For all strategies implemented with shed commands, very few opt-outs occurred during or immediately after a load reduction event and zero complaints were submitted. Opt-outs are not necessarily triggered by dissatisfaction, since they typically lasted 1–3 days and could have been coincidental with scheduled events. However, one participant did opt out indefinitely during the first event of a week that was later excluded, as the wrong event schedule was executed with the targeted strategy and shed commands.

Table 5. Consumer Satisfaction Results.

| Strategy Type | Event Duration | Event Time Range | Command | Weeks | Opt-Outs/Events * | Complaints Reported ** |
|---------------|----------------|------------------------|----------------|-------|-------------------|------------------------|
| Non-targeted | 3 h | 6–11 a.m. 5–10 p.m. | Shed | 6 | 4/4200 | 0 |
| Targeted | 3–5 h | 6–11 a.m. 5–10 p.m. | Shed | 5 | 2/4190 | 0 |
| Smart | 5 h | 6–11 a.m. 5–10 p.m. | Shed | 2 | 0/1160 | 0 |
| Smart | 5 h | 6–11 a.m. 5–10 p.m. | CPP | 2 | 0/1220 | 1 |
| Smart | 5 h | 6–11 a.m. 5–10 p.m. | Grid emergency | 2 | 1/1180 | 2 |
| Smart | Hourly | Hourly price schedule | Shed | 1 | 1/165 | 1 |

* Number of opt-outs tallied for the times participants initiated opt-outs during or within an hour after an event.

** All complaints were reported by participants with an HPWH from Manufacturer A.

Table 5 also shows that implementing more aggressive control commands (e.g., Critical Peak Pricing [CPP] and grid emergency) and the hourly price schedule with the smart strategy triggered a participant's complaint of hot water being unavailable. Participant complaints are a clearer indicator of dissatisfaction compared to opt-outs. Events were discontinued on the first day of executing the smart strategy with the hourly ISO New England price schedule after another complaint was received. This was done to avoid losing participants in the study, since a couple of complaints were also received a week before due to testing grid emergency commands.

All complaints of cold-water experiences were received from participants with a Manufacturer A water heater. For the "smart" strategy, the energy storage capacity status signal was used as feedback; it represents the remaining energy capacity of the storage tank as a result of hot water drawn and standby losses. With further investigation into complaints received for Manufacturer A HPWHs, less hot water was available on demand because of the way the energy storage capacity values are updated and used in real time by the smart algorithm to avoid depleting hot water. Figures 2 and 3 show energy storage capacity overlaid with power consumption and control commands executed for similar time periods at sites with Manufacturer A and Manufacturer B HPWH sites, respectively. Manufacturer A updates the values for energy storage capacity at discrete 628 Wh increments and Manufacturer B at 75 Wh increments. As a result, Manufacturer A water heaters have difficulty tracking the hot water storage capacity when power consumption is less than 500 W, typically when the heat pump is operating. This causes the "smart" algorithm to be delayed in adapting control commands in response to low hot water storage. In addition, a Manufacturer A HPWH does not seem to have any internal logic to override utility/aggregator command signals when the available hot water is low.

Manufacturer B HPWH storage capacity values seem to provide a more reasonable feedback signal that allows smart strategies to react in a timely manner to low hot water storage conditions. In addition, Manufacturer B has included internal control logic to ignore external signals and restore hot water storage in tanks when undesirable tank conditions are detected.

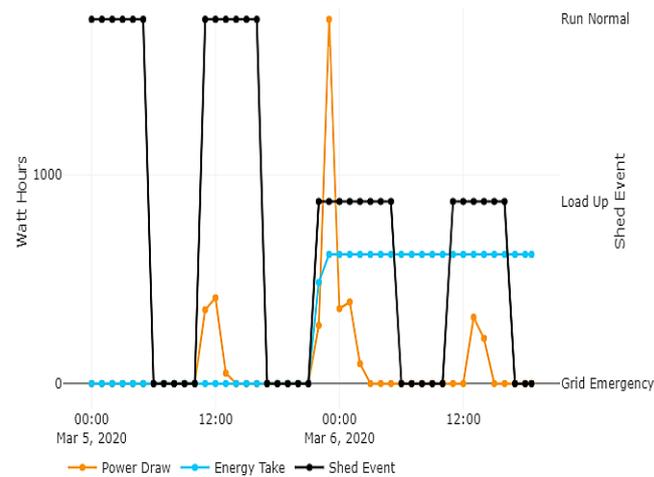


Figure 2. Manufacturer A HPWH behavior 5–6 March that led to a complaint.

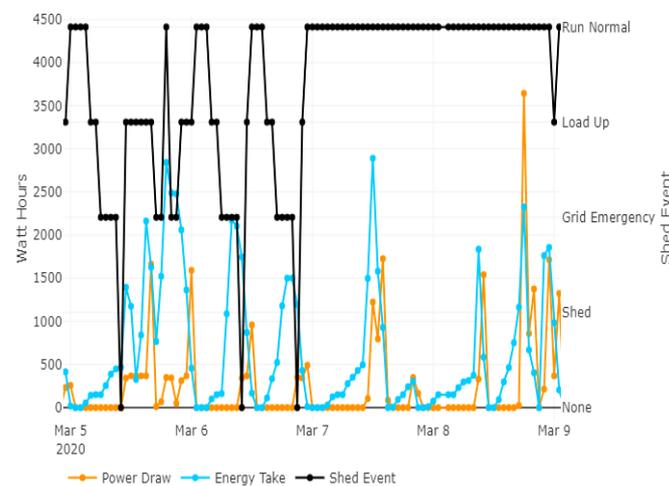


Figure 3. Manufacturer B HPWH behavior 5–9 March.

4.2. Peak Load Shifting

The load shifting results in this paper are presented first in detail for one event period and then as averages over multiple event weeks for each curtailment strategy studied. By presenting the results this way, readers can see some of the trends that occur in detail, as well as the trends that occur in the summary level results.

Table 6 shows interesting sample results from the targeted strategy. This example shows an average load reduction over two Thursday morning events (21 March and 28 March 2019). In this example of morning events, the low a.m. peaker group had a five-hour event, from 6 a.m. to 11 a.m. and the high a.m. peaker group had a three-hour event from 7 a.m. to 10 a.m. There is a large difference in the hourly peak-shaving capability between these two groups.

Figure 4 shows an example of energy consumption for the control and event groups over a day associated with the targeted strategy. The graph is plotted using hour ending values. For example, hour 1 uses data collected from 12 a.m.–1 a.m. This is a graph of only the targeted a.m. related groups on a day when both a.m. and p.m. events were deployed. The 2019 representative control week profile for one day is shown in blue. The gray and yellow lines in Figure 4 show one day from a representative event week for high and low a.m. peakers when only a.m. events are scheduled. Since the a.m. and p.m. peaker groups were determined and managed completely separately, any coincidental shedding that appears in the afternoon occurred because many a.m. peaker water heaters are also p.m. peakers.

Table 6. Example Results from Targeted Group Strategy.

| Hour of Day | Hour of Week | Average Low A.M. Peaker Shaving (Watts/Hour) | Average High A.M. Peaker Shaving (Watts/Hour) |
|-------------|--------------|--|---|
| 4 | 77 | −25 | 73 |
| 5 | 78 | −34 | 48 |
| 6 | 79 | 49 | −50 |
| 7 | 80 | 98 | 461 |
| 8 | 81 | 152 | 401 |
| 9 | 82 | 136 | 340 |
| 10 | 83 | 170 | −229 |
| 11 | 84 | −104 | −113 |
| 12 | 85 | −89 | 14 |

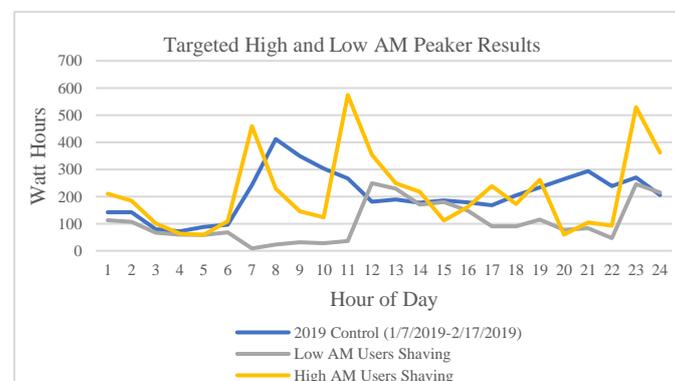
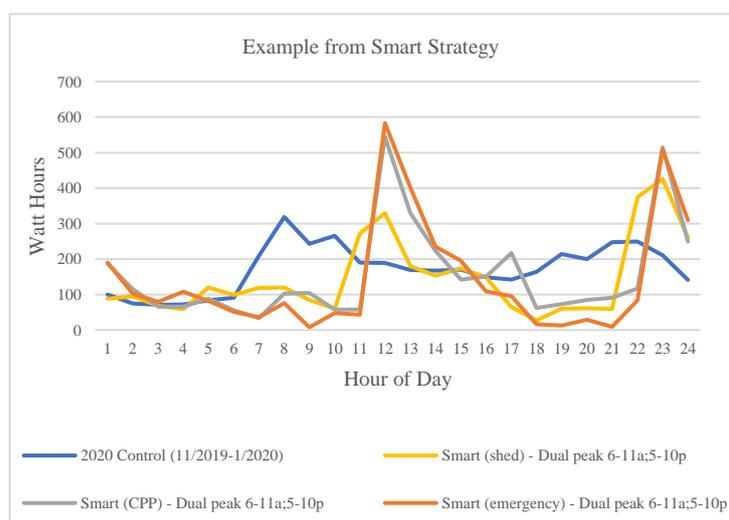
**Figure 4.** Example from targeted high and low a.m. peaker groups.

Table 7 provides load reduction results for example shed, critical peak and grid emergency commands implemented as part of the “smart” strategy, focusing on Thursday morning events between 3 February and 15 March 2019. This example averages the hourly load shaved over each command type. Positive (bold) values indicate a reduction in usage and negative values indicate an increase in usage. Even though the amount of shaving is not always higher for each hour, as the CTA-2045 control commands become more aggressive, the average over the five-hour events typically increases with more aggressive control commands.

Figure 5 shows HPWH energy consumption profiles over a day for control and event groups when executing the “smart” strategy. The blue 24-h 2020 control profile was obtained from one day of the 2020 winter baseline. The example shows dual events for the day: a five-hour event in the morning and another in the afternoon. The other lines on the graph depict hourly energy consumption averaged over two weeks of each corresponding command type (shed, CPP or grid emergency). Notice that over the 6–11 a.m. (hour 7–12) morning event period, the average peak shaving using the shed command is slightly more than the peak shaving using the CPP command on that day. However, the average over two weeks of implementing the shed command results in less peak shaving capability. This is further illustrated in Tables 8 and 9.

Table 7. Example Results from Smart Strategy.

| Hour of Day | Hour of Week | Average Smart Shed Shaving (Watts/Hour) | Average Smart CPP Shaving (Watts/Hour) | Average Smart Emergency Shaving (Watts/Hour) |
|-------------|--------------|---|--|--|
| 4 | 77 | −37 | −5 | 2 |
| 5 | 78 | −9 | 35 | 40 |
| 6 | 79 | 90 | 176 | 173 |
| 7 | 80 | 199 | 216 | 243 |
| 8 | 81 | 159 | 139 | 235 |
| 9 | 82 | 205 | 207 | 218 |
| 10 | 83 | −82 | 133 | 147 |
| 11 | 84 | −140 | −355 | −394 |
| 12 | 85 | −11 | −160 | −232 |

**Figure 5.** Example power profile from smart strategy.**Table 8.** Morning Energy Shifted.

| Strategy Type | Event Duration | Event Time Range | Number of Weeks Averaged | Average Energy Shifted per Event (Wh) |
|------------------------|-------------------------------|------------------------|--------------------------|---------------------------------------|
| Non-targeted (Shed) | 3 h | 6–11 ¹ a.m. | 6 | 620 |
| Targeted (Shed) | High a.m.—3 h Low a.m.—5 h | 7–10 a.m. 6–11 a.m. | 3 | 596 |
| Smart (Shed) | 5 h | 6–11 a.m. | 2 | 608 |
| Smart (CPP) | 5 h | 6–11 a.m. | 2 | 736 |
| Smart (Grid Emergency) | 5 h | 6–11 a.m. | 2 | 863 |

¹ Each event only lasted three hours, although over the course of the six weeks, the events were shifted within this whole time interval.

Table 9. Afternoon Energy Shifted.

| Strategy Type | Event Duration | Event Time Range | Number of Weeks Averaged | Average Energy Shifted per Event (Wh) |
|------------------------|-------------------------------|------------------------|--------------------------|---------------------------------------|
| Non-targeted (Shed) | 3 h | 6–9 p.m. | 1 | 622 |
| Targeted (Shed) | High p.m.—3 h Low p.m.—5 h | 7–10 p.m. 5–10 p.m. | 4 | 740 |
| Smart (Shed) | 5 h | 5–10 p.m. | 2 | 607 |
| Smart (CPP) | 5 h | 5–10 p.m. | 2 | 731 |
| Smart (Grid Emergency) | 5 h | 5–10 p.m. | 2 | 819 |

Tables 8 and 9 summarize the average load shifting from the non-targeted, targeted and smart strategies, arranged by morning and afternoon events. Shifted energy refers to unused peak and/or shifted energy. Averages span different numbers of weeks, as indicated. Non-targeted events were three hours and the events for the targeted and smart strategies were five hours.

Morning results show that with the targeted strategy, ~25 Wh less energy is available to be shifted per water heater per event period than with the non-targeted strategy. The “smart” strategy implemented with shed commands yields ~15 Wh less load shifting per event period than the non-targeted strategy, and less than 10 Wh more than the targeted approach.

Table 8 also highlights that the load shifting per event incrementally increases by more than 100 Wh as the CTA-2045 commands become more aggressive, from shed to CPP to grid emergency. Similar trends are evident from the afternoon results in Table 9. However, the targeted strategy appears to cause a less energy shifting per curtailment event period than the non-targeted strategy in the morning and more in the evening. Less energy shifting in the morning is mainly due to the timing of three-hour high peaker events. In the morning, the three-hour high peaker shed events were scheduled to start one hour after and end one hour before the low peaker shed events, with a one-hour load up just before the high peaker shed event.

As a result, there was relatively high consumption during the first and last hour of the morning curtailment period (as shown in Figure 4). In the afternoon, the three-hour high peaker events were scheduled to start two hours after the low users and end at the same time, with a one-hour load up just before the shed event. As a result, the rebound period for both groups occurs after the peak period, so that it does not impact the amount of energy shifted. The third-party smart strategy also leads to lower energy shifting compared to the non-targeted strategy, as it factors in feedback on the energy storage capacity of the HPWHs to determine and adapt command signals. Therefore, HPWHs may be commanded to load up or operate during shed the curtailment periods specified to avoid cold water events, thereby reducing the energy shifting during the curtailment periods. Except for one case, the average weekly energy, for each strategy, was 1–7 kWh less than the baseline.

5. Discussion

The high a.m. peakers can shave about three or four times as many watts as the low a.m. peakers. However, more energy can be shifted without effects on customers by extending the duration of the low a.m. peaker events. As expected, as the CTA-2045 control commands become more aggressive, the average energy saved increases with more aggressive control commands. Of the three load shifting strategies examined in this paper, namely, non-targeted, targeted and smart, in the morning hours, the non-targeted strategy accounted for the most amount of energy reduction, but in the afternoon hours the targeted strategy shifted the most amount of energy, due to the timing of the high peaker shed

events relative to the timing of the low peaker shed events. Furthermore, the targeted strategy was the best approach, as more appliances and home loads are turned on in the early afternoon or early evening; the targeted strategy optimized the command sent and activated the on signal to the water heater.

6. Conclusions

Overall, the results demonstrate that the targeted curtailment strategies can yield more energy shifting than the non-targeted approach (>115 Wh more per unit per event) and the “smart” curtailment strategy resulted in >10 Wh less energy shifting than the non-targeted strategy. Based on these data, utilities could obtain most of the load shifting benefit from sending shed commands to homes with high hot water usage, without needing to install CTA-2045 controllers on all HPWHs. Alternatively, if they are required to supply CTA-2045 controllers to all water heaters, slightly more energy shifting potential would be available by running longer events on water heaters that are not high users, without occupants noticing. However, when using more aggressive CTA-2045 control commands (e.g., CPP), implementing a smart strategy with two-way communication has more potential to maximize load shifting benefits without negatively affecting consumers. Controls and communications between end users, third-party aggregators and utilities should be carefully coordinated to ensure load shifting is maximized while protecting the consumer experience. To conduct larger scale studies on HPWH load shifting potential, the data collected from this field study may be used to develop and validate behavior models.

7. Industry Recommendations

An electric utility company, a third-party aggregator, appliance manufacturers and third-party communication network developers were entities involved in implementing the load reduction strategies in this study. To scale the adoption of smart grid DR, it is important to understand and mitigate any potential breakdowns in communication across entities that could lead to less predictable responses of the water heater population and less hot water available on demand. From the load shifting studies performed in this work, two lessons highlighted are how feedback signals can have a significant impact on control decisions and how the timing of event periods may impact amount of load shifted.

The first lesson is that smart curtailment algorithms may have limited access to device status data that could be helpful in avoiding effects on consumer service quality (e.g., availability of hot water supply). It is recommended that smart grid device manufacturers ensure that updates to status signals (e.g., energy storage capacity) occur at appropriate, discrete increments to allow timely action to be taken. Updating the CTA-2045 standard to specify appropriate, discrete increments for communicating status updates could raise awareness of this issue. In addition, the standard could mandate making additional data available that would enable “smart” algorithms to have more certainty about device status (e.g., measured outlet water temperature and consumer set-point preferences). As another protection of consumer experience, manufacturers should implement local controls at the device level to override external signals and restore hot water storage if the end use is CTA-2045 enabled. It is also recommended that the standard strongly encourage local controls to avoid poor consumer experiences.

The second lesson learned is that rebound effect and event time periods should be considered when designing and implementing any curtailment strategy to meet grid service objectives (e.g., peak load management, harnessing wind energy at night). Different service objectives will determine when events should be initiated. However, understanding the response at different times of day may allow responses to be maximized. For example, if using a targeted approach, the end of the event period for different groups of water heaters should occur at the same time, and/or a staggered approach could be used to gradually end events of copious hot water use. Ending event periods of high-peaker targeted groups before the event period ends causes a significant rebound effect to begin during curtailment events, which could negate energy shifting to later hour(s). This occurs

because all high-peaker water heaters began to recover hot water storage at the same time after the curtailment period. Additionally, if using a grid service objectives of curtailment strategies are coincidental with 7–10 a.m. and 7–10 p.m. windows, the greatest load shed and shifting can be achieved in the Pacific Northwest region if a non-targeted strategy is chosen. If implementing targeted strategies, the best times to schedule events to get maximum curtailment response are 7–10 a.m. and 7–10 p.m. for high hot water users and from 5–10 a.m. and 5–10 p.m. for low hot water users. Load up commands could also be scheduled outside of curtailment periods for both high and lower peakers to maximize the energy curtailed. For other regions and end uses, the peak periods of a population of smart grid demand devices without control signals should be observed to identify peak shifting periods.

Aggregation of multiple behind-the-meter loads like water heaters, air conditioners and storage systems will be enabled via protocols like CTA 2045, Sunspec Modbus, IEEE 2030.5 and OpenADR. Device aggregations may be coordinated to provide various ancillary services in support of stochastic renewable energy. Aggregation and dispatch will help reduce dependence on traditional electricity generation resources that contribute to climate change. Because of their fast response time, water heaters can benefit the industry in other ways than DSM peak load mitigation strategies [24–27]. In [28], water heaters were used to respond to grid frequency signals in the Pennsylvania New Jersey and Maryland Independent System Operator market and the Mid-Atlantic Independent System Operator (MISO) markets and the authors concluded that the financial gains could bring more benefits to both the consumers and the program administrators.

The reason why water heaters have not been used on a large scale to provide ancillary services is due to the unwillingness of water heater manufacturers to open up their proprietary platforms to allow control access by non-OEM operators and electric utilities. A 2018 report published by Bonneville Power Administration demonstrated that the costs of retrofitting water heaters with communications and control modules that can allow a communication protocol like CTA 2045 or openADR are negligible if rolled out and programmatically implemented at utility-level scale [29].

Recently, there has been concrete efforts to standardize remote access control of water heaters. The State of Washington in 2019 passed a bill that will mandate all new water heaters sold within the state to be CTA 2045 compliant beginning in 2022, and Oregon and California have followed suit [30]. When enacted, this will establish a precedent for allowing control of customer-owned water heaters by third-parties other than OEMs. This should encourage more willingness from both customers and utilities to exploit the capabilities of water heaters for providing utility services. Further policy makers, regulators and the electricity industry at large should support the evolution of open standards and integration platforms to enable DERs and RERs to seamlessly enter and reliably participate in electric power systems.

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