Disaggregating Smart Meter Data to Identify Electric Loads and Control Opportunities

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***Abstract*—As utility data, such as smart meter data, becomes more broadly available, there is general interest in using it to improve utility operations and enable adoption of other advanced technologies, such as solar photovoltaics (PV), energy storage, and controls. Here we explore one such use case–identifying electric resistance water heaters from smart meter data, as well as characterizing their potential for load-shifting to support grid voltage stability under high-penetration PV adoption. This paper shows the limitation of typical 15-minute data, as well as how short-term capturing of additional 1-minute data is needed to enable the desired application. Results indicate about 4 kWh water heating load can be shifted to align with peak sun hours in a low-use home. This methodology is an example and can be adapted to other grid-integrated efficient building use cases.**

***Index Terms*—Non-intrusive load monitoring, load disaggregation, smart meter, photovoltaics**

I. Introduction

Utilities are faced with new challenges as the penetration of distributed solar generation grows. Feeder voltage can be significantly perturbed by coincident production and variability across these PV arrays. Advanced solar inverters can alleviate the problem via autonomous control; however, there are limits beyond which either solar curtailment or load control become necessary. By knowing what appliances exist in a home, and how they are used, a utility could offer appropriate incentives for energy management, thus removing barriers to solar PV adoption. A similar approach could be used to identify candidate customers or loads for other grid services.

It has been unambiguously established that higher frequency data enables non-intrusive load monitoring (NILM) methods to both classify more devices and more accurately assign energy [1]. One method [2] showed strong promise by allowing multiple methods to compete for the highest accuracy. However, it also showed the same trend that low data rates challenge all methods of load disaggregation.

Utilities have historically recorded electricity consumption data from electric meters once per month. Smart meters permit higher-frequency data collection. Most utilities collect meter data on a 15-minute basis and total the monthly bill from these readings. Modern meters have greater capabilities, allowing data capture at 1-minute or even sub-second intervals. However, utilities do not have a clear business opportunity to collect and store data at these rates.

NILM methods with 15-minute data have been shown to have benefits in identifying opportunities for energy retrofits and facility operations [3], where a highly accurate savings estimate is not typically required. Two studies using smart meter data from the Pecan Street Project [4], [5] discuss challenges in deriving accurate load profiles from 15-minute interval data. No prior studies have been identified where appliance-level models were extracted from smart meter data for grid service purposes. We therefore propose, and demonstrate, a process for using smart meter data to identify electric water heaters and to assess their potential for being controlled to support utility feeder voltage stability.

II. Utility Use Case: Voltage Stability Under High-Penetration PV

A. Voltage Stability Under High-Penetration PV

Design of the United States' electric power grid was performed assuming one-way power flow, from central electricity generators to distributed loads in our buildings and homes [6]. Growing rooftop PV adoption is beginning to challenge that infrastructure in some locations. During many hours of the year, power is now flowing out of our PV-enabled buildings and back into the grid. For this to happen, the solar inverter must raise its voltage above that of the local grid so that power will flow away from the house. When this happens simultaneously in many nearby homes, such as on a sunny afternoon in a zero-net-energy neighborhood, the entire feeder voltage is raised significantly. This can be unsafe for grid assets and home appliances alike.

B. Potential Voltage Stability Solutions

1) PV Curtailment: Curtailing solar PV means slowing or stopping the production of energy during daylight hours. Curtailment is affected during high-voltage time periods, through either Volt-VAR or Volt-Watt functions of advanced inverters [7], or through digital control. By reducing the power generation from distributed PV, the solar inverters do not affect the feeder voltage as strongly. Occasional curtailment is leveraged today across all renewable energy sectors, which can challenge renewable energy economics as operation is needed to recoup the upfront investment. Solar curtailment also limits the ability to meet renewable energy targets.

2) Battery Storage: By storing energy within the home, less flows back onto the grid. Scheduling a battery to charge during times a home would otherwise export energy, and discharge when it would otherwise import energy, reduces the bidirectional flow of energy on the feeder. This allows the utility to more easily manage feeder voltage.

3) Load Control: Controlling appliances to shift their energy use into the time periods when solar PV is generating excess energy can have an effect similar to a battery. The benefit of using load control is that the appliances are already paid for and installed, whereas most homes do not have a battery. Many appliances are already grid interactive, and others may only need communication modules to enable load control. However, there are practical constraints on how much energy can be easily stored using some appliances due to their physical constraints and customer preferences. Water heater control must be managed to satisfy homeowner demand. Water heating can be treated as an occupant-driven energy storage asset, with electric energy in and thermal energy out and up to 97% round-trip efficiency. Discharge typically follows a somewhat predictable schedule, enabling control and optimization to benefit both utilities and customers [8].

C. How Can NILM Help?

Utilities do not know what appliances are in customers' homes and buildings, nor how they are used. No individual equipment event-based profiles are available to enable pattern matching. No hot water draw profile is available. Finally, water heating electric load is affected by the climate. These challenges point toward model-based NILM methods to estimate water heater load profiles and voltage support capabilities.

We propose a method for a utility to disaggregate smart meter data to identify effective load-management opportunities. This method can be performed in a targeted manner, at negligible cost, to identify water heater potential for addressing voltage stability issues on problematic feeders. This means fewer homeowners can be impacted by their appliances being controlled, and the utility can offer larger incentives to those whose participation is most beneficial to power system stability. Participant recruitment costs could also be minimized by the data-driven opportunity assessment methodology.

III. NILM-Informed Load Assessment

When a utility faces a voltage stability issue on a feeder, or seeks alternatives to solar curtailment, it can assess individual customers' smart meter data. This process, shown in Figure 1, can be used iteratively until the voltage issue is resolved. NILM is used in the second step, and all following analysis is based on the NILM results. This paper discusses steps 2-3, with some commentary on steps 4-5.

A. Smart Meter Data

As shown in Figure 2, 15-minute interval data was insufficient to identify water heaters. A water heater's runtime often spans measurement intervals and has similar magnitude as other appliances. Solar energy generation throughout the middle of the day further challenged the analysis, especially since it has some variability due to clouds. For this problem, the utility will need to temporarily sample prospective customers' consumption at a higher interval with the smart meter.

We requested and received several weeks' worth of 1-minute real- and reactive-power data from some homes. While NILM literature suggests various features for event detection, only a subset is transferable to analyses using 1-minute smart meter data, which includes real power (P), reactive power (Q), voltage (V), current (I), power factor (PF), etc.

B. Load Disaggregation

We used a two-step NILM algorithm to identify water heater cycles from the 1-minute P and Q data. We first used edge detection to identify possible water heater cycles, and then applied rules based on engineering knowledge to filter the detected events and remove false events.

In the first step, we used step changes in real power (ΔP) and reactive power (ΔQ), the most commonly used signatures in NILM literature, to detect water heater cycles. Electric resistance water heater cycles have ΔP at the magnitude of several kW and negligible ΔQ. This set of constraints was used to detect edges likely caused by water heater cycles:

$$\Delta P \in \Delta P_{wh} \sim \mathcal{N}(\mu_P, \sigma_P) \quad (1)$$

$$\Delta Q \in \Delta Q_{wh} \sim \mathcal{N}(\mu_Q, \sigma_P) \quad (2)$$

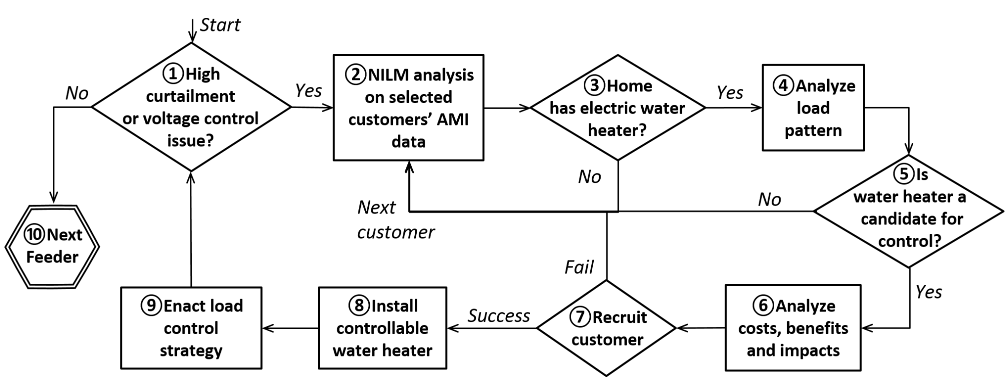

Fig. 1. Flowchart for NILM-enabled method to assess water heater opportunity.

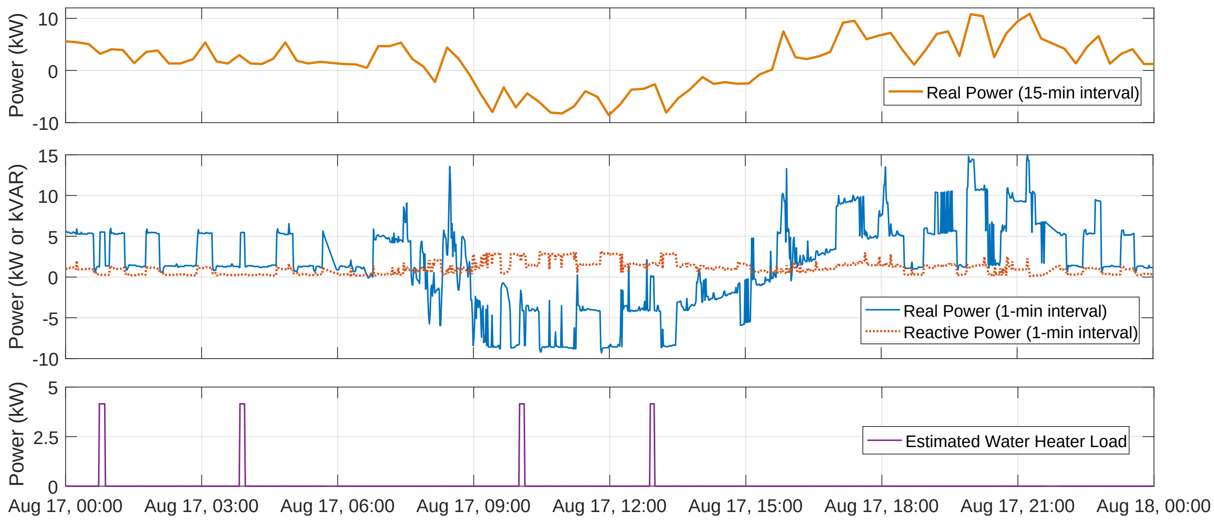

Fig. 2. An example of smart meter data with 15-min interval and 1-min interval. Water heater loads were disaggregated using the 1-min data.

where ΔP_{wh} and ΔQ_{wh} are assumed to follow normal distributions, $\mu_P = 4.5$, $\sigma_P = 0.4$, $\mu_Q = 0$, and $\sigma_Q = 0.1$ were used. If ΔP and ΔQ satisfy Eq. (1) and (2), an event is detected and stored for further analysis in the second step.

After obtaining initial sets of events, rules based on engineering knowledge were applied to filter these events. The following constraints were applied:

1) ON events $\mathcal{E}_{on}^i$ and OFF events $\mathcal{E}_{off}^i$ must appear in pairs: $\forall \mathcal{E}_{on}^i$, $\exists\ \mathcal{E}_{off}^i$ such that $t_{on}^i < t_{off}^i$, where t^i is the time of occurrence of an event, $i = 1, \ldots, N$, and N is the number of ON/OFF pairs. Similarly, $\forall \mathcal{E}_{off}^i$, $\exists\ \mathcal{E}_{on}^i$ such that $t_{on}^i < t_{off}^i$.
2) Histograms of detected ΔP for ON and OFF cycles ($\mathcal{H}_{on}$ and $\mathcal{H}_{off}$) over a certain time period have similar distributions [i.e., distance measure of the histograms must be below a certain threshold: $d(\mathcal{H}_{on}, \mathcal{H}_{off}) \leq \epsilon$].
3) The ON cycle must have a reasonable time duration: $\mathcal{T}_{on} \in [T_{on}^{lb}, T_{on}^{ub}]$, where T_{on}^{lb} and T_{on}^{ub} are set to 5 minutes and 60 minutes, respectively.
4) The water heater must stay OFF for a minimum amount time T_{off}^{lb} after completing a heating cycle. The minimum off time is set to be 5 minutes in the paper.
5) Daily energy consumption of an electric water heater must be within reasonable range: $E_{daily} \in [E^{lb}, E^{ub}]$.

Figure 3 shows the water heater's daily electric energy consumption disaggregated from 4 weeks of smart meter data. The daily energy consumption ranges from 0.1 kWh to 9.1 kWh, implying varying hot water use across different days. The average daily water heating energy use is 4.0 kWh, lower than typical homes in the region. The water heater in this home is a grid-interactive water heater that might have been slightly under control, causing the lower average usage. The lowest daily consumption occurred on August 4; the water heater consumed a minimum amount of energy to recover from standby loss. The peak daily consumption occurred on July 28.

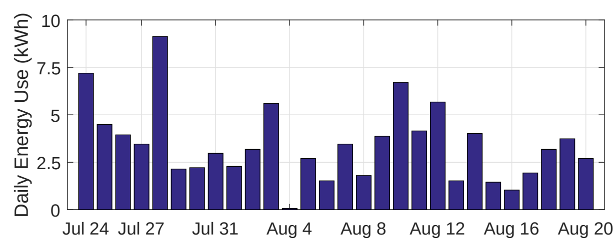

Fig. 3. Estimated daily energy consumption of the electric resistance water heater based on the disaggregated water heater cycles.

C. Control Opportunity Assessment

Water heating cycles are mainly driven by hot water consumption. The water heating cycles scatter across the entire day; about half of the cycles are coincident with a PV generation period, and others may also be shifted to absorb excessive PV power generation to support grid voltage stability. To simulate a water heater and assess its control opportunity under different conditions, a model was fit to the disaggregated load data. In this study, a simple battery-equivalent model was used:

$$\dot{E}_{tank} = \dot{Q}_{heat} - \dot{Q}_{draw} - \dot{Q}_{standby} \quad (3)$$

$$E_{take} = E_{tank}^{ub} - E_{tank} \quad (4)$$

where $E_{tank} \in [E_{tank}^{lb}, E_{tank}^{ub}]$ is the energy stored in the tank, Q_{heat} is the energy input to the tank from the heating element, Q_{draw} is the energy removed from the tank due to water draws, $Q_{standby}$ is the energy loss to the ambient, and E_{take} is the current energy-take capability of the water heater.

In Eq. (3), $\dot{Q}_{heat}$ is equal to the resistance heating element's power when it turns on, and zero otherwise. The nominal value of the power can be estimated from the disaggregated data. $\dot{Q}_{standby}$ is proportional to the difference between water temperature and the ambient temperature, and can be machine-learned over time from data, in particular from low-energy consumption days where standby loss is apparent such as

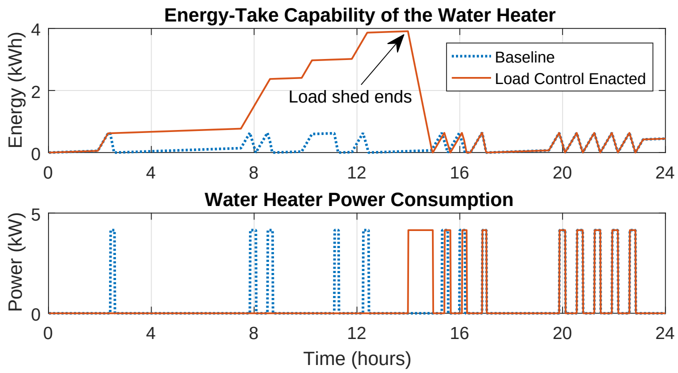

Fig. 4. Simulated water heater control potential, using the estimated water load profile on July 28.

this home on August 4. $\dot{Q}_{draw}$ is obtained through load pattern analysis, which creates a generative model based on the disaggregated water heater cycles and simulates future loads for assessing control opportunities. Water heater load patterns can be estimated via statistical analysis of historical water heating events from the disaggregated data.

For simplicity, we used the estimated water heater load on July 28 to assess the control opportunity on that particular day. Because most water heater cycles are triggered by hot water draws, Q_{draw} was estimated based on the disaggregated water heater load by uniformly distributing the energy across a reasonable time period before the occurrence of the cycles.

Fig. 4 shows the energy-take capability of the water heater for supporting voltage control. The energy-take capability increases slowly over time due to self-discharge (standby thermal losses), increases significantly when a water draw occurs, and decreases to zero just as the water heater finishes a heating cycle. Load control was used to increase the energy-take capability from 0.05 kWh at 2 p.m. if no load control was implemented to 3.91 kWh. The capability could be even greater if a water heater's setpoint can be raised to a higher temperature, as long as safety concerns are managed.

IV. Limitations and Potential Enhancements

The results shown in Fig. 4 are promising; however, there are some limitations to the proposed method such as lack of ground truth and similar load signatures in other appliances.

The smart meter data used in this paper is not accompanied by any ground truth data, so it is not possible to validate the NILM algorithm. Ground truth data can be obtained by submetering devices or communication-enabled appliances, which will incur additional hardware and installation costs. In general, ground truth data are difficult to obtain despite the wide adoption of smart meters. The need for ground truth data may be partly mitigated by conducting a homeowner survey to confirm the existence of an electric resistance water heater and occupancy level, but it is no replacement for sensors.

Some appliances in the home may have similar load signatures as well. For example, resistive loads such as ovens and clothes dryers may have similar ΔP and ΔQ as the electric water heater. Smaller resistive loads may also be difficult to distinguish if they turn on or off simultaneously. Features other than ΔP and ΔQ, time-of-use information, or a higher sampling frequency may be used to resolve these issues.

V. Conclusions

In this paper we demonstrate that smart meter data can be used to identify the voltage control opportunities in building loads via NILM methods. Identifying a water heater using 15-minute interval smart meter data was not possible; the task became feasible with 1-minute interval data. This data, which could come from a smart meter or other supplementary sensor, can help determine which homes' water heaters could provide useful distributed energy resource services. A data-driven battery-equivalent model was created to simulate the water heaters. The water heater model provided real-time information about the water heater's capability for supporting voltage control.

Future research topics include a comprehensive study on the smart meter dataset to validate and improve the proposed methodology; completing an annual simulation with water heater control to quantify the impact on customer curtailment and thermal comfort; and applying the same methodology to identify control opportunities for other major appliances, such as air conditioners and pool pumps.

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