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Training Load Monitoring Algorithms on Highly Sub-Metered Home Electricity Consumption Data

Mario Berges, Ethan Goldman, H. Scott Matthews, Lucio Soibelman**

Civil and Environmental Engineering Department, Carnegie Mellon University, Pittsburgh, PA 15213, USA

Abstract: The growing interest in energy-efficient buildings is driving changes in investment, design, and occupant behavior. To better focus cost and resource conservation efforts, electricity consumption feedback can be used to provide motivation, guidance, and verification. Disaggregating by end-use helps both consumers and producers to identify targets for conservation. While hardware-based sub-metering is costly and labor-intensive, non-intrusive load monitoring (NILM) is capable of gathering detailed energy-use data with minimal equipment cost and installation time. However, variations in measurements between metering devices complicate the process of compiling the necessary appliance profiles. Future work involves the development of NILM algorithms using sensor fusion and detailed appliance-level data gathered from a highly-sensed house currently being constructed near Pittsburgh, Pennsylvania.

Key words: electricity metering; feedback; energy conservation; non-intrusive load monitoring

Introduction

Rising energy prices and technological advances in energy efficiency are creating cost-effective opportunities for improving buildings. Building owners are showing more interest in “green” buildings, but evaluating investment options against the status quo and validating the results both depend on the ability to measure energy consumption accurately. In some cases this is possible because fuel consumption is measured (usually for billing purposes) at a meaningful level of detail, such as when fuel oil is used only for space heating. However, in the case of electricity consumption, residential monthly billing statements are inadequately detailed to guide decision-making[1] This is also true from the perspective of electricity producers, whose administration of demand-side management (DSM) programs would benefit from more detailed end-use data[2].

Quantifiable verification would further justify these efficiency-motivated equipment upgrades. Because actual electricity consumption for a given device depends on many factors, potentially including installation, maintenance, and usage patterns, predicting and verifying the energy savings from an equipment upgrade are best done from actual measurements. By measuring energy savings over the previous baseline, investment in efficiency upgrades could be financed by an electric utility DSM program or the avoided emissions could be sold as CO_2 credits.

Besides upgrading equipment, another form of energy savings that has been repeatedly demonstrated is behavioral conservation[3]. Specific information about electricity consumption could help users to identify conservation opportunities and motivate behavior[4]. By associating energy-consumption metrics with familiar household activities, residents would be able to put home energy use in context with other activities such as transportation. Finally, such verifiable conservation metrics could encourage investment in energy-efficiency programs designed to change behavior.

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** To whom correspondence should be addressed.
E-mail: lucio@andrew.cmu.edu

Studies have suggested that energy demand reductions due to equipment upgrades may be overstated by 10%-40%[5], as consumers sometimes opt to increase their use of a service (e.g., by turning the new air conditioner's thermostat down), thus keeping their costs constant. This is known as the "rebound effect", and is sometimes cited as a reason to focus investment in energy infrastructure elsewhere than energy efficiency. While detailed knowledge of an appliance's electricity consumption alone might not counteract this effect, it does offer a tool with which one could construct incentive programs or other mechanisms to ensure that the desired conservation goals are achieved

1 Background

There are several methods for measuring household electricity consumption and providing feedback to occupants. In each case, it is important to consider the capital cost (for both equipment and installation), the ease of use, and reliability of information.

1.1 Hardware-based sub-metering

One solution to monitor consumption of individual electric loads is to place separate metering hardware on each. Small appliances must be monitored at the outlet level in order to ensure that no other electric loads contribute to the measurement. However, some of the largest energy consumers are either hard-wired (such as electric hot-water heaters) or use different plug styles than standard household appliances. This necessitates a hybrid approach, which may complicate installation. All the meters must also be networked together with the display[6]. The user would then need to identify which load each meter was measuring.

While this approach is able to cleanly separate different uses of electricity, it depends on the configuration of the hardware for data integrity. Therefore, it is most practical only if a small number of devices are to be monitored, as the cost of the installation (both in hardware and time required) scales with the number of data sources. While the software does not need to be very sophisticated in order to ensure reliable data, it does rely on the maintenance of the hardware configuration. If a different appliance is plugged into a meter, the system will have limited means of detecting the error. This reliance on the residents to maintain data integrity limits the appeal of this approach for any sort of outside entity that wishes to validate energy conservation.

1.2 Whole-house continuous monitoring

Several electric meters have recently become commercially available that communicate live measurements of whole-house consumption, and offer an alternative to plug-load metering. These devices connect to the main electric panel of a building with a clamp-on ammeter and voltage sensor in order to accurately calculate instantaneous power usage. Parker et al.[3] suggest a protocol for measuring the steady-state load for all individual appliances in a house using only a metering system called TED (The Energy Detective, www.theenergydetective.com). It involves manually switching all the appliances in the house off and on while another person notes the associated change in power consumption. This technique was reported to take 2-4 hours for 2 people, and can identify the steady-state consumption of most electric loads over 10 W (below which accuracy degrades). However, the only ongoing feedback available is whole-house power consumption, along with some other statistics (peak watts, kWh consumed in month-to-date, expected cost of next bill, etc.) While this approach is inexpensive, it does not have enough resolution to provide the functionality needed.

1.3 Non-intrusive load monitoring

Over the past fifteen years, researchers have been improving the technique of non-intrusive load monitoring (NILM)[7]. In essence, the technique consists of three steps: feature extraction, event detection, and pattern recognition. The feature extraction step deals with the mapping from raw current and voltage waveforms into more compact and informative measurements such as real power, reactive power, harmonics and power factor, etc. Changes in these extracted features, according to static or dynamic thresholds, are then detected and flagged as events (i.e., an appliance turning on or off). Finally, the events are to be classified by the pattern recognition algorithm as belonging to one appliance or another.

The simplest implementation of NILM uses one single feature: real power. Different researchers have explored this approach in the past[8-10]. The limitation of this approach is the inability to distinguish between two different appliances with the same real power consumption. Increasing the feature vector to include other attributes solves this problem.

One such attribute that has been explored is reactive power. Appliances with inductive or capacitive elements that store power can be distinguished from those that are completely resistive by measuring their reactive power consumption. By plotting the changes in real and reactive power from the main feed, it is possible to see clusters of data points that relate to individual appliances turning on/off. This approach has been investigated by Hart[11] and others.

Some appliances are still hard to distinguish given these two features. For instance, variable loads do not remain on a steady-state, and thus, would constantly generate different events to be later classified by the pattern recognition algorithm. To solve this issue, some researchers[12] have used harmonics of the current (up to the 7$^{\text{th}}$) to detect and trace these types of loads. Another feature that has proved to be very successful in commercial building settings is start-up transients[12]. These are characteristic to each appliance, and can also convey information about the health of the appliance.

While NILM applications require minimal hardware and some instances claim over 90% recognition of some loads, this approach is not without challenges. The requisite hardware must be able to report power readings with at least 1.0 Hz of frequency[13] and ideally calculates at least true power, reactive power, and harmonics. Associating a particular electrical signature with the originating appliance either involves a training period or a large database of known loads. Still, given the continuing decreases in hardware costs and the possibility of distributing software costs and signature categorization, the high quality of data and low labor costs for installation make NILM the most promising technology for detailed end-use electricity consumption data.

2 Method

In order to collect disaggregate electricity consumption data, multiple metering systems were installed near the researchers' offices. Before developing NILM algorithms based on these data, the metering system was compared to other power meters in order to establish the broader applicability of the appliance signature library that would need to be populated.

2.1 Sub-metering a university building

The Civil and Environmental Engineering Department at Carnegie Mellon University is housed in Porter Hall, a 100-year-old building that contains classrooms, labs, and offices. Two electric panels were metered at the circuit level using TrendPoint's EnerSure power meters (www.trendpoint.com/enersure.html). The panels contain 13 and 47 metered circuits, respectively. Both panels almost exclusively serve offices; therefore, it is reasonable to believe that the loads detected will resemble a subset of those encountered in a residential building: lights, computers, air-conditioner window units, and various small electronics.

The sensor-polling application thermd (short for "Thermometer Daemon", a free Perl-based application, available from www.klein.com/thermd) was used to log values from the meter every 15 seconds. All available power metrics are stored in a MySQL database: volts, amps, watts, watt-hours, and power factor. The instantaneous and historical data were therefore available for generating real-time displays, performing statistical analysis. This arrangement also allowed the integration of temperature, humidity, and light sensor data, also in real-time.

2.2 Simultaneous load measurement with multiple meters

A test setup comprised of three meters was constructed in order to compare readings from the EnerSure meter with those from two plug-load meters: a Brand

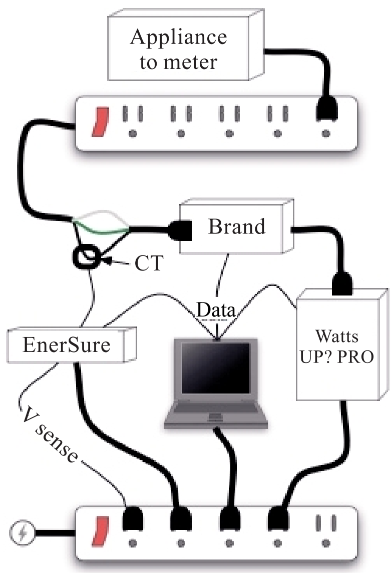

Fig. 1 Three power meters sensing a single load

Electronics 21-1850CI (www.brandelectronics.com) and a Watts UP?PRO (www.wattsupmeters.com). When an appliance was plugged into the test setup (Fig. 1), all three meters were able to sense the load, and a range of metrics (including volts, amps, watts, VAR, and power factor) were logged from each, using the computer interface available from each meter.

3 Results

While the data collection phase of this research is still underway as of this writing, there are several lessons learned about the practical problems associated with deploying electricity metering systems in buildings.

3.1 Hardware-based disaggregation is expensive and difficult

The EnerSure was the first panel-level sub-metering system tested. While its $3000 price is not unusual for its intended commercial applications, it is obviously not intended for home use. This system supports up to 88 channels and up to 3-phase power (120, 240, or 360 volts). It measures amps, volts, watts, and power factor, and uses ModBus protocol to communicate over RS-232 or Ethernet (using a virtual serial port over TCP-IP). Installation required mounting an enclosure near the electrical panel, connecting the two with conduit, pulling the sensor leads through the conduit and connecting them to the meter, clipping the split-core current transducers (CTs) around each circuit's positive conductor, wiring the three-phase plus neutral busses to the voltage transformer (which steps the 120 V down to several millivolts for safe measurement), running conduit for the data connection, and other assorted tasks. This process is expensive and takes a great deal of time setting up 47 channels took over 40 hours. This may have been a worst-case scenario, as the panel is located in a public hallway and required a concealed installation. Another complicating factor was the discovery that some of the CTs were wired backwards by the manufacturer and needed to be reversed in the panel.

While the networking capabilities of the EnerSure make it attractive for commercial and industrial sub-metering and integration in building energy management systems, it adds considerable overhead for simple data collection. The Ethernet port server is first configured for the assigned static IP address, and then the virtual serial port is installed on the client computer. Multi-phase circuits must be identified using the EnerSure's configuration utility so that their power is calculated correctly. Mapping circuits to loads is also time-consuming; though the circuit panel is labeled (room 101 lighting, room 101 receptacles, etc.) these labels were not always completely accurate, and some circuits include outlets from multiple rooms. Even once all the hardware is in place and each circuit is correctly tagged in the database, a good deal of uncertainty persists about what appliances might be plugged into a given circuit, and the appliance-circuit mapping can be expected to change frequently.

3.2 Power meters do not provide consistent output

Initially, it was assumed that the values from any power meter could be used as the basis for load disaggregation. However, real power and power factor (for non-resistive loads) showed differences between meters greater than expected (10%-20%; see Table 1) given that all devices claim accuracy of 3% or better. Further, no pattern for the inter-device variation could be detected in order to establish scaling factors.

While the sampling frequency of various metering devices was established as an important parameter for selecting a suitable device, another feature of the EnerSure was not anticipated: reported values represent a rolling average of approximately 30 seconds. This is presumably to smooth out transient variations so that larger trends are easier to see. However, for the purposes of non-intrusive disaggregation this feature presents a challenge. Instead of showing a 60 W increase in power consumption when a 60 W load is switched on, the EnerSure will show power climbing by 2 W/s over a 30-second period. While this transformation can be reversed by looking at changes in the 1st derivative of the power measurement, the magnitude of the change at the first sample after the event would be dependent on the timing of the event relative to the sampling window. Reducing the sampling rate significantly increases the probability that multiple events will occur within a single sampling period[13]. As it is not possible to reliably recognize events when multiple events occur between samples, this shortcoming was considered too severe to rely solely on data from the EnerSure for the purpose of disaggregation.

Table 1 Range of meter readings for identical loads

Appliance	Metering device	Label	Volts	Amps	PF	Watts
Office Light	Brand Meter 1	Office Light: Brand Meter 1	120.4	0.51	0.53	33.0
	Watts UP?PRO	Office Light: Watts UP?PRO	121.0	0.53	0.65	42.0
	EnerSure	Office Light: EnerSure	121.0	0.53	0.80	50.6
Toaster	Brand Meter 1	Toaster: Brand Meter 1	118.4	6.18	0.99	735.0
	Watts UP?PRO	Toaster: Watts UP?PRO	120.0	6.17	1.00	748.0
	EnerSure	Toaster: EnerSure	119.4	6.24	1.00	826.0

4 Discussion

Though the goal of detailed energy consumption data is alluring, collecting such data reliably and efficiently is challenging. Sub-metering with separate hardware is expensive, time-consuming, and not designed for home deployment. Software-based disaggregation would benefit from an appliance signature library to save users from explicitly identifying all appliances in the home, but such a convenience depends on the alignment of power metrics from different meters, which is not necessarily possible.

Given the uncertainties and inconsistencies present in the internally-calculated values provided by commercial power meters, a more transparent method of sensing power data is needed. The data points required for the power calculations are simply current and voltage; therefore, it is possible to create a power meter with a two-channel data acquisition board, a voltage transformer, and a current transducer. Though this requires some extra effort to program the necessary calculations, it ensures that there is a clear chain-of-custody of the signals all the way from the electric load to the eventual disaggregation algorithm.

For single-phase loads, some of the least expensive high-frequency data acquisition hardware are sold as USB "oscilloscopes". The Picoscope 3224 is a 2-channel DAQ board capable of streaming 12-bit samples over a USB 2.0 connection at over 1 MHz. While it comes bundled with oscilloscope software, it also includes drivers for LabView. For two- and three-phase applications, or if individual circuits (in addition to the electric mains) are to be metered, several options from National Instruments, including the Compact RIO chassis, are more than adequate for the task.

5 Conclusions and Future Work

Several important lessons were learned about the selection of metering equipment. Although the technology for non-intrusive load monitoring is available, there are currently virtually no commercial off-the-shelf solutions in the market. Initial cost, ease of installation and feedback mechanisms need to be improved for this solution to become widespread.

We propose focusing on the software side of the solution. Hardware will keep improving as time passes, and obtaining high frequency samples for current and voltage waveforms will become less costly. In addition to that, we envision using other sensor data to enhance recognition (e.g., light intensity, relative humidity). From this, the next phase of research can begin: development of a NILM system using sensor fusion and automated event categorization.

A long-term data collection is being planned with a local "smart home" manufacturer. Blueroof technologies is constructing a 1000-square-foot prefabricated home near Pittsburgh, which is designed to allow seniors to live independently while offering security and health care via remote monitoring. The house will be equipped with numerous sensors, including temperature, humidity, water flow, motion detectors, and refrigerator and freezer door closure. Many of the major appliances will be provided with dedicated electrical circuits to facilitate isolated metering at the circuit panel while other appliances will be monitored for on/off events with plug-through ammeters. Electricity consumption will be metered for the whole house as well as for most individual circuits using multi-channel high-frequency DAQ hardware.

While this is actually a description of highly intrusive load monitoring, it offers an excellent set of training data for machine-learning algorithms. For example, when a candidate algorithm predicts that a particular change in whole-house consumption indicates that the microwave just turned on, the claim can be compared to actual consumption of the microwave-only circuit. Thus, the extensive sensor deployment provides a large set of labeled electric load event data without any ongoing human intervention. Additionally, the other (non electricity) sensors will provide concurrent data sets that can be overlaid with the whole-house power consumption to test if the additional information improves appliance event detection. Because full-time residents will occupy the house, realistic use patterns will develop. This will allow the testing of sequential analysis as an additional input to event-detection algorithms.

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