SMUD POWERMINDER PILOT EVALUATION

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1. Executive Summary

The SMUD PowerMinder pilot provides customer incentives for enrolling their internet-connected heat-pump water heaters in the pilot by registering and connecting their device to the Virtual Peaker platform. The pilot partners with Virtual Peaker software, which uses cost optimization algorithms to use the water heater as load-shifting energy storage. During event days, the software uses California ISO day-ahead pricing data to minimize energy cost to SMUD. During non-event days, the software minimizes costs to participants using SMUD's residential Time-of-Day Rate. As of December 2020, the pilot has 94 participants. Of these participants, 74 replaced gas units, 11 replaced electric units, and 9 baseline units are unknown.

The SMUD PowerMinder pilot has been evaluated using statistical and physical models and is shown to save energy, reduce emissions, and reduce energy bills for participating customers. The statistical model utilizes whole-house meter data for the participants and a control group feeding into a neural network to calculate the overall impact of the water heater and the software. The physical model utilizes data from the water heaters themselves to investigate their operation, including disaggregating the use of the integrated resistance heaters. The results of the analysis are shown in Table 1: Average annual per-household analysis results.. Values are average per-household on an annual basis.

Table 1: Average annual per-household analysis results.

Replacing electric water heater:		
Energy Saved	1,027	kWh annually
Emissions Reduced	227	kg CO2 annually
Customer Cost Savings	140	Dollars annually before rebates
Customer Cost Savings	164	Dollars annually with $2/mo rebate
Replacing Gas Water Heater:		
Gas Usage Displaced	104	therms annually
Emissions Reduced	444	kg CO2 annually
Customer Cost Savings	31	Dollars annually before rebates
Customer Cost Savings	55	Dollars annually with $2/mo rebate

The analysis had some challenges which can be addressed in future work. The sample size is small for residential statistical analyses, especially in the case of only 11 electric resistance heater replacements. Regarding evaluation of the software, impact analysis would be improved if the software also operated in baseline mode (no optimization) for some days of the week as part of a future study.

2. Project Introduction

Under a contract with SMUD, ADM Associates and the Electric Power Research Institute (EPRI) evaluated the PowerMinder thermal storage load-shifting pilot. This pilot incentivizes residential customers to enroll their heat pump water heater and allow SMUD to optimize their heat pump water heater on their behalf. The pilot has a partnership with Virtual Peaker whose software optimizes water heater energy consumption to minimize costs to the customer by using pricing data and treating the water tank as a thermal energy storage system. As of December 2020, there were 94 pilot participants, 74 of which replaced a gas heater, 11 participants replaced an electric resistance heater, and 9 had unknown baseline fuel.

An illustration showing the operation of a heat pump water heater is shown in Figure 1. The heat pump tends to be located at the top of the unit and has a channel for air to enter and exit the unit to exchange heat. To heat the water, the heat pump working fluid is sent through a submerged condenser coil. The working fluid transfers energy from the air to the water in the tank, providing hot water with lower energy consumption than conventional electric resistance water heaters. The increased heating efficiency results in emissions and cost reductions over conventional electric water heaters. However, many heat pump water heaters, including the units in this study, are equipped with resistance heaters to meet periods of high demand. The overall performance of the heat pumps must account for all operating modes, since efficiency is reduced while resistance heating.

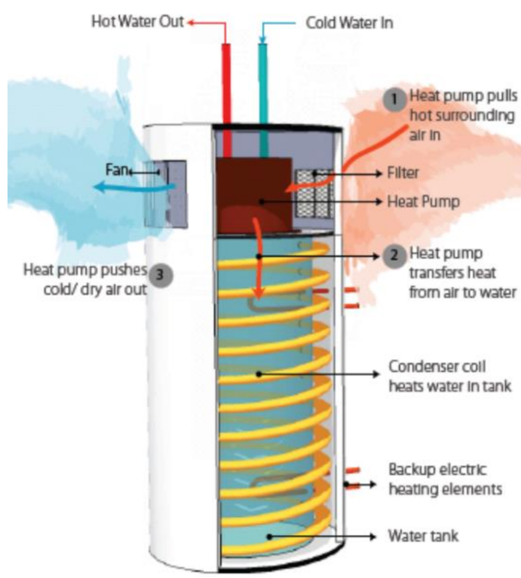

Figure 1: Illustration showing how a heat pump water heater operates.[1]

[1] NREL report: Field Performance of Heat Pump Water Heaters in the Northeast https://www.nrel.gov/docs/fy16osti/64904.pdf

Heat pump water heaters also provide significant energy reductions over conventional gas water heaters. Conventional gas heaters burn gas directly below the storage tank to heat water. This results in a faster rate of replacement of hot water but comes with associated inefficiencies. Approximately 60% of the chemical energy contained in the fuel is transferred to the water, and the remaining 40% is lost to the environment by venting combustion by-products or through heat-leakage.

The Virtual Peaker software uses the water heater as a form of energy storage to shift the load into periods with lower energy costs. During non-event days, the system optimizes to SMUD's residential Time-of-Day (TOD) Rate, shown in Figure 2. During event days, the software optimizes for wholesale market (CAISO) rates. Load shifting technologies have slightly higher power consumption overall due to thermal losses of the water in the tank. Hot water is stored for longer periods of time at higher temperatures. However, heat pumps are superior technologies compared to electric resistance and gas options, and electricity consumed during peak times is often environmentally detrimental, so overall the pilot impact is positive.

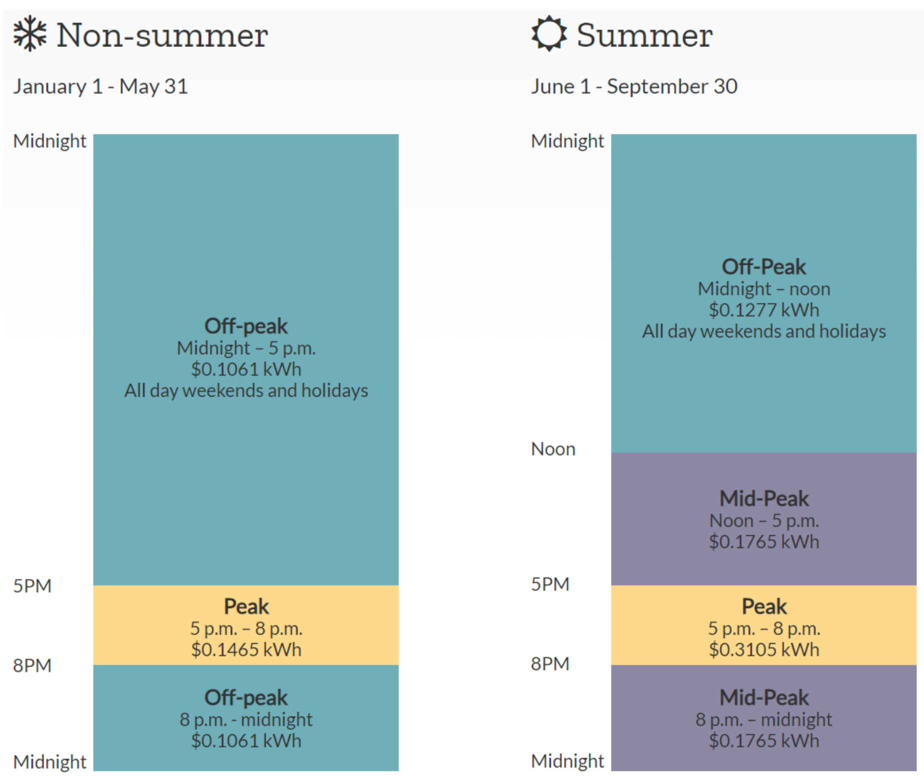

Figure 2: SMUD residential rates. On non-event days, PowerMinder optimizes operation to minimize cost.

3. Energy Use Analysis

This section discusses the analytical methodologies conducted to provide estimates of pilot impacts such as the annual energy impact, peak energy impact, event energy impact, etc. due to participation in the PowerMinder pilot.

The first activity in analyzing pilot energy impacts involved acquiring and cleaning relevant datasets. The datasets utilized in the analysis are the following:

- Participant Tracking Data – contained standard participant premise information such as the installed tank size, whether the unit replaced a gas or electric water heater, and an account number for mapping to other data sets.
- Total Premise Electricity Consumption Data – contained hourly interval time-series data on energy consumption (in kWh).
- Heat Pump Water Heater (HPWH) Consumption Data – contained 15-minute interval time-series data on heat pump water heater consumption (in kWh).
- Weather Data – pulled from the National Oceanic & Atmospheric Administration climate data for Sacramento Executive Airport, McClellan Airport, and Sacramento International Airport.
- Event & Electricity Rate Data – contains California ISO electricity rates (dollar per kWh) at hourly intervals along with dates on which events occurred.
- Control Group Data – contains total premise electricity consumption data for a random sample of 2,000 homes in SMUD territory stratified by zip code to match participant zip code distribution.

All datasets were cleaned and merged into a single panel time-series data set at hourly intervals. Data was aggregated into multiple variations to visualize the energy consumption of the heat pump water heaters to better understand their performance.

The annual impact of the retrofits was calculated using two methods, statistical modeling of the average household consumption, and physical consumption of the individual heaters. The statistical model utilized a neural network with a control group to account for factors like economic change and COVID affects to isolate the retrofit but is subject to error common with modeling human activity for a small sample. The physical model gives less information on whether the water consumption during the time period is typical (a consideration of interest during the pandemic), but it is simple and accurate for basic calculations. It is less sensitive to exogenous effects like COVID-related patterns of energy use, and it is able to account for hardware-related energy uses such as the use of backup resistance heaters.

3.1. Impact of Event Days

The purpose of the PowerMinder pilot is to shift residential electric hot water heating load away from times in which SMUD is expected to approach peak capacity, and to save pilot participants money. Taking advantage of HPWH's high thermal efficiency, during event days

HPWHs that are enrolled in the pilot will have their temperature settings temporarily adjusted to overheat hot water stored in the HPWH during periods of time when the electric grid is predicted to have greater capacity. This overheated water is then mixed with cold water via a mixing valve to achieve the customer's desired water temperature. The Virtual Peaker software utilizes day-ahead pricing to approximate when grid capacity is highest v. lowest and benefits both the utility and the customer by reducing demand during peak hours and shifting energy usage to periods of time when costs to the customer and utility are lower.

Figure 3 presents the average daily load profile for HPWHs on event and non-event days as well as the hourly wholesale price per kWh. From the plot, it appears that the morning and evening loads are temporally shifted relative to the morning and evening peak price on event days. This is further evidenced in Figure 4, which shows a tighter distribution around an earlier peak both in the morning and afternoon, suggesting that the HPWHs are being pre-heated in advance of the peak price.

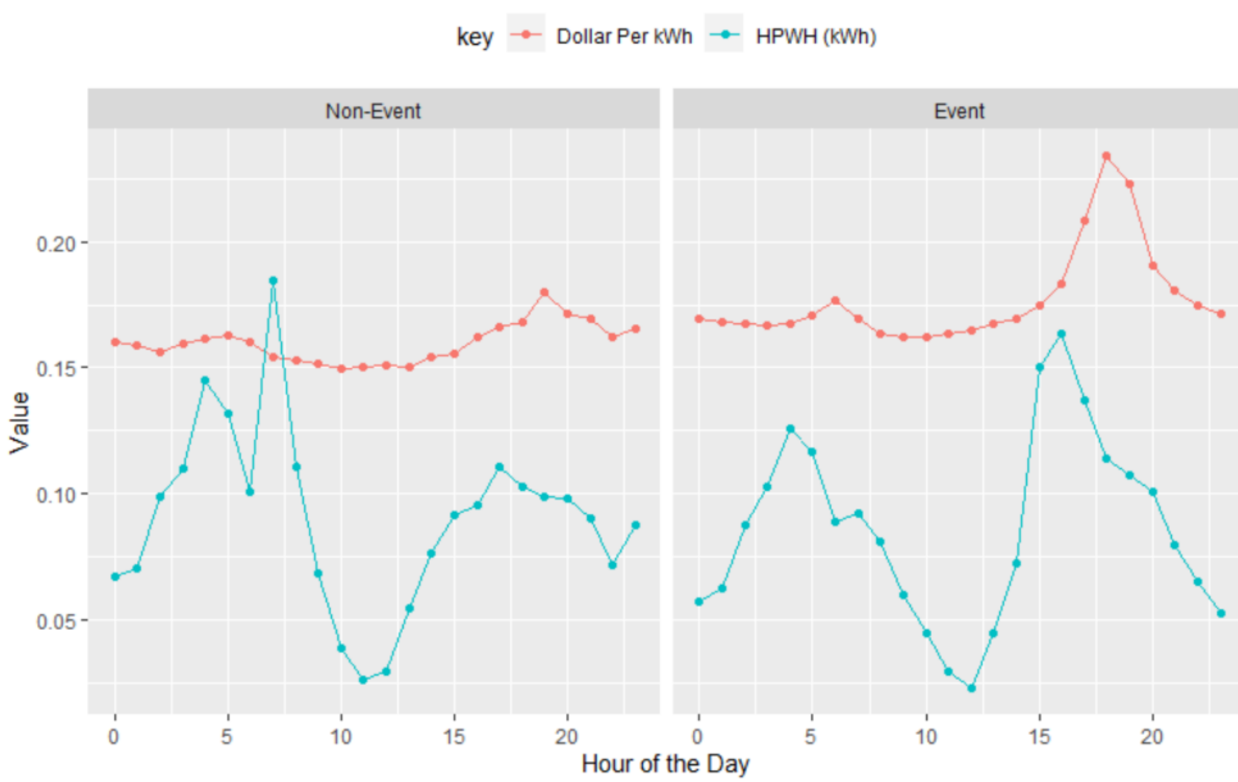

Figure 3: Event impact and cost by hour. During the event (right image) the energy consumption (blue line) shows some pre-heating before the cost peaks (red line).

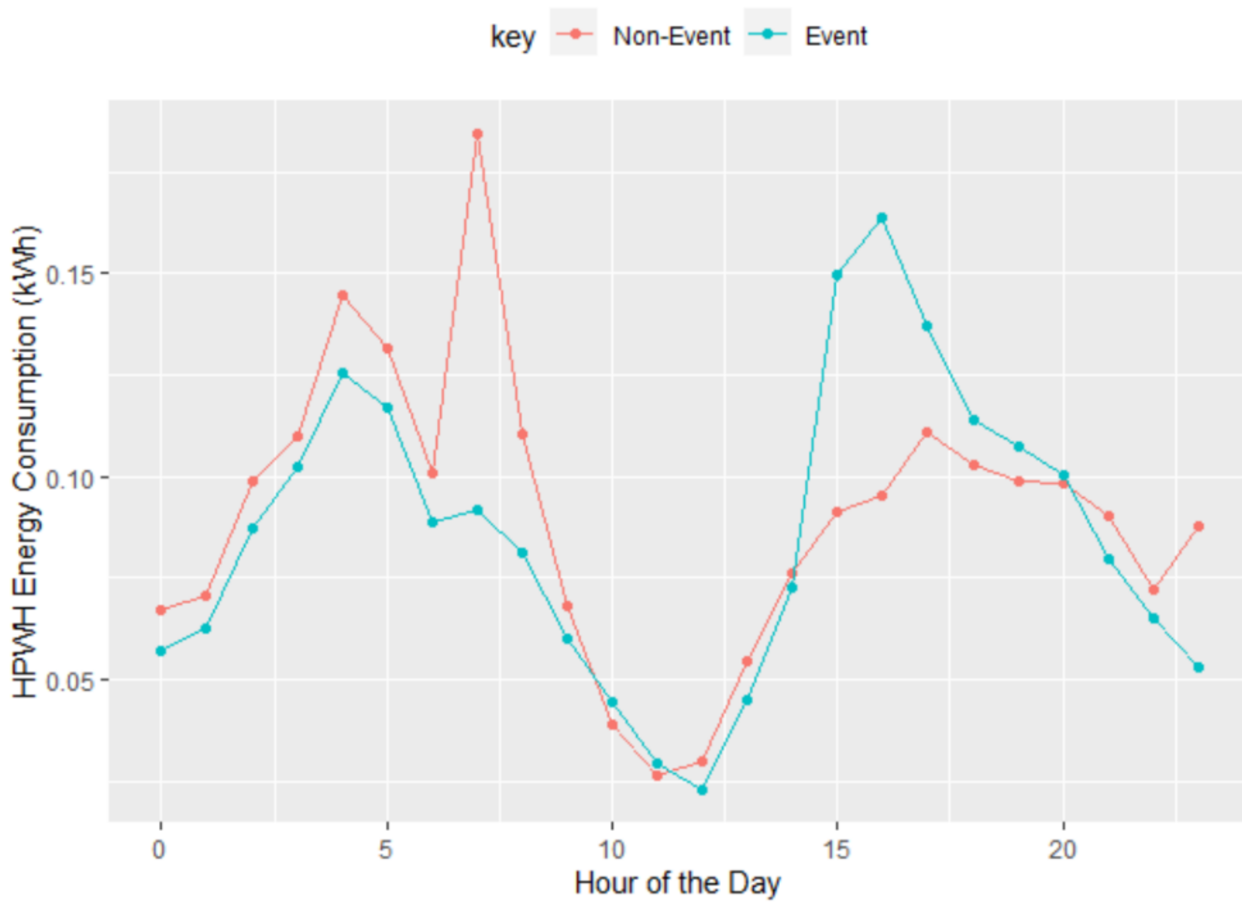

Figure 4: Average heat pump water heater energy consumption during event days (blue) and non-event days (red). The morning peak appears lower on event days but the afternoon peak appears higher.

To confirm whether event days had a significant impact on the 24-hour load profile of HPWHs, a statistical analysis was performed on the following parameters:

- A regression analysis was performed to determine whether there was a significant difference in the time of the morning and afternoon peak on event v. non-event days,
- A regression analysis was performed to determine whether there was a significant difference in the HPWH load at the peak price on event v. non-event days,
- A regression analysis was performed to determine whether there was a significant difference in HPWH hours of use between event v. non-event days,
- A regression analysis was performed to determine whether there was a difference in the total kWh consumed on event v. non-event days.

For all analyses, data was restricted to the time between March 11, 2020 and December 17, 2020—the dates at which the first and last HPWH event occurred. Additionally, cluster-robust standard errors were used throughout all regression analyses to correct for usage of panel data in linear regression.[2]

Peak Time Analysis

To determine whether there is a significant difference in the time of the morning (before 12 p.m.) and afternoon (after 12 p.m.) peaks for event v. non-event days, we first isolated the peak hour for the morning and afternoon for each day for each customer by finding the hour in the morning and afternoon at which the highest energy demand for HPWHs occurred. A regression analysis was then performed for mornings and afternoons separately using the following equation:

$$peak\ hour_i = \alpha + \beta_{1a} \cdot month_a + \ldots + \beta_{1n} \cdot month_n + \beta_{2a} \cdot event \cdot month_a + \ldots + \beta_{2n} \cdot event \cdot month_n + \varepsilon$$

Where:

- $peak\ hour_i$ represents the hour at which the morning or afternoon peak occurs for each customer for each day,
- $month_a$ through $month_n$ are indicator variables that represents each month represented in the data set,
- $event$ is an indicator variable that represents event days v. non-event days,
- β_{1a} through β_{1n} represent the main effect of month on peak hour,
- β_{2a} through β_{2n}, the parameters of interest, represent the difference in peak hour between event and non-event days,
- α is the intercept, and
- ε is the error term.

The results of this analysis are presented in Table 2. Values in the Difference column represent the non-event peak hour minus the event peak hour. In general, there is a statistically significant decrease in the morning peak on event days for most months except March, July, and August, which show no difference in the peak hour. Despite this shift being statistically significant, the impact is minimal, with the difference being approximately four minutes at the lowest and 20 minutes at the highest.

A similar pattern emerges for the afternoon peak, with most months showing a statistically significant decrease in the peak hour except for: March, November, and December, in which the decrease is not statistically significant; and April, in which there is a statistically significant increase in the peak hour. As with the morning peak, the magnitude is on the order of approximately four minutes to 11 minutes.

[2] https://cran.r-project.org/web/packages/clubSandwich/vignettes/panel-data-CRVE.html

Table 2: Peak Hour for Non-Event and Event Days

Morning or Afternoon	Month	Peak Hour (Non-Event Days)	Peak Hour (Event Days)	Difference (Hours)	P-Value	Statistically Significant? ($p < 0.05$)
Morning	3	5.40	5.38	0.03	0.71	No
Morning	4	5.53	5.27	0.26	0.00	Yes
Morning	5	5.50	5.42	0.08	0.00	Yes
Morning	6	5.69	5.40	0.28	0.00	Yes
Morning	7	5.43	5.42	0.01	0.70	No
Morning	8	5.52	5.61	-0.09	0.20	No
Morning	9	5.53	5.47	0.06	0.04	Yes
Morning	10	5.48	5.35	0.13	0.00	Yes
Morning	11	5.58	5.46	0.13	0.00	Yes
Morning	12	5.72	5.39	0.33	0.00	Yes
Afternoon	3	17.93	18.04	-0.10	0.45	No
Afternoon	4	17.81	18.00	-0.19	0.03	Yes
Afternoon	5	17.62	17.56	0.06	0.04	Yes
Afternoon	6	17.44	17.31	0.14	0.00	Yes
Afternoon	7	17.47	17.26	0.20	0.00	Yes
Afternoon	8	17.38	17.27	0.12	0.03	Yes
Afternoon	9	17.56	17.38	0.18	0.00	Yes
Afternoon	10	17.61	17.54	0.07	0.03	Yes
Afternoon	11	17.73	17.68	0.04	0.25	No
Afternoon	12	17.72	17.68	0.04	0.61	No

HPWH Load at Peak Price Analysis

Although the analysis on pilot impact on peak time yielded a statistically significant shift in the timing of the morning and afternoon peak, the magnitude of the impact was within a few minutes to up to 20 minutes, rather than shifting the peak HPWH load by hours. Thus, we sought to see whether the pilot was effective at reducing electric demand from HPWHs during the periods at which grid capacity was lowest. To accomplish this, we used peak pricing as a proxy for peak grid demand and isolated, for both mornings and afternoons, the hours at which the price per kWh was highest. A regression analysis was then performed for mornings and afternoons separately using the following equation:

$$kWh_i = \alpha + \beta_{1a} \cdot month_a + \ldots + \beta_{1n} \cdot month_n + \beta_{2a} \cdot event \cdot month_a + \ldots + \beta_{2n} \cdot event \cdot month_n + \varepsilon$$

Where:

- kWh_i represents the energy consumed by HPWHs during the hours at which energy cost was highest for each day for each customer,
- $month_a$ through $month_n$ are indicator variables that represents each month represented in the data set,
- $event$ is an indicator variable that represents event days v. non-event days,
- β_{1a} through β_{1n} represent the main effect of month on kWh,
- β_{2a} through β_{2n}, the parameters of interest, represent the difference in kWh during peak price hours between event and non-event days,
- α is the intercept, and
- ε is the error term.

The results of this analysis are presented in Table 3. In general, the pilot had a mixed effect on the demand associated with HPWHs during the grid peak on event days. Four months out of 10 showed a statistically significant difference in HPWH demand during the morning grid peak, with a statistically significant reduction in demand for May, June, August, and October. An inverted effect was observed for afternoons, however. HPWH demand showed a statistically significant increase during the afternoon grid peak for April, May, and September.

Table 3: HPWH Load at Peak Price for Non-Event and Event Days

Morning or Afternoon	Month	kWh (Non-Event Days)	kWh (Event Days)	Difference (kWh)	P-Value	Statistically Significant? ($p < 0.05$)
Morning	3	0.18	0.11	0.07	0.05	No
Morning	4	0.13	0.11	0.01	0.52	No
Morning	5	0.09	0.06	0.03	0.03	Yes
Morning	6	0.11	0.07	0.03	0.04	Yes
Morning	7	0.06	0.07	-0.01	0.44	No
Morning	8	0.06	0.04	0.02	0.05	Yes
Morning	9	0.05	0.05	0.00	0.63	No
Morning	10	0.12	0.08	0.04	0.00	Yes
Morning	11	0.15	0.14	0.01	0.75	No
Morning	12	0.17	0.16	0.01	0.75	No
Afternoon	3	0.15	0.28	-0.12	0.07	No
Afternoon	4	0.15	0.24	-0.08	0.00	Yes
Afternoon	5	0.09	0.13	-0.04	0.00	Yes
Afternoon	6	0.07	0.10	-0.03	0.09	No
Afternoon	7	0.06	0.06	0.00	0.97	No
Afternoon	8	0.07	0.06	0.01	0.61	No

Afternoon	9	0.08	0.12	-0.03	0.00	Yes
Afternoon	10	0.10	0.12	-0.02	0.11	No
Afternoon	11	0.16	0.15	0.02	0.50	No
Afternoon	12	0.10	0.13	-0.02	0.20	No

Hours of Use Analysis

In addition to looking at the pilot's impact on shifting peak load, we also reviewed whether there was a significant change in the hours of use (HOU) associated with event v. non-event days. To accomplish this, for each customer and each day, we counted the number of hours that exhibited some level of HPWH energy consumption, regardless of the magnitude. A regression analysis was then performed using the following equation:

$$HOU_i = \alpha + \beta_{1a} \cdot month_a + \dots + \beta_{1n} \cdot month_n + \beta_{2a} \cdot event \cdot month_a + \dots + \beta_{2n} \cdot event \cdot month_n + \varepsilon$$

Where:

- HOU_i represents the number of hours the HPWHs were active for each day for each customer,
- $month_a$ through $month_n$ are indicator variables that represents each month represented in the data set,
- $event$ is an indicator variable that represents event days v. non-event days,
- β_{1a} through β_{1n} represent the main effect of month on HOU,
- β_{2a} through β_{2n}, the parameters of interest, represent the difference in HOU between event and non-event days,
- α is the intercept, and
- ε is the error term.

The results of this analysis are presented in Table 4. Six of the ten months showed a statistically significant difference in the HOU associated with HPWHs for event days when compared to non-event days. For March, May, August, October, and December, the HOU for HPWHs was significantly reduced during event days. For June, the HOU significantly increased. This may suggest that the pilot is achieving part of its goal in reducing HPWH load distribution by overheating water during specific periods of time, reducing the overall need for the HPWH to continue heating water during other periods of time.

Table 4: HOU for Non-Event and Event Days

Month	HOU (Non-Event Days)	HOU (Event Days)	Difference (HOU)	P-Value	Statistically Significant? ($p < 0.05$)
3	9.74	8.64	1.10	0.01	Yes
4	8.62	8.29	0.34	0.24	No
5	7.63	7.19	0.44	0.04	Yes
6	6.23	6.92	-0.69	0.00	Yes
7	6.37	6.12	0.24	0.14	No
8	6.27	5.84	0.43	0.02	Yes
9	5.96	6.25	-0.29	0.24	No
10	7.80	7.01	0.79	0.00	Yes
11	8.79	8.84	-0.04	0.81	No
12	10.20	9.56	0.64	0.02	Yes

Daily HPWH Energy Consumption Analysis

Although the HPWH events primarily targeted load shifting rather than energy efficiency, to fully describe the potential impact of the pilot, we also looked at whether there was a significant difference in the daily HPWH energy consumption on event v. non-event days. A regression analysis was then performed using the following equation:

$$kWh_i = \alpha + \beta_{1a} \cdot month_a + \dots + \beta_{1n} \cdot month_n + \beta_{2a} \cdot event \cdot month_a + \dots + \beta_{2n} \cdot event \cdot month_n + \varepsilon$$

Where:

- kWh_i represents the total kWh consumed by the HPWHs for each day for each customer,
- $month_a$ through $month_n$ are indicator variables that represents each month represented in the data set,
- $event$ is an indicator variable that represents event days v. non-event days,
- β_{1a} through β_{1n} represent the main effect of month on kWh,
- β_{2a} through β_{2n}, the parameters of interest, represent the difference in kWh between event and non-event days,
- α is the intercept, and
- ε is the error term.

The results of this analysis are presented in Table 5. Of the 10 months, May, October, and November showed a statistically significant reduction in HPWH consumption during event days while June and July showed a statistically significant increase in HPWH consumption during event days.

Table 5: HOU for Non-Event and Event Days

Month	Daily kWh (Non-Event Days)	Daily kWh (Event Days)	Difference (Daily kWh)	P-Value	Statistically Significant? ($p < 0.05$)
3	3.29	3.30	0.00	0.98	No
4	3.08	2.96	0.12	0.42	No
5	1.93	1.66	0.27	0.00	Yes
6	1.60	1.89	-0.28	0.00	Yes
7	1.58	1.76	-0.18	0.00	Yes
8	1.60	1.57	0.03	0.61	No
9	1.58	1.68	-0.10	0.22	No
10	2.00	1.62	0.38	0.00	Yes
11	2.75	2.53	0.23	0.02	Yes
12	3.02	2.73	0.29	0.13	No

3.2. Statistical Model

The neural network statistical model predicts premise energy consumption as a function of temperature, event day, hour of day, day of week, and other factors. The applied methodology involved the development of a synthetic baseline model trained on pre-period consumption data that could then predict consumption in the post-period. The difference between the predicted and actual consumption data in the post-period averaged across an entire year provided the estimate for savings. A control group of 2,000 randomly sampled homes was used to control for other variables, such as economic growth and the pandemic, to better isolate the impact of the retrofit itself.

To start, the analysis was split into two separate cohorts; defined by whether the installed HPWH replaced an electric or gas water heater. Because the gas replacement premises would not have any reported electricity consumption due to water heating in their pre-period they had to be treated separately as an accurate model would predict increased electricity consumption after installation of the HPWH. Of the 94 unique participants in the tracking data, 74 were identified as having replaced a gas water heater, while 11 had replaced an electric water heater (with the remainder unknown). Pre- and post-periods were defined for each premise based on the earliest available timestamp for that premise's heat pump water heater consumption data.

The synthetic baseline model was built using a neural network with the Keras framework. It consists of a sequential feed forward architecture shown in Figure 5, below. The training set consisted of 70% of the total pre-period data, selected at random, with the validation set making up the remaining 30% of data points. Four input parameters were used to develop predictions: the month, hour, day of the week, and temperature. The model attempted to minimize mean-squared-error as its measure of loss and used the Adam optimizer.

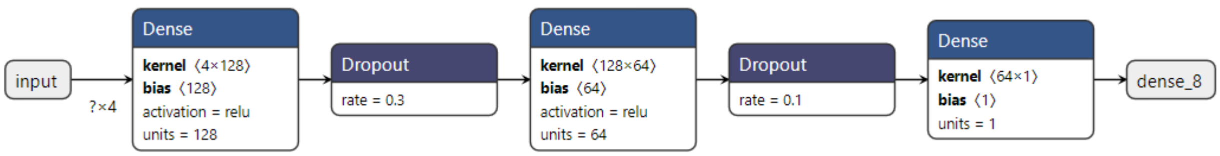

Figure 5: Neural Network Architecture for Synthetic Baseline Model

In the case of the electric replacement homes, the trained model can then be applied to the post-period data to develop a predicted energy consumption; the difference between the predicted and actual consumption averaged across a full year provides the estimate of average hourly savings due to the installation of the heat pump water heater. Alternative confounding effects across time are accounted for by repeating the process with a control group premise set and removing the estimated consumption change.

Alternative confounding effects across time are accounted for by repeating the process with a control group premise set and removing the estimated consumption change. The control group was developed by identifying, for each treatment premise, a corresponding control premise with the closest matching average hourly energy consumption across identical time periods.

For gas replacement premises, this neural net model can show changes in consumption by adding the heater to the electric load but the gas usage is not modeled. Analysis of gas usage is explained in later sections using heat pump water heater data. Electricity cost will be higher with a gas replacement due to the fuel switch. Gas efficiency was developed using efficiency factors from a NREL paper on water heater efficiencies.[3]

For the ten treatment premises that had an electric water heater replaced, the analysis found an annual energy savings estimate of .142 kWh in the post-period. Annually, this equates to 1,245 kWh saved per premise installing the smart heat pump water heater. Due to the small population size, the root mean squared error is quite high: 3,791 kWh. Qualitatively, this result can be interpreted by saying that while the average home was likely to reduce their energy consumption through the HPWH installation, some premises showed an increase in energy

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[3] Comparison of Advanced Residential Water Heating Technologies in the United States, NREL.gov. https://www.nrel.gov/docs/fy13osti/55475.pdf, accessed 4/23/2021.

consumption likely due to confounding effects that we could not conclude to be due to confounding effects. Higher population counts could help support this result.

Evaluation of the control group alone, comparing the predicted and actual consumption, showed a difference of .014 kWh. This indicates that the control group, also consisting of 10 premises matching the pre-period energy consumption of the treatment group, did not undergo significant energy consumption changes across the intervention effect. While it's difficult to draw absolute conclusions based on the population size, it suggests a scenario where there were no large changes in external variables (no changes in premise occupancy, no changes due to COVID stay-at-home orders, etc.) or where the changes balanced out. Multiple control group sets were evaluated to ensure this result stayed approximately consistent.

Figure 3 shows the average daily modeled and actual energy consumption across the pre- and post-periods. HPWH consumption data is also shown for context relative to the total.

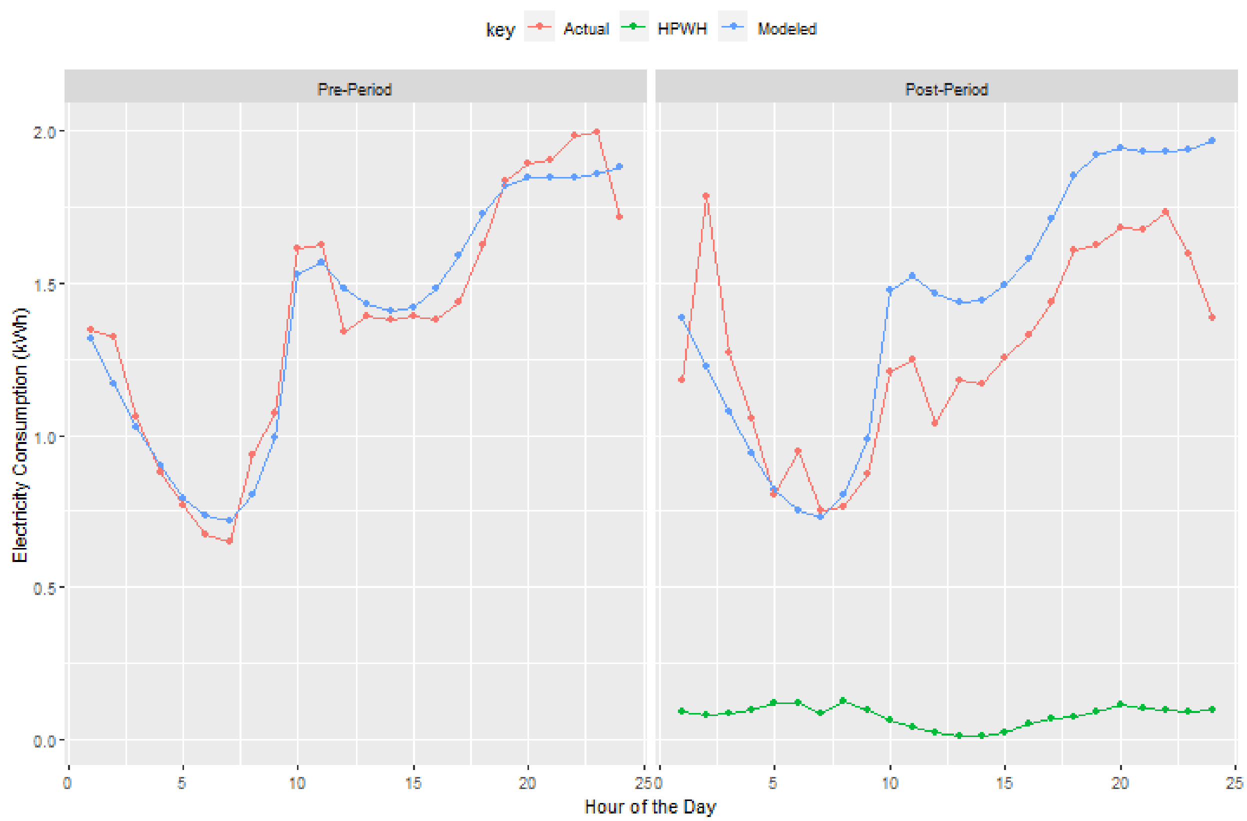


Figure 6: Comparison of energy consumption across time domains

The demand reduction estimate used the same procedure as the annual savings analysis, but by filtering the savings curve to the peak hours in the peak month and averaging the hourly savings result. The peak, in this case, was determined by the exact hour in which premise energy consumption was highest. The peak was found to be in July for the hour between 6 PM – 7 PM. The demand reduction was found to be .69 ± .46 kW.

The neural net approach was useful for investigating the impact of the combination of hardware and the software algorithms, but it is difficult to separate the magnitute of the affects. The physics-based approach explained in the following section is able to separate out the resistance heating from the heat pump operation.

3.3. Individual Water Heater Analysis

Heat pump water heaters primarily use the heat pump to heat the water in the storage tank. However, the heating power provided by the heat pump is generally limited and is smaller than the heating power of the resistance element or gas burner of similarly sized conventional storage heaters. As a result, the charging process for heat pump water heaters is generally slower. To prevent cases where end users do not have sufficient hot water to meet their needs (generally cases where water use is higher than normal, e.g., when guests are present), heat pump water heaters use a backup resistance element to augment the heating provided by the heat pump. The resistance element is activated when the temperature at a specific location in the tank, as measured by a temperature sensor, goes below a certain threshold.

The power consumption of a typical water heater in the fleet is shown in Figure 7. The operation of the resistance element is clearly identifiable. Inspection of the figure also reveals that power measured when the heater is active is not at specific levels, as one would expect given that both the heat pump and the resistance element operate at specific power levels, but rather it is continuous.

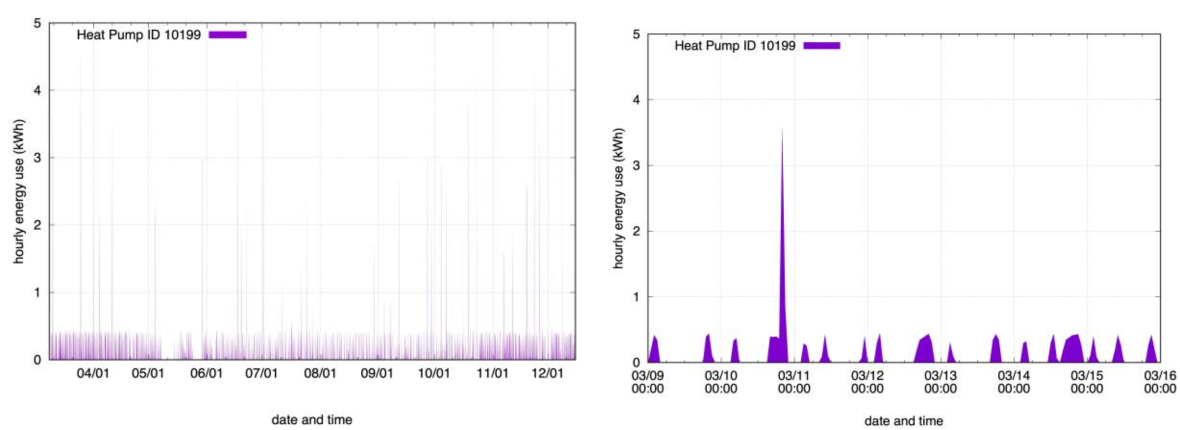


Figure 7: heater power as a function of time for the entire test period (left) and for one week (right)

The reason is that the heat pump, the resistance element, or both may be active for only part of the time during each hour-long sampling period. However, it is clear from the figure that there are two modes of operation: heat pump only, and heat pump plus resistance heater. Because the efficiency of each component in converting electric power to heat used to heat water is different, it is important to distinguish between the two.

As a first approximation, we consider all power above a threshold as resistance power, and all power levels below the threshold (including the portion of power at any given time that is below the threshold) as heat pump power.

To ensure that there is a common threshold, independent of heat pump manufacturer and model (at least to a first approximation), we sampled and binned the power level for all heaters over the entire test period. The results of the process, in the form of probability density functions (PDFs) for the power level for each individual heat pump water heater, are shown in Figure 8.

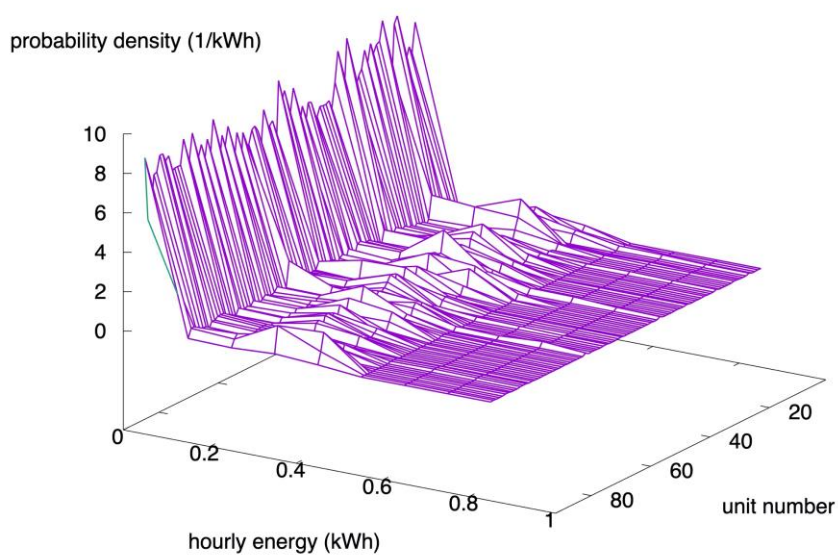


Figure 8: approximate probability density functions for power for individual heat pump

There is a primary peak at 0 power, as expected since the water heaters spend most of the time inactive, and a secondary peak at around 0.4 kW (this depends on the water heater in question, but this is a reasonable generalization). Therefore, 0.4 kW is assumed to be the threshold beyond which the operation of the resistance heater is assumed.

Given hourly data of heat pump and resistance element operation, it is possible to reconstruct the water draw for that particular hour, assuming that the water draw coincides with the heating operation (this is generally a reasonable approximation, although certain HPWHs may choose a more favorable electricity to recharge the tank, either before or after a high-price period. In any event, even if there is a temporal shift, the total water draw on a given day is accurate.

The water draw is calculated as follows:

$$m = \frac{3.6 \times 10^6}{c_p \Delta T}(\eta_{HP} e_{HP} + \eta_R e_R)$$

where m is the water draw for the hour in kg, c_p is the heat capacity of water in J/kg, ΔT is the temperature difference between the storage temperature setpoint and the water supply temperature in °C, η_{HP} and η_R are the efficiencies of the water heating for the heat pump and resistance component respectively, and e_{HP} and e_R are the electric energy supplied for the hour to the heat pump and resistance heater components, in kWh.

To calculate the energy consumption for the conventional electric water heater, we assume that the water draw would be the same independently of the type of water heater used. While it may be possible that a customer who chooses a heat pump water heater would use more DHW as a result of the lower cost to heat it, it is also as likely that the type of customer who chooses to install a high efficiency water heater will also be concerned about water use, so we assume that the two behaviors cancel each other out.

Given an hourly water use m, then the corresponding energy use e_R for the equivalent electric heater is given by:

$$e_R = \frac{1}{3.6 \times 10^6 \eta_R} m \times c_p \times \Delta T$$

Similarly, the quantity of gas e_G required over the course of an hour to heat the same quantity of water is given by:

$$e_G = \frac{0.0341296}{3.6 \times 10^6 \eta_G} m \times c_p \times \Delta T$$

where e_G is in therms.

4. Cost and Emissions Analysis

The energy cost and emissions analysis are conducted using two separate methodologies, each providing specific insights into the benefits of switching to heat pump water heating with smart energy management. The first methodology uses the statistical model, that considers aggregate water heating cost differentials. This methodology yields insight into the combined effect of hardware substitution and intelligent energy management. The second methodology assumes that water charging is managed in exactly the same way for all hardware types (HPWH, conventional electric and conventional gas), so that changes in cost result only from hardware substitution.

Cost was considered from two different perspectives: the cost to SMUD, and the cost to the customer. The cost to SMUD is estimated using the hourly CAISO price data provided by SMUD for the test period. The electricity cost to the customer is estimated using SMUD's residential Time-of-Day Rate for the year of 2020, available to the customers in the pilot[4]. The natural gas cost to the customer is estimated using PG&E's residential average monthly gas prices for the year of 2020[5].

Analysis following statistical model

The statistical approach compares the actual total electricity use at the meter (obtained directly by reading the meter) with a model of the total cost of the meter with the technology that the heat pump water heater replaces (conventional electric or gas). The quantity of interest is the cost differential between operating the original water heater and the heat pump water heater. A positive differential indicates a cost saving, and vice versa. The average hourly differential cost of energy to SMUD to operate each water heater is shown in Figure 9, for the electric replacement and for the gas replacement, respectively.

For the electric water heater replacement, there is a substantial hourly and daily variation in cost, but overall energy cost differential is negative in the early morning and increasingly positive as the day progresses to the late afternoon. This reflects both the higher efficiency of the HPWH compared to the resistance electric heater it replaces, and a charging strategy that seeks to take advantage of lower energy prices (reflected, for example, in a higher average cost of energy in the early morning). Overall, there is a net annual energy cost differential to SMUD of $265 per water heater, obtained by summing the individual hourly energy cost differential for the test period and scaling to extrapolate an annual amount. The period of January 1st to

[4] https://www.smud.org/-/media/Documents/Rate-Information/2019-Rate-Action/GM-Report-Volume-1.ashx rates 2020

[5] https://www.pge.com/tariffs/Residential.pdf

March 5th, 2020 did not have data, the results from the spring period in which there was data: March 6th to May 31st 2020 was extrapolated to complete the spring portion in the annual summation to account for the missing data. The period of December 16th to December 30th did not have hourly CAISO pricing data, the results from the winter period in which there was data: October 1st to December 17th 2020 was extrapolated to complete the winter portion of SMUD's cost in the annual summation to account for the missing data.

For the gas replacement, the average cost differential to SMUD is negative throughout the day, reflecting the fact that more electricity is used when a heat pump water heater replaces a gas water heater. We note that, on individual days, the cost differential can be positive, but this is likely a function of exogenous factors not fully accounted for in the statistical model. Overall, there is a net annual energy cost differential to SMUD of -$141 per water heater, obtained by summing the individual hourly energy cost differential for the test period and scaling to extrapolate an annual amount. The negative differential means that SMUD must pay an additional amount to provide the electricity to run the heat pump water heaters that replace gas heaters. This is offset by the additional revenue from the customer, considered below.

From the point of view of the customer, a similar methodology is used. Again, daily average cost profiles are plotted to understand daily and hourly variations, shown in Figure 10. For the electric replacement, the cost differential results solely from the difference in electricity consumption between the HPWH and the conventional electric heater it replaces, multiplied by the applicable SMUD electricity rate for the date and hour of day. As with the SMUD cost differential, HPWH costs more than the conventional electric heater in the early morning, due to charging strategy, and less for the remainder of the day, due to a combination of charging strategy and higher efficiency. Overall, the annual cost differential to the average customer is $233.

For the gas replacement, the cost differential is a result of the increase in electricity cost and corresponding decrease in gas cost associated with the switch from gas to HPWH. The annual cost differential is $76, composed of an additional electricity cost of $141, and a reduction in gas bill of $217.The overall cost differentials, broken up seasonally, are presented in Table 6. The period of January 1st to March 5th 2020 did not have data, the results from the spring period in which there was data: March 6th to May 31st 2020 was extrapolated to complete the spring portion in the annual summation to account for the missing data. The period of December 16th to December 30th did not have hourly CAISO pricing data, the results from the winter period in which there was data: October 1st to December 17th 2020 was extrapolated to complete the winter portion of SMUD's cost in the annual summation to account for the missing data.

For the analysis using results obtained from the statistical approach, the cost of energy for the study period included a data file provided by SMUD with CAISO's hourly cost of energy.

On average the heat pump water heaters that replaced the electric water heaters used less energy and had a lower cost of energy per hour for both the customer and SMUD. Since replacing a gas water heat with heat pump water heater uses more electricity SMUD observed negative cost savings of about -.25 for most hours of the day. However, the customer saves money with the gas replacement most of the day besides 1 AM and 10 AM, due to the avoided cost of gas with the heat pump water heater, which is more expensive on average than electricity from SMUD. Negative cost savings are observed for the electric replacement during some hours- meaning at those particular times the cost of energy for the original water heater was less than the replacement, this is primarily due to differences in the time and intensity that water is heated between the original and replacement water heaters. In the summer, the average electric replacement had more cost savings for both the customer and SMUD. While in the spring period SMUD had the most cost and in the winter the customer had the most cost savings with the gas replacement. The average daily profile for cost savings over the analysis period is shown in Figure 9 for SMUD and Figure 10 for the customer**Error! Reference source not found.**. The red lines represent each day's hourly cost savings while the blue line represents the average cost savings for each hour over the analysis period. This was calculated by taking the cost savings for each particular hour of the day over the entire analysis period and dividing by the total number of days. The customer savings have more variation in each day's hourly cost savings than SMUD's as seen by the variation in cost savings between the red lines. This is due to the daily time-of-use pricing rate present under the customer's residential rate.

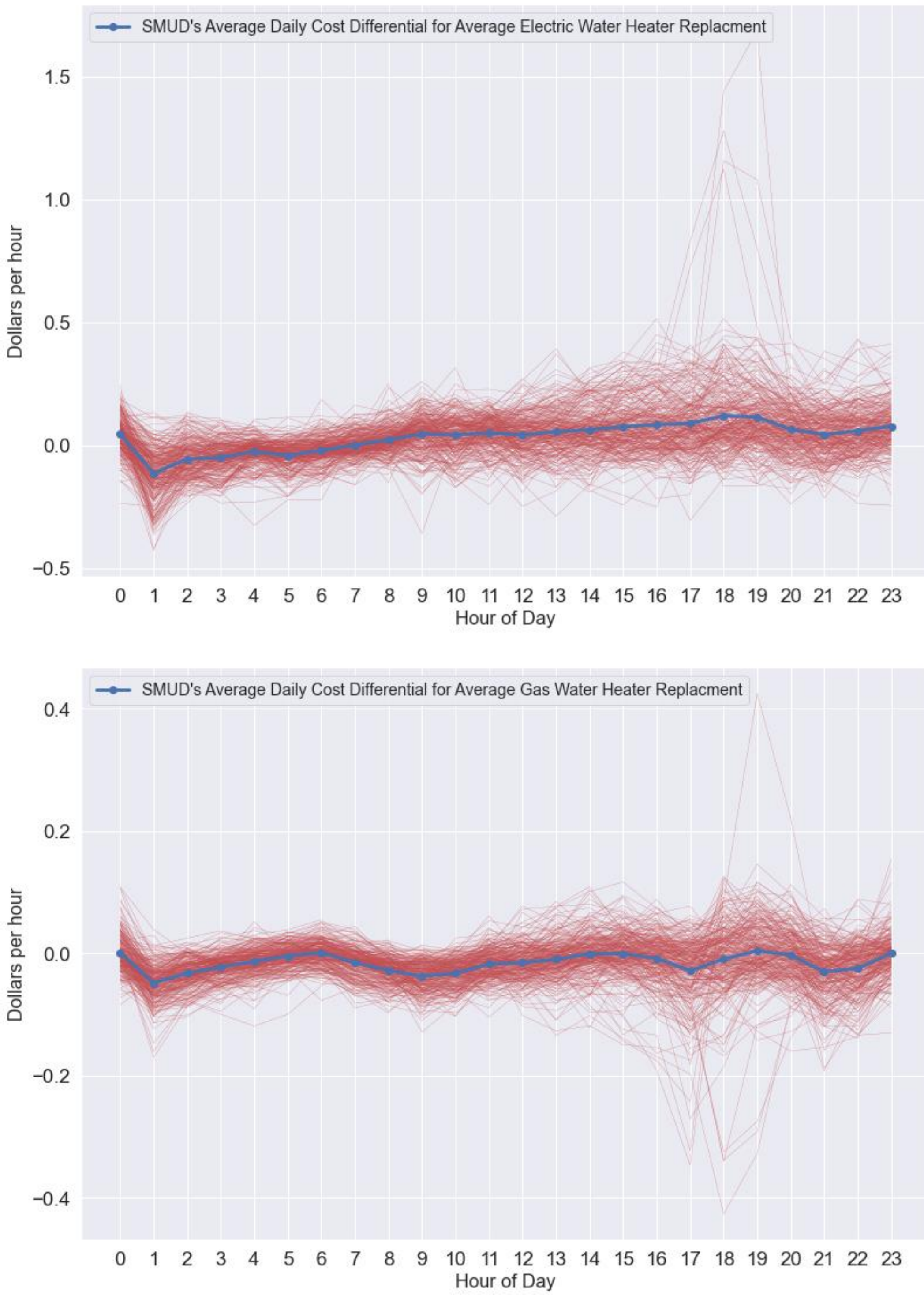
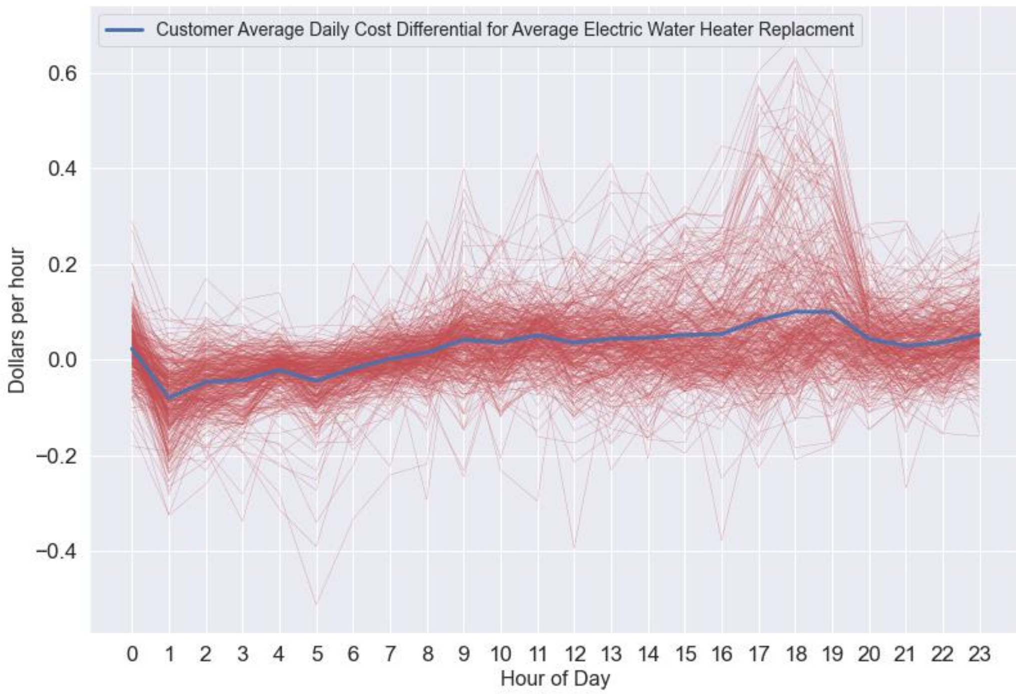


Figure 9: SMUD cost differential by hour for each day (red lines) compared to average over whole period (blue line) for the average electric water heater replacement (top) and the average gas water heater replacement (bottom)



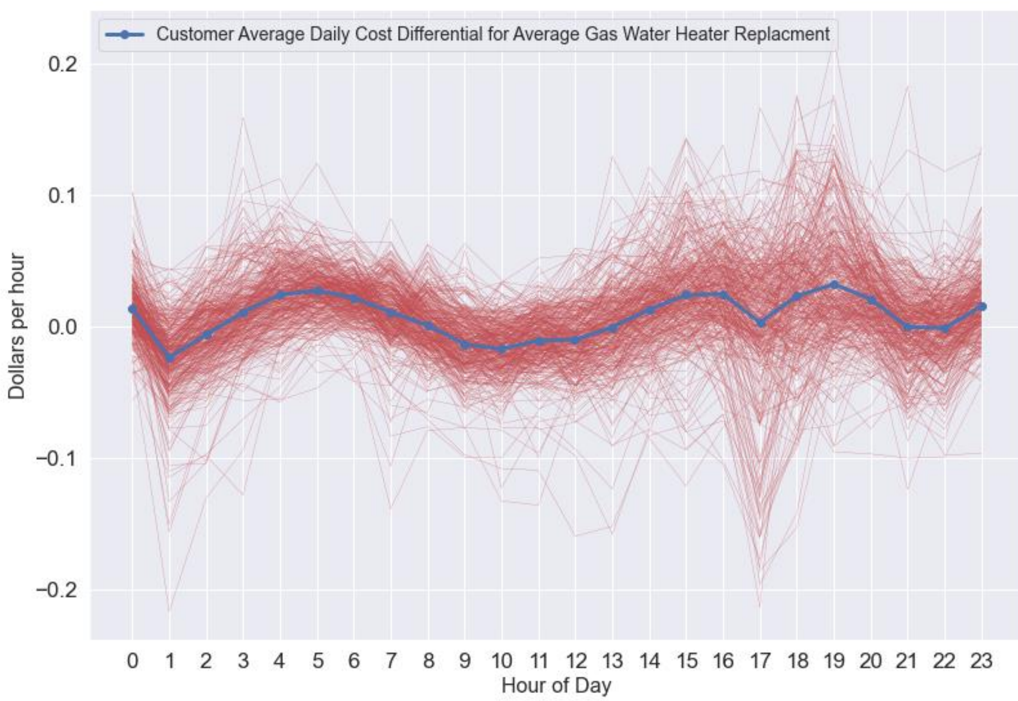


Figure 10: Customer cost differential by hour for each day (red lines) compared to average over whole period (blue line) for the average electric water heater replacement (top) and the average gas water heater replacement (bottom)

The total energy usage cost differential per device for electric replacements for SMUD each seasonal period is calculated by taking the hourly kWh that was saved from all electric replacements and dividing by the total number of replacements in the given hour, multiplied by the kWh cost of energy described in the hourly CAISO pricing data provided by SMUD, summed for each hour in the period: $\sum_{i=0}^{n} e * p$, where n is the number of hours within that in seasonal period, e is the average energy saved per device in the given hour (kWh), and p is CAISO's electricity usage price for the given hour (dollars/kWh). Energy cost differential for the average electric replacement for customer was calculated by taking the hourly kWh that was saved from all electric replacements and dividing by the total number of replacements in the given hour, multiplied by the kWh cost of energy described in SMUD's 2020 residential time-of-use rate, summed for each hour in the period: $\sum_{i=0}^{n} e * p$, where n is the number of hours within that in seasonal period, e is the average energy saved per device in the given hour (kWh), and p is SMUD's 2020 residential time-of-use rate for the given hour (dollars/kWh). The differential in energy cost for the average gas replacement for SMUD is the hourly kWh accrued from all the gas replacements, divided by the total number of replacements in that hour, multiplied by the kWh cost of energy described in the hourly CAISO pricing data provided by SMUD, summed for each hour in the period: $\sum_{i=0}^{n} e * p$, where n is the number of hours within that in seasonal period, e is the additional average energy per device in the given hour (kWh), and p is CAISO's electricity usage price for the given hour (dollars/kWh). The total savings per device for gas replacements for the customer was computed by taking the hourly avoided cost of gas as described by the therms the gas water heater would have used if not replaced multiplied by PG&E's average monthly gas per therm price for the given month in 2020. This number is summed with additional cost of electricity accrued from the heat pump water heat as described by the additional hourly kWH used for the average gas replacement multiplied by SMUD's residential time-of-use rate for the given hour: $\sum_{i=0}^{n} e * s + \sum_{i=0}^{n} t * p$, where e is the additional electricity used from the average heat pump water heater replacing a gas water heater for the given hour (negative avoided kWh), s is SMUD's 2020 residential time-of-use rate for the given hour (dollars/kWh), t are the avoided therms the average gas water heater would have used if not replaced, p is PG&E's monthly average cost of gas for the given month (dollars/therm), and n is the number of hours in the given period. The annual estimation for cost savings per device is the sum of three periods. The period of January 1st to March 5th 2020 did not have data, the results from the spring period in which there was data: March 6th to May 31st 2020 was extrapolated to complete the spring portion in the annual summation to account for the missing data. The period of December 16th to December 30th did not have hourly CAISO pricing data, the results from the winter period in which there was data: October 1st to December 17th 2020 was extrapolated to complete the winter portion of SMUD's cost in the annual summation to account for the missing data. A summary of the estimated cost savings for the average replacement is shown in Table 6.

Table 6: Summary table for average cost savings per replacement

Replacement Water Heater	Period	SMUD Average Cost Savings per Device ($)	SMUD Annual Average Cost Savings per Device ($)	Customer Average Cost Savings per Device ($)	Customer Annual Average Cost Savings per Device ($)
Electric	January to May	25 (87 days)		24 (87 days)	
Electric	June to September	163 (122 days)	255	143 (122 days)	233
Electric	October to December	43 (78 days)		48 (93 days)	
Gas	January to May	-44 (87 days)		13(87 days)	
Gas	June to September	-39(122 days)	-141	19(122 days)	76
Gas	October to December	-20(78 days)		25(93 days)	

The replacement heat pump water heaters were primarily 50-gallon Rheem generation 4 heat pump water heaters, with a few 65- and 80-gallon units. Additionally, there were a few GE heat pump water heater units. Specific details such as the model number and cost of the original and replacement units were not given. In order to account for the variation in possible models that could have been used for the replacements, all Rheem's generation 4 heat pump water heater models were considered in estimating the upfront cost for the replacements. Upfront cost for the replacement heat pump water heaters, the original gas water heaters, and the original electric water heaters were estimated by averaging the average market price for the given models. The gas and electric water heater models used in this estimation were comparable Rheem models of similar quality. The estimated upfront cost for the replacement heat pump water heater was $1,425. The gas and electric water heaters that were used to estimate the upfront cost for the original water heaters were $733 and $616 respectively. The specific models used in the estimation of upfront cost are found in Table *7*. SMUD also offers a one-time incentive of $150 as well as $2 off the monthly energy bill for customers who purchase an internet-connected heat pump water heater. Considering this $150 rebate, 12$ annual reduction energy cost, and using the estimations for upfront cost and cost savings- the heat pump water heater has an estimated simple payback of about 14 years if it replaced a gas water heater and 5 years if it replaced an electric water heater assuming the 12$ monthly credit applies each year of payback for both replacement. This was calculated by subtracting the $150 rebate from the averages upfront cost then dividing the estimated upfront cost by the estimated annual cost savings for each replacement type plus the $12 annual bill credit.

Table 7: Rheem Water Heaters Average Market Cost

50 Gallon Rheem Models	Average Cost for Model
Professional Prestige ProTerra Heat Pump Water Heater	$1,600
Performance Platinum ProTerra Heat Pump Water Heater	$1,400
Performance Platinum Series Heat Pump Water Heater	$1,300
Professional Prestige Series Heat Pump Water Heater	$1,400
Performance Platinum Gas Water Heater	$800
Performance Plus Gas Water Heater	$700
Performance Gas Water Heater	$650
Marathon Electric Water Heater	$850
Performance Plus Electric Water Heater	$550
Performance Electric Water Heater	$450

To calculate an average emissions intensity for SMUD, ADM used data from a recent California Energy Commission (CEC) staff report titled: "Review of Sacramento Municipal Utility District's 2018 Integrated Resource Plan", which contained SMUD's overall generation mix.[6] SMUD's generation mix is relatively clean, meaning their mix of resources used for generation contains a large proportion of renewable or low-carbon resources. The resources that contribute to CO_2 emissions in SMUD's generation mix are natural gas, spot purchases, large hydroelectric, and geothermal. It should be noted that the CO_2 emitted from geothermal plants are not from power production but rather a natural, minor biproduct of all geothermal reservoirs. This CO_2 would eventually vent into the atmosphere without power plant development, but dry steam and flash steam power plant production significantly accelerates this process to the point that it is not negligible. Similarly, hydropower dams will release greenhouse gases due to the decomposition of flooded organic material, rather than from actual power production. Details

[6] California Energy Commission. "Review of Sacramento Municipal Utility District's 2018 Integrated Resource Plan." Energy.ca.Gov, 2018, www.energy.ca.gov/filebrowser/download/1903.

on SMUD's generation mix can be found in Table *8*:. The emission intensity for natural gas was calculated by taking the mean emission intensity from all the natural gas plants that serve SMUD. Details of SMUD's natural gas plants' emission intensities can be found in Table 9:, which is taken from the aforementioned CEC staff report. After taking the mean and converting from metric ton of CO_2 per Megawatt-hour (MWh) to kg of CO_2 per kWh, the emission intensity for natural gas electricity production was 0.5078 kg of CO_2 per kWh. It is assumed that SMUD purchases spot imports from CAISO (California's largest wholesale energy market). The spot purchase emission rate is therefore CAISO's average emission rate which comes out to .2907 kg of CO_2 per kWh. The emission rate for hydroelectric used in this analysis was 0.0185 kg of CO_2 per kWh, using data from a detailed report done by the International Hydropower Association (IHA), which covered 500 empirical emission measurements from more than 200 reservoirs worldwide[7]. The project team was unable to determine whether SMUD's geothermal generation is from dry steam and flash steam power plants or from closed loop binary-cycle plants. The later captures emissions and stores it underground producing little to no emissions. To reflect the possibility of multiple types of geothermal plants in SMUD's mix an average was taken from the emission rate of dry steam and flash steam power plants (60 lbs CO_2/MWh) and binary plants (0 lbs CO_2/MWh). This gives an average of 30 lbs of CO_2 per MWh (0.0136 kg CO_2/ kWh). The emission intensity data for geothermal power plants was collected from the U.S. Department of Energy[8]. Each resource's emission rate was then multiplied by the given resources' percentage of SMUD's total generation mix to get its contribution to SMUD's average emission intensity. This process is seen in Table *10*:.

Table 8: SMUD Generation Mix Data from CEC Staff Report

Resource	**2019**	**2025**	**2030**
Total Net Energy for Load	11,404	11,637	12,286
Non-RPS Resources			
Solar PV	362	608	798
Large Hydroelectric	2,282	2,271	2,274
Natural Gas	3,940	4,032	3,058
Nuclear	0	0	0
Storage	0	0	347
Spot Purchases	3,133	2,534	2,306
Spot Sales	(1,509)	(1,852)	(1,851)

[7] International Hydropower Association. "Hydropower Status Report." Hyrdopower.Org, 2018, hydropower-assets.s3.eu-west-2.amazonaws.com/publications-docs/iha_2018_hydropower_status_report_4.pdf.
[8] U.S. Department of Energy. "Geothermal Power Plants — Meeting Clean Air Standards." Energy.Gov, 2003, www.energy.gov/eere/geothermal/geothermal-power-plants-meeting-clean-air-standards#:%7E:text=4.1%20million%20tons%20of%20carbon,80%2C000%20tons%20of%20nitrogen%20oxides.

RPS Resources			
Biofuels	1,146	1,225	1,205
Geothermal	274	362	351

Resource	**2019**	**2025**	**2030**
Small Hydroelectric	88	88	90
Solar PV	53	546	816
Wind	1,636	1,822	2,899
Total Energy Procured	11,405	11,636	12,293
Undelivered RPS Energy	0.63	0.81	9.10
Surplus/(Shortfall)	0	0	0

Table 9: SMUD Natural Gas Plant Emission Data from CEC Staff Report

Source	**Fuel Type**	**GHG Intensity (MT CO2e /MWh)**	**2019 Total Emissions (MMT CO2e)**	**2025 Total Emissions (MMT CO2e)**	**2030 Total Emissions (MMT CO2e)**
Campbells CC	natural gas	0.46	0.128	0.262	0.039
Carson CC	natural gas	0.601	0.001	0	0
Cosumnes CC NG	natural gas	0.378	1.284	1.105	0.927
Proctor Gamble	natural gas	0.474	0.201	0.247	0.181
McClellan	natural gas	0.706	0.002	0.001	0
Net Spot Market	system	0.428	0.695	0.292	0.195
Total Portfolio emissions	NA	NA	2.311	1.906	1.342

Source: California Energy Commission staff, based on SMUD IRP filing.

Table 10: SMUD Generation Mix Emission Rates

Resource	Generation Mix Contribution (MW)	Percentage of Total Contribution	Emission Rate kg of CO_2 per kWh	SMUD Average Emission Contribution CO_2 per kWh
Biomass & Biowaste	1,146	10%	0	0
Geothermal	274	2%	0.01360	0.00033
Renewable Hydro	88	1%	0	0
Solar	415	4%	0	0
Wind	1,636	14%	0	0
Coal	0	0%	0	0
Large Hydro	2,282	20%	0.01850	0.00370
Natural Gas	3,940	35%	0.50780	0.17543
Nuclear	0	0%	0	0
Spot sales	1,624	14%	0.29070	0.04139
Total	11,405	100%	N/A	0.22085

The kilograms of CO_2 avoided per hour for the electric replacement is calculated by taking the hourly kWh that was saved from switching to the heat pump water heater and dividing by the total number of replacements in the given hour, then multiplying by SMUD's average emission intensity given by the "total" row in Table 9. For the gas replacement, an emission intensity of 6.1 Kg of CO_2 per therm was obtained from PG&E[9]. This emission intensity was multiplied by the estimated avoided hourly therms usage that a gas water heater would have used if not replaced by the heat pump water heater- this represents the avoided CO_2 emissions from not having a gas water heater. Next the additional hourly CO_2 emissions associated with the customer's increase in electricity usage due to switching from gas to heat pump water heater was summed with the avoided CO_2 from gas to give the net avoided CO_2 from replacing the gas water heater. Note the additional CO_2 from the gas replacement heat pump water heater was calculated using the same method as the electric replacement and also used SMUD's average emission intensity. The average electric replacement avoided more CO_2 in the summer period, while the average gas replacement avoided more CO_2 in the other two periods. Some negative avoided CO_2 values are observed for the heat pump water heaters- meaning that at those time the original water heater emitted less CO_2 than the replacement, this is primarily due to differences in the time and intensity that water is heated between the original and replacement water heaters. On average however, the average heat pump water heater used less energy and emitted less CO_2 than the water heaters they replaced. The daily profile for avoided CO_2 emissions for both gas and electric replacements using SMUD's average emission intensity and

[9] https://www.pge.com/includes/docs/pdfs/about/environment/calculator/assumptions.pdf

PG is shown in Figure 11. The red lines show each day's hourly CO_2 emissions profile, while the blue line shows the average daily profile from the entire period. This was calculated by taking the CO_2 emissions for each hour of the day over the entire analysis period and dividing by the total number of days. It can be seen that the electric replacement emits more CO_2 on average during the morning hours of the day before consistently avoiding an estimated 0.75 kg of CO_2 after 8 AM. The gas replacement avoids less CO_2 at 1 AM and at noon and avoids more CO_2 the remainder of the day.

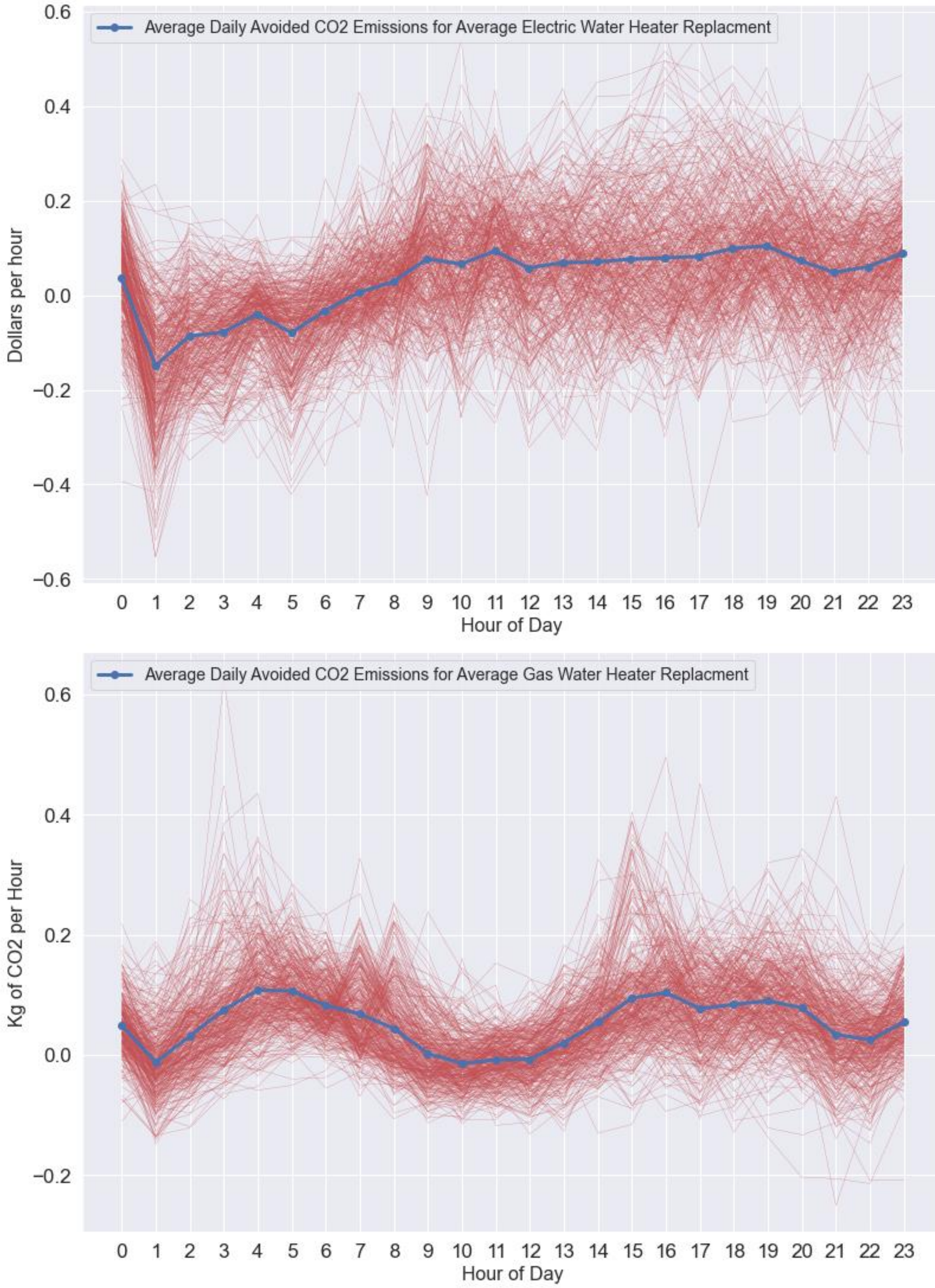


Figure 11: Avoided kilograms of CO_2 *by hour for each day (red lines) compared to average over whole period (blue line) for the average electric water heater replacement (top) and the average gas water heater replacement (bottom)*

The total estimated CO_2 avoided for the average electric replacement for each period is calculated from the following summation: $\sum_{i=0}^{n} e * s$, where e is the saved electricity from the average heat pump water heater replacing the electric heater for the given hour (avoided kWh), s is SMUD's static average emission intensity (kg of CO_2 per kWh), and n is the number of hours in the given period. The total estimated CO_2 avoided for the average gas replacement for each period is calculated from the following summation: $\sum_{i=0}^{n} e * s + \sum_{i=0}^{n} t * p$, where e is the additional electricity used from the average heat pump water heater replacing a gas water heater for the given hour (negative avoided kWh), s is SMUD's static average emission intensity (kg of CO_2 per kWh), t are the avoided therms the average gas water heater would have used if not replaced, p is PG&E's emission intensity (Kg of CO_2 per therm), and n is the number of hours in the given period. The annual estimation for avoided CO_2 is the sum of three periods. The period of January 1st to March 5th 2020 did not have data, the results from the spring period in which there was data: March 6th to May 31st 2020 was extrapolated to complete the spring portion in the annual summation to account for the missing data. A summary of the estimated avoided CO_2 emissions for the average replacement is shown in Table *11*.

Table 11: Summary table for average avoided kilograms of CO_2 per replacement

Replacement Water Heater	Period	Average Avoided CO_2 Emissions per device (kg of CO_2)	Average Avoided Annual CO_2 Emissions per device (kg of CO_2)
Electric	January to May	44 (87 days)	308
Electric	June to September	160 (122 days)	
Electric	October to December	71 (93 days)	
Gas	January to May	106 (87 days)	537
Gas	June to September	121 (122 days)	
Gas	October to December	139 (93 days)	

Cost and Emissions Analysis Following Individual Unit

To calculate the CO_2 emissions from the use of electricity, the emissions intensity for the SMUD system was used, as described by:

$$g_e = 0.22085 \times e_S$$

where g_e is the CO_2 emitted for the hour by using the quantity of electricity e_S associated with an electric-driven heater, either heat pump or resistance. Similarly, for the gas heater, the hourly CO_2 emission associated with gas consumption e_G is:

$$g_g = 6.091 \times e_G$$

where e_G is in therms.

The cost of energy is calculated using:

$$c_e = p_e \times e_S$$

for electric heating, where p_e is the unit cost of electricity in $/kWh, and by:

$$c_g = p_g \times e_g$$

where p_g is the unit cost of gas in $/therm.

To estimate the impact of switching DHW service from either gas or conventional electric to heat pump, the following procedure was used:

- For each HPWH unit enrolled in the pilot, and for each hour where data are available, we calculate:
    - Water draw
    - Energy use for equivalent resistance heater
    - Energy use for equivalent gas heater

- CO2 emissions for HPWH, conventional electric heater and gas heater
- Cost for HPWH, conventional electric heater and gas heater

- For each unit, we estimate the annual water draw, energy use, annual emissions, and annual cost, for the original HPWH and for the equivalent conventional electric and gas heaters. The annual quantities are normalized by the time that each individual water heater is enrolled in the pilot, which varies considerably between different premises.

The total energy consumption, as a function of annual water draw, is shown in Figure 12.

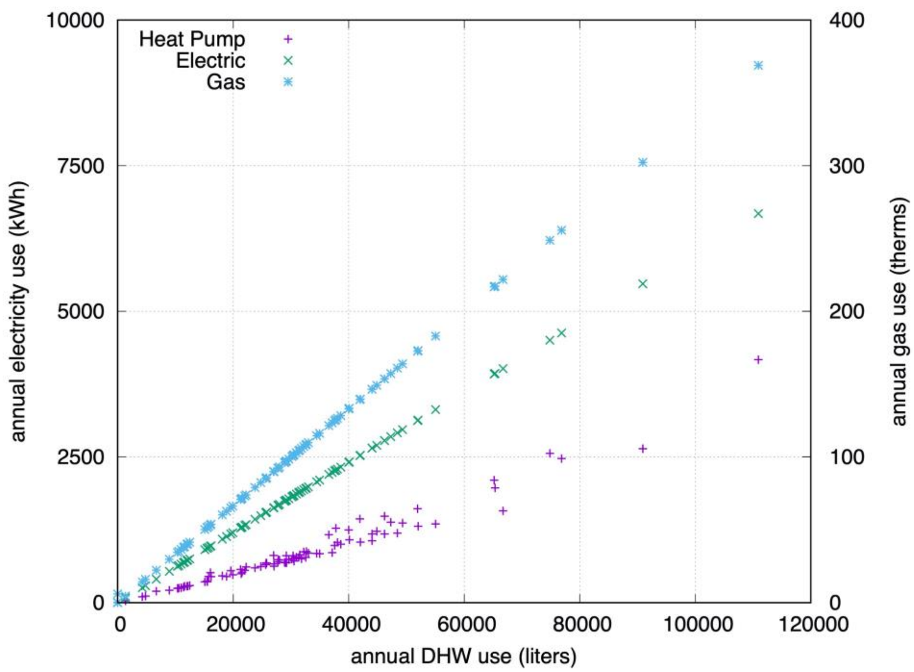


Figure 12: annual energy use as a function of annual water draw. Note that each data point corresponds to an individual heater.

First, it should be noted that the normalized water draw per household varies considerably, from almost zero (perhaps in the case of second homes) to more than 100,000 liters per year (potentially households with large families). It is clear that the electricity consumption of the conventional electric heater is substantially higher than that of a HPWH. While the electricity consumption for the conventional water heater is directly proportional to water draw, the electricity consumption of the HPWH also depends on how water is drawn. When water is drawn in short, large bursts, the resistance element is activated, so that the energy consumption is higher than when the same amount of water is drawn more slowly over a more protracted time. It is more difficult to compare the energy consumption of the heat pump water heater with the energy consumption of the gas water heater because the primary source of energy is different. However, to a first approximation the energy consumed by a gas water heater is also linear in water draw, independently of the way that water is drawn.

The comparison in emissions for the three types of water heater is shown in Figure 13.

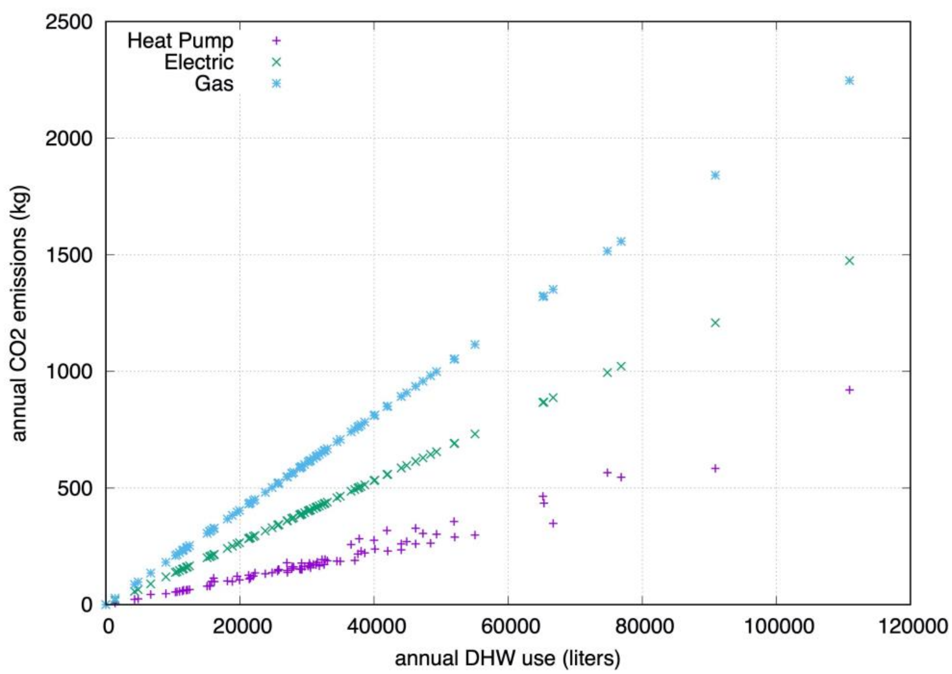


Figure 13: annual CO2 emissions as a function of annual water draw for each type of water heater. Each point corresponds to a unit ID.

The plot shows that the HPWH is by far the lowest emitter. Again, HPWH-associated emissions per unit water draw are a function of how water is drawn, increasing when the resistance element is activated frequently. Gas water heaters are the greatest GHG emitters, also as a function of their relatively low efficiency. The electric heater, while resulting in fewer CO_2 emissions than gas water heaters, in part due to the relatively low-carbon energy mix provided by SMUD, still result in greater emissions than HPWH.

Finally, we consider the impact on operational cost of the HPWH in comparison to conventional electric and gas counterparts, for SMUD and for the customer respectively. The cost to SMUD, evaluated using the CAISO wholesale prices, is shown in Figure 14.

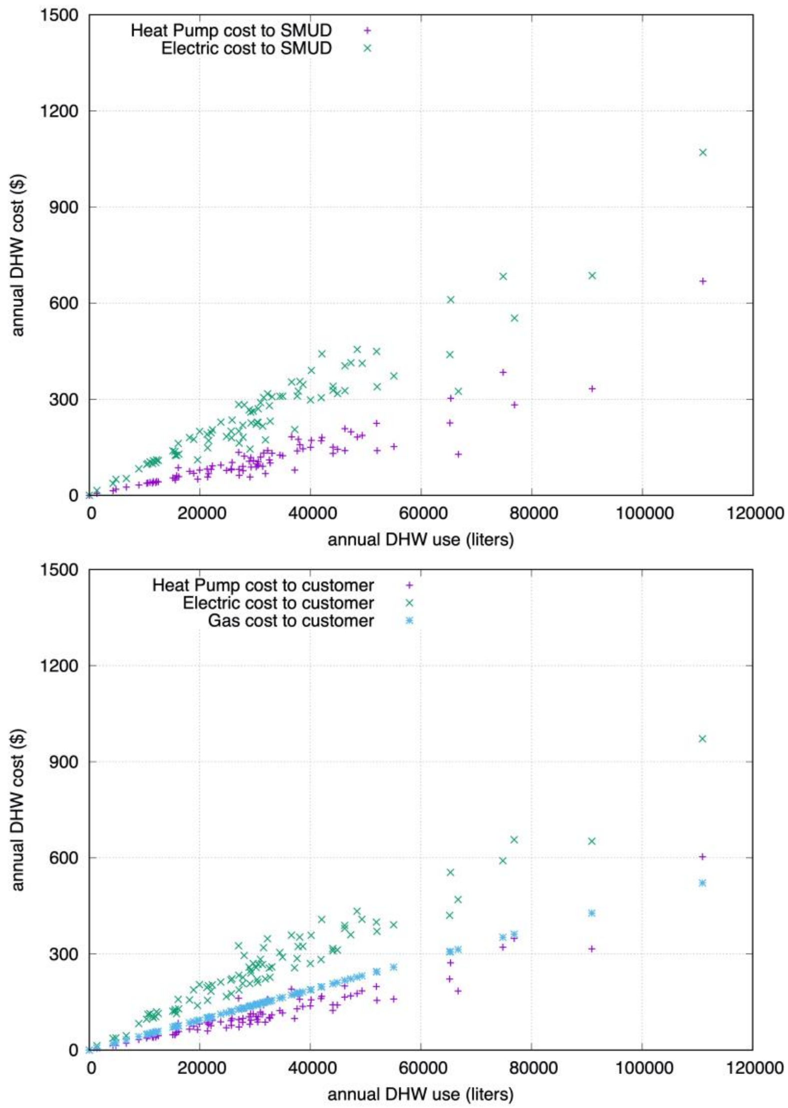


Figure 14: annual cost of energy as a function of annual water draw for conventional electric and HPWH to SMUD (top panel), and annual cost of energy as a function of annual water draw for conventional electric, HPWH and conventional gas water heater to the customer (bottom panel). Note that each point corresponds to a unit ID.

We note that the energy cost is generally lowest for the HPWH, as expected. However, this cost is not substantially lower that the energy cost to run a gas heater, because gas is much cheaper than electricity as a raw source of energy. However, while the cost of energy for gas is linear as a function of water draw, using electricity to heat water offers opportunities for saving resulting from leveraging the variability of the cost of electricity, in combination with the capacity of water heaters to store energy. The HPWHs used in this study offer built-in strategies to take advantage of lower prices, and this is shown clearly by the fact that cost of energy for larger water users is sub-linear, meaning that the strategy was successful in taking advantage of lower electricity prices. While a similar effect is shown for the conventional electric water heater, this is merely an artifact since water draws for the equivalent resistance heaters are the same as for the HPWHs. In reality, water draws for conventional electric heaters would not be managed by rate-conscious strategies, as these are only implemented in modern high-end HPWHs, and would therefore costs would be higher. This is reflected in the finding that overall savings found using the neural network approach, which inherently include both technology and optimization.

The overall results, averaged over the entire fleet, are shown in Table 12. One salient result is that, on average, the annual operational (energy) cost of a HPWH is only about $30 lower than the operational cost of a conventional natural gas heater, the primary target for electrification via HPWHs. This cost reduction serves to offset the additional upfront costs for purchase and installation of a HPWH (average of $692 more expensive than a comparable gas heater, somewhat mitigated by the rebate of $150). However, it is likely that the decision to participate in a pilot HPWH pilot will be driven more by environmental considerations, primary among which is the fourfold reduction in CO2 emissions, compared to a gas heater, rather than economic considerations. We also note that GHG emissions from HPWHs are solely a product of their energy use, as refrigerant leaks are made extremely rare by the fact that the entire HP system is hermetically sealed at the factory, and that a leak could only result from physical damage to the appliance, such as a puncture.

Table 12: Average annual performance metrics for HPWHs, conventional electric heaters, and gas heaters. Note that the savings advantage due to operation optimization for the electric and HPWH is not reflected in this calculation, because both types of heaters are assumed to use the same charging strategy.

	Usage (hours)	Water Draw (liters)	Energy Use			CO_2 Emissions (kg)			Cost to SMUD		Cost to Customer		
			HPWH (kWh)	Elec (kWh)	Gas (therms)	HPWH	Elec	Gas	HPWH	Elec	HPWH	Elec	Gas
avg	7,026	31,255	855	1,882	104	189	416	633	116	256	116	256	147
max	17,523	110,926	4,169	6,678	369	921	1,475	2,247	668	1,070	604	972	522

We also note that the cost savings for the electric heater replacement obtained using the individual unit analysis are $140, compared to the $232 obtained using the statistical analysis. The difference may be attributed to the fact that the statistical analysis compares optimized

HPWH with un-optimized conventional electric heater, while the individual unit analysis compares optimized HPWH with optimized equivalent electric resistance heater. The difference between the two ($92 annually) can be attributed to the optimization, a ratio of 0.4 approximately. In other words, optimization contributes approximately 40% of the energy cost savings observed with the heat pump water heater.

5. Conclusion

Heat pump water heaters are a well-established efficiency upgrade to resistance water heaters and an electrification option for gas water heaters. Partnering with PowerMinder software algorithms offers benefits to the participants and to SMUD and demonstrates deployment of connected devices capable of load shifting.

Based on the analysis of the impact of HPWH events, both software operating modes (event and non-event days) reduce cost for the customer. The results showed that loads generally shifted by a few minutes to 20 minutes earlier when compared to non-event days. Customers saved an average of $164 per year after rebates if replacing an electric resistance heater, and $55 per year after rebates if replacing a gas heater. Gas replacements displaced usage of 104 therms per year to electrification, resulting in 444 kg of CO_2 annual emissions reduction. Customers replacing electric systems consume 1,027 kWh less per year, reducing emissions by 227 kg CO_2.

The PowerMinder Pilot evaluation benefited from a near-real-time data stream for monitoring pilot activity. The data stream, provided through a pilot API, allowed ADM to access up-to-date information from pilot water heaters, including consumption rates and energy use. Real-time data adds value to an evaluation by allowing pilot activity to be continually monitored, rather than evaluated once at the end of the pilot year. The advantages are twofold: first, real-time monitoring allows problems to be captured and addressed more quickly, increasing pilot efficacy; second, real-time evaluation, if paired with a pilot dashboard to communicate results, can increase participant buy-in and satisfaction by allowing pilot participants to see a near-live feed of the impacts of their participation in the pilot. For small, pilot pilots this can be especially valuable, as participants are more likely to have participated for environmental reasons and be engaged with the pilot.

Some aspects of the data and approach could be improved in a future study. The sample size of 94 is rather small for residential analyses, especially when whole-house metering data is used in the analysis. With small samples, irregular water and energy consumption can have a greater influence the analysis. Most of the pilot data for this study was collected during the COVID-19 pandemic, during which more people were at home and consumption may not represent typical conditions. Regarding the evaluation of the software, we recommend the software be set to a baseline mode (no optimization) for several days per week along with the other two modes (event and non-event days) to enable more accurate impact analysis.