Non-Intrusive Load Monitoring of Water Heaters Using Low-Resolution Data

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ABSTRACT

Electric water heaters consume approximately 19% of the total energy in residential buildings and may be used as virtual batteries to provide a variety of ancillary services for the electric grid. With the proliferation of advanced metering infrastructure (AMI) smart meters, vast amounts of data have become available for non-intrusive load disaggregation. Disaggregating major appliances such as water heaters using low-resolution AMI data may assist in assessing residential virtual battery potential at a regional level. In this paper, we assess the use of a graph signal processing algorithm for non-intrusive load disaggregation of a hybrid heat pump water heater. Algorithm performance is evaluated for disaggregating the water heater signal in the presence of a variety of other loads and operational modes. Real-world data sampled in the field at a frequency of 1 minute and downsampled for the purpose of this study to 15 minutes were used to simulate typical AMI meter sampling frequency. Results demonstrate that F-measures (the harmonic mean of precision and recall values) > 0.90 are achievable for water heater disaggregation.

CCS CONCEPTS

• Applied computing ~ Physical sciences and engineering ~ Mathematics and statistics

KEYWORDS

Advanced metering infrastructure, smart meter, low-resolution non-intrusive load monitoring, water heater disaggregation

ACM Reference format:

Christy Green and Srinivas Garimella, 2020. Non-Intrusive Load Monitoring of Water Heaters Using Low-Resolution Data. In *Proceedings of The 5th International Workshop on Non-Intrusive Load Monitoring (NILM'20), Nov 18, 2020, Virtual Event, Japan, 5 pages.* https://doi.org/10.1145/3427771.3427853

NILM'20, November 18, 2020, Virtual Event, Japan

ACM ISBN 978-1-4503-8191-8/20/11…$15.00
https://doi.org/10.1145/3427771.3427853

1 Introduction

Water heaters are one of the greatest energy consumers in residential buildings. The U.S. Energy Information Administration estimates water heaters consume 19% of the total energy consumed by houses in the United States [1]. Water heaters are a potential energy storage source for the electrical grid; they may be referred to in this context as a "virtual battery" [2]. The amount of virtual battery energy available from a single residence is low, but aggregating this potential across a region may be possible, depending on the availability of relevant power data. Advanced metering infrastructure (AMI) smart meters are rapidly outnumbering conventional manual meters, with approximately 56% of homes equipped with AMI meters in 2019 [3]. Disaggregating signals from AMI smart meters would allow for appliance-level monitoring and energy forecasting, which would subsequently allow utilities to characterize the flexibility of demand-side resources.

Smart meters typically report power usage at 15-minute or 1-hour intervals, which are very low sampling frequencies. Many studies have been conducted in an effort to solve the unique challenges presented by low-resolution load disaggregation. Popular methods of disaggregating low-resolution data include factorial hidden Markov model (FHMM) and deep learning methods [4-7]. Basu, et al. [8] used a multilabel classification approach to disaggregate residential loads including water heaters. The water heater was disaggregated with the highest accuracy among all appliances tested at 10-minute and 1-hour sampling rates. The proposed algorithms performed better than a standard hidden Markov model applied to the same data, with F-measure scores ranging from 0.89 – 0.99 for the proposed algorithms.

Zhao, et al. [9] describe a method for using unsupervised graph signal processing to disaggregate residential loads that was evaluated using the Residential Energy Disaggregation Dataset (REDD) and a data set from the Personalized Retrofit Decision Support Tools for UK Homes Using Smart Home Technology (REFIT) project. The method proposed demonstrated performance superior to that of several variations of the FHMM algorithm. In Zhao, at al. [10], the graph signal processing algorithm was improved by integrating a graph corresponding to the hour of day into the adjacency matrix. Appliances disaggregated in these studies include most appliance types available in a residence, from low-power, consistently operating appliances such as refrigerators to high-power, intermittent devices like microwave ovens. One appliance that has not been included in these disaggregation studies is the water heater. The high accuracy demonstrated by the algorithm in disaggregating appliances with fairly consistent operational patterns and a range of power draws, such as the refrigerator and air conditioner, indicates that the water heater load may be a good candidate for disaggregation using this algorithm.

In this study, we investigate the disaggregation of electric hybrid heat pump water heaters (HPWHs). These water heaters use a combination of an electric air-source heat pump and electric resistive elements to heat water. The heat pump and electric resistive elements may operate simultaneously or independent of one another, depending on the selected operational mode. To the best of the authors' knowledge, no research has been published on the disaggregation of electric hybrid heat pump water heaters at low sampling frequencies. The disaggregated HPWH signals may be used to forecast the energy consumption of groups of HPWHs and evaluate their flexibility for demand-side grid management applications.

2 Graph Signal Processing Algorithm

Graph signal processing (GSP) is an emerging field in which the correlation between samples (the nodes of the graph) at a given time are found by embedding the signal structure in a graph [11]. The GSP algorithm used in this study follows the algorithm structure presented by He, et al. [12]. He, et al. [12] benchmarked this algorithm against a hidden Markov model and a decision tree method using the REDD and REFIT data sets. A graph $G = (V,A)$, is formed using an adjacency matrix and a vector corresponding to a time series of real power values. The set V contains a set of nodes corresponding to change in power values, ΔP. The adjacency matrix represents weights between these graph nodes. These weights indicate the similarity between the nodes they are connecting [13]. In this study, the adjacency matrix uses a Gaussian kernel weighting function (1), where the distance is the Euclidean distance between two ΔP values within V. The scaling factor σ is heuristically determined.

$$A_{i,j} = \exp\left(\frac{\left(\Delta P_i - \Delta P_j\right)^2}{\sigma^2}\right) \tag{1}$$

Classification is performed by evaluating the smoothness of the graph signal. The total Lipschitz smoothness of the graph is defined using (2) [14]:

$$\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} A_{i,j}\left(s_i - s_j\right)^2 = s^T L s \tag{2}$$

where the Laplacian matrix L is defined as $L = D - A$, and D is an $N \times N$ diagonal matrix in which for m = 1,…,N, $D_{m,m} = \sum_{j=1}^{N} A_{j,m}$. A graph signal is defined for each appliance (3):

$$s^m = \begin{cases} +1, & \text{for } \left|\Delta P_i^m\right| \geq Thr_m \text{ and } i \leq n \\ -1, & \text{for } \left|\Delta P_i^m\right| < Thr_m \text{ and } i \leq n \\ 0, & \text{for } i > n \end{cases} \tag{3}$$

where n is the number of samples in the training set, m corresponds to an appliance in a set M, and Thr_m is a threshold power value corresponding to appliance m. Thr_m values were selected by halving the mean operational appliance power value, as in He, et al. [12].

We would like to minimize the difference in the power measured at the mains signal and the sum of disaggregated appliance power. Lower values of this function mean that more appliance loads have been disaggregated from the main power signal.

$$f\left(r_i\right) = \left\| \Delta p_i - \sum_{m=1}^{|M|} \Delta p_i^m \right\|_2^2 \tag{4}$$

Equation (4) represents the minimization of the aggregated load signal and the total graph variation from (2). Here, ω is a weighting factor.

$$\min_{\left(r_{n+1},\dots,r_N\right)} \sum_{i=n+1}^{N} f\left(r_i\right) + \omega \sum_{m\in M} \left\| s^{m^T} L s^m \right\|_2^2 \tag{5}$$

An approach is considered in which an approximate solution for the optimization problem using only the total graph variation classifier term (2) is used. Because this is a supervised algorithm and $s_{1:n}^m$ is known, the minimization problem can be simplified and solved for the total graph classifier (6) [15]:

$$s^{m*} = L_{n+1:N,n+1:N}^{\#}\left(-s_{1:n}^{m^T}\right) L_{1:n,n+1:N}^T \tag{6}$$

The total graph classifier s^{m*} is then compared to a threshold value T_S for all s_i^{m*} in $i = 1,\dots,n$. The threshold value was set to T_S = 0.5, as in He, et al. [12]. He, et al. [12] remove loads from the mains signal as they are disaggregated. The order in which loads are removed from the aggregate signal affects the performance of the algorithm. Consider an inaccurate disaggregation of a frequently operating, high power draw appliance such as an HVAC system. If this inaccurately disaggregated signal is removed from the aggregate load, subsequent disaggregated signals will also be of poor accuracy. In this study, we assess the algorithm performance using aggregate signals composed of only two loads, to investigate signifiers for high disaggregation accuracy.

3 Data Set

The data used in this study were collected at the Oak Ridge National Laboratory Yarnell Station test facility [16]. Real power measurements were collected at 1-minute intervals for a hybrid heat pump water heater and other selected appliances. These power measurements were downsampled to 15-minute intervals by taking the mean of the power values measured over each interval. Other appliances monitored in this house include the indoor (IDU) and outdoor (ODU) units of an HVAC system, pool pump, two electric heaters, and two humidifiers. Unmonitored devices include unknown plug loads and lighting. The HVAC system includes a continuously variable compressor and variable speed fan. Mean power values and their respective standard deviations and variances are provided for each appliance in Tables 1 and 2. Table 1 presents data from a period in which the HPWH was operating only in heat pump mode. Table 2 presents data from a period where the HPWH operated in a hybrid mode, with the electric resistive elements activating periodically, in addition to the air-source heat pump.

Table 1: Power statistics for HPWH (HP only) period

Appliance	Mean [W]	St. Dev. [W]	Var. [W]
HPWH (HP only)	370	79	6299
IDU	69	104	10906
ODU	588	370	136990
HVAC Total	483	485	234980
Pool Pump	105	47	2184

Table 2: Power statistics for HPWH (HP+ER) period

Appliance	Mean [W]	St. Dev. [W]	Var. [W]
HPWH (HP+ER)	453	704	495153
IDU	101	111	12428
ODU	814	518	267990
HVAC Total	789	646	417600
Pool Pump	14	2	4

4 Methodology

The GSP algorithm proposed by He, et al. [12] was used to disaggregate the water heater signal from the aggregate load. Aggregate load signals were developed using real power measurements from the water heater and other appliances within the house. The water heater was paired with the pool pump, the HVAC indoor unit (IDU), HVAC outdoor unit (ODU), the total HVAC signal, and the whole-house energy signal for disaggregation. The whole-house signal is the signal from the electrical mains for the entire house and includes the HVAC system, pool pump, two electric resistive heaters, two humidifiers, lighting, and miscellaneous unknown plug loads. In this study, only two supervised signals are present in the aggregate signal for each disaggregation scenario. This was done to simulate the disaggregation capability for the water heater in the presence of a variety of other real loads and investigate the performance limits of the algorithm. Disaggregation was performed for two cases. In the first, the HPWH operates only the electric air-source heat pump element. In the second, the HPWH operates both the heat pump and two electric resistive elements. Approximately two days of training data were used, followed by 21 days of testing for each of the two cases.

The coefficient of correlation (R^2) between the change in power of the aggregate signal and the change in power of the water heater at corresponding time intervals was calculated. This R^2 value captures two features expected to affect the algorithm performance: difference in mean power magnitudes, and total number of on/off operational events [12]. Higher R^2 values are expected to correspond to higher accuracies, as the appliance signal is more pronounced if it is highly correlated with the aggregate signal.

5 Results

GSP was used to disaggregate the real power signal of the hybrid heat pump water heater in the presence of a variety of other appliances. Factors influencing the accuracy of the algorithm include the difference between the mean power of the appliance being disaggregated and mean power of other appliances present in the mains signal, the variance of appliance power draw, and the correlation between on/off event power change and the power change observed in the mains power draw at the same time interval. The coefficient of correlation between the power change for the aggregate signal and the appliance being disaggregated was compared to the resulting appliance disaggregation F-measure. F-measure, or F-score, is a metric commonly used to evaluate NILM accuracy [17]. F-measure (7) is the harmonic mean of the precision and recall values. Precision (8) is the ratio of true positives (*TP*) to the sum of *TP* and false positives (*FP*). Recall (9) is the ratio of *TP* to the sum of *TP* and false negatives (*FN*).

$$F_M = 2*\left(PR*RE\right)/\left(PR+RE\right) \quad (7)$$

$$PR = TP/\left(TP+FP\right) \quad (8)$$

$$RE = TP/\left(TP+FN\right) \quad (9)$$

Algorithm performance was assessed for the combinations of appliances presented in Tables 3 and 4. Results are presented in Figures 1 and 2. The results demonstrate that the water heater, in

Table 3: Performance for HPWH (HP only) disaggregation

Appliance Combination	F_M	R^2	HPWH % Total Energy Consumption
HPWH, Pool Pump	0.93	1.00	99
HPWH, IDU	0.77	0.96	52
HPWH, ODU	0.39	0.65	14
HPWH, HVAC	0.28	0.56	12
HPWH, Whole House	0.27	0.35	5

Table 4: Performance for HPWH (HP+ER) disaggregation

Appliance Combination	F_M	R^2	HPWH % Total Energy Consumption
HPWH, Pool Pump	0.91	1.00	63
HPWH, IDU	0.94	0.76	65
HPWH, ODU	0.66	0.12	24
HPWH, HVAC	0.46	0.10	22
HPWH, Whole House	0.16	0.02	6

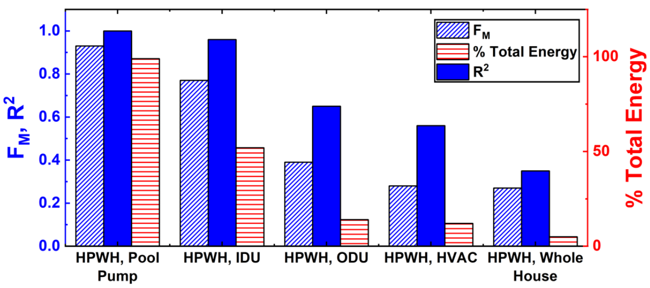

Figure 1: Performance for HPWH (HP only) disaggregation

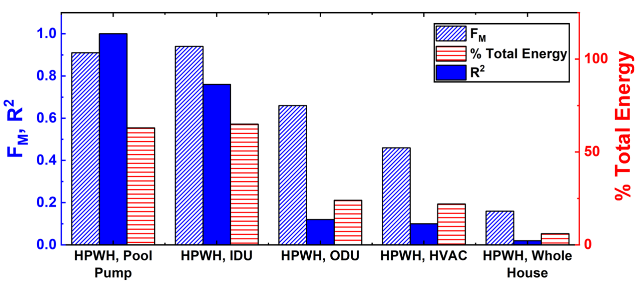

Figure 2: Performance for HPWH (HP+ER) disaggregation

all operational modes considered, may be effectively disaggregated in favorable operating conditions. There is some correlation between the F_M score and the R^2 value calculated using the difference in the water heater on/off events and the corresponding power change of the mains signal. There is also a potential correlation between the total percentage of energy consumed by the HPWH during the training period and the algorithm accuracy. This may explain the high F_M score for the HPWH+IDU case observed in Table 4. The R^2 value in this case was lower than the R^2 value for the HPWH+IDU in Table 3, but the resulting F_M score was greater.

The water heater had higher F_M scores when operating in hybrid mode with both the electric resistive and heat pump components

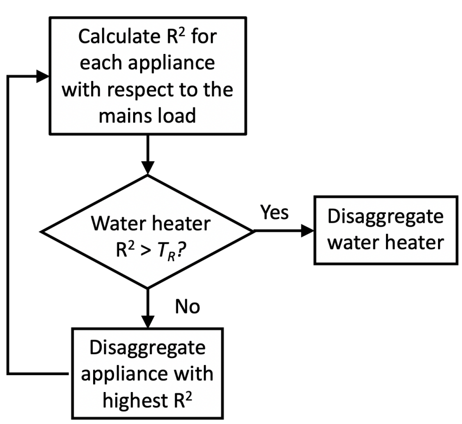

Figure 3: Sequence for disaggregating water heater

operating. This may be attributed to the greater difference in power draw between the HPWH in this mode and other devices. Disaggregation from the pool pump resulted in F_M scores greater than 0.90. This is because there is a significant difference between the operational mean power of the two devices, with the HPWH having a greater mean power draw, and because both appliances operate frequently. Frequent operation, coupled with a much greater power draw for the HPWH, results in a high R^2 value, as well as a higher percentage of total energy consumption. The HVAC system monitored in this house has both a continuously variable compressor and a variable speed fan. This results in a high level of variance for the appliance load. Continuously variable appliances are often misinterpreted as multiple appliances by NILM algorithms.

In a supervised algorithm, the training data may be used to assess the coefficient of correlation or other metrics for each appliance to select disaggregation order and improve disaggregation accuracy for all appliances. An algorithm similar to that shown in Figure 3 could be used to evaluate the expected effectiveness of disaggregating an appliance from a corresponding aggregate signal in a supervised context. Performing a quick calculation involving a metric like R^2, rather than evaluating the disaggregation performance of all appliances prior to removing one from the load in an iterative manner, would greatly improve computational speed.

Further study of the predictive capability of the R^2 value and other metrics must be conducted on larger datasets to prove the suitability of the metrics in assessing disaggregation ability and order.

6 Conclusions

The heat pump water heater may be disaggregated from an aggregate signal when the operational conditions of the signals being disaggregated are both smooth and distinct from each other. It may be possible to assess these qualities using values like the total appliance energy consumption as a percentage of whole house consumption and R^2 as described in this paper. Preliminary results demonstrate a correlation between the R^2 value for a given appliance and the associated mains signal and the resulting F-measure of disaggregation. A correlation between these values would allow the algorithm to disaggregate appliances in order until an acceptable R^2 threshold between the water heater signal and aggregate signal is reached, reducing the computational time required to disaggregate the water heater load.

To further validate the use of the coefficient of correlation as a tool for preliminary NILM assessment in a supervised algorithm, the method will be applied to a larger dataset with a wider range of appliances. Additionally, the effect of seasonality and location on disaggregation of appliances such as heat pump water heaters and HVAC systems may be investigated. Successfully identifying metrics that may be used to assess disaggregation potential and choose the most effective disaggregation order may improve the computational time of the graph signal processing algorithm, particularly when disaggregating a specific appliance, such as a water heater.

ACKNOWLEDGMENTS

The authors acknowledge support from Oak Ridge National Laboratory through Grant #: 4000170418 for this research.

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