Nonintrusive Appliance Load Monitoring

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A nonintrusive appliance load monitor determines the energy consumption of individual appliances turning on and off in an electric load, based on detailed analysis of the current and voltage of the total load, as measured at the interface to the power source. The approach has been developed to simplify the collection of energy consumption data by utilities, but also has other applications. It is called nonintrusive *to contrast it with previous techniques for gathering appliance load data, which require placing sensors on individual appliances, and hence an intrusion onto the energy consumer's property.*

An interesting aspect of this research is the interdisciplinary manner in which it combines power systems theory and communications theory—power consumption is decoded as an act of information transfer. The theory and current practice of nonintrusive appliance load monitoring is described, including goals, applications, load models, appliance signatures, algorithms, prototypes, field-test results, current research directions, and the advantages and disadvantages of this approach relative to intrusive monitoring. Because of its many advantages, we expect that nonintrusive techniques will supersede conventional intrusive techniques for a wide variety of load monitoring applications.

I. Introduction

A nonintrusive appliance load monitor (NALM) is designed to monitor an electrical circuit that contains a number of devices (appliances) which switch on and off independently [1]–[20]. By a sophisticated analysis of the current and voltage waveforms of the total load, the NALM estimates the number and nature of the individual loads, their individual energy consumption, and other relevant statistics such as time-of-day variations. No access to the individual components is necessary for installing sensors or making measurements. This can provide a very convenient and effective method of gathering load data compared with traditional means of placing sensors on each of the individual components of the load. The resulting end-use load data is extremely valuable to consumers, utilities, public policy makers, and appliance manufacturers, for a broad range of purposes.

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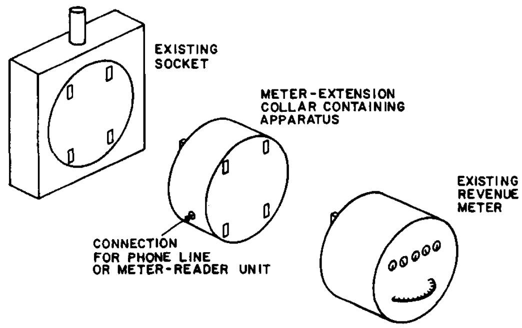

Fig. 1. Collar mounted nonintrusive appliance load monitor.

In a utility application, a NALM connects with the total load using the standard revenue meter socket interface, as shown in Fig. 1. This permits very easy installation, removal, and maintenance compared with traditional intrusive load monitoring techniques that require "submetering" and interior wiring. The NALM monitors the total load, checking for certain "signatures" which provide information about the activity of the appliances which constitute the load. For example, if the residence contains a refrigerator which consumes 250 W and 200 VAR, then a step increase of that characteristic size indicates that the refrigerator turned on, and a decrease of that size indicates the turn-off events. Other appliances have other characteristic signatures. After determining the exact on and off times from the signature events, any desired statistics, such as energy consumption versus time of day or temperature, can be tabulated.

To appreciate how this works, consider Fig. 2, which shows total (real) power consumption versus time for a single-family home over a fairly busy forty-minute period. During this interval, the total load shows a great deal of activity, due mainly to cooking. Four different-sized step changes are clearly present, providing characteristic signatures of the refrigerator, two oven elements, and a stove burner element. By also considering measurements of the total reactive power or harmonic current, along with the real power shown, changes in the resulting vector function of time would reveal even more information about the particular appliances.

Traditional load research instrumentation [40] involves complex data-gathering hardware but simple software. A

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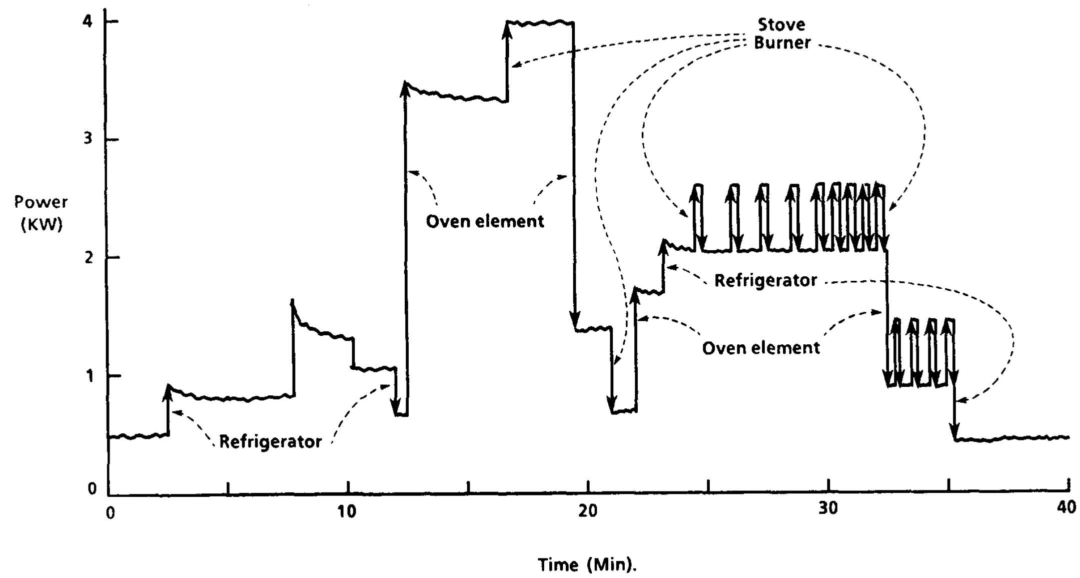


Fig. 2. Power versus time (total load) shows step changes due to individual appliance events.

monitoring point at each appliance of interest and wires (or sometimes power-line carrier techniques) connecting each to a central data-gathering location provide separate data paths, so the software merely has to tabulate the data arriving over these separate hardware channels. The NALM approach reverses this balance, with simple hardware but complex software for signal processing and analysis. Only a single point in the circuit is instrumented, but mathematical algorithms must separate the measured load into separate components. In many load-monitoring applications, this is a very cost-effective trade-off, which is a major advantage of the NALM. Balancing this are certain disadvantages, discussed below, which can dominate in other applications.

In order to accurately decompose the aggregate load into its components, a model-based approach for describing individual appliances and their combination is used. These models suggest certain signatures which can be detected in the total load to indicate the activities of the separate components. This leads naturally to practical architectures and algorithms for the NALM. We have implemented these ideas and carried out a number of initial field tests on residential loads to compare the NALM with traditional load monitoring techniques employed by electric utilities. Some results are presented to contrast the advantages and disadvantages of the two methods.

The following sections of this paper describe the goals, envisioned applications, load models, appliance models, signatures, algorithms, architectures, prototypes, field tests, and current directions of our NALM research. Space does not permit a discussion of certain topics in full depth. The list of references at the end includes a bibliography of publications directly discussing NALM, which is exhaustive to my knowledge, and should be consulted for further details.

II. Goals

There are two NALM goals, of different degrees of nonintrusiveness The second, less intrusive one is more ambitious technically, but has greater advantages:

(MS) "Manual-Setup": A MS-NALM is a nonintrusive appliance behavior tracker which requires a one-time intrusive period for setup. During the intrusive setup period, signatures are observed and named as appliances are manually turned on and off. It is distinguished from conventional intrusive instrumentation in that no hardware ever enters the premises being monitored.

(AS) "Automatic-Setup": An AS-NALM sets itself up as it measures the load, using *a priori* in formation about the characteristics of possible appliances. It must determine the important signatures, and the appliances with which they are associated, without the benefit of any entry or appliance survey.

The MS-NALM has been a stepping stone in the development of the AS-NALM, and will likely serve as an analysis tool for situations where the AS-NALM fails, but the AS-NALM should eventually dominate in most applications. Both types have been constructed and field tested; the first MS-NALM was built in 1984 [12], and the first AS-NALM a year later [11].

With changes in power[1] used as the signatures, as described in the introduction, the setup and operation of the MS-NALM could be as outlined in Table 1, with refinements to be described below. The AS-NALM is distinguished from the MS-NALM by the elimination of steps (1) through (4) in Table 1. Instead, it builds its own

[1] Here and throughout, *power* refers to complex power, or equivalently, the ordered pair of real and reactive power.

Table 1 Outline of monitoring Procedure with Manual Setup (MS-NALM)

(1)	A manual survey of the major appliances is taken.
(2)	The MS-NALM is installed (Fig. 1) and a keyboard is temporarily connected to it. When turned on, it is in "setup mode," in which it is taught the appropriate signatures.
(3)	Each appliance of interest is turned on and off individually, and the name of the appliance is typed to the keyboard. As this happens, the NALM monitors the power and a step change detector determines the size of the signatures and records them in a table along with the appliance name.
(4)	A command is given to place the NALM in "normal mode," and the keyboard is disconnected.
(5)	The NALM operates nonintrusively, continuously measuring the power level, checking for step changes, and comparing them to the sizes of the stored signatures. Whenever an observed step change is close enough to one of the known signatures, it is known that the appliance turned on or off, so the appropriate energy statistics for that appliance are updated.
(6)	At weekly, monthly, or other intervals, the collected energy statistics are transferred by telephone, meter reader, or other communication medium to the utility load research center.
(7)	Eventually the NALM is removed, simply by unplugging it from the socket and reinstalling the revenue meter.

table of signatures by observing and analyzing all step changes. They are then named based on *a priori* information programmed into it about what types of appliances are typically associated with what types of signatures. A further discussion of this "automated naming" process is given in subsection IX-I below.

Because of its total nonintrusiveness, the AS-NALM is clearly superior from the user's point of view if it can be as accurate as the MS-NALM. Results from field tests discussed below suggest that the AS-NALM can be made sufficiently accurate, but wider testing and a more complete implementation are required to confirm this. It is possible that certain difficult cases may be found which are best resolved with a manual setup. The MS-NALM is also the likely goal of the first current commercialization effort, both because of its relative simplicity and because it will provide information to enrich the appliance data base needed for the AS-NALM.

III. Applications

The primary application which has driven this research is monitoring for load research. Large electric utilities typically monitor dozens to hundreds of their residential customers with intrusive load monitors placed on two to eight major loads such as electric heat, water heaters, refrigerators, and air conditioning. This data is statistically averaged within demographic classes and used for a range of purposes by many audiences, including load forecasters, rate forecasters, public policy makers, and appliance designers [29]. NALM techniques are especially useful for utility monitoring of residential loads. The ease of installation will allow more appliances to be monitored in more homes, providing broader data, and in many cases more accurate data (see Section XII), than has been feasible with current technology. Lower cost, finer resolution, and ease of installation, removal, and maintenance (without requiring an appointment with the residents to gain entry) are very valuable features from the utility perspective [1].

A related application is the monitoring of individual utility customers for the purpose of an "energy audit." A NALM can be installed temporarily at the customer's request in order to analyze the characteristics of the appliances. After a week to a month, it would output a detailed energy consumption report which would be useful in suggesting ways to reduce consumption and costs. The report could be in the form of a "disaggregated" utility bill which appears much more like a telephone bill in that it itemizes charges. A second audit is often valuable to confirm the savings resulting from conservation measures.

Another use is power monitoring for failure analysis or security purposes. Failed appliances can often be detected by their unusual power consumption or duty cycles. As a by-product of one field test, a failed underground septic pump was detected by its abnormally low power consumption [6], [11]. In another field test, a refrigerator which was on almost all of the time was detected and replaced [20]. "Home automation" [39] is a closely related application area.

As a security example, a vacation home which is unoccupied for long periods can be monitored at a single point, yet check on many functions. The monitor could be programmed to automatically generate a phone message to report appliance usage above or below specified thresholds. If the refrigerator failed, if a security light burned out, if garage-door openers were activated, if the water pump was on excessively (perhaps indicating a burst pipe), etc., the owner would be notified immediately. Unfortunately, these applications also suggest issues of privacy, and surveillance applications in which the NALM can be abused. Those topics are treated at length in [6].

Another application involves the verification of demand-side load management control. Many electric utilities install appliance controllers on deferrable loads throughout their customer base, to shed them during times of peak power usage [30], [38]. A NALM can verify that the system is in fact operational, and has not been defeated by radio or customer interference. It can also be incorporated into "appliance interlock" forms of load control strategies. For example, a load controller could be designed to operate a deferrable load as a function of the on/off state of other, nondeferrable loads. The NALM can determine the state of the nondeferrable loads from a single sensor without the need to run sensor wiring from them.

The above applications may be residential, commercial, or industrial—three classes of utility customers that are treated only slightly differently, due to the different types of loads they contain. So far, the implementations and field test have been focused on residential loads because intrusion is more of a problem there, but with some consideration of commercial loads [2].

There is a final class of applications where the NALM may be an extremely valuable tool, but which we have not yet seriously explored: situations where one cannot get physical access to individual loads, so there is no way

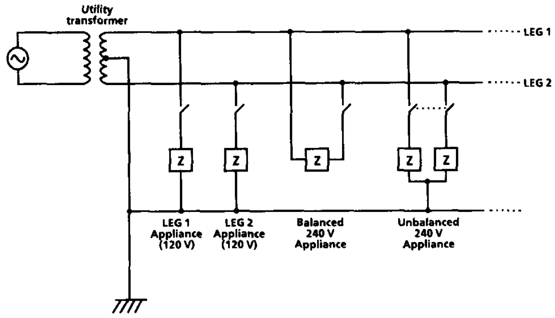


Fig. 3. Typical U.S. residential wiring, indicating a 120 V appliance on each leg, and a "balanced" and "unbalanced" 240 V appliance.

to monitor them with individual sensors. Examples might include circuits which are inaccessible within a VLSI chip[2] or because of submarine or extraterrestrial locations.

IV. Total Load Model

In order to decompose the total load into its components, we need models of individual appliances and their combination. Electrically, the combination appears straightforward, as appliances are simply wired in parallel on a power bus. Thus, to a first order approximation, the power they consume is additive. Fig. 3 shows the two-phase circuit used in most U.S. residential loads. The electric utility provides two 180° out-of-phase "legs," each at a nominal 120 V. All 120 V appliances are wired to one of two effectively at random. The 240 V appliances are wired from one leg to the other, and include a connection to ground if the load is "unbalanced" (meaning that the power consumption is not the same on the two legs).

Each load indicated with a Z in Fig. 3 might be an arbitrary nonlinear circuit, such as an electronic power supply. However, many are purely resistive, e.g., heating elements and incadescent lights; and many, e.g., motors, have a reactive component, but can still be modeled as linear. In this section, we will assume a linear model and associate a time-invariant complex power with each appliance. The imaginary part is zero for resistive appliances.

The model of Fig. 3 is inadequate in that many appliances contain several individual loads as building blocks. For example, an electric clothes dryer may contain a 120 V motor and 240 V thermostatically switched heating element, controlled so that the motor may be on while the heating element is off, but not vice versa. Another complication is that a portable 120 V appliance, such as an iron or a vacuum cleaner, may appear on both legs (at different times) according to which wall socket it happens to be plugged into. These and other aspects of modeling individual appliances are discussed in later sections; here we assume the model of Fig. 3 and focus on issues related to their combination.

[2] Fault detection in VLSI, based on excessive power consumption, but not changes in power, is discussed in [27].

The total load clearly depends on which applicances are switched on at any given moment, so we must describe a *switch process*, $a(t)$. Suppose there are n appliances, numbered 1 to n and let $a(t)$ be an n-component Boolean vector describing the state of the n switches at time t:

$$a_i(t) = \begin{cases} 1, & \text{if applicance } i \text{ is on at } t, \\ 0, & \text{if appliance } i \text{ is off at time } t \end{cases}$$

for $i = 1 \cdots n$. The switch process modulates the power consumption of the individual appliances.

A multiphase load with p phases can be modeled as a p-vector in which each component is the load on one phase. The total load p-vector is the sum of the individual appliance load p-vectors for those appliances switched on at any given point in time. This will be a vector function of time which steps in characteristic increments whenever an appliance switches on or off. For $i = 1 \cdots n$, let P_i be the p-vector of the power that the ith appliance consumes when it is operating. For the two-phase circuit of Fig. 3, each P_i is a two-component complex vector. The real and imaginary parts for the complex power in the jth component of the vector correspond to the real and reactive power consumed on the jth leg. One of the two components is zero for 120 V appliances, as only one leg is involved; the two components are equal for balanced 240 V appliances; and an arbitrary vector represents an unbalanced 240 V appliance. Then we model

$$P(t) = \sum_{i=1}^{n} a_i(t) P_i + e(t), \tag{1}$$

where $P(t)$ is the p-vector as seen at the utility at time t, and $e(t)$ is a small noise or error term. This sum of steps and noise can clearly be seen in Fig. 2.

The model (1) suggests a straightforward criterion for estimating the state of the individual appliances. If all n of the P_i are known and the measured power $P(t)$ is given, at each t choose the n vector $a(t)$ which minimizes $|e(t)|$, under the constraint that a is an n-dimensional Boolean vector. This is a well-studied combinatorial optimization problem:

$$\hat{a}(t) = \arg\min_{a} \left| P(t) - \sum_{i=1}^{n} a_i P_i \right|. \tag{2}$$

Even with scalar P variables it is an NP-complete "weighted set" problem [28]. This means it is computationally intractable, and one could not hope to solve it exactly other than by exhaustive techniques that are impractical unless n is very small. However, heuristic algorithms might be devised which provide reasonable solutions to (2) most of the time.

Although mathematically attractive, there are a number of difficulties in estimating $a(t)$ with (2). The fundamental problem with the approach of (2) is that the complete set of P_i are never known. Indeed, it is not clear that one should model a residence as having a well-defined number, n, of appliances, because appliances come and go due to purchases, visitors, seasonal changes, etc. If (2) were used in the presence of unknown appliances, it would spuriously attempt to describe their behavior as a combination of other known appliances.

A more subtle problem is that the nature of the solution that (2) provides can be very inappropriate to the problem, even if all the P_i are known. A small change in the measured $P(t)$ would often be analyzed as a big change in the switch process, $a(t)$, with a number of appliances turning on or off simultaneously in such a way that the net change in (1) approximates the observed change as well as possible. For example, suppose a residence contains four loads of sizes $P_1 = 100$, $P_2 = 200$, $P_3 = 300$, and $P_4 = 401$ W. If the measured total load at time t is 500 W, the best estimate is that the second and third appliances are on, i.e., $\hat{a}(t) = [0, 1, 1, 0]$, as that uniquely gives $e(t) = 0$ in (1). If a moment later, at time $t + \Delta t$, the measured load increases slightly to 501 W, the best estimate would then be $\hat{a}(t + \Delta t) = [1, 0, 0, 1]$, which again has $e = 0$, but implies that every appliance changed state in a short interval Δt. Our intuition that every appliance in a residence could not change state simultaneously reflects our knowledge of the physical independence of different appliances. This suggests a criterion which is not described in the model (1):

Switch Continuity Principle: In a small time interval, we expect only a small number of appliances to change state in a typical load.

Unfortunately, it is rather difficult to quantify this principle in a meaningful way that would lead to an improvement to (2). Perhaps (2) could be modified for NALM applications if we added a term to the right-hand side proportional to the number of state changes in $a(t)$, but we have not pursued that avenue of research. Thus, we do *not* use the total-matching principle of (1) and (2) as the basis for the NALM. We present it here both to point out its difficulties and because it may be appropriate for similar problems in which switch continuity is less important and the set of P_i is fixed and completely known. Perhaps the case of circuits switching within a VLSI chip, suggested in Section III, could be approached in this manner.

Instead, we begin with the switch continuity principle as the foundation for the NALM. It has a consequence that in any small enough time interval, we expect the number of appliances which change state to be usually zero, sometimes one, and very rarely more than one. But, we cannot expect to quantify these cases probabilistically for residences in general based on prior knowledge, as it depends on the type of resident-dependent appliance behavior that the NALM is designed to collect.[3] However, examination of measured data such as Fig. 2 shows that it is relatively easy to segment the total load into periods in which it is approximately steady, separated by clearly defined step changes. We thus have the signature approach—to examine the measured $P(t)$ and determine if a step change occurs by heuristic procedures. The particular step-change detector we designed for the prototype NALMs is described in subsection IV-C below.

Given the times and sizes of the step changes, one can look through a given list of P_i (and the negatives of the P_i) to determine which appliance turned on (or off) causing each change. This is the essence of our MS-NALM, with additional refinements to be discussed below. Note that this approach does not suffer the problem described above concerning the power increase from 500 W to 501 W. A change of 1 W is far too small to be considered a step change at all. The method is also not confused by an incomplete set of P_i. By specifying a tolerance condition for matching, the MS-NALM simply ignores any observed change which is not sufficiently close to any of the given P_i. Thus it can be given a list of the appliances of interest to monitor, and all other activity is ignored.

This model is still somewhat simplistic, however, and can be improved in many ways, to handle simultaneous state changes of more than one appliance, other signatures than power, multistate appliances, etc., as described in the following sections. One problem which can only be partially remedied is that electrically identical appliances cannot be distinguished. For example, one may not be able to separately totalize the power consumed by two 1200 W resistive appliances on the same leg, e.g., a toaster and a quartz space heater. However, this is not a major drawback in the primary utility applications, and can be alleviated by the use of "tags" as discussed in subsection VI-B-1.

V. Appliance Models

We have considered three classes of appliance models. In order of increasing generality, we call them:

- ON/OFF
- Finite State Machine (FSM)
- Continuously Variable.

The discussion in Section IV is only relevant to the ON/OFF model, where the Boolean switch function allows that an appliance may be either on or off at any given time, but allows for only a single type of ON state. This is a good model for most household appliances, such as a toaster, light bulb, or water pump. However, it makes no provision for electrically distinct types of ON states as found in a typical toaster oven (bake/broil/toast), three-way lamp (low/medium/high), or washing machine (fill, agitate, spin).

The finite state machine (FSM) model allows for an arbitrary set of discrete states and state transitions. Fig. 4 shows FSM models for some typical appliances. The circles indicate the states, which are identified here by a name and an operating power level. The arcs indicate the allowed state transitions, and are labeled with the signature which is observed to accompany the state transition. For clarity, the figure only shows scalar real power changes as signatures, but these should be understood as schematic for more general complex p-vector signatures, as in Section IV.

[3] Simultaneous events, or nearly so within 2–3 seconds, accounted for 4% of the events in one field test where they were carefully counted [12], but this will vary considerably, depending on the appliance inventory and usage.

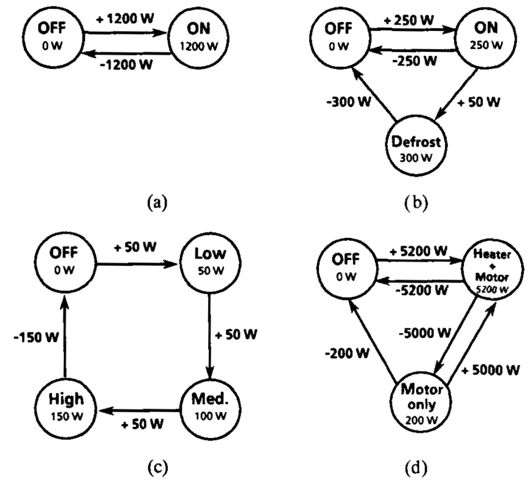


Fig. 4. Finite-state appliance models: (a) generic 1200 W two-state appliance, e.g., toaster; (b) refrigerator with defrost state; (c) "three-Way" lamp; (d) clothes dryer.

Many common appliances, including frost-free refrigerators, heat pumps, dishwashers, washing machines, and an increasing number of new microprocessor-controlled appliances, are well described by the FSM model, but inadequately represented by the ON/OFF model. In order to implement a MS-NALM with FSM models, we need a procedure to track the state transitions of a known FSM. For the AS-NALM, we need algorithms to learn FSM representations. Solutions to these problems are discussed in the following sections.

Our prototype NALMs have used only the ON/OFF model so far, and therefore have not been able to properly account for multistate appliances. When an FSM device is analyzed with the NALM algorithms designed for ON/OFF devices, field tests show that a number of different errors can result. In the most pleasant case, a complex device is simply divided into components. For example, if the motor and heating element of the dishwasher operate independently, they are learned as two devices, and the energy is appropriately apportioned between the two. In other cases, part of the appliance is not learned at all. For example the motor and heating element of a clothes dryer (Fig. 4(d)) always start together; then the heating element cycles thermostatically. While most of the heating cycles can be detected, the motor never turns on by itself to generate ON events that match the OFFs, and our ON/OFF algorithms do not detect it. In a third class of appliances, e.g., Fig. 4(c), no ONs and OFFs match, so nothing is reported.

For these reasons, we consider FSM algorithms to be a priority in future field tests. Preliminary experiments [14] suggest that the methods can be developed to an accuracy comparable to ON/OFF appliances without an undue increase in computation.

An important point to notice about the FSMs in Fig. 4 is that the signatures labeling the arcs cannot all be chosen arbitrarily. In parts (a) and (b) of the figure, the transition from ON to OFF is the negative of the transition from OFF to ON. Furthermore, the sum of the signatures encountered in cycling around the three-state loops of parts (b) and (d) or the four-state loop of (c) is zero. Generalizing, we have the following constraint:

Zero Loop-Sum Constraint (ZLSC): The sum of the power changes in any cycle of state transitions is zero.

The ZLSC is analogous to Kirchhoff's voltage law, and is the discrete-space analogue to the constraint that the curl of a conservative vector field is zero. It arises for a similar reason: because the change in power is the difference between the operating power levels of two states, and so is analogous to the gradient of a scalar potential. Constraints of this sort are very important for the AS-NALM as they limit the possibilities which must be considered in the learning process. We will see in Section VI that the ZLSC holds for certain types of signatures (e.g., power step changes) but not others (e.g., transients), and its presence determines a number of other factors about the processing and information value of different signature choices.

Generalizing from the FSM model, we come to the third class of appliance models: continuously variable appliances, which have an infinite number of states. A few small appliances, e.g., light dimmers, sewing machines, and variable-speed drills, have a truly continuous range of operating power levels, and so do not generate consistent step-chage signatures. They therefore do not fit into the ON/OFF model or the FSM model, and cannot be handled by the methods of this paper. Currently, this is not a significant limitation for residential load monitoring purposes because of the insignificant amount of energy consumed by this class of appliance. It is likely to be more important in commercial and industrial applications, where variable-speed drives are more prevalent. It may also assume more importance in residential loads in the future, as continuously variable heat pumps will become more common [37]. Techniques for learning and tracking the behavior of continuously variable appliances remain an important topic for future work. The discussion in the remainder of the paper is applicable to only the ON/OFF and FSM appliance models.

One final, minor constraint can be mentioned which applies to all three appliance model classes. In the learning part of the AS-NALM we assume that the operating real power of an appliance is never negative. This is because at the utility interface, one cannot tell the difference between a load turning on and a power source turning off. To eliminate the ambiguity, we assume there is no power generation taking place in the load. This is reasonable in practice, as a utility congenerator would be monitored by other techniques.

VI. Signatures

The role of appliance signatures should be clear from the above discussion—they are the essence of the NALM and so deserve very careful consideration. Generally, an appliance signature can be defined as a measurable parameter of the total load that gives information about the nature

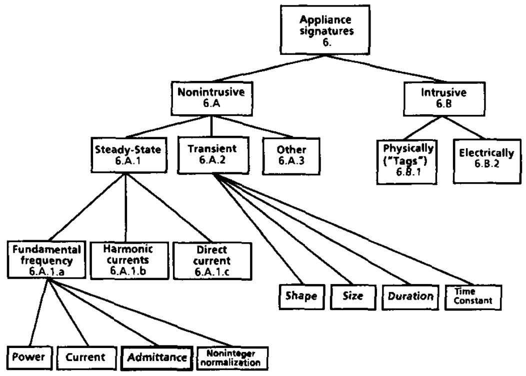


Fig. 5. Signature Taxonomy. Out of many possible informative signatures, our prototypes have relied only on admittance.

or operating state of an individual appliance in the load. A vector format is natural for representing signatures, in which each component can be a parameter of one of the following types as measured for one phase of the total load. For introductory purposes, the previous sections were confined to using changes in power as a two-dimensional signature vector, but in fact, power is not the optimal signature for our purposes.

A partial taxonomy of the types of signatures we have considered is presented in Fig. 5, with power appearing at the bottom left. Fig. 5 also serves as a table of contents for the following subsections, which follow the tree structure shown, from top to bottom and left to right. The top-level breakdown is between "intrusive" and "nonintrusive" signatures.

A. Nonintrusive Signatures

A nonintrusive signature is one which can be measured by passively observing the normal operation of the load, e.g., a step change in the measured power. This is in keeping with the general NALM philosophy of nonintrusiveness, and contrasts with the intrusive signatures discussed in subsection VI-B below. Within the nonintrusive signatures there is a natural dichotomy according to whether information about the appliance state change is continuously present in the load as it operates ("steady-state signatures") or only briefly present during times of state transition ("transient signatures").

1) Steady-State Signatures: Steady-state signatures derive from the difference between steady-state properties of operating states, e.g., the changes of power labeling the arcs in Fig. 4, calculated as the difference between the operating levels of the connected states. The particular parameter of interest need not be power, however, and need not be measured at the utility fundamental frequency. The following subsections explore some of the possibilities. Our prototype NALMs have relied only on steady-state signatures, for three reasons:

The first is that a continuously present indication of an appliance's operating state is much easier to detect than a momentary indication. For example, the sampling rates and processing requirements necessary to detect a step change in power are far less demanding than those required to capture and analyze a transient current spike. If the turn-on of a device of interest is characterized equally well by its power consumption or starting spike, system requirements argue for the former.

The second important property of steady-state signatures is that they are exactly the set which satisfy the ZLSC of Section V. (In contrast, transient currents occurring at state changes need not satisfy any similar constraint.) This has two consequences. One is that it provides a basis for the FSM learning algorithm of the AS-NALM, described in subsection IX-E below. The second is it implies that turn-off events have a signature. In contrast, most appliances which generate a transient at turn-on generate no transient at turn-off.[4] Thus a detector for steady-state signatures provides information about a larger number of state changes than a detector for transients.

The third reason for using steady-state signatures is that they are additive when two happen coincidentally. For example, the simultaneous turning on of a 4 kW water heater and turning off of a 250 W refrigerator result in a 3750 W step increase being detected in the total load. In accordance with the switch continuity principle of Section IV, this is rare, but not negligible. The additivity of steady-state signatures allows simultaneous events to be properly analyzed when their sum is received, as discussed below in Section VII. Transient properties, in contrast, are not additive.

a) Fundamental frequency signatures: At the utility fundamental frequency (60 Hz in the U.S.) we can measure the power, current, or admittance of the total load and look for step changes as signatures.[5] It might appear at first that these are proportional and hence equivalent, being simply related by successive factors of the line voltage, V. The situation is not that simple, however, because V is really the time varying $V(t)$. While U.S. utilities provide a nominal 120 V, the actual voltage varies within $\pm 10\%$, often with fairly rapid fluctuations and step changes. See [12] for some measured data. A linear device plugged into this varying voltage supply will draw a current which also varies $\pm 10\%$. The power consumption will then vary by over $\pm 20\%$.

The essence of the NALM is that changes detected in the total load should give information about events within the load. Therefore, power consumption which varies $\pm 20\%$ for reasons external to the load does not provide an ideal signature. To vitiate the vicissitudes of V, the linear model suggests that admittance is preferable to power and current as a signature. It is a voltage-independent property of a

[4] The only appliance we have observed to have a consistent turn-off transient is an old fluorescent desk lamp which produces a large current spike at turn-off. See [3] for a figure. Turn-off transients from induction motors are described in another context in [35, p. 118].

[5] Power, current, and admittance are intended here in the complex sense, or as an ordered pair of an in-phase and out-of-phase component; however, either of the components alone could also be used as a (less informative) signature, e.g., the conductance or susceptance of the load. More generally, any invertible linear transformation of the signature space provides an equivalent space, and a projection onto a subspace may be adequate.

linear device, and is additive when appliances are wired in parallel as they are in Fig. 3. The load admittance, $Y(t)$, can be calculated from the measured power, $P(t)$, and RMS voltage, $V(t)$ as

$$Y(t) = \frac{P(t)}{V^2(t)}. \quad (3)$$

While formally proper, admittance is an unfortunate choice of signature because it is somewhat unfamiliar and one lacks engineering intuition about the values to expect and their units (siemens). Thus we prefer to deal with admittance in the guise of "normalized power":

$$P_{\text{Norm}}(t) = 120^2 Y(t) = \left(\frac{120}{V(t)}\right)^2 P(t). \quad (4)$$

This is just the admittance adjusted by a constant scale factor, resulting in the power normalized to 120 V, i.e., what the power would be if the utility provided a steady 120 V and the load obeyed a linear model. It is a far more consistent signature than power, as evidenced by data in [11] and [12]. All of our prototype NALMs use step changes in the normalized power (4) as the signature.

The resulting "signature space" of one field-test site is plotted in Fig. 6. In order to map the four-dimensional space (real and reactive power on each of two legs) onto a two-dimensional image, Fig. 6(a) shows the 120 V appliances on leg 1 and Fig. 6(b) shows those on leg 2 along with the 240 V appliances. First a scatter plot was generated of the step changes in normalized total power observed over one week. What is shown are regions of the complex power plane which were found to contain a large number of those events, calculated according to a cluster analysis algorithm described below in subsection IX-D. If power was not normalized, the scatter within each cluster would be significantly larger, reducing the discrimination between appliances.

To further reduce the within-cluster scatter, a slightly different normalization may be preferred. While (4) makes sense based on a linear appliance model, measurements show that most appliances are not linear devices. A more general model for the power–voltage relationship is

$$P(t) = \alpha V^{\beta}(t),$$

which reduces to the linear model if the exponent, β, is 2. Then (4) generalizes to

$$P_{\text{Norm}}(t) = \left(\frac{120}{V(t)}\right)^{\beta} P(t). \quad (5)$$

This is generalized further by allowing separate exponents for the real and reactive components of the load.

The resulting model, (5), was fit to measured data collected by varying the voltage applied to individual appliances in a laboratory environment. Table 2 shows the exponents found to give the most voltage-independent normalized power in the range 115–125 V [11]. It is interesting that only the coffee pot shows the theoretical value of 2. The water in the coffee pot stabilizes the temperature of the heating element, which keeps its resistance constant. It is therefore well approximated by a linear circuit element. The light bulb, in contrast, shows a distinct nonlinearity. Its power consumption increases slower than quadratically because the filament resistance increases at the higher temperatures that result from higher voltages.

Table 2 Optimal Normalizing Exponents, β, for Individual Appliances

	Real	Reactive
Coffee Pot	2.0	—
Light Bulb	1.5	—
Table Fan	1.2	2.4
Refrigerator	0.7	2.9

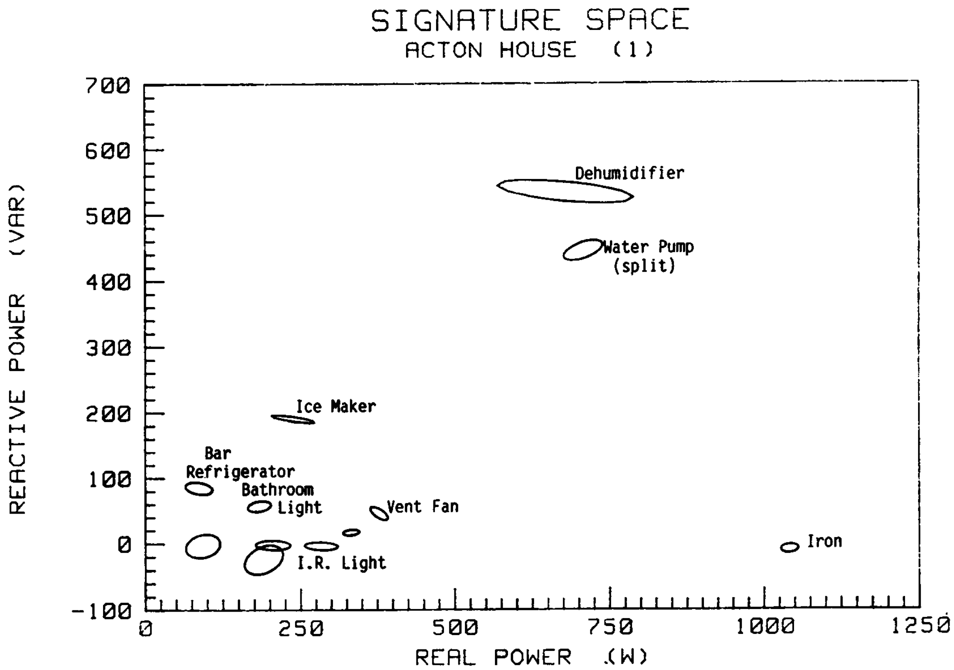
The effect in induction motors of a faster than quadratic reactive component and a slower than quadratic real component is to tilt the corresponding ellipses in Fig. 6 to the upper left and lower right. When one component is higher than average, the other is lower than average. This may provide useful information for naming appliances; see subsection IX-H.

These trends are consistent with a larger study of voltage dependence reported in [24]. Thus, it seems that normalization could be improved with noninteger exponents below 2 for the real portion of the load, and above 2 for the reactive component. It remains unclear, however, how far from 2 the values should be to optimize performance over the widest range of target appliances. Because of these uncertainties we used $\beta = 2$ in our prototype NALMs, but future work should address this issue more definitively.

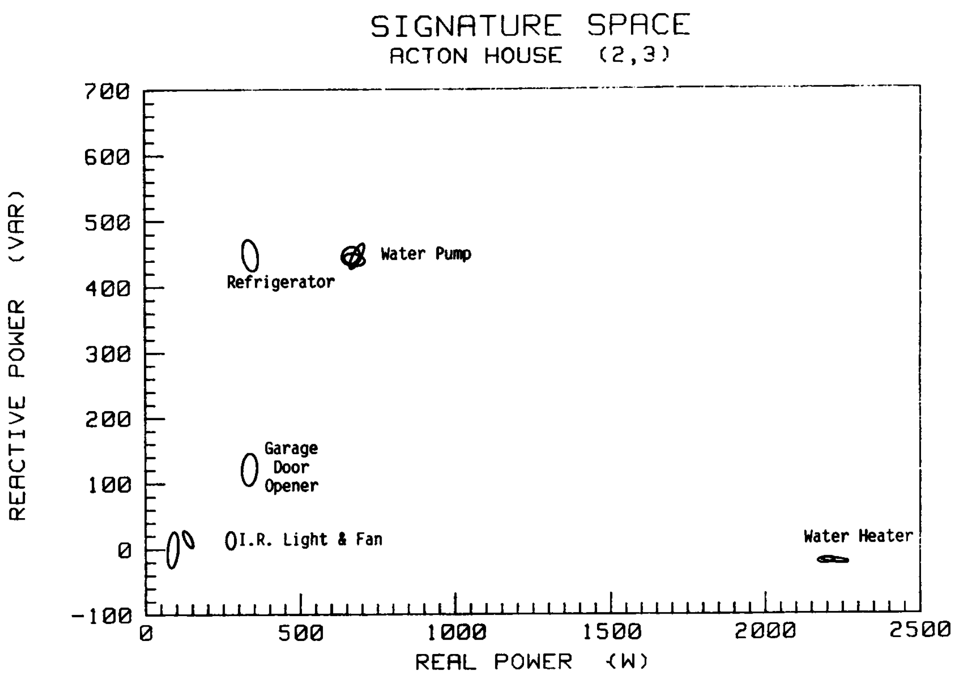
b) Harmonic frequency signatures: Additional information can be obtained by examining the harmonic currents generated by appliances. A linear model suggests that with a sinusoidal utility voltage waveform, the current response would be sinusoidal, but many appliances are decidedly nonlinear in this respect. Many motors have a triangular current waveform which contains significant third, fifth, and other low-order odd harmonics. Many electronic power supplies generate significant current at higher frequencies, often switching in the ultrasonic (20–40) kHz) range so they do not affect human listeners. Light dimmers, small motor controllers, televisions, and virtually all appliances other than resistive heaters and incandescent lights produce an assortment of harmonic currents [12].

Given an appropriate sensor for the frequency range of interest, these can be treated as steady-state signatures on a par with the fundamental frequency signatures. The dimension of the signature vector is simply increased to whatever number is desired. As discussed in Section XIII below, harmonic current signatures may be very useful if it is desired to identify certain small appliances which are too similar to distinguish looking only at the 60 Hz real and reactive power.

c) Direct current signatures: The direct-current consumption of an appliance is another nonlinear property like harmonic currents. Some small heating appliances (curling irons and crock pots) with two heating levels (low/high)



(a)



(b)

Fig. 6. Normalized complex power signature space. Resistive appliances (water heater, iron, infrared light) appear on the real power axis. Motors have a reactive component.

apparently place a diode in series with the heating element to implement the low setting. This results in a half-wave rectified current waveform with a significant dc component. See [12] for a current waveform figure. However, we have encountered no appliance of significant interest to utilities that has a substantial dc current flow.

2) *Transient Signatures:* As discussed in subsection VI-A-1, transients are more difficult to detect and provide less information than steady-state signatures. However, they are worth investigating if they provide useful information to augment that from steady-state signatures. For example, two types of appliances which consume identical amounts of power may have very different transient turn-on currents. Analysis of the transient could provide the deciding information to determine which of the two is actually present in the load. This would be most useful when only one of the two appliance types was present in the load. If the load contained one of each, the transient could also determine which of the two turned on when the common steady-state signature was observed. However, turn-on transients would not distinguish between two appliances that are on when one turns off, so accurate statistics could not be tabulated if both were on simultaneously.

A more detailed discussion of transients, with oscilloscope tracing of the start-up current transients captured from a number of household appliances, can be found in [12]. (Additional figures are given in [3].) Here we summarize some of those observations.

Transients in consumer applicances appear to come in different shapes, corresponding to the generating mechanism. Here are three categories we observed: (a) Many motors have a starting coil which provides torque for starting but is then switched off automatically after a brief delay. These transients have a flat character with a sudden step power drop to the steady-state operating level. (b) A second class of motors consume sudden large increases in power followed by exponentially enveloped decays lasting several seconds. These are the electrical consequence of the mechanical transient of the shaft coming up to speed. (c) A third class of transients, found in miscellaneous appliances, are very variable and typically shorter than one or two voltage cycles. These include both what are presumably truly transients in the linear circuit theory sense, and also the surge and drop in current associated with incandescent filaments heating up from their cold resistance.

Other parameters for categorizing transients are their size, duration, time constants, or parametric variables in models which can be fit to the observed waveforms. They are easily incorporated into the FSM model by labeling each arc with whatever transient parameters are relevant for the associated state change. For reasons discussed above in subsection VI-A-1, and because of the variability of transients (which often depend on the exact point in the voltage cycle at which the switch opens or closes), we have not pursued them as signatures in our prototype NALMs.

3) *Other Nonintrusive Signatures:* Examination of total house power has revealed a few other types of signatures which are hard to categorize in the terms introduced so far. While these are very specific to particular appliances of somewhat low interest to utilities, they are very informative for those appliances, and may lead eventually to other more valuable results.

One very specific signature of a washing machine is an approximately 1 Hz ripple in power consumption caused by cyclic reversals of the tub during agitation. This is in essence a subharmonic which should be very easy to detect with a filter designed for that frequency range. Although it is not present during the complete wash cycle, it is present during the periods in which most of the washing-machine energy is consumed. See [12] for a figure.

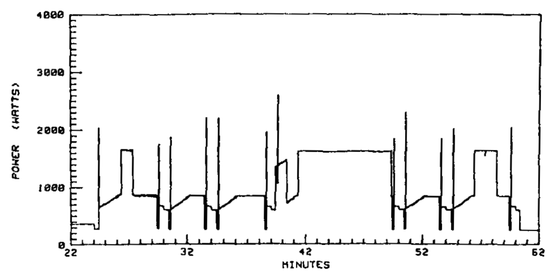


Fig. 7. Dishwasher power consumption.

A most unusual signature of a dishwasher is a ramp in its power consumption. Fig. 7 shows a plot of dishwasher power versus time in which six ramp periods are clearly visible. It also suggests how complex FSM models might have to be in order to fully capture appliance behavior. We believe the ramps are a consequence of an increasing head on a pump as the water level rises during a filling cycle. No other appliance we have observed displays any similar ramping behavior. Detecting ramps is an interesting problem because of their extended duration—notice that the fourth ramp of Fig. 7 is divided into two portions by a downward step change. The "weak rod" method described in [21] is one approach to ramp detection which may be explored in future work.

B. Intrusive Signatures

Intrusively generated signatures require some form of physical or electrical intrusion, and so are less desirable than the nonintrusive signatures discussed above. They may be necessary in situations where passive techniques are not sufficiently informative. We have not yet tested any of the ideas presented in this subsection, as we have focused our research on seeing how much can be accomplished with nonintrusive techniques alone.

1) Physically Intrusive Signature Generators: One technique, requiring a brief physical intrusion, we call a tag. Various devices can be constructed which are attached to an appliance during a single initial intrusion and then generate a signal whenever it operates. For example, a circuit can be constructed which generates a certain current harmonic, or which injects a radio frequency signal on the power line whenever the appliance consumes power. This could be made lightweight and attached to the power cord of portable appliances such as hair dryers or vacuum cleaners to provide a signal indicating their activity no matter where they are plugged in. Tags can also be used to distinguish between two otherwise identical appliances. While the intrusion to install tags is somewhat akin to conventional instrumentation, it has significant advantages:

it would only be required in difficult cases, the tags can be installed very quickly, and no intrusive wiring is required.

Many different techniques might be employed in the signal generated by the tag. Any of the nonintrusive signature types discussed above could be mimicked. For example, a constellation (in the coding theory sense) of regions of the complex power plane not populated by existing appliances could be chosen. The capacitive axis is a natural choice because no energy would be consumed and there appear to be no appliances in use with a highly capacitive power factor.[6] The advantage to this strategy is that the same decoding techniques already in place in the NALM are all that is necessary in the receiver. For maximum ease of detection, these tags, which use portions of the existing signature space, could have a small delay built in between when they detect current flowing into the appliance and when they generate their signal. Alternatively, tags could generate transients or higher frequency signatures, requiring a small increase in the complexity of the receiver.[7]

2) Electrically Intrusive Signature Generation: An electrically intrusive signature involves injecting a signal such as a voltage harmonic or transient at the utility interface. By noting the change in the current waveform, information can be gleaned concerning the types of devices active at the moment. This type of estimation technique can be likened to radar or sonar, in that a signal is sent into the load, and the "echo" which comes out is examined for information. Because of concerns about interference and power quality in general, utilities have been understandably reluctant to endorse this form of active signature. Accordingly, we have not pursued these sonar-like signatures beyond the conceptual stage. Their potential advantage, of course, is that they provide new dimensions of information, with no physical intrusion required, in keeping with the ideals of the NALM.

VII. Communication Model

It is insightful to consider the NALM in the context of a communication model. Appliances can be thought of as "transmitters," inadvertently broadcasting information as a by-product of their operation. The communication "channel" here is the house wiring. Any of the many signatures presented in Section VI may be the "codes" used in this communication scheme. Our task is to design a "receiver" for these codes which can decode them in terms of appliance state-change "messages."

The channel here has a number of excellent properties from the communications point of view. It is a relatively short and thick piece of copper, and the messages are transmitted over it at a low rate. The 24-hour average found in field tests is typically 20 to 30 appliance events per hour, with peak activity of 20 to 30 per minute. Furthermore, the transmission power levels are quite high, e.g., a 4 kW signal is present for several minutes to encode the message that the water heater is on.

Balanced against these favorable conditions are several factors making for a poor communications system. Most seriously for the AS-NALM is that we are not given the transmitter's code table. We do not know in advance what the messages or codes will be, how many distinct messages there are, or how to interpret the codes we do find. For example, while most homes have a refrigerator, and there is a certain electrical similarity among refrigerators owing to the economics of appliance manufacturing and marketing, there is still a wide range of variability within this class. Also, the power consumption range of refrigerators overlaps the classes of other appliances such as window air conditioners and water pumps. This problem is overcome in the MS-NALM by manually identifying the messages to build a code table. Our "adaptive receiver" for learning the appliance FSMs in the AS-NALM will be discussed in the next section.

A second problem with this channel is that it is a multiple-access channel, meaning that several transmitters might want to send messages simultaneously. Traditional techniques for dealing with multiple access channels such as computer buses or earth-satellite links involve contention resolution mechanisms in the transmitters. Here, the transmitters are the given appliances—an immutable part of the system—so other techniques are necessary. Our solution is to exploit the linearity of the channel in a new decoding algorithm referenced below.

A third difficulty from the communications perspective is the nature of the "errors" introduced in the channel. Assume now that we have FSM models for the appliances of interest, and we have a stream of measured step changes or other signatures. We need then to assign the individual events to particular appliances, choosing paths through each FSM which specify the states visited and the time of each state change. (From this, tabulating the energy statistics is straightforward bookkeeping.) Of course, there must be some tolerance allowed between the expected signature and the measured signature, to account for noise, variability in the load, or the coincidentally simultaneous activity of some small appliance.

The well-known Viterbi algorithm (VA)—a form of dynamic programming—is an optimal decoding technique designed for situations similar to this [42]. However, our channel includes several types of data corruptions not allowed for by the VA. The VA corrects errors in which one symbol is corrupted into another in the channel, but not errors in which symbols are inserted into or deleted from a message sequence—it is only valid for symbol-synchronized channels. Owing to the independent activity of unidentified appliances, our channel will appear to insert many symbols not generated by the known FSM. There will also be apparent deletions and mergers of expected symbols when different appliances happen to change state simultaneously.

[6] A pump found in dishwashers is the only residential device we have encountered with any capacitive reactive power [11].

[7] For 240 V appliances, a device which pumps power from one leg to another (e.g., a solid-state device analogous to a 120 V motor on one leg physically tied to a 120 V generator on the other leg) would produce a unique class of signatures.

To deal with these problems, we have designed a decoding algorithm which vastly generalizes the VA. Given an FSM representing the message source, it optimally corrects insertions, deletions, mergers, and many types of errors which can occur in the channel [13], [22]. One type of channel error which it corrects is the blending of a specified pair of codes into a third code. This is used to correct the mergers resulting from simultaneous transitions. A further discussion and detailed example with simulated data is given in [13]. Our field-test NALMs have not yet caught up with these developments; they only decode two-state (ON/OFF) FSMs and correct simultaneous events by a more exhaustive method described in [11] and [20].

A final comment about the communication model is that it suggests the notion of "jamming." The NALM is easily defeated by purposely charging and discharging an energy storage device using random step function as a control, e.g., a motor/generator/flywheel. This is an option for anyone concerned about the privacy of their transmissions [6].

VIII. Learning FSMs

Even more difficult than tracking behavior is the task of learning FSM models from examples of their behavior. For FSM models, as with ON/OFF models, the task is simpler in the MS-NALM than the AS-NALM. For the MS-NALM in setup mode, we need to learn FSMs one at a time as the appliance is manually operated in isolation. For the AS-NALM, we need to learn each individual FSM model from the interleaved combination of all their behaviors. Many signatures may be involved in each FSM, and the proper graph structures must be determined. The algorithms sketched here are tentative in that they have been tested with small amounts of data only; future work includes extensive field testing with monitored home data.

Considering the MS-NALM first, the problem is to construct a FSM given a sequence of signatures which it generates. We assume that everything else in the load is not changing state. Surveys of general techniques for constructing individual FSMs from streams of data they generate are listed in [7]. Our approach here takes advantage of special algebraic properties of steady-state signature events, such as the ZLSC.

As a simple illustration, suppose we receive signatures

$$+50\ +50\ +50\ -150\ +50\ +50\ +50\ -150\ +50$$
$$+50\ +50\ -150\ \cdots$$

as a three-way lamp is manually operated. We seek the FSM which models it. The correct solution is clearly Fig. 4(c), a cycle of four states. The solution is not unique, however, as a cycle of eight (or 12, or any multiple of four) states can be made which is just two (or more) copies of Fig. 4(c) spliced together into a larger loop. To avoid these spurious solutions, we propose a second constraint on FSMs:

Uniqueness Constraint (UC): Distinct states in an FSM appliance model have distinct operating power levels.

This means there cannot be two *Off* states with a power level of 0 W, or two *Low* states at 50 W, etc. The UC is in fact the converse to the ZLSC. The UC says that if a sequence of state transition events add to zero, ie., if the beginning and ending states of the sequence have the same power level, then the sequence is in fact a cycle. The eight or 12-state cycle violates the UC because pairs of states four events away from each other have the same power level but are not identical. So, for the sample data above, only the correct four-state FSM Fig. 4(c) results. The UC is not essential to appliance design and construction, but it appears that it is rarely violated. For example, each of the FSMs in Fig. 4 satisfies the UC. Note that the UC generalizes to all steady-state signatures.

Given the UC, the MS-NALM FSM learning algorithm is straightforward. Each observed power level (relative to the constant background power if some appliances are left constantly on during the setup period) corresponds to a unique state. Each observed signature then indicates the presence of an arc in the FSM between the previous and subsequent states. Some issues to work out involve noise tolerances, e.g., criteria for deciding when two operating levels are close enough to be considered a single state versus distinct enough to be considered two states.

For the AS-NALM, where the data include the event streams of many FSMs merged together, the situation is much more complex, and will only be sketched here. Our solution is to learn one FSM at a time from this merger. After each FSM is learned, we remove its events from the data and learn the next FSM from the reduced data. FSMs are learned by hypothesizing several that satisfy the ZLSC and UC, and choosing the one which best fits the data. A number of heuristics have also been developed to constrain the hypothesis generation. To see how well each hypothesized FSM fits the total data, we employ our optimal decoding algorithm [13], discussed above in Section VII, which can ignore the events of other FSMs as insertions into the data stream. An information criterion [7], [8], [23], [43] is used to prevent overly complex answers. Based on simulated data, the method appears to be accurate and fast. A detailed description of the current state of this algorithm, with examples of it learning FSMs from measured load data, is given in [14].

An important point to note about FSM learning algorithms is that they work for two-state ON/OFF appliances as well. The same is true for the behavior tracking algorithm of Section VII. Therefore they are not so much additions to the current prototype algorithms as replacements for them.

IX. Algorithm

Taking all the above into account, we arrive at the NALM algorithm shown in Fig. 8. Many variations are possible; the indicated one is that of our most recent prototype, but with many details omitted. Normalized power, equivalent to admittance, is the signature. The following eight subsections follow the structure of the diagram. Note that steps D, E, and H are only required in the AS-NALM—the data they provide would be determined from the manual setup of a MS-NALM.

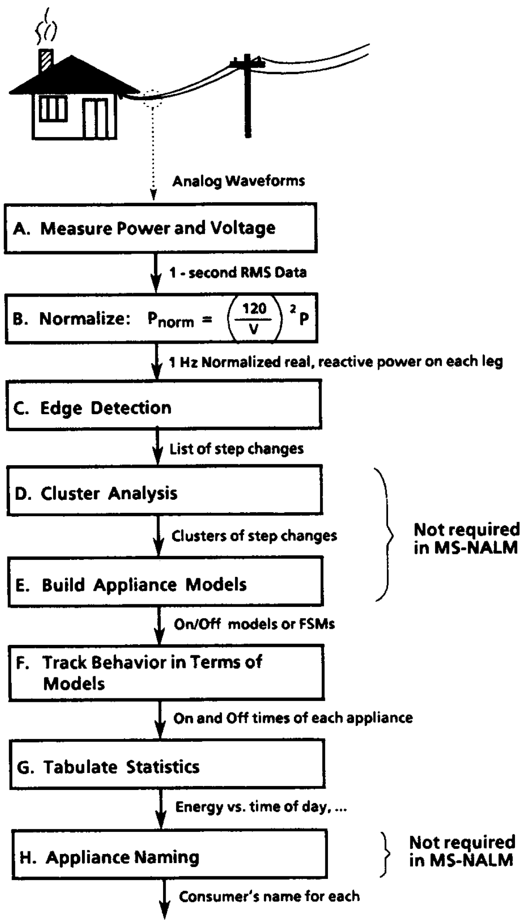


Fig. 8. NALM algorithm.

A. Measure Power and Voltage

Sensors at the load/utility interface measure average power and RMS voltage on the two legs over 1-second intervals. In all three of our prototypes, the sensor has been a *digital ac monitor* [32], [33] configured to calculate RMS voltage, and real and reactive power digitally, based on rapid samples (7680 Hz) of current and voltage waveforms for the two legs.

The choice of averaging period strongly affects the number of simultaneous events which are reported. If the data were collected more slowly than the current 1 s intervals, events would be combined which were actually separated by a couple of seconds, thus increasing the burden on the simultaneous-event decomposition software of subsection IX-F. Increased time resolution can alleviate this problem only to the extent that appliances have clean square steps in their starting power (i.e., minimal transients) because two extended start-ups that overlap will appear as their sum regardless of sampling rate. A slightly faster rate, of 2–10 Hz, now appears prudent, to improve the recognition of electric burners; see Section XI.

B. Calculate Normalized Power

Normalized total load power is computed for each leg, using (4), at 1 s intervals. Note that it is important to normalize at this point, before the edge detection, i.e., one cannot switch blocks B and C of Fig. 8. Utility voltage routinely contains both gradual and step changes due to factors such as load-dependent voltage drops in transmission lines and tap-changing transformers. We do not want the consequent changes of measured power to be fed to the step detector, as it presents a very un-steplike signal in which the few real steps of interest are blurred.

C. Edge Detection

The normalized power is input to an edge detection algorithm which finds the times and sizes of all steplike changes. Many well-known signal processing techniques, such as filtering, differentiating, and peak detection, could be used to find the times at which a signal changes rapidly. The "weak string" method of visual image processing [21] and an information-based method of [7] could also be adapted to this problem. A key requirement here is that the procedure must not be affected by start-up transients which often accompany steps.

Our transient-passing step-change detector first segments the normalized power values into periods in which the power is steady and periods in which it is changing, as indicated with a one-dimensional power signature in Fig. 9. A steady period is defined to be one of a certain minimum length (we have used three samples in the prototypes) in which the input does not vary by more than a specified tolerance (15 W or VAR) in any component. The remaining periods, between the steady periods, are defined to be the periods of change. The samples in each steady period are averaged to minimize noise, and differences between the averages across each period of change give the step size. The time of the first sample in each changing period provides a time stamp. A sequence of time-stamped step-change p-vectors is the output.

The algorithm is easily implemented in a recursive form which passes once through the data using a minimal amount of storage. The complete procedure is described in [11]. As a practical matter, all outputs below a size threshold are also discarded (1) to save storage, (2) because utilities are not interested in small appliances, and (3) because we do not expect to be able to recognize and distinguish very small appliances. This threshold could be site-specific, and would be relatively large if we were only interested in a few specific major appliances, e.g., water heaters, thereby simplifying the computations below.

Most further processing uses only time-stamped edges as data, so the 1 s measurements can be discarded. Some voltage and total power data may be preserved for "un-normalizing" the power, calculating the "residual energy,"

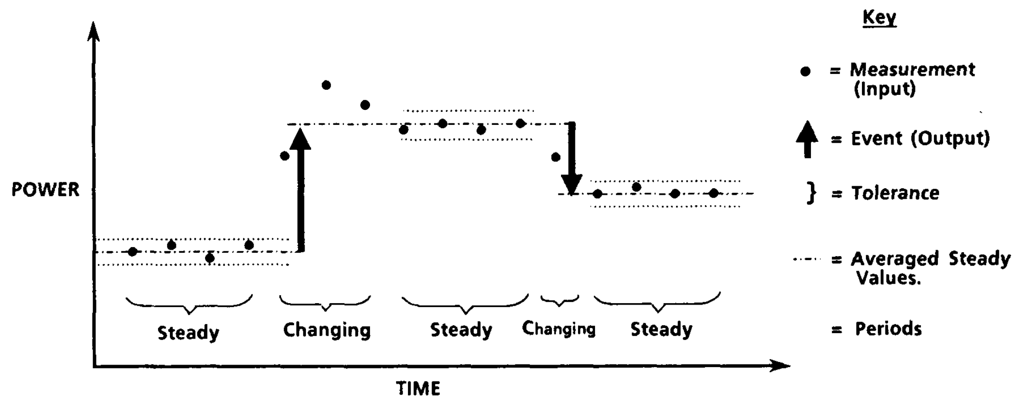


Fig. 9. Detecting step-changes in sampled data.

(see Subsection IX-G), and because total load data is also kept as an end in itself, but at a lower time resolution e.g., 15 minute averages.

D. Cluster Analysis

Ignoring time stamps for the moment, the observed changes define a scatter plot in p-space. These are then grouped into clusters, i.e., sets of events which are all approximately the same in all components, as shown in Fig. 6. Ideally, each cluster represents one kind of state change of one appliance. Small-sized clusters result from very consistent appliances, especially resistive heaters. The largest-sized clusters we have found in our field tests result from appliances with compressors, in which the start-up load can be very variable due to variations in the temperature or back pressure of the refrigerant.

There are many algorithms for grouping multidimensional scatter plots into clusters. An excellent recent survey can be found in [31]. Many of those would probably be adequate if we knew how many different clusters to look for. The most difficult aspect of cluster analysis is to automatically determine the number of clusters. Information-based criteria for this are presented in [7] and [43].

The particular algorithm we developed operates in one pass through the data, and determines the appropriate number of clusters as it goes along. It involves "split" and "merge" operations which can divide and/or combine clusters according to statistical tests which incorporate a number of parameters specific to this problem domain. The algorithm appears to function well, but is too complex to present here. Details can be found in [11] and [20].

E. Build Appliance Models

Given the clusters of step changes, we need to automatically generate ON/OFF or FSM models of each appliance in the load. Constructing FSMs was discussed above in Section VIII. To construct and ON/OFF model, all we need is to find a pair of clusters symmetrically placed across the origin of the p-space cluster plot; i.e., the centroid of one is approximately the negative of the centroid of the other. The two centroids then label the ON and OFF arc in Fig. 4(a), and the ZLSC is satisfied by construction.

The cluster-pairing procedure we developed for constructing ON/OFF models is detailed in [20]. It involves a number of tolerance criteria for matching the centroids[8] and numbers of events in clusters. It also checks that the time stamps of the events in the two clusters largely alternate to give an ON/OFF/ON/OFF$\cdots$ sequence. The procedure will also merge a pair of nearby clusters found on one side of the origin when their union is a better match by these criteria to a single cluster on the opposite side of the origin. It can thereby correct for occasional oversplittings in the clustering procedure above.

F. Track Behavior

Once the ON/OFF or FSM models of the appliance are available, tracking them is straightforward using the decoding approach of Section VII. An example is given in [13]. The current prototype uses a more primitive method however. Every time-stamped signature event corresponds to an appliance changing state, and we can determine which cluster the event is in, since the clusters label the FSM arcs. With ON/OFF appliances, this generally gives a sequence of alternating ON and OFF events, with occasional "anomalies" in which two ON's or two OFF's are found in a row. The most likely cause of such anomalies is that an intervening complementary event was not clustered properly due to a simultaneous event of another appliance. To undo a simultaneous event, one seeks another appliance with an anomaly during an overlapping time period, and an unusual event which is the sum of the two missing events. A "brute-force" method for doing this appears to work well in our prototypes. [20]

G. Tabulate Statistics

Given the power levels and exact times of each state change, any conceivable statistics can be tabulated for each

[8]The on event is larger than the off event in most appliances, due to a gradual temperature increase or motor acceleration during operation, causing power to decrease slightly over time. See [3] and [12] for a number of figures.

appliance. Utility load forecasters are most interested in operating power, total energy, energy broken down by time of day or weekday/weekend, and correlation factors between energy and temperatures.[9] At this point, it may be necessary to convert back from normalized power to measured power if the actual power consumption, determined by the particular voltage supplied, is the quantity of interest. This is the data comparable to conventional monitoring results. However, for many purposes normalized power is adequate, and sometimes preferred.

One energy statistic of special interest is the "residual power," defined as the total house power minus the total of all identified individual appliance consumption, analogous to $e(t)$ in (1). It is a measure of the completeness and accuracy of the NALM results. Should the real part of the residual be substantially negative at any time, it indicates a significant error. The most common serious error in tracking appliance behavior is that when an OFF event and the immediately following ON event of a device are both missed, perhaps due to simultaneous events of other appliances, the algorithm connects the previous ON with the subsequent OFF. Although uncommon, the resulting cycle could span days if the appliance had been off for a long period, with an apparent energy consumption dwarfing the actual total. These errors can be corrected with special checks for long cycles and times when the residual goes negative.

In addition to power and energy statistics, we also tabulate sample statistics on the duration of time each FSM state is visited. For ON/OFF models, this amounts to a probability distribution for how long the appliance stays on when it goes on, and how long it stays off when it goes off. These will be seen to be very useful below.

H. Appliance Naming

The steps above all proceed without knowing the consumer's name for each appliance. A final task for the AS-NALM is to name each appliance based on the collected data. The most informative data for this decision is the operating power level, the 120 V versus 240 V nature, and the duration statistics. Standard techniques from detection theory—Bayesian or maximum likelihood multiple hypothesis methods [41]—appear perfectly adequate based on the range of appliances we have encountered so far [18]. However, we need more experience with more field sites before we can be confident that any particular decision procedure is attuned to the full diversity of the extant appliance inventory.

To illustrate the values of duration statistics, consider Fig. 10, which shows the typical ON and OFF durations for a range of monitored appliances. The abscissa and ordinate of each point are the peaks (modes[10]) of the sample holding

[9] A temperature sensor can easily be incorporated into the NALM as with conventional load monitors, but shares the usual microclimate problems due to shading, lawn sprinklers, etc. A radio or power-line carrier receiver for broadcast temperature information would provide a more standard regional temperature statistic.

[10] The median of the distribution appears to be as informative as the mode. The mean, however, is not as useful a statistic because of the logarithmic scaling.

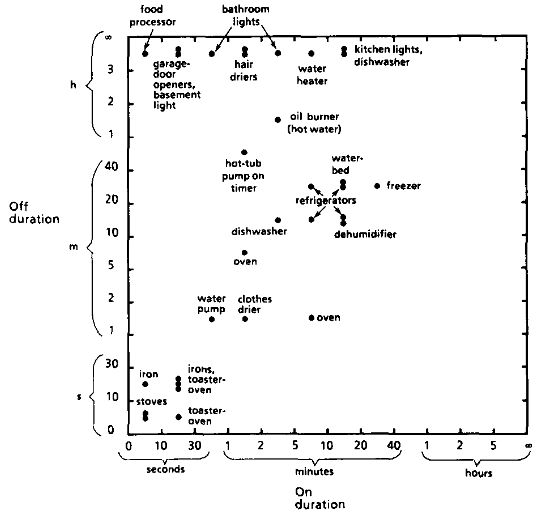


Fig. 10. Typical ON and OFF periods for monitored appliances.

time distributions for the ON and OFF states. The data comes from [11]; five of the points can be determined from figures given below in Section XI. The scales are quasi-logarithmic, coarsely quantized between round-numbered boundaries. Appliances controlled by regulators, such as thermostats or pressure switches for water pumps, appear in the main diagonal band, e.g., four refrigerators near the middle of the figure with typically ten minutes on and 20 minutes off. Heaters for smaller thermal masses are at the lower left, with short on and off times. At the top is a sequence of appliances under human control. Their on times vary with the function, but the off times are long because people do not return to turn appliances back on after consistent short time periods.

X. Architectures

The initial measurement of power takes place at the site being monitored, while the final outputs are needed by load researchers at a utility office. Thus, at some point along the processing shown in Fig. 8, data is transferred from the monitored site to a central location. The major architectural issue in designing a NALM system is where in the algorithm to make the information transfer or, equivalently, which blocks of Fig. 8 to compute on site.

For field testing, a natural break is between blocks C and D. Edge detection significantly reduces the bulk of the data (from one second intervals down to one event every two or three minutes), saving on communication costs, and cluster analysis is a complex function with many parameters that one might want to tweak during development for optimum performance. For these reasons, our major field-test unit [20] measured, normalized, and detected edge events on site, and then transferred them to a central station (IBM PC compatible) for further processing. Thus steps D–H could be optimized in the lab by rerunning the same event data.

The disadvantage of this architecture is that steps D–H constitute a significant amount of processing which one would not want to do centrally for a large sample (100's or 1000's) of monitored loads. Thus we anticipate that the commercial unit will perform steps A–G on site, and transfer only the statistics rather than the edge data, again reducing communication requirements. This does not require a substantial processor on site, because it has a whole week to run the algorithm to process a week's data. It also has the advantage that it helps preserve the privacy of the occupants; the details of their every electrical act do not get stored in a central computer [6].

While step H—appliance naming—could ultimately be decided at the monitored site, it makes sense at this time to do this centrally. A large data base of known appliances and their energy and duration statistics may be required which will certainly evolve over time as new appliances are manufactured and encountered.

XI. Field Tests

We have carried out three field tests with prototype NALMs installed on monitored homes. All are based on ON/OFF models only. For detailed reports on the results and the evolution of the algorithms used, see the following references:

1) A MS-NALM on one home (1984) [12];
2) A first-generation AS-NALM on three homes (1985) [11];
3) A second-generation AS-NALM on ten homes where parallel instrumentation was already in place by the local utilities (Rochester Gas and Electric, and New England Electric Systems) to provide a comparison (1987–88) [4], [20].

The first two prototypes used general-purpose hardware and sensors wired to the house by electricians. The third used a special-purpose package, like Fig. 1, but larger, designed for us by American Science and Engineering.

All tests were extremely successful. Where problems were found in the first two, they led to improvements in the algorithm of the third prototype—improvements reflected in the description given in this paper. All the major ON/OFF appliances were identified in all homes, except in the most recent test, the electric stove in two homes and the refrigerator in a third were missed [20]. The difficulty with the refrigerator appears to be that with a frequent defrost cycle it is more of a FSM than an ON/OFF device [14]. The problem with the stoves is discussed below.

Typical results from the second test are shown in Figs. 11–15; for comparable results from the most recent test, see [20]. Each figure is broken into four parts: (A) The top part indicates the individual on and off events detected for the appliance during a five to 12 day monitoring period. Horizontal bars indicate time periods the appliance was reported to be on; ticks above the bar indicate ON events; ticks below the bar indicate OFF events. (B) The second part of each figure shows the percentage of time the appliance was on during each clock hour, i.e., the kind of time-of-day statistic that utilities are interested in. It is calculated by averaging down the columns of part A. (C) The third part of each figure is the tabulated distribution of how long the appliance stays on when it goes on. The columns add to 100%. (D) The bottom part of each figure is the analogous distribution of OFF durations. Individually examining Figs. 11–15, we see:

Fig. 11: **2 kW Water Heater.** Fifty ON/OFF cycles are correctly reported during the seven-day monitoring period. Six unmatched ticks in part (A) of the figure show that the NALM missed some activity. This is most likely attributable to the fact that the second prototype did not implement a procedure for decomposing simultaneous events. The noontime peak of this appliance (B) was verified against the occupants usage (showing), and serves to emphasize how user-dependent appliance activity can be. The distributions (C, D) show it is typically on for 5–10 minutes, and off for over 3 hours, giving the point at the top-center of Fig. 10

Fig. 12: **700 W Stove Burner.** This is the same burner seen cycling in Fig. 2. The individual ON/OFF events are too closely spaced to be seen on the scale of part (A) except when it is set on *High.* From (C, D), it is noted that the burner cycles on and off with typical periods less than 10 seconds, placing it at the bottom left of Fig. 10. The usage activity (B) shows a clear three-meals-per-day pattern.

Fig 13: **680 W, 530 VAR Dehumidifier.** Unmatched ON and OFF events in part (A) indicate poorer accuracy for this appliance. Even so, the NALM singled it out as the major energy consumer in the home. It is typically ON and OFF for 10–20 minutes, with roughly 50% duty cycle.

Fig. 14: **400 W, 140 VAR Basement Lighting.** (Multiple lights on single switch) Strongly user-dependent activity is apparent, with broad duration distributions.

Fig. 15: **700 W, 500 VAR Hot Tub Circulator Pump.** A timer turns the pump on for one minute every hour, designed to prevent water from freezing in the pipes. This leads to very narrow duration distributions. In addition, two extended usage periods are evident.

The algorithm clearly works well, but can be improved. Figs. 13 and 15 show that only a small fraction of the events are missed. Exact NALM accuracy is very difficult to quantify, however. In the first two field tests there was no parallel instrumentation, so the fraction of events detected was used as a criterion, but that can differ markedly from the fraction of energy detected. Data from the third (1987–88) field test has not been fully analyzed and compared. Preliminary results in [4], [16], and [20] suggest that the NALM usually reports energy consumption within ±10% of the independent sensors; however, there

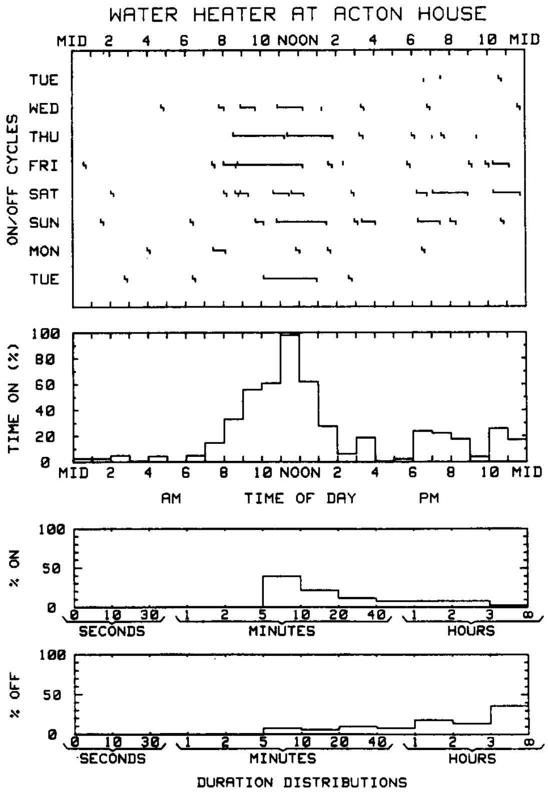


Fig. 11. NALM results—water heater.

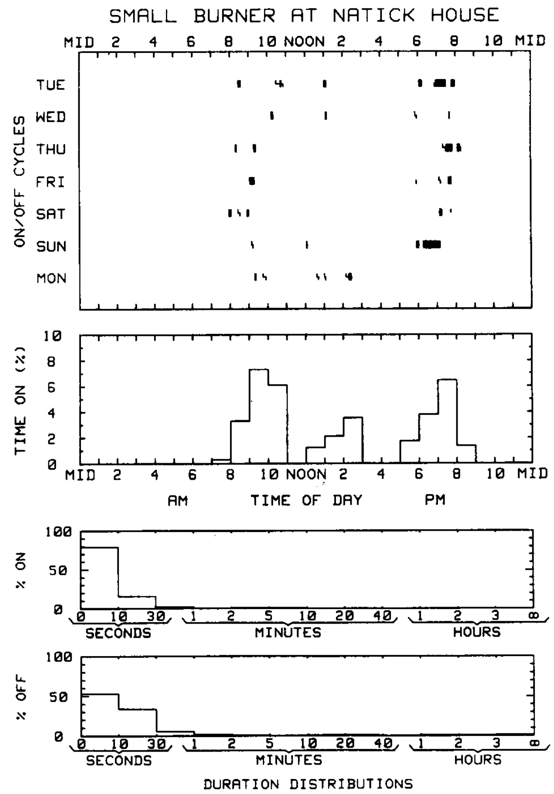


Fig. 12. NALM results—stove.

are uncertainties in the calibrations and comparisons.

The difficulty identifying the stoves may be that they produce too many simultaneous events or that they are continuously variable. The main contributor to simultaneous events in our field tests has been electric stove heating elements. The control knob activates a duty-cycle controller which produces a continuously variable range of heat settings by turning the elements on and off for adjustable periods on the order of seconds. The burner in Fig. 2 was originally on *High* (constantly ON for 5 minutes), then *Low* (four short ON periods separated by longer OFF periods), then *Medium* (final nine cycles). Because several burners are often used simultaneously during cooking periods, simultaneous events often result. The difficulty recognizing stoves in most recent field tests suggests that they may have cycled faster than the stove in the initial field tests (Figs. 2 and 12). If the period is less than a few measurement samples, the appliance must be modeled as continuously variable, rather than in the ON/OFF class. A faster data rate for the input to the edge detector would alleviate this problem.

XII. Advantages and Disadvantages of NALM

Compared with intrusive load monitors, the NALM has a number of important advantageous properties. Obviously, there are fewer components to install, maintain, and remove. This results in lower equipment and manpower costs, greater reliability, smaller space requirements, and fewer types of parts to stock. NALM cost and complexity are independent of the number of monitored appliances. The nonintrusive nature of the equipment should also engender better customer acceptance and less financial liability. Perhaps most important is the possibility of increased accuracy, which comes from a number of sources:

a) Complex hardware is prone to many types of failure. In comparisons with the NALM, field tests showed examples where conventional instrumentation suffered losses of individual channels [20].
b) The AS-NALM automatically adjusts to changes in the appliance inventory and unreported appliances. This overcomes a common problem with intrusive instrumentation in which appliances which the utility is unaware of remain unmonitored.
c) NALM technology is not constrained in the number of channels of data which can be recorded. Traditional systems are usually limited to four or eight appliances, and so cannot decompose the total load as finely as the NALM.
d) Being less expensive, NALMs can be placed at more sites, reducing the biases that result from small samples.
e) Being nonintrusive, the NALM can be used with utility customers who would not approve the intrusion of utility workers to install, maintain, and remove

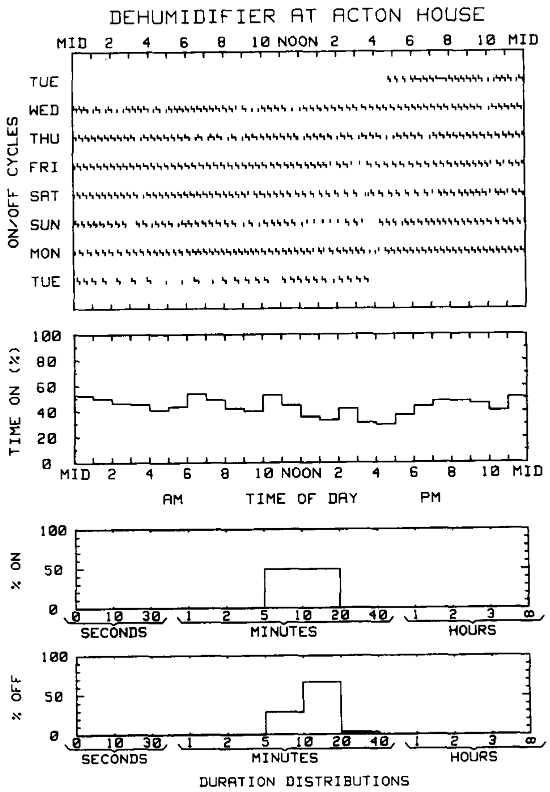


Fig. 13. NALM results—dehumidifier.

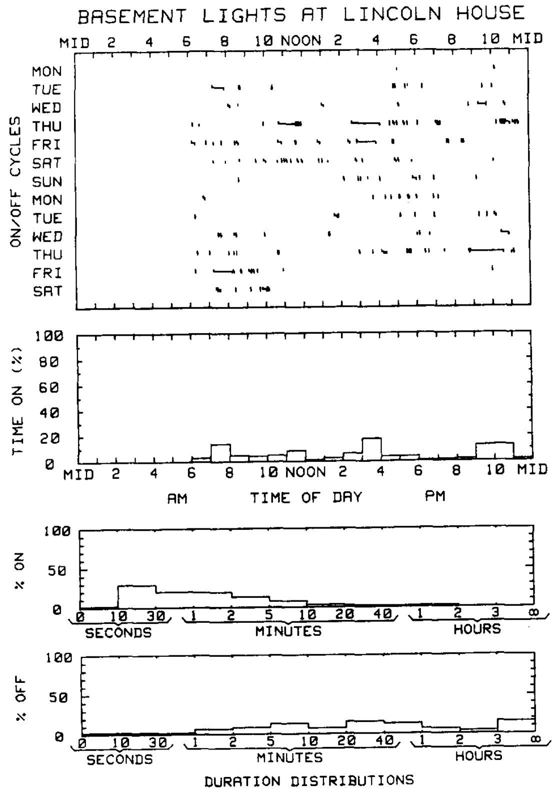


Fig. 14. NALM results—basement lights.

conventional load monitoring equipment. This reduces the possibility of a customer sample skewed toward energy-conscious users.

f) Intrusive load monitoring equipment and wiring may provide a constant utility presence to the customer, causing a conscious or unconscious change in energy consumption habits.

Balancing these benefits are three disadvantages of the NALM:

a) The NALM has a restricted set of target appliances, as it is not currently suitable for detecting very small devices (under 100 W), continuously variable appliance (e.g., light dimmers), or appliances which operate constantly (e.g., clocks); nor can it distinguish between electrically identical appliances (e.g., two burners of the same size on an electric stove). However, these restrictions do not appear to exclude any of the appliances of current interest to load researchers except for lighting, discussed below. Harmonic current signatures and tags may be cost-effective means for alleviating these restrictions.

b) The NALM may have a greater potential for undetected error. As the total load is disaggregated in software rather than the hardware of separate sensors and communication channels, there is a greater potential for the reported data to contain significant errors. An unusual appliance, not encountered in field tests, might have properties which confuse the software. This is clearly a matter to be concerned about, which we can only address with more extensive field tests.

c) The method has not yet been fully specified or field tested for multistate appliances such as dishwashers, washing machines, and heat pumps. It has not been specified at all for continuously variable appliances. These are topics of ongoing research.

The NALM can also be compared to the conditional demand analysis (CDA) [34], which uses regression methods to estimate certain load components. CDA techniques result in multivariate models with end use parameters based on appliance surveys, utility billing records, weather data, demographic information, energy costs, and thermal properties of dwellings. While CDA can be applied to nation-sized data sets, it involves many uncertainties, and is not intended to be as complete and accurate as the NALM.

XIII. Marginal Value of Improvements

Any nonintrusive appliance monitoring method is certain to fail for appliances below some power level. Our current prototype is not reliable for appliances below approximately 150 W. This is a consequence of the proliferation of appliances at low power levels, and problems of measurement and noise. The exact level at which a method fails (for

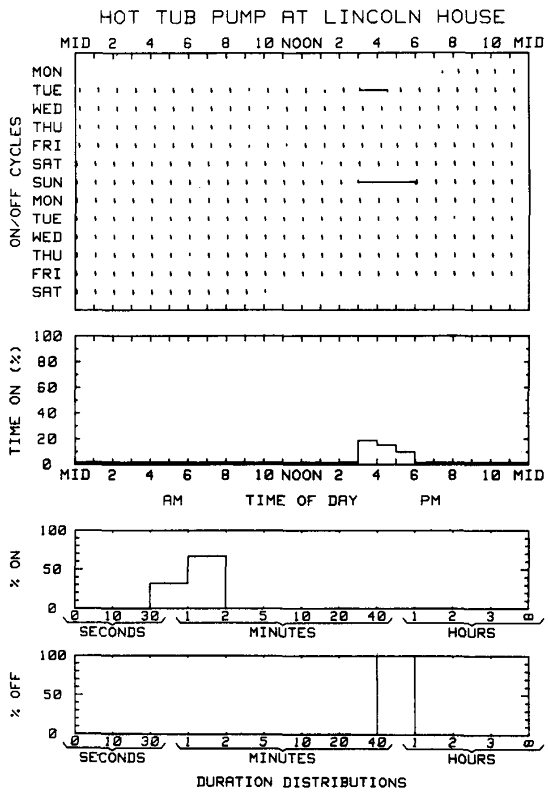


Fig. 15. NALM results—hot tub pump.

a given appliance mix) will depend on details of the algorithm. Additional effort may improve an algorithm so that it identifies lower-power appliances, but the decision to expend this effort requires some knowledge of the value of the additional data that may be collected. If appliances with small power levels consume, in total, a large amount of energy, more important information is being missed than if almost all energy is consumed in easy-to-detect large step increments.

In order to find an approximate answer to this question for typical U.S. residential loads, we need initial estimates of the annual energy consumption of household appliances. This is exactly the kind of hard-to-determine data the NALM is designed to collect. Using data from [25], [26], and [36], Table 3 gives an average operating power level and a recent estimate of the total U.S. residential energy consumed by 38 appliance types. Asterisks indicate my entries, where data were not available or to be conservative. The largest appliances have been arbitrarily entered as 2 kW, as they do not affect the analysis below.

The data is presented as a scatter plot in Fig. 16 and in a cumulative form in Fig. 17. As a scatter plot, the horizontal axis indicates how easy it is to find the appliance in noise (with the most difficult appliances appearing at the left edge) and the vertical axis indicates importance in terms of energy consumption. The most important load which is difficult to detect nonintrusively thus appears near the left edge of Fig. 16: lighting. This is currently the biggest problem for the NALM.

Table 3 Typical Power Consumption and Estimated Annual U.S Residential Energy Consumption of Household Appliances From data in [25, 26, 36]. Asterisks indicate the author's entries.

Appliance	Power (W)	Energy (TWH)
Refrigerator	200*	145.1
Resistance Heat	≥ 2000*	137.3
Water Heater	≥ 2000*	128.
Lighting	75*	100.*
Central AC	≥ 2000*	82.
Heat Pump	≥ 2000*	45.9
Freezers	250*	44.1
Stove/Oven	1800	40.
Furnace Fan	500	22.5
Color TV	193	21.8
Window AC	860	18.8
Dishwasher	1200	17.9
Central Heat Pump AC	≥ 2000*	17.5
Waterbed	347	12.6
Microwave	1450	8.6
Pool pump	1008	6.0
Aquarium	100*	5.5
Crankcase heater	100*	5.4
Hot tub	675	4.6
Clock	2	4.5
Well pump	1300	4.4
Dehumidifier	257	4.4
Toaster oven	1146	4.3
Audio	71	4.1
Hair Dryer	600	3.4
Electric blanket	177	3.2
Vacuum	630	2.7
Grow light	40	2.4
VCR	20	2.4
Coffee maker	1200	1.8
B+W TV	73	1.8
Computer	100*	1.7
Iron	950	1.6
Humidifier	177	1.1
Engine heater	100*	1.0
Ceiling fan	88	.9
Exhaust fan	200	.8
Attic fan	370	.6
Other	100*	2.0
Total		914.5

Fig. 17 shows the same energy versus power data in a cumulative form. The vertical axis shows the percentage of the total energy in Table 3 which is consumed by all appliances larger in size than the point on the horizontal axis. For example, if only appliances over 400 W were recognized, 60% of the total U.S. residential energy would be accounted for, according to this data. But, if the NALM were refined to the point where 75 W appliances (e.g., incandescent lights) were detectable, then this would improve to 99%. If lighting is not recognized, the figure indicates that any threshold in the 150 W range results in about 86% recognition.

Thus we conclude that if further development effort is to be exerted to improve the method to lower power appliances than the (already attained) power level of refrigerators, and energy consumption is the criterion of interest, then that effort should focus on techniques for recognizing lighting appliances. A more detailed analysis could replace the entries of Table 3 with distributions that reflect the range

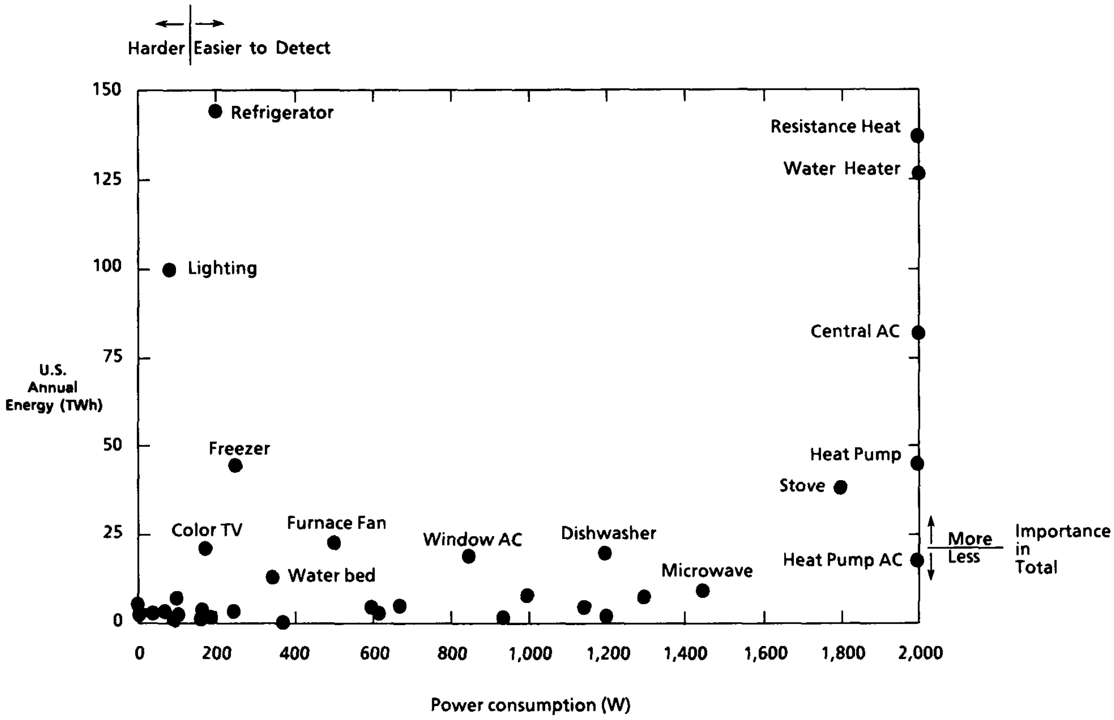


Fig. 16. Operating power and annual energy consumption of appliances.

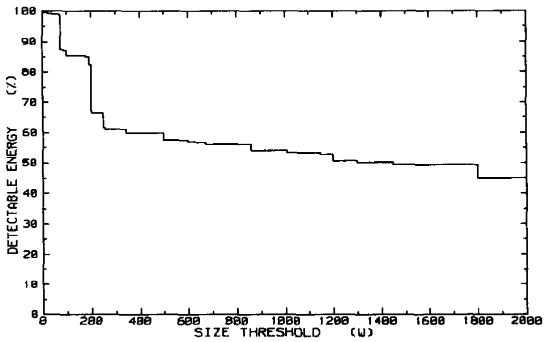


Fig. 17. Fraction of U.S. residential energy consumption estimated to be consumed by appliances at or above the given (real) power threshold.

of power levels of different appliance models and different-sized light bulbs. This would smooth out the stair steps of Fig. 17 somewhat. For example multiple lights on one switch are easily detected, as shown in Fig. 14 above and with a pair of flood lamps in [11], so the recognizable energy may be higher than the above numbers indicate. However, this does not change the conclusion that lights remain the major obstacle, as there would still be relatively steep slopes only in the refrigerator range and the light bulb range, with relatively flat slopes elsewhere.

If a criterion other than energy were relevant—for example if a survey of compact fluorescent bulbs or videocassette recorders were commissioned—then other signatures than power might be added in to the signature vector. Harmonic currents appear to be the most promising for distinguishing small appliances.

XIV. Conclusions

Nonintrusive appliance load monitoring is a novel, effective means for collecting appliance end-use load data, with many other important applications. The theory is well developed, and has led to a practical implementation. Testing to date has concentrated on methods suitable for ON/OFF appliances, with good results. This technology is currently being commercialized [4] and market surveys suggest thousands will be installed in the first few years of manufacture. Because of its many advantages, we expect that nonintrusive techniques will supplant conventional intrusive techniques for a wide variety of load monitoring applications.

The theory presented here is important for understanding the limitations of the method. For example, small appliances, continuously variable appliances, and appliances which are always on should not be chosen as targets for this approach. Multistate appliances require more sophisticated methods which have been largely developed [14], and should be field tested in the near future. Techniques for nonintrusively monitoring continuously variable appliances are currently lacking.

Important future work includes developing and testing improved algorithms based on these or new models; refinements aimed for higher accuracy and smaller appliances; exploration of other signatures; modifications optimized towards commercial and industrial buildings; and finalization of naming algorithms based on a larger survey of appliances. Other services than electric power may also be explored. For example, natural gas and water usage may be monitored by similar methods.

The NALM is an especially interesting research topic because of the way it blends power engineering with communication engineering—two subdisciplines of electrical engineering which often appear disjoint. By treating power consumption as an act of communication, and treating our problem as one of designing a receiver for energy consumption messages, the two fields blend together in a new way.

ACKNOWLEDGMENT

The concept of analyzing power flows to determine the set of appliances in a home and report on their on and off events occurred to me in 1982 at MIT Lincoln Laboratory while collecting and analyzing load data as part of a D.O.E. residential photovoltaic systems study. Our project was unique in that we collected load data from neighborhood monitored homes at 5 second intervals—a much higher data rate than the 15-minute standard in use by utilities. In analyzing and plotting this data, I was immediately struck by the fact that I could "read" the plots by eye and tell what was happening in the monitored homes. There, I benefited from conversations with J. Solmon about various household appliances. I also realized that I could formalize the steps to write a computer program which does a similar analysis, but at that time I did not appreciate that such a monitor had any significant value to utilities. Then, at the MIT Energy Laboratory, I discussed the idea with E. Kern, who discussed it with the late F. Schweppe of the MIT Department of Electrical Engineering. Schweppe immediately recognized the value of the concept for utilities and suggest a joint research venture, funded by EPRI, to develop and test it.

I have carried out the basic research and development with EPRI sponsorship through a number of moves, first at MIT (while completing my Ph.D. [7] with Schweppe at the Laboratory for Electrical and Electromagnetic Systems, and with J. Tsitsiklis at the Laboratory for Information and Decision Systems) and currently at Columbia University. I designed and implemented the first two prototypes, and, before leaving MIT, specified the algorithms described here for the third prototype. The MIT project then supervised its construction, programming, field testing, and evaluation, but was tragically hurt by the death of Schweppe. A parallel project at MIT is exploring modifications tuned toward commercial building applications. R. Abbott kindly provided his home as an initial test site. Rochester Gas and Electric and New England Electric Systems each provided five homes for field testing, collected data, and provided independent data for comparison.

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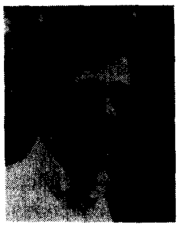

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