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Data Extraction for Effective Non-Intrusive Identification of Residential Power Loads

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ABSTRACT: A completely effective technology for monitoring energy consumption and switching patterns of multiple electrical loads is desired yet not available. While parallel metering of multiple loads is possible, it is rarely cost effective and requires several installations and maintenance checks that disrupt a monitored business or residence. This report describes how non-intrusive monitoring methods for residences have been extended with several novel techniques to identify electrical loads and measure energy consumed by each.

I. INTRODUCTION

Electric loads consume energy within a residence. Loads can be parallel monitored for energy consumption; however, these parallel meters need to be installed and maintained causing a disruption at the monitored business, residence, or other site. A non-intrusive method of inexpensively monitoring loads is desired.

To non-intrusively monitor loads, voltage and current samples obtained from the power meter socket of a residence are processed initially to extract salient features that identify loads. These features are post-processed into events demarking discrete changes in real and reactive power. Finally, loads are distinguished by studying the sequence of events using a load identification algorithm. This concept of non-intrusive load monitoring is shown in Fig. 1.

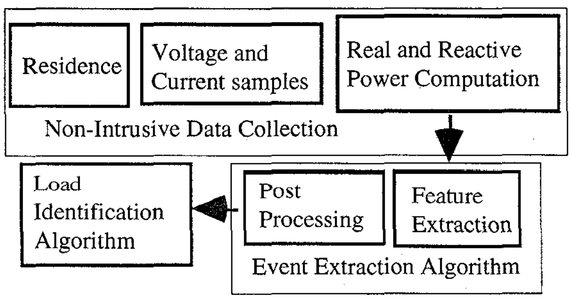


Fig. 1. Feature Extraction and Load Identification Algorithms.

This paper describes the feature extraction portion of a Non-Intrusive Appliance Load Monitoring System (NIALMS)[1]. The feature extractor portion is shown in the context of the NIALM system. Also, several methods are presented to calculate the energy consumed by a separate load from the extracted features.

II. FEATURE EXTRACTION

A. Transient vs. Steady State Features

For non-intrusive monitoring, electric loads should be physically present within a residence and must vary in energy consumption. For example, the energy consumption of an electric stove not consuming electricity or permenantly ON will not be recognized as any load must change power consumption within the monitoring period of time to be identified. Loads must also change power consumption in discrete levels. Continuously varying loads like dimmer switches on lights or adjustable speed drives on motors may not be suitable for monitoring without implementing rather expensive feature detectors [1].

Any load can be distinguished by either its transient changes, its steady-state power levels, or some combination of the two. In Fig. 2, the transient changes and the steady-state power levels of two typical residential loads are shown.

Steve Leeb [2] worked on identifying parallel monitored loads by screening the output of FIR filters that were matched to transient features of particular loads. Leeb's FIR filters processed the current of typical residential loads. By correlation of current transient features with a particular load, Leeb identified flourescent lighting like that typically found in large buildings. While lighting detection is valuable, the use of Leeb's matched filters for every kind of load is prohibitively expensive.

Robertson [3] explored the use of the wavelet transform in software to identify and recognize the transients created by power systems. Robertson used wavelets as the basis for a filter bank of feature detectors. Using a traditional Baysian classifier for statistical pattern recognition, Robertson classified several unknown transient behaviors as

[1]NIALMS is a trademark of a system developed by the Enetics Company, Inc. in Victor, NY.

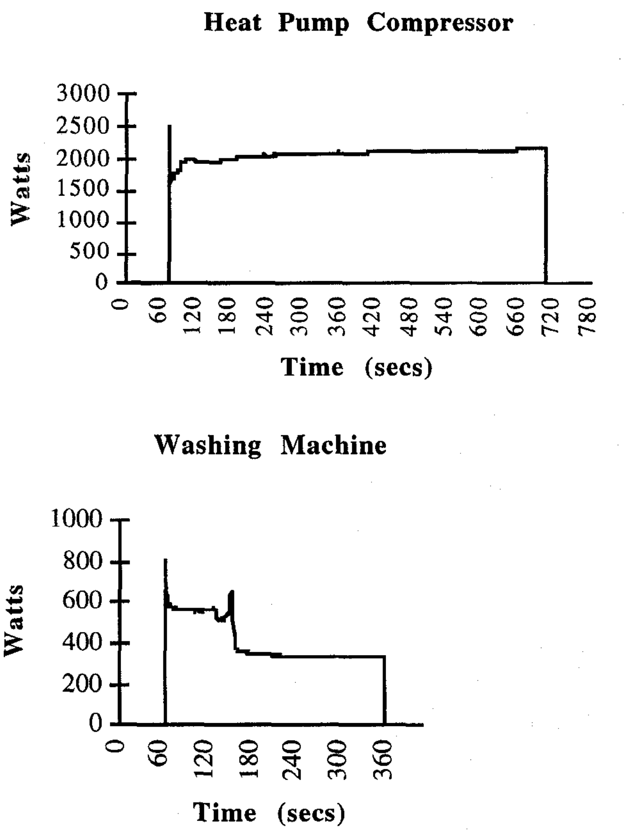


Fig. 2. Real power consumption of one operation cycle for a heat pump compressor above (a) and a washing machine below (b).

capacitor switching or as fault transients. While Robertson applied the wavelet transform to power disturbance transients, wavelets could be potentially applied to transients for load identification. However, wavelet processing for the detection of transients are also expensive and thus not applicable for residence monitoring. Moreover, the detection of transient behavior can be obscured by the simultaneous transients of other loads.

Alternately, George Hart [4] found an inexpensive method of load identification by examining steady-state behavior. Hart examined the normalized real power in watts and reactive power in vars consumed by an isolated load as an indicator of its operation. The normalized watts and vars reflected the changes in impedence over time normalized to a constant ideal voltage suppy. Because impedence for most residential loads does not oscillate like the current, simple algorithms could be applied to extract discrete changes in power level. Discovering that most residential loads have stable steady-state power levels, a simple detector for discrete level changes could distinguish a particular load from other loads.

Our work extends Hart's work to identify multiple loads seen from the power metering socket of a residence. At the meter a detected steady-state power level depends on the power consumption of all the loads that are ON, not just a single load, as shown in Fig. 3. Since the number of loads which are ON is not known a steady-state power level is not indicative of load's presence.

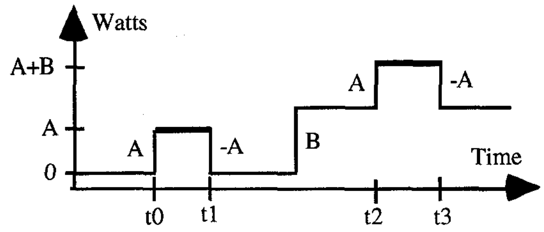


Fig. 3. A detected steady-state depends on loads that are ON. The steady-state power levels between t0 and t1 as well as t2 and t3 while load A is ON are not the same.

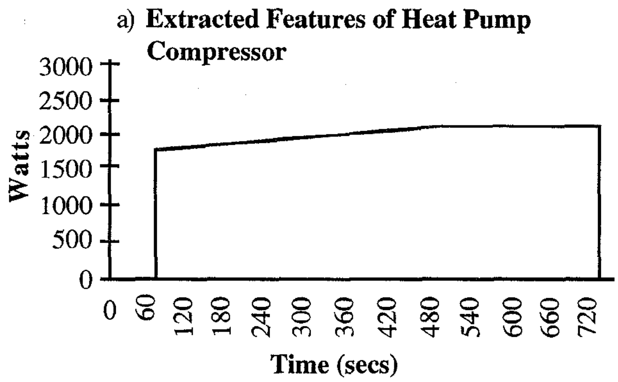
Instead, changes between steady-state power levels can indicate the presence of a load. Assuming these changes are distinct enough and are easily recognized in discrete levels, the loads can be discriminated. However some residential loads like heat pumps, dishwashers, or refrigerators do not conform to discrete changes in power level. Our work focuses on finding a new feature detector to recognize these complex loads.

B. Recognizing Residential Loads' Turn-on

At the power metering socket, all loads consuming power are seen at the same time. Many loads with compressors like heat pumps, dishwashers, refrigerators, have oscillating, ramping, or other variations following a discrete change in power. They eventually settle to a stable steady-state level. Consider Fig. 2a. and 2b. again. It is clear that the loads presented settle to a stable steady-state power level after some variation in power consumption. Then, they finally turn off with a sharp decrease in power level. Notice that turn-offs are not only sharp, but also of the value fixed for a particular load. Therefore, they can serve as a distinctive feature of loads. It is also clear that the load's turn-on actions are more complex as their values change over time. A closer investigation of the turn-ons of loads is thus required before they will be used as a distinguished feature of a load.

All of the complex residential loads investigated have turn-on's that can be characterized by three phases: an initial upward spike in power, slower changing variations, and a settled power level. These three phases will be called edges, slopes, and steady-states respectively.

In Fig. 4, the loads shown in Fig. 2. have been processed into edges, slopes, and steady-states. Notice, again that given that multiple loads are monitored at once, the power level during a particular load's steady-state is not unique. Therefore, steady-state can not serve as a reliable load discriminator. Only edges and slopes are unique features to distinguish loads.



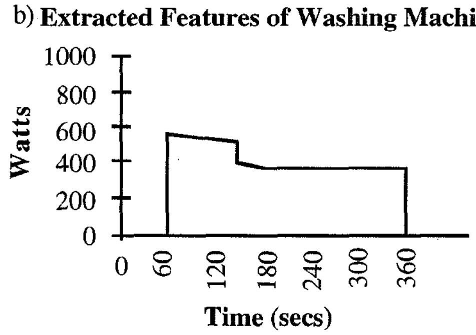


Fig. 4. Edges, slopes, and steady-states are extracted from sampled loads in Fig. 2.

III. ENERGY CALCULATION

A. Calculating Energy Consumption of Loads

To construct the turn-ons and turn-offs of the loads, a processing of edges, slopes, and steady-states as shown in Fig. 5 is needed. As steady-state features can not distinguish a load, they are neglected leaving only slopes and edges. The slopes must be assigned to their corresponding edges. This is a tedious process when a slope of one load is interrupted by an edge of a slope of the other load. The idea for slope assignment is not presented in this paper. It can be found in [5].

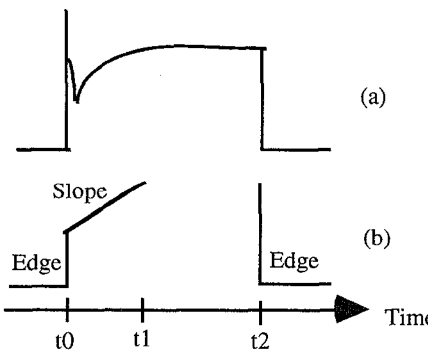
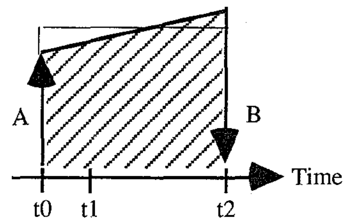


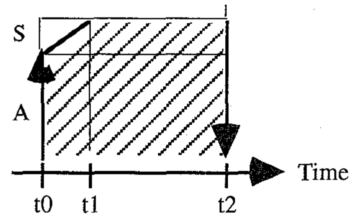
Fig. 5. Features in (b) extracted from load wavefrom in (a). Steady-state neglected yielding only edges and slopes.

After slope assignment, a load's turn-on is approximated by an edge and the linear change in power of a slope. For typical residence loads, several approximation methods for slopes were studied. Although polynomial or other approximations proved to be better than linear ones, a linear slope was choosen because it is easy to compute and it gives acceptable (compare Table 1) consumed energy estimates. A linear approximation of a slope begins at the end of an initial spike in power and continues until the beginning of a stable power level. Now, knowing the edges corresponding to a particular load and the time moments for each edge, the energy consumed can be calculated.

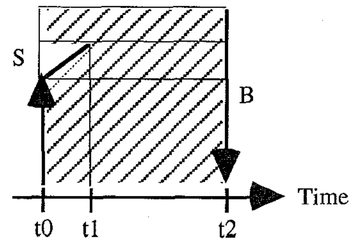
Several methods to calculate the energy consumed from extracted features within time ($t_0 = 0$, t_2) are shown below.



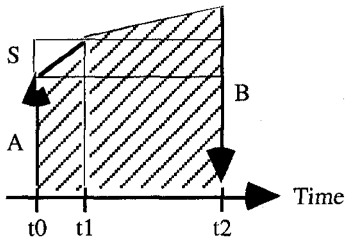
1) Given edges A and B and time markers t_0 and t_2, the energy is $E = (|A| + |B|)t_2/2$.



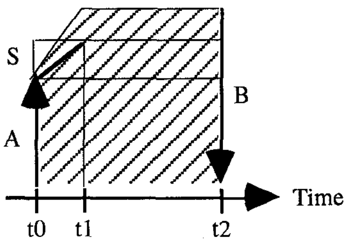
2) Given edge A and slope S and time markers t_0, t_1, and t_2, the energy is $E = (|A| + S)(t_2) - S\,(t_1)/2$. Note that S here is the 'length' of the slope times the sine of the gradient of the slope.



3) Given edge B and slope S and time markers t_0, t_1, and t_2, the energy is $E = |B|(t_2) - S\,(t_1)/2$.



4) Given edges A and B, slope S, and time markers t_0, t_1, and t_2, the energy is $E = (|A|+|A|+S)(t_1)/2 + (|A|+S+|B|)(t_2 - t_1)/2$.



5) Given edges A and B and time markers t_0, t_1, and t_2, the energy is $E = |B|(t_2 - t_1) + (|A|+|B|)t_1/2$.

Table 1 evaluates the methods for a heat pump compressor and a washer. The energy calculated from power samples (one sample per second) during a time interval of 15 minutes was considered as a reference (i.e. 100%). Then, the energy was calculated upon each method from the extracted edges and slopes. As the real power calculation is of greater interest than reactive power, method three gives the best results.

Methods	HP Compressor %	Washer %
1	93.0/100.0	101.3/99.6
2	91.8/98.7	97.5/99.7
3	95.5/101.4	97.4/99.3
4	91.9/98.8	97.5/99.7
5	93.8/100.1	97.4/99.8

Table 1. Percentage Watt/Var energy consumption of five methods with integral of data samples being 100%.

B. Comments on Precise Energy Calculations

Consider the expanded plot of a load in Fig. 5a. Extracted edges and a slope are shown in Fig. 5b. Notice, the change in power level of the rising edge is much less that the peak power, and clearly, not all of the energy consumed during the initial spike of the turn-on is represented by the rising edge. This is also true of the slope (and the steady-state if considered). For example, the slope shown in Fig. 5b. underestimates the energy consumed during the time of turn-on.

It was found that recording not only the beginning and ending power levels , but also a running average of the power samples defined as $\overline{X}_n = \frac{x_n}{n} + \frac{n-1}{n}\overline{X}_{n-1}$ times the duration of each feature gives within 1% of the heat pump compressor and the washing machine's energy consumption and is not computationally expensive. In the equation, x_n is the nth sample and $\overline{X}_n$ and $\overline{X}_{n-1}$ are the running average after the nth and (n-1)th sample respectively.

IV. SUMMARY

Using the features extracted from voltage and current sampling called the edges of power waveforms and slopes as well as a load identification algorithm, the distribution of the consumed residential energy among the loads can be determined. This information for each residence may then be used for rescheduling energy consumption, identifying inefficient or defective loads, and recognizing unknown or unauthorized uses.

ACKNOWLEDGEMENT

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