Price-Responsive Control Strategy for Heat Pump Water Heaters Using Day-Ahead Pricing Schedules

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***Abstract*—Price-based demand response programs are crucial for optimizing distributed energy resource operations and lowering electricity costs. This paper presents a dynamic price-responsive control strategy for residential heat pump water heaters that aligns operation with day-ahead electricity pricing, while maintaining hot water availability. Leveraging California Load Flexibility Research and Development Hub price signals, ANSI/CTA-2045-B communication commands, and the OCHRE modeling framework, a rule-based controller was developed and tested in two case studies: functional validation and large-scale simulation. Results demonstrate 11–33% cost savings and 86–91% peak-period load reduction, though with a 6–8% increase in total energy use due to strategic preheating, confirming the efficacy of the strategy and its practical value for demand response applications.**

***Index Terms*—Heat pump water heaters, demand response, price-responsive control, day-ahead pricing, ANSI/CTA-2045-B, CalFlexHub, OCHRE, distributed energy resources, dynamic pricing**

I. Introduction

Electricity demand continues to rise due to the expanding use and electrification of residential and commercial loads, including space conditioning, water heating, lighting, and high-performance computing systems [1]. Over time, existing grid infrastructure may struggle to meet this increasing demand, motivating the need for new or increased generation capacity [2]. Renewable energy resources, such as solar and wind, offer sustainable generation that can support the grid, but are inherently variable and weather-dependent, often resulting in a mismatch between peak output and peak electricity demand [3]. To help resolve this imbalance, demand response programs are increasingly being deployed to enable more efficient coordination of customer-side distributed energy resources (DERs) [4]. DERs are customer-owned generation, storage, and controllable load assets that are grid-enabled and located behind the customer meter [5]. Through coordinated operation, these resources can help balance grid demand and reduce energy costs. Among these technologies, heat pump water heaters stand out as a highly efficient residential appliance, capable of significantly lowering electricity use due to their thermal storage characteristics [6].

Recent research has demonstrated the strong potential of price-responsive control strategies for heat pump systems operating under dynamic pricing. Grant et al. [7] developed an ANSI/CTA-2045-B (CTA-2045-B)–price–based control algorithm that customizes service command schedules based on the look-ahead hours and occupant behavior patterns for heat pump water heaters (HPWHs). Their simulation-based approach, evaluated using 148 monitored hot water draw profiles, achieved 29% cost savings and 80% peak load reduction while also increasing mid-day solar energy utilization by nearly 100%. Extending the concept to multi-function systems, Green et al. [8] implemented a rule-based control algorithm for a heat pump that provides both space conditioning and water heating services. Their field deployment in an occupied residence achieved 12–14% cost savings and 16–29% peak load reduction.

Building on this foundation, this work develops a price-responsive control strategy for HPWHs to optimize residential energy use under dynamic electricity pricing. By simulating daily and seasonal price variability, the study evaluates how price-based scheduling can lower electricity costs, shift consumption away from peak periods while maintaining occupant comfort.

The objective of this work is to implement a cost-effective, rule-based load-shifting strategy that reallocates energy consumption from high- to low-price periods. The control schedule is designed using electricity price signals and executed through the CTA-2045-B communication protocol. The approach integrates the California Load Flexibility Research and Development Hub (CalFlexHub) tool [9], a dynamic price reception platform that generates price-based control schedules, with Object-oriented, Controllable, High-resolution Residential Energy (OCHRE) [10], a high-resolution residential energy modeling environment used in this work to simulate a unitary residential HPWH. HPWHs provide substantial efficiency gains, reducing electricity consumption by approximately 70% compared to conventional electric resistance water heaters [11].

Accordingly, this study implements and evaluates the proposed price-responsive control strategy by comparing controlled and baseline HPWH operations to assess its effectiveness in reducing electricity costs and peak-period demand.

II. Methodology

The foundation of this work is a price-signal-based control strategy designed to manage the operation of a HPWH to reduce costs for customers. The primary objective is to reduce energy consumption during periods of high electricity prices

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by shifting usage to lower-price intervals and ensuring reliable hot water availability.

A. Control Strategy Rules

The price-signal-based control strategy was developed from a set of rules to respond effectively to hourly electricity price variations. These rules use the price signals to identify the highest price rates and determine the peak periods within a 24-hour cycle. The rules are as follows:

1) Peak Identification: The control algorithm begins by dividing the 24-hour price profile into two distinct time blocks: a morning period from 00:00 to 11:59 and an evening period from 12:00 to 23:59. This structure enables independent detection of high-price events within each block.

2) Price Thresholds for Service Commands: Based on the peak price, two price thresholds were defined to determine the service periods during which HPWH operation is controlled. The first threshold triggers a load-adding command, prompting the HPWH to heat the tank water to the setpoint temperature or beyond it. The second threshold issues a load-shedding command to minimize electricity consumption during high-price periods.

These thresholds are defined as fixed proportions of the detected peak price within each time window. Let P_{peak} denote the peak price; then, the load-adding and load-shedding thresholds are given by:

$$P_{\text{add}} = \alpha \cdot P_{\text{peak}}, \quad P_{\text{shed}} = \beta \cdot P_{\text{peak}} \tag{1}$$

where $\alpha = 0.40$ and $\beta = 0.70$ are empirically determined constants selected through testing to achieve a balanced trade-off. These values ensure sufficient preheating, prevent premature activation, and effectively capture high-price intervals.

3) Seasonal Variation Adoption: To account for seasonal differences in electricity price profiles and HPWH performance, the proposed control strategy incorporates a seasonal adaptation mechanism. Studies show that residential demand flexibility varies across seasons [12], and HPWH coefficient of performance ranges from approximately 1.6–1.8 at 50°F ambient air temperature to 2.2–2.5 at 70°F [13], [14]. The load-adding threshold is adjusted accordingly: 35% of peak price in winter to enable earlier preheating under lower efficiency, 40% during transitional seasons, and 45% in summer when coefficient of performance improves.

B. CTA-2045-B Commands

This work implements the CTA-2045-B communication protocol to translate algorithmic decisions into actionable service commands that can be executed by the HPWH.

The HPWH model was configured using a default set point temperature of 130°F, which is consistent with the set point temperature of the HPWHs in the testing laboratory at Portland State University, where the power engineering group conducts conformance testing and performance evaluations on commercial water heaters from various manufacturers [15]. The default deadband used in this study is 5°F.

To implement the load-shifting logic, three CTA-2045-B-based service commands were used: *Load-Up* during the morning to heat water in the tank to 130 °F, *Advanced Load-Up* in the evening to raise the setpoint to 145 °F for additional thermal storage, and *Shed* during peak-price periods to reduce the setpoint to 120 °F and minimize energy use.

The sequencing of these commands is structured to address the asymmetric price patterns observed in the CalFlexHub data. During the morning period, a standard *Load-Up* command is issued prior to the brief high-price window, followed by a *Shed* command to limit consumption during the peak. In contrast, the evening period typically exhibits higher and more sustained price peaks; therefore, a more aggressive *Advanced Load-Up* is applied to increase thermal storage capacity before the peak, followed by a *Shed* command to curtail usage during elevated price hours. The overall sequence and timing of these control actions relative to the dynamic price signal are illustrated in Fig. 1.

C. Testing Scenarios

This work considers two scenarios reflecting different levels of information availability and operational characteristics. The baseline scenario represents standard HPWH operation and serves as a reference for evaluating the proposed control strategy. The day-ahead scenario introduces temporal uncertainty consistent with utility practices in which price schedules are published one day in advance. In this case, each day control schedule is generated using the next day price profile and evaluated against the corresponding baseline performance.

D. Performance Analysis

1) Performance Metrics: To comprehensively evaluate the effectiveness of the price-signal-based control strategy, a multi-dimensional analytical framework was developed focusing on three primary performance domains: energy efficiency, economic impact, and grid support capability. For each simulation, evaluated across all four seasons, several core performance metrics were calculated. These include the total energy consumption (kWh), representing the energy used by the HPWH over the entire simulation period; the electricity cost ($/kWh), determined by applying the time-varying CalFlexHub price signals to the 15-minute energy consumption profile; and the peak-period energy consumption (kWh), which quantifies the energy drawn during high-price intervals where electricity prices exceed 70% of the daily peak value.

2) Performance Indicators: From the primary metrics above, three comparative indicators were derived to evaluate the relative performance of the control strategy. These indicators were computed as percentage differences between the baseline scenario and the control-based scenarios, using the following equation:

$$\textit{Percentage Difference} = \frac{\text{Controlled Value} - \text{Baseline Value}}{\text{Baseline Value}} \times 100 \tag{2}$$

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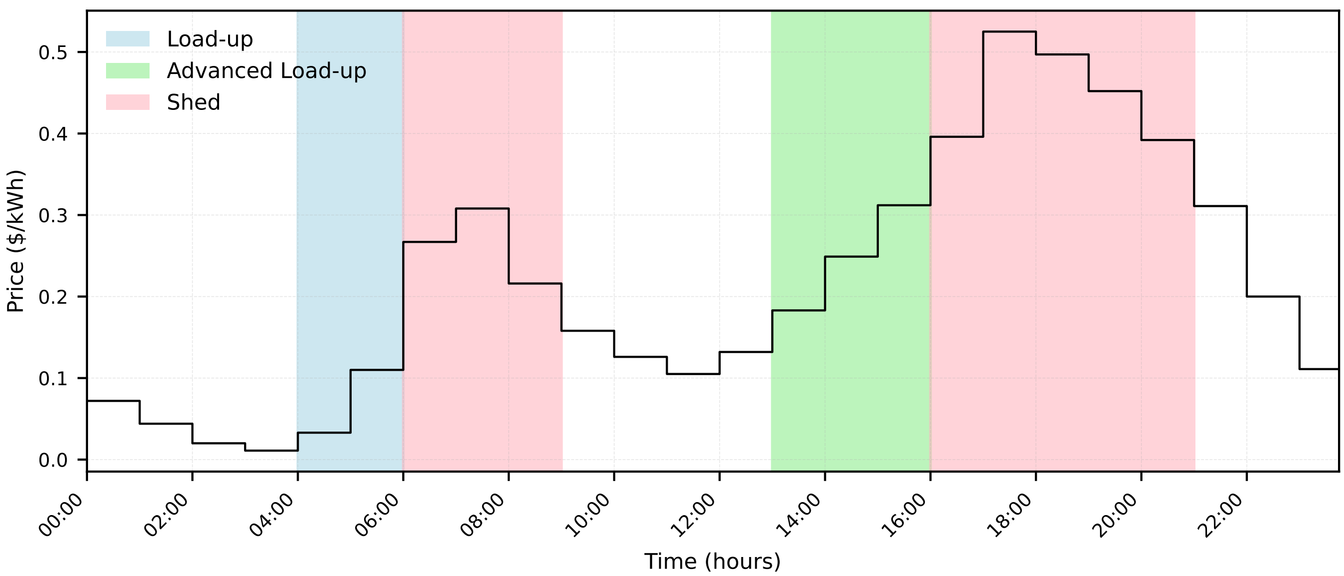

Fig. 1. Shown is the sequencing of CTA-2045-B commands in response to dynamic day-ahead price signals. The controller anticipates high-price periods by issuing a *load-up* command during low-price hours to increase thermal storage within the HPWH, followed by a *shed* command to reduce power draw during peak-price intervals. In the morning period, a standard load-up is applied prior to the short peak window, whereas the evening period employs an advanced load-up of longer duration to store additional thermal energy before shedding load over a sustained high-price interval. This coordinated sequencing enables effective load shifting while maintaining adequate hot-water availability and minimizing operating costs.

This approach enables a normalized assessment of energy savings, cost reductions, and peak-demand mitigation across all scenarios and seasonal conditions. The evaluated indicators include the percentage change in total energy consumption relative to the baseline, *Energy Change*; the percentage reduction in electricity cost compared to the baseline, *Cost Savings*; and the percentage reduction in energy consumption during peak-price intervals relative to the baseline, *Peak Load*.

III. Case Studies

This study comprises two case studies designed to evaluate the performance of the proposed price-signal-based control strategy under varying conditions. The evaluation was conducted through both small-scale and large-scale simulations performed across all four seasons. Each simulation spanned a 14-day period, consistent with the pricing data provided by CalFlexHub. The small-scale case study represents a controlled simulation using a fixed water-draw profile, while the large-scale case study encompasses multiple simulations incorporating diverse water-draw profiles to emulate realistic variations in residential hot-water demand.

A. Case Study I

This case study was conducted during the development stage of the control strategy to verify its core functionality and seasonal adaptability. It serves as the baseline testing framework for evaluating the control logic under controlled and repeatable conditions.

In this case study, a single fixed water draw profile was used and simulated once per season, resulting in a total of four simulations per year. This approach allows performance evaluation across seasonal weather variations, which can significantly influence HPWHs operation and efficiency.

B. Case Study II

This case study was conducted during the implementation stage to validate and evaluate the control strategy under realistic, large-scale operating conditions. It simulates a practical deployment scenario in which the control algorithm is applied across a variety of households, each with distinct hot water usage patterns. This scale-up enables statistical evaluation of control robustness under diverse demand patterns, providing distributional insight that cannot be captured through limited single-profile simulations.

In this case study, eight different water draw profiles were used and executed 48 times per season, totaling 192 simulations per year. Each draw profile was applied in six non-overlapping time periods throughout each season, resulting in 24 simulations per profile annually. This configuration enables a comprehensive evaluation of strategy effectiveness across a broad range of user behaviors and temporal conditions.

IV. Results

A. Case Study I

This case study demonstrates that the control strategy consistently reduces electricity costs by 14–32% and shifts load away from high-price periods by 86–98% across all seasons, even when price information is not perfectly aligned with the day of operation. Concurrently, a we observe a modest increase in total energy consumption of 6–8%, representing a reasonable trade-off given the substantial economic and grid-support advantages.

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TABLE I
COMPARISON OF BASELINE AND PRICE-RESPONSIVE CONTROL STRATEGIES UNDER DAY-AHEAD PRICE CONDITIONS USING A FIXED WATER DRAW PROFILE (SINGLE SIMULATION PER SEASON). REPORTED METRICS REPRESENT PERCENTAGE CHANGES RELATIVE TO BASELINE PERFORMANCE OVER A 14-DAY EVALUATION PERIOD.

Season	Total Energy (%)	Cost (%)	Peak Load (%)
Winter	+6.6	-22.3	-85.6
Spring	+6.6	-32.1	-86.4
Summer	+7.7	-14.3	-98.0
Fall	+7.0	-23.1	-92.0

Table I shows that, despite the 24-hour temporal displacement between price data and control execution, the control strategy in the uncertainty scenario achieved consistent cost savings and substantial peak load reductions across all seasons.

B. Case Study II

This multi-simulation case study demonstrates that the control strategy consistently achieves substantial benefits across all seasons, including electricity cost reductions of 12–33% and peak-period load reductions of 86–91%, though with a modest increase in total energy consumption of 7–8%.

TABLE II
DISTRIBUTIONAL PERFORMANCE RESULTS ACROSS 48 SIMULATIONS PER SEASON. REPORTED VALUES INDICATE MEAN PERCENTAGE DIFFERENCES AND STANDARD DEVIATIONS BETWEEN PRICE-RESPONSIVE AND BASELINE OPERATION FOR TOTAL DAILY ENERGY USE, ELECTRICITY COST, AND PEAK-PERIOD LOAD.

Season	Total Energy		Cost		Peak Load	
	Mean (%)	SD	Mean (%)	SD	Mean (%)	SD
Winter	+6.5	0.8	-21.0	1.7	-86.3	5.6
Spring	+7.1	0.9	-32.9	2.0	-90.6	5.3
Summer	+7.5	0.6	-11.6	2.4	-90.7	4.6
Fall	+6.5	0.7	-19.2	2.1	-90.3	5.1

While the mean and standard deviation values in Table II provide important summary metrics of the control strategy performance, they capture only limited aspects of the underlying data characteristics. These summary results were complemented with distributional analysis using violin plots to examine the complete probabilistic outcomes of the control strategy. Narrower violin shapes indicate that results are tightly clustered across households, while the absence of long tails suggests that unusual or extreme behaviors are unlikely under realistic usage variability.

Figure 2 presents violin plots of seasonal energy consumption changes relative to baseline operation. Across all seasons, changes in energy consumption remain modest, with standard deviations below 1%, indicating highly predictable performance across diverse usage conditions. The distributions exhibit limited spread and no notable outliers, demonstrating stable operation across households. While slight seasonal shifts in mean values appear, particularly in spring and summer due to variations in ambient conditions and hot-water usage patterns, the differences remain small, and the overall distribution shapes remain compact, confirming that the control strategy delivers consistent energy performance throughout the year.

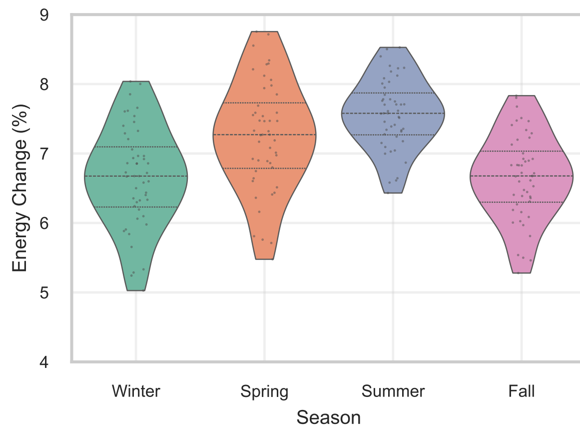

Fig. 2. Seasonal distribution of total daily energy consumption changes under price-responsive control, based on 48 simulations per season. Slight increases are observed across all seasons, primarily due to preheating during low-price hours, while the narrow spread indicates consistent performance and limited variability among households.

The violin plots in Figure 3 illustrate the distribution of electricity cost savings achieved by the price-responsive control strategy across all four seasons. Across scenarios, variability remains modest, with standard deviations ranging from approximately 1.7–2.4%, indicating that the control strategy consistently delivers notable cost reductions under diverse hot water usage behaviors. Each season exhibits a compact central distribution with no instances of cost increases, confirming that the strategy consistently reduces operational costs relative to the baseline. Seasonal differences are evident: spring demonstrates the greatest cost savings because its price profile provides longer low-cost intervals and less pronounced peaks, allowing the controller to optimize operation more effectively. Nonetheless, all seasonal distributions remain sufficiently narrow to ensure confidence in the predictability and stability of the economic benefits achieved by the control strategy.

Figure 4 shows the seasonal distributions of peak load reduction achieved by the price-responsive control strategy, expressed as the percentage decrease in demand during high-price periods relative to baseline operation. Across all seasons, reductions are substantial, typically exceeding 85%, with standard deviations remaining below 6%. Spring, summer, and fall exhibit particularly narrow distributions, indicating highly reliable avoidance of peak-period consumption. Winter performance displays slightly greater variability due to increased heating demand and reduced heat pump efficiency, yet remains strongly effective, with the majority of simulations achieving reductions above 80%.

Overall, the results demonstrate strong performance across seasons and households, with modest daily energy increases, consistent cost savings, and high peak load reductions. These outcomes confirm the reliability of the day-ahead scheduling strategy under diverse usage conditions, supporting scalable residential demand response deployment. Furthermore, HPWHs provide dependable peak-demand flexibility using only

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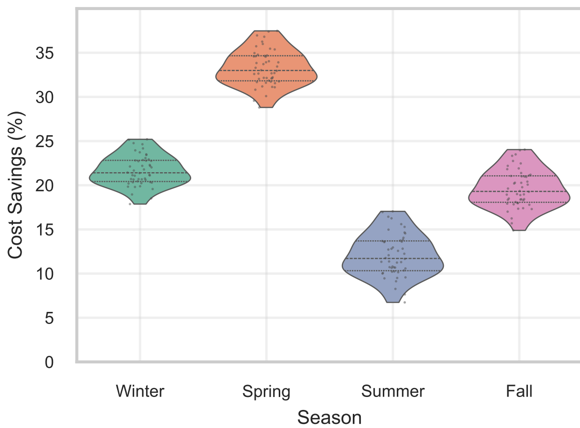

Fig. 3. Seasonal distribution of electricity cost savings under price-responsive control, based on 48 simulations per season. Spring exhibits the highest savings due to more favorable price differentials between peak and off-peak hours, whereas summer shows slightly smaller reductions. The narrow spread across households indicates consistent economic performance and strong control behavior.

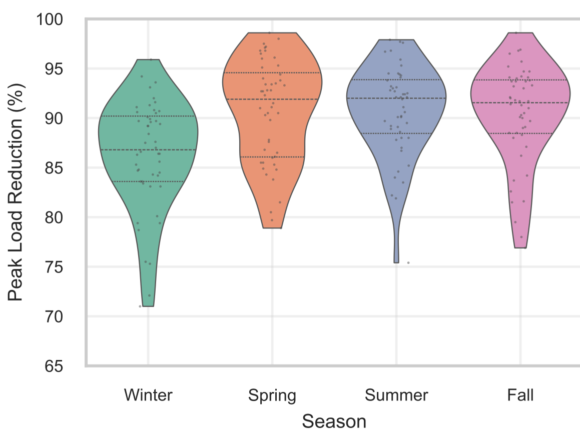

Fig. 4. Seasonal distribution of peak-period load reductions under price-responsive control, based on 48 simulations per season. Substantial reductions are achieved across all seasons, with spring, summer, and fall showing highly consistent performance. Slightly greater variability in winter reflects increased heating demand and broader operational range of HPWHs.

day-ahead price signals, aligning with existing utility tariffs. This capability reduces reliance on peaking power plants, mitigates grid congestion during critical hours, and advances the role of HPWHs as distributed thermal storage assets within future grid-interactive demand response programs.

V. Conclusion

This paper presents a price-responsive control strategy for residential HPWHs that integrates dynamic electricity pricing with CTA-2045-B-based command logic to reduce operating costs and shift demand away from high-price periods. Using the CalFlexHub price reception tool and the OCHRE simulation platform, the strategy was evaluated under both fixed and stochastic water-use profiles to capture realistic residential operating conditions.

Across all seasons and households, the controller achieved notable economic and grid benefits, including up to 33% cost reductions and 86–91% peak-period load reductions, though with modest energy consumption increases of approximately 6–8%. The narrow variability observed across seasonal distributions further indicates robust performance despite uncertainty in usage patterns and schedule timing.

Real-world outcomes may differ due to deviations between published day-ahead price schedules and actual market conditions, as well as stochastic occupant behavior. Future work can focus on forecast-error modeling, field demonstrations incorporating comfort constraints, and coordinated control of aggregated HPWHs to quantify system-level grid impacts and enhance scalability within residential demand response programs.

References

[1] C. Fant, B. Boehlert, K. Strzepek, P. Larsen, A. White, S. Gulati, Y. Li, and J. Martinich, "Climate change impacts and costs to US electricity transmission and distribution infrastructure," *Energy*, vol. 195, 2020.

[2] C. Silva, P. Faria, and Z. Vale, "Demand response implementation: Overview of Europe and United States status," *Energies*, vol. 16, no. 10, 2023.

[3] G. Karagiannakis, M. Panteli, and S. Argyroudis, "Fragility modeling of power grid infrastructure for addressing climate change risks and adaptation," *Wiley Interdisciplinary Reviews: Climate Change*, vol. 16, no. 1, 2025.

[4] M. H. Albadi and E. F. El-Saadany, "Demand response in electricity markets: An overview," in *IEEE P. & E. Soc. General Meeting*. IEEE, 2007.

[5] S. Widergren, R. Melton, A. Khandekar, B. Nordman, and M. Knight, "The plug-and-play electricity era: Interoperability to integrate anything, anywhere, anytime," *IEEE Power & Energy Magazine*, vol. 17, no. 5, pp. 47–58, 2019.

[6] C. Colon, E. Martin, D. Parker, K. Sutherland, and Center, "Measured performance of ducted and space-coupled heat pump water heaters in a cooling-dominated climate," Florida Solar Energy Center, Tech. Rep., 2016.

[7] P. Grant, M. Stübs, B. Nordman, and C. Gehbauer, "Stabilizing the grid and reducing utility bills through price responsive controls for heat pump water heaters," Lawrence Berkeley National Laboratory, Tech. Rep., 2023.

[8] C. Green, S. Chakraborty, and D. Vernon, "Load flexibility of a residential multi-function heat pump using dynamic pricing," University of California, Davis, Tech. Rep., 2024.

[9] A. K. Prakash, D. Gerber, L. Paul, and USDOE, "California load flexibility research and development hub (CalFlexhub)."

[10] M. Blonsky, J. Maguire, K. McKenna, D. Cutler, S. P. Balamurugan, and X. Jin, "OCHRE: The object-oriented, controllable, high-resolution residential energy model for dynamic integration studies," *Applied Energy*, vol. 290, 2021.

[11] H. Gong, T. Rooney, O. M. Akeyo, B. T. Branecky, and D. M. Ionel, "Equivalent electric and heat-pump water heater models for aggregated community-level demand response virtual power plant controls," *IEEE Access*, vol. 9, 2021.

[12] M. Waseem, I. A. Sajjad, R. Napoli, and G. Chicco, "Seasonal effect on the flexibility assessment of electrical demand," in *Int. Universities Power Engineering Conf.*, 2018.

[13] B. Sparn, K. Hudon, and D. Christensen, "Field performance of heat pump water heaters in the Northeast," National Renewable Energy Laboratory, Tech. Rep. NREL/TP-5500-64904, 2016.

[14] D. Paresa and R. B. Bass, "Estimating electric power consumption of grid-enabled residential heat pump water heaters," in *IEEE Conf. on Tech.for Sust.*, 2025.

[15] D. Paresa, M. Adham, G. Heiken, and R. B. Bass, "ANSI/CTA-2045 conformance testing: Are smart appliances ready for large-scale deployment?" in *IEEE P. & E. Soc. General Meeting*, 2024.