Estimating residential hot water consumption from smart electricity meter data

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Keywords: residential electricity consumption, water heating, smart meters, domestic hot water

Supplementary material for this article is available online

Abstract
Residential water heating is among the most energy-intensive aspects of the water sector; however, residential hot water use is often poorly quantified. Estimating hot water consumption from smart electricity meter data can help advance the body of knowledge regarding the residential energy-water nexus by employing data to fill this knowledge gap, potentially promoting community resilience through energy and water resources efficiency. Using a non-intrusive load monitoring algorithm calibrated with fine-resolution data, we disaggregated electricity for water heating from half-hourly smart electricity meter data, demonstrated with data organized at the zip code level for areas in the city of Chicago. From these electricity for water heating signals, we estimated residential hot water consumption with quantified uncertainty. Results indicate that water heating accounted for 7%–20% of total electricity consumption in the analyzed single-family residential homes, representing an average of 1–8 kWh d−1 of electricity consumption and 7–55 gallons (26–208 l) of hot water per day. These results also demonstrated significant spatial variability, such that some areas of Chicago show higher per household hot water use. With the challenges of deploying advanced water metering infrastructure, using isolated water heating signals from smart electricity meters to develop a first-order estimate of domestic hot water use represents a valuable quantification of an energy-intense flow.

1. Introduction

Water heating represents nearly 14% of total residential energy consumption in the United States [1]. According to the US Energy Information Administration (EIA) Residential Energy Consumption Survey, water heating is the second most energy-intensive activity in the residential sector, following space conditioning (i.e., heating and air conditioning) [2]. Residential water heaters generate a considerable amount of greenhouse gas (GHG) emissions, either directly through fuel combustion or indirectly through electricity consumption [3]. Most US household water heating units use natural gas (51.7%), electricity (41.3%), and oil-derived fuel sources (6.7%), with the remainder using solar or other energy sources [2]. To effectively recommend a domestic water heating technology that could reduce energy consumption and GHG emissions, a thorough analysis of the available water heating technology, residential water heater energy consumption, and domestic hot water (DHW) use is crucial. To that end, we estimate DHW consumption from residential electricity consumption for water heating, disaggregated from smart electricity meter data of single-family households with a non-intrusive load monitoring (NILM) technique. We demonstrate this approach in the city of Chicago through the following key research questions:

(a) How can electricity for water heating be disaggregated from half-hourly total electricity consumption?
(b) How can DHW volumes be estimated from electricity for water heating?
(c) What temporal and spatial DHW use variations can be detected from the estimated values?
We anticipated that electricity consumption for water heating would vary spatially, as different households have different physical characteristics, occupancy levels, and appliance stock. Smart electricity meter data can provide some insight on households’ high-consumption appliances or activities, such as space heating, air conditioning, and electric water heaters, which are attractive targets for load shifting programs [4, 5].

2. Background

2.1. Interdependence of energy and water resources

The energy-water nexus—the interdependence of energy and water resources—is especially pronounced in the residential environment [6]. Understanding the complex connections between water and energy in residential buildings is necessary to solve water and energy issues simultaneously and avoid moving problems from one resource dimension to another. Effective solutions that address the main drivers of consumption for both resources could avoid situations where a water supply-related issue creates an energy-use burden [7]. As the United Nations projects that a majority of the world’s population will reside in cities by 2050 [8], the large ecological and economic footprint of cities will likely continue to increase. As of 2012, cities were estimated to be responsible for approximately 75% of total greenhouse gas emissions [9, 10]. Increased urban population, coupled with climate change, droughts, floods, and pollution, are putting additional stress on already-limited water and energy resources [11]. Water and energy co-involvement in nexus studies can help identify interdependencies as well as enable optimization of infrastructure for water and energy simultaneously to potentially create savings on peak loads for both resources [7]. Many studies on the influence of residential water use on energy consumption found that water heating and cooling use significantly more energy than drinking water supply and wastewater services [12–14], motivating analysis of DHW use and its energy implications.

2.2. Residential water heating

Residential water heating is among the most energy intensive aspects of the residential sector, following space heating and air conditioning [15]. Hot water serves multiple purposes, including human health and hygiene through showers or baths, disinfection and sterilization of medical equipment at hospitals, and dish and clothes washing in homes, among other uses. In 2010, energy consumed for water heating represented between 13% and 17% of residential energy consumption in the United States [16]. In Australia, water heating accounted for 23% of total residential energy consumption in 2008 [17]. Residential water heating required nearly 25% of the total energy consumed for water and steam supplied to the residential, commercial, industrial, and power sectors in 2010 [3]. Water heating is also a significant source of GHG emissions; therefore, reducing the energy consumed for water heating presents an opportunity for synergistic energy conservation and GHG emissions reductions in the residential sector [1]. Sanders and Webber [1] quantified regional water heating trends in the United States and analyzed the tradeoffs in primary energy consumption and GHG emissions from shifts in regional water heating technologies, finding that states with large fractions of coal-fired power generation have the largest potential for emissions reductions from a shift from electric to natural gas water heating.

To meet residential buildings’ energy demand and improve supply efficiency, it is important to analyze and understand the temporal flexibility of activities giving rise to energy demand [18]. Despite the energy implications of residential water heating, DHW use is often poorly quantified. Proper DHW energy quantification studies could support identification of household hot water demand, along with development of related policy measures [17]. Multiple studies [19–26] have monitored appliance-level hot water uses and developed models to estimate energy for water heating. Unfortunately, these studies are either limited in scope and number of participating households [19–22], or cannot easily be scaled [23–26]. Some studies have used low-resolution electricity data because they lacked access to submetering technologies [27–32]. For example, conditional demand analysis has been used to estimate residential energy end uses; however, this approach requires data on housing characteristics, appliance presence/absence, and demographics [33, 34], which can compromise privacy. Fine temporal resolution smart meter data can support residential electricity end use estimation in the absence of these exogenous data.

2.3. Factors affecting residential energy and hot water consumption

Residential buildings account for approximately 39% of the total electricity use in the United States [35]. A thorough understanding of the determining factors that drive residential energy use is needed to effectively plan and execute energy efficiency programs that can reduce residential energy consumption and mitigate its impact on the environment [36, 37]. Social factors such as demographics, income levels, and household expenditure can influence energy and water resource consumption patterns [38]. According to Kavousian et al [37], weather, location, and physical characteristics of dwellings such as floor space, construction date, and construction materials are among the most important determinants of residential electricity consumption. Household size is often correlated with affluence, socioeconomic status, number of occupants, and appliance...
stock. Satre-Meloy et al [39] conducted a statistical analysis of household activities in 173 households in the United Kingdom, demonstrating that the number of occupants and high-consumption appliances such as space heaters, air conditioning, and water heaters were the most significant determinants of daily maximum electricity consumption, while daily minimum consumption was influenced most by weather, location, and physical characteristics of the building. Many studies on the effect of zip code and cooling load on electricity consumption have reported that cooling degree day (CDD) is the dominant factor in the summer, explaining a considerable portion of the variability in total electricity consumption [37, 40–42]. Locality and household size show considerable correlation with residential electricity consumption, most likely because they are correlated with several other variables that influence energy consumption, such as climate, building type, building materials, and socioeconomic status of the household [37].

A single focus on the promotion of more energy efficient technology might not be sufficient to slow the growth in total energy consumption and GHG emissions. Moezzi and Lutzenhiser [43] found that ‘higher efficiency does not necessarily translate to lower consumption or emissions, and houses (and ‘lifestyles’) with less efficient goods may use less energy than those with more efficient goods’. Multiple studies have demonstrated how lifestyle is relevant to energy consumption [4, 44–47]. Similarly structured households with the same physical characteristics could have widely varying energy and water usage, emphasizing behavioral differences among household occupants. For instance, in most houses, bathing uses the largest volume of hot water, followed by kitchen-related activities such as dishwashing, cleaning, and cooking [48]. DHW use in a household will reflect the differences in bathing and showering habits. Understanding the patterns of energy and water consumption associated with lifestyle factors can be beneficial to developing more effective and better tailored policies [47]. Age of occupants is another important factor that has a significant correlation with energy consumption. Kempton [48] showed that older household members tended to be more conscious about their electricity consumption and use less electric gadgets, while 19–35 year-old occupants’ consumption reflected their lifestyles, which often coincided with less time spent at home because of employment status. Besides lifestyle factors and climatic influences, residential electricity consumption is also affected by social, economic, and demographic conditions [49].

2.4. Data-driven approaches for resource consumption estimation

There are a variety of approaches used by researchers to estimate household electricity consumption at appliance end uses: NILM, sub-metering, load disaggregation, and modeling. The analysis of appliance end-use electricity consumption could enable a better understanding of energy consumption and translate into meaningful energy feedback to households [18, 50], as demonstrated by different commercial analysis tools [51]. NILM discerns individual loads from a single metering point by disaggregating to appliance end uses without appliance-level monitoring [52–54]. NILM techniques can effectively infer load profiles from smart meter data, but performance is highly dependent on data resolution [18]. Coarse-resolution smart electricity meters, on the order of minutes to hours, add complexity to the design of efficient NILM algorithms.

Electricity disaggregation was first proposed by Hart in 1970 [55], and subsequent research has created new data-driven approaches to estimate energy consumption. Liao et al [50], aiming to address the challenges of scalability and intrusiveness, proposed two algorithms for power load disaggregation at coarse-sampling rates (greater than 1 s): supervised approaches based on decision trees and unsupervised methods based on dynamic time warping. These algorithms define an activity recognition approach for cooking, showering, and home entertainment, using NILM applied to smart meter active power readings and qualitative data such as appliance surveys. Wilson et al [56] combined qualitative data from household interviews and video ethnography with NILM and appliance-level power sensors to infer reliable time profiles for a range of domestic activities for two homes. Kolter et al [57] used discriminative sparse coding to disaggregate hourly electricity data for unseen houses using appliance-level power consumption models built from weekly training datasets. Others have disaggregated heating and/or cooling energy consumption from multiple houses using piece-wise functions of power consumption versus outdoor air temperature [58–61]. Perez et al [62] developed a NILM algorithm using edge detection and k-means clustering to disaggregate air conditioning energy usage from 1 min, 5 min, and 15 min whole-house power consumption data.

Research has also focused on machine learning and NILM methods specifically applied to residential water heating. For example, Green and Garamella [63] used a graph signal processing NILM approach to discern hybrid heat pump water heaters from electricity loads at 1 min resolution, downsampled to 15 min resolution. Similarly, Rehman et al [64] used ensemble learning with NILM to disaggregate household water heating signals from 1 min resolution electricity data. However, limited studies have examined data with coarser temporal resolution, reflecting grid scale observations. We leverage these NILM advancements to estimate residential electricity for water heating and DHW consumption from 30 min resolution smart electricity meter data using a NILM algorithm inspired by Perez et al’s [62] decomposition method based on a decision tree.
3. Methods

3.1. Data
To demonstrate this disaggregation approach, we use meter-level electricity consumption data from Commonwealth Edison (ComEd) providing electricity service to Chicago and northern Illinois. We obtained ComEd smart electricity meter data from the Environmental Defense Fund through an agreement to share and analyze energy usage data for environmental and consumer benefit. ComEd is the largest electric utility company in Illinois and provides electricity to more than 4 million customers across northern Illinois [65]. The data include anonymized 30 min interval electricity usage for 2016, organized on a meter level for 366 zip codes across 24 counties in the ComEd service territory. The data are assembled by their delivery service classes: single-family residential households, multi-family residential households, single-family residential households with electric space heat, multi-family residential households with electric space heat, commercial buildings, small buildings, mid-size buildings, and large buildings.

In addition to the half-hourly electricity consumption data, whole-house and appliance level electricity consumption data for six single-family homes were obtained from the Pecan Street Inc. Dataport, collected in Austin, TX. The Pecan Street Inc. dataset contains sub-metered 1 min, appliance-level energy consumption data for 750 households, most of which are located in Texas with additional homes in Colorado, California, Maryland, New York, and Oklahoma [66]. Despite considerable climatological differences between Illinois and Texas (shown in the supporting information (https://stacks.iop.org/ERIS/2/045003/mmedia)), these households were selected to generate the disaggregation model’s parameters because they were among the few monitored single-family households with electric water heaters and a full year dataset. The Pecan Street Inc. dataset was filtered to only include the months where Austin’s water intake temperatures were similar to Chicago’s June water intake temperatures, shown in the supporting information. The average surface water temperature of the Colorado River, the city of Austin’s primary source of drinking water, averaged 50–70 °F (10 °C–21 °C) over March 2015 [67] (among the period of Pecan Street Inc. data records); therefore, the disaggregation parameters were extracted from the Pecan Street Inc. dataset for water heater electricity consumption during March as training data. Though water heating is not as strongly correlated with weather as space heating and cooling, electricity for water heating, $E_{W\text{H}}$ (kWh d $^{-1}$), loads are still sensitive to temperature conditions since the difference between the temperature of the water supplied to the water heater, $T_{\text{in}}$ (°C), and the hot water setpoint temperature, $T_{\text{tank}}$ (°C), affects the water heater’s energy consumption:

$$E_{W\text{H}} = \frac{\rho C_p V}{\text{EF}} (T_{\text{tank}} - T_{\text{in}})$$

where $\rho$ is the density of water (kg l $^{-1}$), $C_p$ is specific heat of water (kWh kg$^{-1}$ °C$^{-1}$), $V$ is the daily hot water volume (l d $^{-1}$), and EF is the storage tank electric water heater energy factor (EF).

Historical daily average outdoor air temperature data were obtained from the National Oceanic and Atmospheric Administration to assess the potential impact of outdoor air temperature on daily domestic electricity use. We assumed that Chicago households were less likely to use space heating or cooling in the period starting from late-May to mid-June; therefore, households’ electricity consumption data could present a higher signal-to-noise ratio for water heating specifically during that period. Further analysis of historical climate data revealed that May 2016 in Chicago had an average daily temperature of 59.7 °F (15.4 °C), 255 heating degree days (HDDs) and 67 CDDs, while June’s average monthly temperature was 71.6 °F (22 °C) with 13 HDDs and 216 CDDs [68]. Considering the effect of outdoor air temperatures on domestic electricity consumption (shown in the supporting information), we selected a sample from the ComEd data that would minimize the potential error due to noise associated with space conditioning in the data, focusing our analysis on June 1–14.

Additional analysis of fall was considered but ultimately excluded due to partial data recording errors during October in the smart electricity meter dataset and limited continuous periods (e.g., ≤3 days) that were likely to have minimal space conditioning, based on reported HDDs and CDDs [68]. Thermal mass of residential buildings affects energy consumption for heating and cooling [69], so we constrained our analysis to the 2 week period in June, and acknowledge this limitation as an area of future work.

We demonstrated the disaggregation on single-family households with electric space heat. The main assumptions leading to this approach, aiming to minimize bias, in the study are:

(a) Single-family households with electric space heat are more likely to use an electric water heater.
(b) Single-family households without electric space heating might use natural gas-fired water heaters, which will not allow isolating water heating signals from the electricity data.
(c) Multi-family households and other buildings might share a common water heater across several units, introducing bias in the estimating approach.
In the Midwest East North Central region (including Illinois), the Residential Energy Consumption Survey estimates that 35.4% of homes use electric water heating [2], while 17% of Illinois households use electricity for space heating [70]. In the absence of additional data designating residential water heater fuel types, we make the above assumptions, acknowledging the data limitations of the analysis.

Figure 1 illustrates the spatial distribution of the data for single-family households with electric space heat in Chicago, IL considered in this study. There were a total of 1042 single-family households with electric space heat in the city of Chicago located in 24 different zip codes. In this study, a sample of 120 households representing 8 different areas (or 'sides' [71]; see the supporting information for zip code locations) of the city was selected from the total to provide an equal number of households across all areas. The city Central area (which covers the larger downtown area including the Loop, Near North Side, and Near South Side community areas) does not have single-family households with electric space heat.

3.2. NILM disaggregation algorithm
Our model implements a NILM technique to identify the electricity signal of water heating and disaggregate water heater electricity use from half-hourly whole-house electricity consumption data. We use a decision tree approach that measures, at each timestep, the magnitude of change in load that could indicate that the electric water heater is turning on or off, which is then used to identify single on and off events of electric water heater use for each day. The key assumptions of the model are:

(a) All water heater appliances of the sampled households are assumed to be electric resistance water heaters with simple on/off states.

(b) The Pecan Street Inc. training data reflect water main temperatures that are similar to the Chicago households' inlet water temperatures to minimize differences in energy required for water heating.

(c) The power demand of residential water heaters is assumed to be the same in Austin and Chicago, and the same among all single-family homes in the analysis sample. This assumption introduces unquantified bias since power demand varies with size. The Residential Energy Consumption Survey estimates the Midwest East North Central region (including Illinois) has 9.6% small, 53.5% medium, and 32.9% large water
heaters, while the South West South Central region (including Texas) has 9.4% small, 38.2% medium, and 47.3% large water heaters, with all else tankless [2].

(d) The electric water heating load is assumed to be the dominant load during June 1–14, 2016, in Chicago since the daily average temperature during that period was 69 °F (20.6 °C), ranging from 59–81 °F (15.0 °C–27.2 °C), likely not requiring significant heating or cooling [72].

Figure 2 illustrates the three essential steps followed by the NILM algorithm to disaggregate water heating energy use from half-hourly whole-house electricity data: signal acquisition, features extraction, and water heating events classification.

Since the ComEd smart electricity meter data do not include appliance-level ground truth information, the Pecan Street Inc. data were used as training data to extract the main disaggregation parameters. These disaggregation parameters were then used to classify ‘on-off’ events of water heaters in Chicago households. A first set of disaggregation parameters was extracted using the 1 min electricity consumption data, with a second training dataset downsampled to 30 min resolution to match the sampling rate of ComEd whole-house load data. The electricity consumption data for each of the six Pecan Street Inc. households are separated by day and the electricity difference between each time step, \( \delta E_i \), is calculated as shown in equation (2). The value of \( i \) in the study, the time interval between each electricity measurement, was 30 min based on the underlying data resolution

\[
\delta E_i = E_{i+1} - E_i
\]

where \( \delta E_i \) is the change of electricity between time \( t_i \) and the following time step \( t_{i+1} \), \( E_i \) is the total electricity use measured at time \( t_i \), and \( E_{i+1} \) is the total electricity use measured at time \( t_{i+1} \).

Following signal acquisition, the NILM algorithm proceeds to the extraction of appliance features or signatures. The algorithm assumes only one class of water heating power signature: steady-state. In other terms, electric resistance water heater signals were assumed to modulate from ‘on’ to ‘off’ states, though, in reality, the normal actions of electric water heaters include turn-on, turn-off, and electrical energy adjustment between upper and lower heating elements or mode changes that are termed as transients. Though analyzing transient states could provide better features—shape, duration, size, and harmonics of transient power fluctuations—to distinguish multiple appliances, extracting these types of signatures would require finer temporal resolution data than the 1 min or 30 min data used in this study. Fine-resolution data are rich in informative transients and have the potential to broaden the research field and improve accuracy of load disaggregation, but available data are limited [73]. The water heater features extracted from the training dataset constitute the NILM algorithm’s main disaggregation parameters: \( \delta E_{\text{ON}} \), \( \delta E_{\text{OFF}} \), \( WH_{\text{ON}} \), and \( WH_{\text{OFF}} \). The training dataset was filtered to only include March 1–31 data from Austin, TX homes since the average water main temperature in Austin during that period, 67.8 °F (19.9 °C), was close to Chicago’s June average water main temperature [67]. We selected midnight to 6:00 AM as the training period to minimize interference of other appliance signals, which are more prevalent during later hours of the day, as load profiles approach peak electricity consumption. To best isolate the signal, it was critical that the water heater be the dominant load during the training period. The signal size parameters \( \delta E_{\text{ON}} \) and \( \delta E_{\text{OFF}} \) represent the changes in magnitude large enough to indicate that the water heater has either turned on or off.

The electricity difference between each time step, \( \delta E_i \), from March 1–31, was stored and used to generate \( \delta E_{\text{ON}} \) and \( \delta E_{\text{OFF}} \). For instance, if the recorded water heater power went from 0 kW at time step \( t \) to a positive value at time \( t_{i+1} \), it indicates an ‘on’ event and the corresponding total electricity value at time \( t_{i+1} \), \( E_{i+1} \), is recorded as \( \delta E_{\text{ON},i} \). Each household has an equivalent absolute \( \delta E_{\text{ON}} \), which is the minimum of all the \( \delta E_i \) values corresponding to an ‘on’ event. Similarly, if the recorded water heater power consumption went from a positive value at time step \( t \) to 0 kW at time \( t_{i+1} \), it indicates an ‘off’ event and the same procedure described for an ‘on’ event is followed to extract \( \delta E_{\text{OFF}} \). Table 1 shows the different disaggregation parameters extracted for
each of the six households from the Pecan Street Inc. Dataport dataset, converted from units of power (kW) to electricity (kWh) for ease of comparison based on the given time step. The averages of these parameters were used as the main parameters of the NILM algorithm to disaggregate electricity for water heating from the ComEd dataset reporting electricity consumption in 30 min time steps. In addition to signal size parameters, we derived two constraints to minimize false detection of ‘on’ and ‘off’ events: WHON and WHOFF. These constraints mitigate noise from other appliances from signaling a water heater ‘on’ or ‘off’ event because there were multiple instances where \( \delta E \geq \delta E_{\text{ON}} \) but electricity used at time \( t + 1 \) was inferior to the lower limit \( WH_{\text{ON}} \). On days where multiple appliances were running simultaneously, non-water heater electrical loads could reach similar orders of magnitudes as water heating loads; therefore, the model could misinterpret the electricity loads and assimilate other appliance loads as water heating loads. WHON is the minimum total electricity required to signal that the water heater did turn on, while WHOFF is the upper limit signaling that it turned off. The system first had to be in an ‘off’ state to signal an ‘on’ switch; similarly, it needed to be ‘on’ to signal an ‘off’ switch. The WHON parameter was obtained from the total electricity data by taking the maximum power value between midnight and 6:00 AM, during which the water heater unit dominated the power consumption profile, over a defined time step to provide units of kWh for consistency with \( \delta E_i \) values. WHOFF was calculated as half the value of WHON. We then used the disaggregation parameters derived from the training dataset with the ComEd data for Chicago to extract information about electricity for water heating in single-family households. Figure 3 shows the boundaries imposed on a typical day, WHON and WHOFF, to prevent noise from other appliances such as the refrigerator from signaling a water heating ‘on’ or ‘off’ event.

The final step in the load disaggregation process, appliance classification, refers to analyzing features extracted from whole-house electricity data to categorize specific water heater ‘on’/’off’ events. There are two types of scenarios under which the water heater element turns on [74]:

(a) When the water temperature inside the storage tank drops below the minimum setpoint temperature as a result of conduction heat losses, the heating element will be on for approximately 18 min during a normal cycle, but it could last longer depending on the volume of water drawn.

(b) When a large amount of water is drawn from the storage tank and replaced with incoming cold water, the water temperature can be far below the setpoint; therefore, the length of time that the element will be in use will vary.

As illustrated in the algorithm decision tree (see figure 4), once the algorithm establishes that the water heater is either in an ‘on’ or ‘off’ state, it compares the stored difference in electricity use between two consecutive data points to the signal size parameters \( \delta E_{\text{ON}} \) and \( \delta E_{\text{OFF}} \). Following the first test, it then compares the total electricity use at the following time step \( t_{i+1} \) to the constraints or boundary parameters, WHON and WHOFF. If the difference in electricity is large enough to signal that the water heater turned on \( (\delta E_i \geq \delta E_{\text{ON}}) \) and the electricity used at time \( t_{i+1} \) is greater than the lower limit \( (E_{i+1} \geq WH_{\text{ON}}) \), then the time step is stored as the system being turned on and in use.

The algorithm steps forward in time until the following two conditions are met:

(a) \( \delta E_i \leq \delta E_{\text{OFF}}, \) or

(b) \( E_{i+1} \leq WH_{\text{OFF}}, \) which means that the decrease in the electricity consumption was large enough to indicate that the water heater turned off and the total electricity used at time \( t_{i+1} \) was below the lower electricity use threshold.

Once the algorithm detects that the water heater is turned off, it steps forward in time until another signal indicating a water heater switch-on event is found. The decision process, illustrated in figure 4, is repeated until the end of each day. The sum of the time step values stored during ‘on’ events represents the total duration of the water heater operation. Electricity for water heating was estimated as shown in equation (3) by multiplying the accumulated water heater ‘on’ events duration for each day with the average water heater power demand values shown in table 1 based on the Pecan Street Inc. training data. Since the average water heater power demand is

### Table 1. NILM algorithm disaggregation parameters.

| House | Poweravg (kW) | WHON (kWh) | WHOFF (kWh) | \( \delta E_{\text{ON}} \) (kWh) | \( \delta E_{\text{OFF}} \) (kWh) |
|-------|---------------|------------|-------------|----------------|----------------|
| House 1 | 1.82         | 1.47       | 0.74        | 0.066         | −0.102        |
| House 2 | 1.53         | 0.87       | 0.44        | 0.141         | −0.037        |
| House 3 | 1.68         | 2.43       | 1.22        | 0.177         | −0.029        |
| House 4 | 1.78         | 2.44       | 1.27        | 0.058         | −0.139        |
| House 5 | 1.19         | 1.73       | 0.87        | 0.098         | −0.027        |
| House 6 | 1.74         | 1.60       | 0.80        | 0.061         | −0.101        |
applied to the entire day, the estimated daily electricity for water heating values do not reflect differences due to appliance efficiency

\[ E_{WH} = P_{AVG} \times t_{ON} \]  \hspace{1cm} (3)

where \( E_{WH} \) is the estimated electricity used for water heating in kWh, \( P_{AVG} \) is the average power demand of water heating element in kW, and \( t_{ON} \) is the estimated total duration of daily water heating ‘on’ events in hours.

3.3. Domestic hot water use estimation from extracted water heater load

We estimated DHW use from the isolated water heating signal for single-family households with electric space heat, assuming use of conventional storage tank water heaters, the most common type of water heater in the residential sector [75]. Taking into account energy losses, inefficiencies, and waste heat, a measure rating the overall efficiency of a domestic water heater is necessary to calculate the actual volume of water heated as a function of energy consumption. The efficiency of electric storage water heaters is represented with an EF [16], defined as follows:

\[ EF = \frac{E_{output}}{E_{WH}} \]  \hspace{1cm} (4)

where \( E_{output} \) is the useful water heater energy output and \( E_{WH} \) is the total amount of energy delivered to the water heater.

Water heater EFs take into account standby losses estimated as the percentage of heat lost per hour from the stored water compared to the heat content of the water [76]. EF values for electric storage water heaters range from 0.90 for a standard model to 0.95 for a high-efficiency model, based on insulating conditions [16, 77]. We estimated DHW consumption with quantified uncertainty based on the following assumptions:

(a) The inlet water temperature ranged from 57 °F to 66 °F during the first two weeks of June 2016 in Chicago.
(b) Water density ranges from 988.5 kg m\(^{-3}\) at 66 °F (or 18.9 °C) to 999.1 kg m\(^{-3}\) at 57 °F (or 13.9 °C) [78].
(c) Specific heat of water ranges from 4.182 kJ kg\(^{-1}\) °C\(^{-1}\) for 57 °F (or 13.9 °C) to 4.187 kJ kg\(^{-1}\) °C\(^{-1}\) for 66 °F (or 18.9 °C).
(d) The constancy of the thermostat setpoint temperature at 120 °F (or 48.9 °C), based on recommendations [79].
Figure 4. NILM algorithm decision tree to infer power signal of electric water heater and classify ‘on’ and ‘off’ events.

(e) The effect of the ambient indoor temperatures on DHW use is negligible.

(f) Water heater units are small-to-medium electric storage systems operating on continuous tariffs, meaning electricity consumption roughly tracks hot water use with a small delay.

For a given water heater electricity consumption rate, we estimate DHW consumption, \( V (\text{l d}^{-1}) \), as a rearrangement of equation (1) from the disaggregated \( E_{\text{WH}} \), accounting for ranges in parameter values as an estimation of uncertainty. This quantitative relationship between water heater electricity consumption and hot water use has previously been demonstrated in the context of electricity demand response [5], emphasizing the sustainability implications of water heating in the built environment.

4. Results

4.1. Disaggregation model validation

Our analysis demonstrates the potential of smart electricity meter data to reveal DHW use. Using the NILM disaggregation parameters shown in table 1, we quantified the performance of the NILM algorithm with electricity meter and water heater sub-meter readings from the Austin dataset at both 1 min and 30 min intervals, as shown in figure 5. The algorithm showed satisfactory performance with 1 min data and minimal error during early hours of the day (midnight to 8:00 AM), which corresponds to the period of time when the water
Figure 5. Comparison of the ability of the NILM algorithm to estimate electricity for water heating for a single day at different sampling resolutions: 1 min data (top) and 30 min downsampled data (bottom). As temporal resolution gets coarser, the model disaggregates the water heating load less accurately.

heater is the dominant load. During later times, closer to peak consumption hours, the algorithm showed increasing error and greater tendency to overestimate water heating loads due to lower signal-to-noise ratio; the algorithm could not always distinguish loads of the same magnitude as water heating loads. Aggregating loads to 30 min intervals led to overestimation in our analysis because the average duration of water heater consecutive ‘on’ times was less than 15 min in the ground-truthed training data; however, this aggregation to 30 min resolution was necessary to explore the potential usefulness of grid-scale smart meter data. Overestimation of energy for water heating is consistent with previously reported results of disaggregation models applied in district heating contexts [80]. However, overestimation or underestimation might vary with spatial scale, motivating further data collection and instrumented ground truth observations.

At the 30 min resolution, anomalies and spikes of water heating-related events cannot be detected by the NILM algorithm. Table 2 shows differences between the model prediction accuracy, quantified as the coefficient of variation of the root mean square error, CV(RMSE), for different temporal resolutions for each house in the Pecan Street Inc. training dataset. CV(RMSE) was adopted in the American Society of Heating, Refrigerating and Air-Conditioning Engineers Guideline 14 as a measure to evaluate prediction uncertainty of energy inverse models [81]; the minimum acceptable level of performance of an energy prediction model corresponds to a CV(RMSE) within ±30% when using hourly data. The average CV(RMSE) for the 6 houses in the training data set at 1 min intervals is 1.2%, while the corresponding data downsampled to 30 min intervals yielded a value of 33%. When summing to a daily scale, the algorithm overestimates the corresponding daily electricity for water heating disaggregated from downsampled 30 min data versus the estimates obtained from the 1 min ground-truthed data.

4.2. Electricity for residential water heating estimate

We then applied the NILM disaggregation algorithm to the 120 Chicago single-family households from the ComEd dataset to generate estimates of daily electricity for water heating as a measure of hot water consumption. The 120 households, spanning 20 different zip codes, were grouped according to their respective region, or ‘side’ as defined by the City of Chicago [82] and shown in the supporting information, to evaluate spatial variability in water heating energy loads and corresponding DHW use volumes. Estimated electricity for water heating categorized by Chicago ‘sides’ is shown in figure 6, with the underlying data given in the supporting information. Results indicate that water heating in the analyzed single-family residential homes accounted for
Table 2. Coefficient of variation of the root mean square error, CV(RMSE), for the NILM disaggregation model applied to 6 houses with ground-truthed data in the Pecan Street Inc. dataset at different temporal resolutions.

| House  | CV(RMSE) at 1 min | CV(RMSE) at 30 min |
|--------|------------------|--------------------|
| House 1| 2.0%             | 38.0%              |
| House 2| 0.8%             | 22.9%              |
| House 3| 1.1%             | 35.3%              |
| House 4| 0.9%             | 41.6%              |
| House 5| 1.4%             | 23.4%              |
| House 6| 1.4%             | 33.9%              |

Figure 6. Daily electricity for water heating varies across different Chicago areas over the study period (June 1–14, 2016) from a sample of 120 single-family households. These single-family residential homes used an average of 1–8 kWh of electricity per day for water heating, which accounted for 7%–20% of total electricity consumption.

7%–20% of total electricity consumption, representing an average of 1–8 kWh of electricity consumption per day. As validation, the EIA estimates that electric water heating consumes 3 kWh d⁻¹ per household on average in the Midwest East North Central region [2]. Notably, these estimates do not distinguish between electricity for water heating and energy loss in the water heater itself. Though the NILM disaggregation model tends to overestimate the duration of water heater ‘on’ events, the overall average estimated electricity for water heating aligns well with the EIA-estimated average because the average power demand of the water heater used in the disaggregation calculations was 2 kW, which was obtained from the six training households, with most water heater element sizes around 3–4 kW [2]. Additional ground truth information about water heater sizes would improve the accuracy of this analysis. The 15 sampled Chicago households located in the Far North Side, which averaged a daily total electricity consumption of 42 kWh, had the highest estimated daily electricity for water heating at 8 kWh (see the supporting information), while the 15 sampled Chicago households representing the South Side, which had the lowest total daily average electricity use of 13 kWh, showed the lowest average daily electricity for water heating (1 kWh). Most neighborhoods located in the Far North Side of Chicago have median household income and median home values that are higher than the average [83]. Comparisons across different Chicago ‘sides’ and visualizations for each day of the study period are available in the supporting information.

Using the disaggregated electricity for water heating data, we estimated DHW usage profiles for the sample of 120 single-family Chicago households, based on an assumed range of efficiency factors for water heating appliances. Note: DHW use is reported here in US customary units (with SI units following), based on the typical units of measure for residential water heaters in the study area. Results indicate that single-family residential homes analyzed in this study used an average of 7–55 gallons (26–208 l) of hot water per day, with
Figure 7. Results show considerable temporal and spatial variation in estimated DHW use during the study period (June 1–14, 2016). Average daily hot water use ranges from 7–55 gal.

high variability across different ‘sides’ of Chicago and days of the week as shown in figure 7, with the underlying data given in the supporting information. The range in estimated DHW consumption spanned a low of 7 gallons (26 l) for households sampled from the South Side to a high of 95 gallons (360 l) for households in the Far North Side. Regarding temporal patterns, households across the 8 considered Chicago ‘sides’ consistently showed higher water heating electricity consumption on Saturday, June 11, 2016, compared to other days analyzed in this study. The Far North sample also exhibited greater spread in electricity consumption compared to other regions.

4.3. Model limitations

The estimated DHW use profiles rely on the assumptions that the majority of the water heaters in residential households in Chicago are small-to-medium electric storage systems and the water heater is the dominant load. Small hot water systems, where electricity consumption roughly tracks hot water use with a small delay, are usually installed in smaller homes and rental houses, while large electric storage systems are more prevalent in larger homes [17]. Large electric storage hot water systems generally operate on off-peak tariffs with overnight boosting; therefore, electricity consumption and hot water use with these large systems are disconnected. These assumptions regarding residential water heating systems are not always valid and could introduce bias in the estimated results in the absence of ground-truthed water heating data. Furthermore, the degree to which the estimated electricity for water heating is close to the actual electricity used by the water heater is dependent on how many loads mimic the electric water heater. The NILM algorithm does not always successfully discriminate between changes in electricity use induced by the water heater and other appliances if they are of the same magnitude. Consequently, when the electric water heater is not the dominant load, the disaggregated load can be incorrectly classified as the water heater, contributing to our overestimation of hot water use. The overestimation of hot water use is also partially attributable to the model’s lack of distinction between electricity for water heating and energy loss in the water heater itself, a limitation of our work that could be overcome with ground-truthed energy and water data. However, this estimation of hot water use from smart electricity meter data adds valuable information in areas lacking widespread household-level water meters, as is prevalent in the city of Chicago where only 400,000 homes—less than one-third—have water meters installed [84].

For a more effective analysis and understanding of the temporal and spatial variation of residential electricity demand, better data are needed. In our study specifically, finer temporal resolution data (i.e., <30 min) could increase the NILM algorithm accuracy and better reflect electricity end uses with typical cycles <30 min in duration. Ground-truthed data, even if limited in installations through sub-metered
appliances in selected study homes within the region, can also provide necessary training data for implementing supervised machine learning approaches to better understand residential electricity consumption. Such ground-truthed data for water heaters specifically could support further analysis of centralized (storage tank and branch systems) versus distributed (point-of-use) hot water systems. Beyond our study, comprehensive energy data are critical for empowering consumers to improve their behavior, for designing effective policies, and for driving energy innovation [85]. Accessible and high quality energy data could help evaluate current energy policies, but also proactively design more efficient and customer-centric energy policies [85]. Residential customers who have access to their own electricity consumption data, and can infer appliance-level end uses through these data, can realize considerable energy savings by adapting their energy consumption behavior and opting for energy-saving products. Furthermore, customers who are aware of the different types of time-variant electricity pricing can adjust their energy use to save money and reduce pollution [86]. Advances in data analytics could help utilities, researchers, and policy makers extract increased benefits from large volumes of energy consumption data generated by smart meters. Additionally, consistent data formats could help achieve optimal interoperability for smart meters, customer devices, and communications systems [87]. As smart grid efforts continue to expand [88], additional focus on data collection, quality, privacy, and sharing could advance the field in quantifying residential sustainability efforts.

5. Conclusion

Through this study, we show that a NILM algorithm can disaggregate smart electricity meter data and generate a first-order estimate for household electricity for water heating and hot water use. This technique requires a training period in which the water heater is the dominant load to extract proper disaggregation parameters. Additionally, the NILM algorithm performance depends on the resolution of the input data; a comparison between two different sampling periods (1 min and 30 min) reveals that a 30 min sampling period yields increased error in the algorithm to distinguish between water heating electricity loads and other appliance loads. However, from midnight to 6:00 AM, during days when space heating or cooling are minimal and water heating is the dominant load, a 30 min sampling period yields reasonable results for estimating DHW use.

We estimated daily household-scale DHW use at 7–55 gallons (26–208 l) in the sample of 120 single-family homes in our study area of Chicago, Illinois. Since many Chicago customers have unmetered drinking water service [89], a first-order estimate of DHW use from zip code-level electricity data offers a valuable quantification of population-scale hot water consumption for different regions, which adds actionable information within the residential energy-water nexus and can support focused, data-informed conservation and efficiency measures [90].

Understanding the residential energy-water nexus is critical to improving energy and water resources supply and management efforts, given increasing urbanization and resource strain. Integrated analysis of the energy-water nexus presents additional benefits of understanding resource interdependencies and opportunities for mutual benefit (e.g., energy utility rebates on efficient water-consuming appliances that save water and energy [91]; water reuse efforts that can increase or decrease energy consumption, depending on location-specific context [92, 93]). Conversely, conventional independent sectoral analyses can overlook tradeoffs (e.g., biofuels energy policies that exacerbate water challenges [94]; restricting hot water use to save energy [95] while increasing water quality risks from stagnation [96]). These energy-water nexus examples motivate additional in-depth, site-specific resource sustainability analyses. With water heating being one of the most energy-intensive activities of the water sector [1], estimating electricity for water heating and DHW use could inform improved resource consumption estimation to assist policymakers and utility managers in promoting residential energy and water efficiency measures, in the absence of metered hot water data.

Author contributions

J.L.B. analyzed data, created and implemented the NILM algorithm and quantified accuracy, and summarized results; P.W.F. and S.L.G. assisted with disaggregation of electricity for water heating and contributed to scoping the analysis; A.S.S. formulated the analysis scope, supervised the research, and acquired funding to support the analysis; all authors contributed to writing.
Acknowledgments

This work was supported in part under the provisions of section 104 of the Water Resources Research Act annual base Grants (104b) program made possible and distributed through the Illinois Water Resources Center and the United States Geological Survey. Additional support was provided by Civil and Environmental Engineering at the University of Illinois Urbana-Champaign. Training data for the analysis were provided by the Pecan Street Inc. Dataport. Commonwealth Edison electricity data were obtained through a partnership with the Environmental Defense Fund, under a data sharing agreement with the University of Illinois.

Data availability statement

The data generated and/or analysed during the current study are not publicly available for legal/ethical reasons but are available from the corresponding author on reasonable request

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