An Event Window Based Load Monitoring Technique for Smart Meters

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***Abstract*—The data collected by smart meters contain a lot of useful information. One potential use of the data is to track the energy consumptions and operating statuses of major home appliances. The results will enable homeowners to make sound decisions on how to save energy and how to participate in demand response programs. This paper presents a new method to breakdown the total power demand measured by a smart meter to those used by individual appliances. A unique feature of the proposed method is that it utilizes diverse signatures associated with the entire operating window of an appliance for identification. As a result, appliances with complicated middle process can be tracked. A novel appliance registration device and scheme is also proposed to automate the creation of appliance signature database and to eliminate the need of massive training before identification. The software and system have been developed and deployed to real houses in order to verify the proposed method.**

***Index Terms*—Demand response, load management, load signatures, nonintrusive load monitoring, time-of-use price.**

I. Introduction

THE INCREASED public awareness of energy conservation in recent years has created a huge interest in home energy consumption monitoring. According to a recent market research report [1], consumers show substantial interest in tools that can help them manage their household energy use and expenses. A critical link to address this need is the smart meters. However, the smart meters currently available in the market can only provide the energy consumption data of a whole house. They cannot tell which appliances in the household consume the most energy or are least efficient. Also, to take full advantage of time-of-use rates, householders need to be informed of their usage patterns. Such information is essential for a household to make sound energy saving decisions and participate in utility demand response programs [2], [3].

In response to this need, two research directions have emerged. One is to connect energy monitors to individual appliance of interest and to communicate the recorded data to a data concentrator [4]. While such a sensor network based system can provide accurate measurement of appliance energy consumption, it can be costly and complex to implement. The second direction is to identify and track major home appliances based on the total signal collected by utility meters, which is called nonintrusive load monitoring (NILM) method [5]. Compared to the former, the NILM direction is more attractive to customers and utilities due to its high cost efficiency and less effort on installation.

The problem to be solved by NILM approach can be stated as follows: All the load signals aggregate at the entry point of a house as $P(t)$ and NILM algorithms do the reverse—decode the overall signal into various components $P_i(t)$ that are attributed to specific loads (appliances) i

$$P(t) = P_1(t) + P_2(t) + \cdots + P_n(t). \tag{1}$$

It must be noted that the goal of the above approach is to extract the $P_i(t)$ trends of large appliances in a home. It is not intended to and there is no need to track small devices such as phone chargers. Such devices do not consume significant amount of the energy and signatures of them can be "submerged" in aggregated signal; however, signatures of major appliances are better kept in aggregated signal. In a typical home, there are about 10 to 20 large power consuming appliances. The decoding process makes use of the unique signatures of such appliances observable at the smart meter location of a house to extract the $P_i(t)$ trends.

Example of smart metering data is shown in Fig. 1. Appliance events are observed as ON/OFF edges (arrows). Existing NILM algorithms [5]–[11] treat all the appliances as a single-state model which has a pair of identical ON/OFF edges and a constant power demand between them. This is because original studies mainly aim to help utilities conduct load studies without intrusion [5], [6] and thus adopt simplified models. However, for accurate energy monitoring purpose, real operation processes of complex loads such as continuous-varying appliances and multi-state appliances shown in Fig. 2 need to be captured and treated.

Continuous-varying appliance usually has a pair of different ON/OFF edges and a gradual varying power demand in the middle. Multistate is more commonly seen as heavy or complicated loads such as furnace and washer. Furnace has more than one working stage according to environmental temperatures and washer has more steps like rinse and drainage following a certainoperation pattern. Examples are given in Table I.

The other challenge faced by some of the published works is that they need a time-consuming training/learning process to

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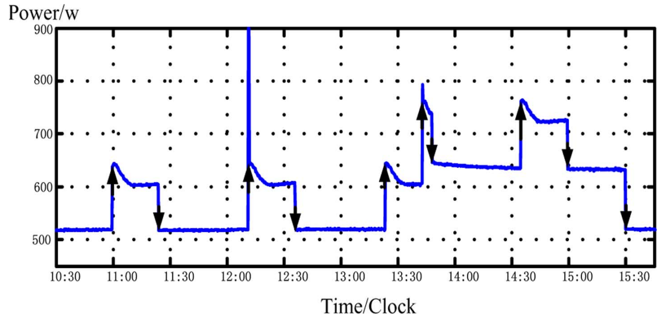


Fig. 1. Real-time data acquired via smart meter.

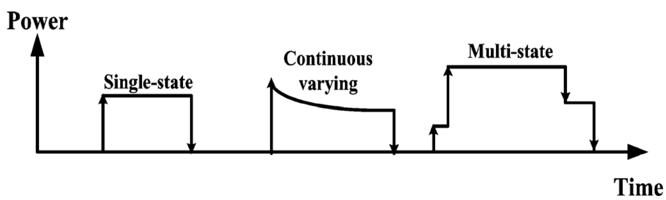


Fig. 2. Power curves of three types of loads.

TABLE I
LOAD TYPE AND EXAMPLES

Load type	Examples	Event	Power demand
Single-state	Light bulb; Toaster	ON=OFF	Flat
Continuous varying	Fridge; Freezer	ON≠OFF	Varying
Multi-state	Furnace; Washer	Multiple events	Varying or flat

support their algorithms such as genetic and neural-network before they can work [7]–[9]. Such combination based approaches are vulnerable to changes in the appliance inventory. Once a major appliance is replaced, retraining has to be conducted.

To address these issues, this paper presents a novel NILM technique to identify all three types of loads. The key idea is to use the various signatures of the entire operating window of an appliance for identification. Since an event window contains various operating states and other information of the appliance, the proposed technique is also much more reliable. Furthermore, a convenient appliance registration method is proposed to automate the creation of appliance signature database, which reduces users/algorithms' efforts from training.

II. THE CONCEPT OF EVENT WINDOWS

Anevent window is defined as the collection of all signatures between any pair ofrising/falling step-changes (events) of the power demand as measured by the smart meter. Sample load windows are shown in Fig. 3. Window 1 contains one ON and one OFF event associated with one appliance. There is no activation of other appliances in between. This is called the non-overlapping window. Non-overlapping window contains complete signature information about an appliance. Window 2 is called overlapping window as it contains an ON event associated with another appliance. In reality, only short duration (toaster) or always-on appliances (fridge) have more chances to present themselves in the form of non-overlapping windows. Most of them will overlap with others. The main idea of the

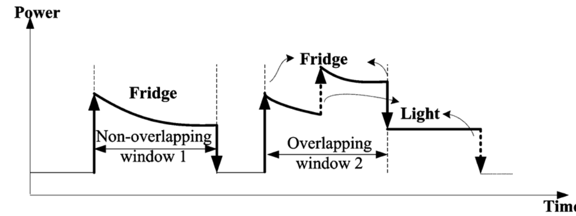


Fig. 3. Nonoverlapping window and overlapping window.

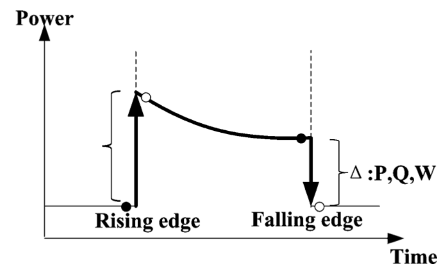


Fig. 4. Edge signature subtracted from steady points.

proposed technique is to identify and pick out the right windows that are represented by interested appliances. This is accomplished with the assistance of window signatures or characteristics. Each window contains five types of signatures listed as below.

- edge signatures;
- sequence signatures;
- trend signatures;
- time/duration signatures;
- phase signature.

A. Edge Signatures

An edge refers to the event of the operating state of an appliance, which can be seen as a step change in its power demand. The edge can be either rising or falling. Each edge can be characterized by the changes in power (P), reactive power (Q), and current waveform (W) as shown in Fig. 4 [10], [12]–[14]. Those attributes are generally fixed for each appliance if the system voltage does not change sharply. In single-state model, only one set of P-Q-W needs to be considered since OFF is assumed to be identical reverse of ON [5]. In event window model, however, the number of P-Q-W sets depends on how many events really happen.

B. Sequence Signatures

Sequence signature describes the logical sequence of operation events of a load. In another word, it represents the sequence of appearances of edges. For example, a washer usually follows the following operating modes: water-fill, immerse, rinse, drainage, and spin-dry. In a cycle, a fixed pattern such as $+50$ W, -50 W, $+100$ W, -80 W, $+480$ W, -500 W will be seen. This power pattern, the sequence signature, is very unique and is essential for identifying multi-state appliances. There are three types of basic event sequences: repetitive sequence, fixed sequence, and the combination of the two.

Stoves, dryers, or some coffee makers are typical multistate appliances with repetitive sequence due to their integer-cycle controllers [15]. An example of fixed sequence is a washer.

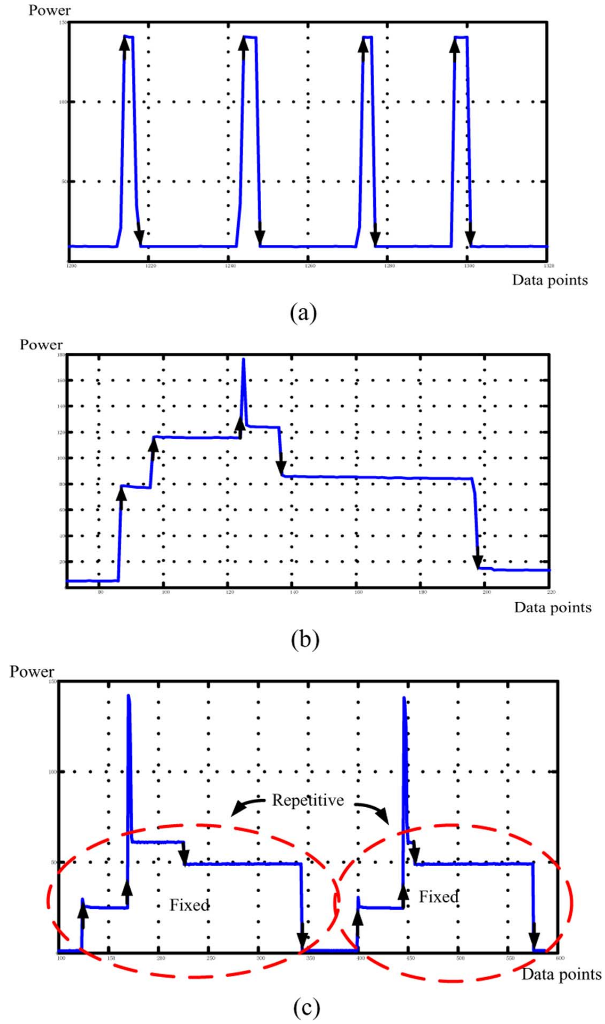


Fig. 5. Different sequence patterns. (a) Repetitive sequence. (b) Fixed sequence. (c) Combination.

TABLE II
SEQUENCE PATTERN AND EXAMPLES

Load type	Examples
Repetitive sequence	Dryer; Stove; Some coffee makers
Fixed sequence	Incandescent light bulb; Fluorescent light bulb; Kettle; Microwave; Toaster; Oven; Fridge; Freezer; Computer
Combination	Furnace, Some dishwashers

Sometimes, a combination of repetitive and fixed sequence occurs. Fig. 5(c) shows a furnace. It has repetitive heating cycles. Besides, each heating cycle includes a fixed sequence pattern. According to the environment temperature, the heating cycle may show up 2–5 times closely to each other. Table II shows some examples of appliances with the sequence patterns as discussed above measured through experiment.

C. Trend Signatures

A trend signature refers to variation of power demand between two edges. For example, an inductive motor often accompanies with a rising spike at start due to its large inrush current; after start, as the motor speed increases, the current drawn may decrease and form a gradual falling curve; some electronic devices may experience an instant interruption. A TV set may experience a falling spike at moments of switching channels; pulses are usually caused by electronic switches. A lot of stoves have pulses because they have an integer-cycle controller in it. It prevents itself from overheating. Another example is an inverter based motor device that adjusts its frequency all the time; a lot of appliances have a negligible transient term and present as almost flat curve; in contrast, some appliances may have continuous fluctuations all the time instead of a steady state. Table III lists up 7 types of variation which include all types of curve trends seen in appliances. It should be noted some appliance such as fridge may have more than one type of trend signatures. Those trends are not only found in one type of appliance but usually several types of appliances due to their common electrical characteristics.

From continuous power points measured from smart meter, trend signatures can be represented and detected by slope ($\Delta P/\Delta t$) variation modes described in Table III. Those slope features are also used as a scanning method for identification purpose.

D. Time/Duration Signatures

The time of load window appearance relates close to its function. There are some statistical studies on residential load modeling which present typical load on-hours shown in Fig. 6 [16], [17].

As can be seen, microwaves are more expected to be seen before breakfast, lunch, and supper; lights are usually turned on in the early morning or after dark; fridge and furnace are likely to run throughout 24 h.

Duration of load window is also determined by its function characteristics. No one keeps microwave on for more than 30 min at a time. One working cycle of fridge is barely longer than 40 min. As for lights, depending on its location, it might be on from minutes to hours. Based on statistical survey, some universal load window lengths are given in Table IV.

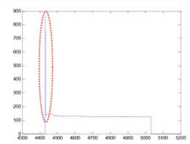
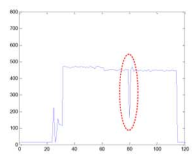
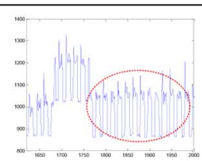
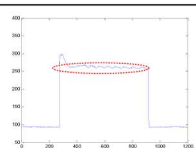
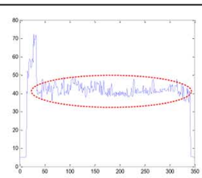
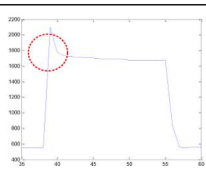
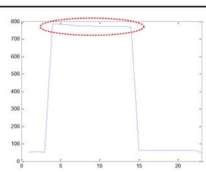
E. Phase Signature

There are two 120 V hot wires installed in a typical North American residential house as shown in Fig. 7. Hereby, the two wires can be named as A and B. Most appliances are connected between A or B and neutral. However, some heavy appliances such as stove and dryer are connected between A and B to gain a 240 V voltage. Inside a meter, two CTs are connected to A and B individually. As a result, from aggregated signals of CTs, one can tell if one appliance is phase-A, phase-B or phase A-B type. It should be noted phase-AB appliance has symmetrical edges detected by both CTs. For most energy consuming appliances, once they are placed or installed in a house, they will never be moved. Examples are stove, fridge, microwave, furnace, lights, and even large TVs. Only very a few of them have uncertain phase signatures such as a laptop.

III. LOAD IDENTIFICATION PROCEDURE

Load identification is the most essential task for NILM algorithm. Events of interested loads are detected, identified, and even reorganized from meter side instead of direct load-end

TABLE III
TREND SIGNATURES

Type	Curve example	Power slope feature
Rising spike		A large negative slope following a larger positive slope
Falling spike		A large positive slope following a large negative slope
Pulses		Continuous pairs of large slopes
Fluctuation		Continuous small slopes; signs of slopes slowly change
Quick vibrate		Continuous small slopes; signs of slopes quickly change
Gradual falling		Continuous small negative slopes
Flat		Continuous small slopes

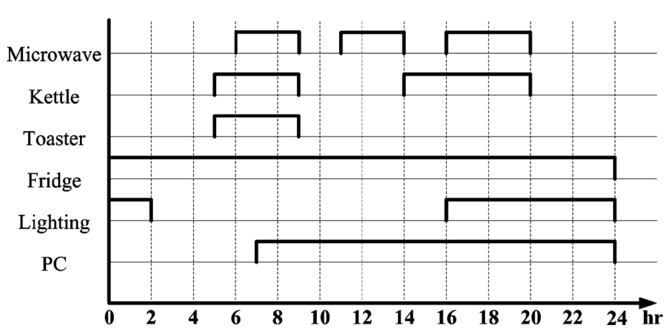


Fig. 6. Typical appliances on-hours for weekends.

monitoring. To achieve identification, load signatures are usually collected ahead of time to formulate a signature database and this is discussed in Section V. This section discusses general load identification procedure using event window models

TABLE IV
TYPICAL LOAD WINDOW LENGTHS

Load name	Min length	Max length
Fridge(cycle)	>10 mins	<40 mins
Freezer(cycle)	>10 mins	<40 mins
Furnace(cycle)	>5 mins	<30 mins
Stove	>3 mins	<45 mins
Kettle	>3 mins	<15mins
Washer	>20 mins	<90 mins
Dryer	> 20 mins	<75 mins
Bedroom light	>0 min	<5 hrs
Living room light	>0 min	<8.5 hrs
TV	>0 min	<10 hrs

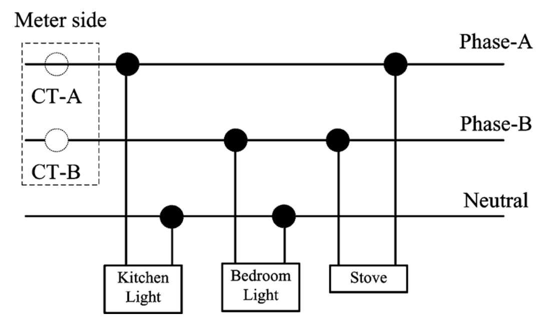


Fig. 7. North America residential wiring.

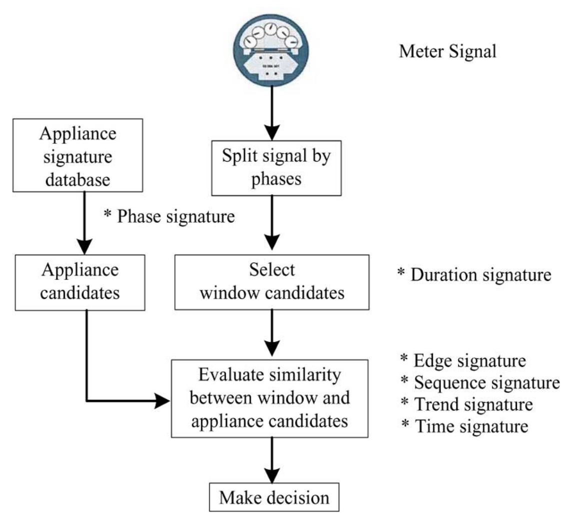


Fig. 8. General identification procedure.

and signatures already discussed in Section II. As stated in Section I, traditional NILM algorithms only focus on single state/edge of appliance and thus cannot identify appliances from entire process perspective. Theproposed NILM uses the procedure from Fig. 8 to identify loads.

A. Split Signal by Phases

Two CTs inside meter naturally divide overall signal acquired by smart meter into signals of two phases: phase-A signal and phase-B signal. Accordingly, to deal with phase-A signal, only phase-A loads will remain as candidates. So it is for phase-B signal. Normally, a phase-B connected light bulb will never be seen from CT-A.

Two exceptions should be addressed: for phase A-B appliance, since any of its edges shows up simultaneously at both phases, it will be left as appliance candidates only if two CTs can

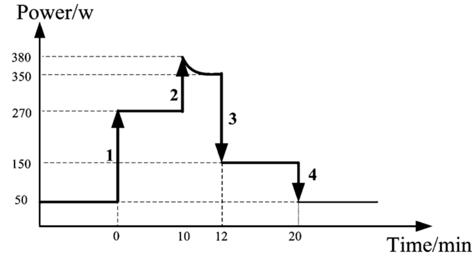


Fig. 9. A section of meter signal collected from CT-A.

TABLE V
WINDOW CANDIDATES VS. APPLIANCE CANDIDATES (1)

Appliance candidate	Window candidate 1-3	Window candidate 2-4	Window candidate 1-4	Window candidate 2-3
Kettle				
Fridge				
Light				
Furnace				

detect two identical edges at the same time. Since the processes at both phases are the same, any phase signal can be chosen for identification purpose; for portable appliance, on the other hand, since it has an uncertain phase signature, it will be left as candidates for both phase signals.

B. Select Window Candidates

After signal split, suppose a section of aggregated signal from CT-A is measured as shown in Fig. 9.

Firstly, applying power slope analysis to the data, 2 rising edges and 2 falling edges can be located (two large positive slopes and two large negative slopes) and labeled. As discussed in Section II, signal collection between any pair of rising and falling edge is considered as a window candidate. In Fig. 9, there are in total 4 window candidates: 1–3, 2–4, 1–4, 2–3. Those window candidates are waited to be compared throughout appliance candidates one by one.

Typically, a residential house may have more than 500 rising and falling edges per day. It indicates the potential number of window candidates per day can be 250 000 in maximum. This will bring too much computing burden. One way to reduce window number is to trim these window candidates through appliances' possible window lengths.

According to Table V, window candidate 2–3 is too short to be possible for kettle, fridge and furnace. Candidate 1–4 is also too long for kettle. Those windows are firstly ruled out even before they enter into the next evaluation step. In fact, this window length limit has much greater on refining longer period data. For a day period, only 120–200 window candidates will be left based on multicase studies.

C. Evaluate Similarity Between Candidates

This is the core step of identification. In this step, each of the rest window candidates will be compared through each of the rest appliance candidates after step A and B according to their rest signatures on edge, sequence, trend and time. At first, all of those 4 signatures will be compared respectively to get similarity indices on each one $(S_{edge}, S_{seq}, S_{trd}, S_{time})$.

TABLE VI
EXAMPLES OF LOAD ω AND γ

Load name	Distinctive signatures	ω^T	γ
Fridge	Edge, trend	[0.53 0.17 0.22 0.08]	0.85
Microwave	Edge, time	[0.65 0.19 0 0.16]	0.85
Furnace	Edge, sequence	[0.53 0.47 0 0]	0.85
Stove	Edge, sequence, time	[0.51 0.3 0 0.19]	0.85
Washer	Edge, sequence	[0.55 0.45 0 0]	0.8
Kettle	Edge	[0.86 0.14 0 0]	0.85
Laptop	Edge, trend	[0.5 0.25 0.25 0]	0.8
Average	---	[0.59 0.28 0.07 0.06]	0.85

Then those 4 indices will be synthetically considered to judge if this window candidate is matching an appliance candidate. The mathematical calculation is completed through a linear discriminate classifier.

$$g(x) = \omega^T x - \gamma \tag{2}$$

with

$$x = \begin{bmatrix} S_{edge} \\ S_{seq} \\ S_{trd} \\ S_{time} \end{bmatrix}, \omega = \begin{bmatrix} \omega_{edge} \\ \omega_{seq} \\ \omega_{trd} \\ \omega_{time} \end{bmatrix}. \tag{3}$$

x includes similarity indices of each signature. Their determination will be elaborated in Section IV. ω is the weight vector since for different types of appliances, importance of different signatures is different. γ is a qualification threshold. This classifier deals with two classes: when $g(x) \geq 0$, this window is determined as this appliance; otherwise not. γ can be adjusted to achieve a balance between identification rate and accuracy. Table VI listsup typical ω and γ values for some appliances.

Those weights ω are firstly estimated based on observation and analysis of appliances. For example, knowing furnace and washer have unique sequence signatures, S_{seq} will be emphasized; knowing microwave is often used before meals, S_{time} is emphasized. Generally, edge signature is always important since it determines the electric characteristics of a window. Sequence signature is important too, especially for multistate appliances. Trend signature is important for motor related and some electronic appliances. Time signature functions accessorily and is more effective for time-oriented loads such as kitchen appliances. After weights are predefined, their values will be optimized and verified through a simulation program. This program generates numerous testing windows based on existing load signatures and then it adjust values of ω and γ to ensure that maximum number of correct identification can be made for each type of load.

Usually weight vector ω stays the same for the same type of load even when moving from one house to another. The row "Average" in Table VI gives a rough setting without load type known, which can be used to cope with unfamiliar loads. The advantage of the weight vector is that when comparing, there is no absolutely strong signature—various signatures are bonded together to ensure fairness and accuracy of system.

Identification threshold γ is normally set as 0.8–0.85 for most cases. It can be lowered if imposed signal noises are significant.

TABLE VII
CANDIDATE WINDOWS VS. CANDIDATE APPLIANCES (2)

Appliance candidate	Window candidate 1-3	Window candidate 2-4	Window candidate 1-4	Window candidate 2-3
Kettle	**0.15**	-0.45		
Fridge	-0.3	**0.15**		
Light	-0.85	-0.85	-0.85	
Furnace	-0.75	-0.75	-0.75	

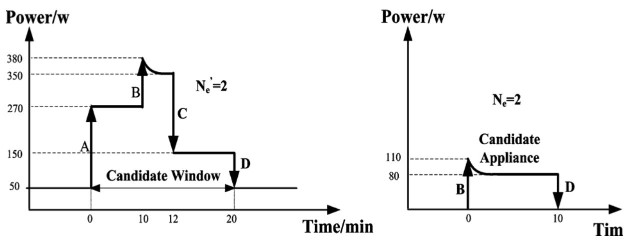


Fig. 10. Edge similarity comparison.

D. Make Decision

In the end, Table V is calculated according to (2)–(3) and the $g(x)$ values are filled in in Table VII.

From the signs of classifier values, window 1–3 is determined as a kettle while window 2–4 is a fridge since their values are greater than 0. If no positive value is found, it means the edges are caused by an unknown appliance not registered in database yet (maybe not interested by users either.)

This linear classifier can also be substituted by more advanced classifiers such as neural networks or decision tree. Those variations are not discussed here.

IV. SIGNATURE COMPARISON

This section addresses on how to compare signatures to obtain similarity indices $S_{edge}, S_{seq}, S_{trd}, S_{time}$. Those quantities should be able to effectively reflect how similar awindow signature is with respect to a database signature of a certain appliance.

A. Edge Similarity S_{edge}

From the signature database, an appliance candidate only includes its own P-Q-W edge sets. In contrast, a window candidate may include other edges caused by overlapped appliances. The comparison is trying to answer if this window candidate includes all of the appliance candidate's edges. Thus the process is like this: each of registered edges will be compared throughout all the edges in window candidate one by one. Then

$$S_{edge} = \frac{N_e'}{N_e} \tag{4}$$

where N_e is number of edge types defined in appliance candidate and N_e' is recognized number of appliance edge types in window candidate.

As shown in Fig. 10, both of the two registered edges B-D are found in the window ($N_e = N_e' = 2$). However, if only B exists, it is very likely the window candidate is only one part of the appliance process and its $S_{edge} = 0.5 (N_e = 2, N_e' = 1)$.

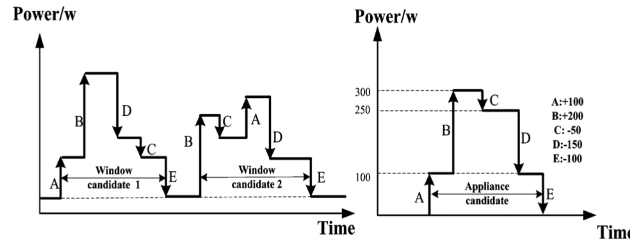


Fig. 11. Sequences of two candidate windows compared to the appliance candidate.

TABLE VIII
EXAMPLE OF POSITION CHANGE

Window candidate	Position change of letters	Length of changed position
A-B-D-C-E	C:3→4 D:4→3	|4-3|+|3-4|=2
B-C-A-D-E	A: 1→3 B: 2→1 C: 3→2	|3-1|+|1-2|+|3-2|=4
C-B-A-D-E	A: 1→3 C: 3→1	|3-1|+|1-3|=4

P, Q can be easily compared since they are quantitative values. As for current waveform W, one can conduct comparison in either time-domain or frequency domain [12]. Selecting proper harmonic orders can also eliminate the impact from noises and dc offset.

Since an edge is determined by three sub-attributes, again, different weights can be set to those attributes: for linear and active load such as stove, P should be emphasized; for non-linear load such as microwave, W should be emphasized; for reactive load such as fridge, Q should be emphasized. Those weights can be predefined for appliance candidates. Synthesizing them together, two edges can be determined as identical or nonidentical.

Overall, S_{edge} indicates the existence of edges of appliance candidate in window candidate.

B. Sequence Similarity S_{seq}

For ON/OFF type appliance, it has a fixed sequence of edges; for multistate appliance, as discussed in Section II, fixed sequence and repetitive sequence may either be found.

For fixed sequence edges, they always follow a certain order pattern. For a window candidate, its edge order should comply with the order pattern defined in appliance candidate. For example, as shown in Fig. 11, a space heater has 5 edges in the order of A-B-C-D-E. It is expected to find A-B-C-D-E in the window. On the other hand, an A-B-D-C-E sequence may imply a different appliance process and B-C-A-D-E is even more different.

To quantify the difference of two sequences, a simple method based on calculating the position changes of letters is proposed. Suppose the appliance candidate abovehas a sequence labeled using letters A-B-C-D-E. Window candidate 1 has A-B-D-C-E; window candidate 2 has B-C-A-D-E; window candidate 3 has C-B-A-D-E. Then we have Table VIII.

It is easily known that B-C-A-D-E and C-B-A-D-E are more disordered than A-B-D-C-E compared to the original sequence

A-B-C-D-E based on their lengths of changed positions. For a given sequence composed of n letters/edges, the maximum possible length of changed position is

$$M = \sum_{k=0}^{L} [n - (2k+1)],\ L < \frac{n-1}{2}. \tag{5}$$

From (5), it can be calculated that:

- for ON/OFF appliance, $n = 2$, $M = 2(\mathrm{AB} \to \mathrm{BA})$;
- for three-edge appliance, $n = 3$, $M = 4(\mathrm{ABC} \to \mathrm{CBA})$;
- for four-edge appliance, $n = 4$, $M = 8(\mathrm{ABCD} \to \mathrm{DCBA})$;
- for five-edge appliance, $n = 5$, $M = 12(\mathrm{ABCDE} \to \mathrm{EDCBA})$.

Based on the discussion above, S_{edge} for appliance with fixed sequence can be quantified as

$$S_{trd} = 1 - \frac{N_f}{M} \tag{6}$$

where N_f is the length of changed position of a window candidate as calculated in Table VIII.

For example, sequence C-B-A-D-E's $S_{trd} = 0.67(N_f = 4)$ while sequence E-D-C-B-A's $S_{trd} = 0$ since it is completely opposite to the original sequence A-B-C-D-E $(N_f = 12)$

One exception is if S_{edge} is already found smaller than 1, S_{seqf} will be automatically set to zero due to mismatch in the number of relevant edges.

The appearances of repetitive edges are also counted in the step of determining S_{edge} and only if its number is more than one, it is recognized as a repetitive edge.

$$S_{seqr} = \frac{N'_r}{N_r} \tag{7}$$

where N_r is number of repetitive edge types defined in appliance candidate and N'_r is recognized number of repetitive edge types in window candidate.

As for a combination sequence load such as a furnace, S_{seq} can be decided based on its two subindices, S_{seqf} and S_{seqr}, which can respectively evaluate similarities of repetitive and fixed sequence characteristics.

C. Trend Similarity S_{trd}

As discussed in Table III, power slope based scanning can effectively scan the window candidate and further determine the existences of trend signatures with respect to appliance candidate.

$$S_{trd} = \frac{N'_t}{N_t} \tag{8}$$

where N_t is the number of trend signature types defined in appliance candidate and N'_t is the recognized number of trend signature types in window candidate.

D. Time Similarity S_{time}

In the end, the moment of appearance of window candidate t is also compared with time signature defined in appliance candidate. As shown in Fig. 6, the time signature of appliance candidate is defined as one or several hour ranges T such as $\{17–23\}$, $\{6–8, 11–13, 16–18\}$.

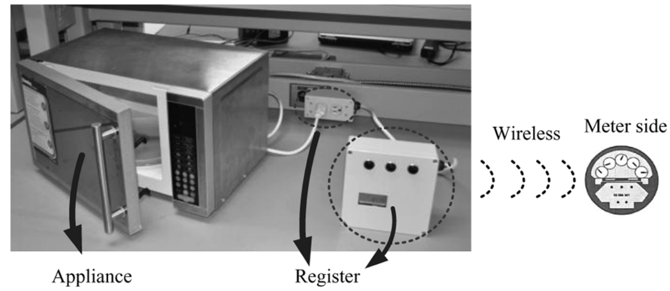


Fig. 12. Connection of register and system.

$$S_{time} = \begin{cases} 1, t \in T \\ 0, t \notin T \end{cases} \tag{9}$$

V. Creation of Signature Database

NILM needs a customized signature database to realize identification since appliance characteristics are usually different from house to house. In this paper, since more process signatures are involved, convenient creation of signature database for ordinary householders is really important. In this work, we propose to create a small signature database tailed for each home utilizing a device called appliance register.

An appliance register is a device inserted between the appliance to be registered and the electric outlet the appliance is plugged in originally (Fig. 12). The device contains a current sensor and a wireless transmitter. Once a current change is detected (an event), the device will send a signal to the smart meter (or the device which does appliance identification). Smart meter does two things: capture the event window of this appliance and determine the signatures of event window.

Firstly, phase signature can be determined by the smart meter. Then captured event window will be scanned through and all events associated with the appliance (labeled by the register device) are picked out. Edge signatures can be directly extracted. Sequence signature can be determined based on appearance number of edge types. Trend signature can be detected based on slope modes explained in Table III. In the end, time/duration signatures are automatically learned when the appliance is named by users.

After waiting for one or two operating cycles of the appliance, all signatures of the appliance will have been collected. The register is then removed. This approach has another advantage in term of privacy: the customer can control which appliances are to be registered for identification.

VI. Application and Verifications

A. Application and Verification Based on Real Life Data

The above algorithms and devices were tested in two real residential houses for several weeks with no special intention from the owners. A laptop based data acquisition system was hooked to the electricity panel and behave like a smart meter. A Zig-bee transceiver was connected to its USB port to bridge the communication with the appliance register. After registration was finished, a computer program based on proposed algo-

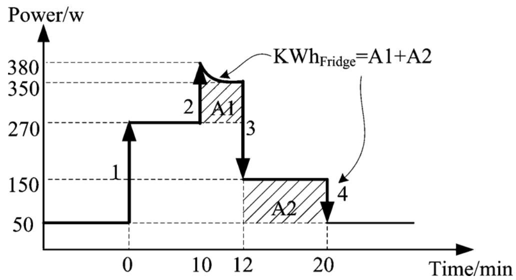


Fig. 13. Area integration based energy calculation.

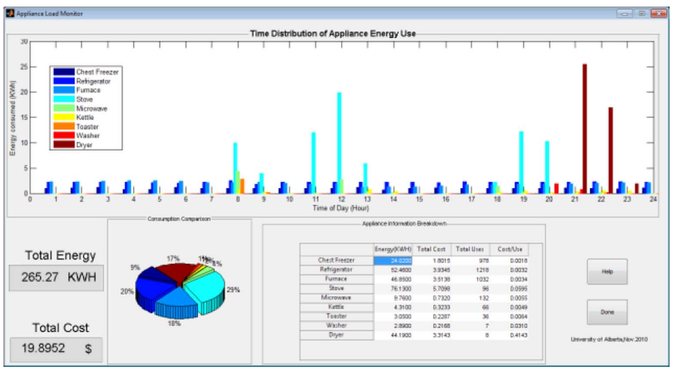


Fig. 14. Appliance energy decomposer software.

rithms was launched and kept running. In real time, the overall power was decomposed into appliance level. Interested appliance events are firstly identified. Then their energy consumption is calculated through area integration illustrated in Fig. 13. This method is much more accurate than traditional single-state based energy calculation since the detailed power variation of process can now be tracked and counted. This is especially significant for continuous-varying and multistate appliance energy.

The results are updated every half an hour and displayed in the interface shown in Fig. 14. As can be seen, appliance electricity consumption information is formatted into the table and charts. The table summarizes the total energy counted from a certain date and converted expenses with respect to local electricity rates (say, 7.4¢/KWH). The pie chart presents the percentage composition of individual appliance so users can be aware of the significance of reducing a certain appliance's consumption. Finally, from the time distribution of energy use chart, user can understand his energy usage pattern statistically with respect to hours. This information is quite essential for residential house owners to adopt proper demand response strategies such as load shifting according to utility's TOU rates.

To verify the identification rates, controlled trials were conducted continuously for 5 days. Interested appliance events were manually checked and recorded as comparison. The results listed in Table IX are very satisfactory for all types of appliances including continuous-varying and multi-state appliances. The column "False identified operation times" indicate the mistakenly identified times caused by events of other loads.

B. Comparison With Other Solutions of NILM

This paper also presents a detailed comparison between proposed solution and traditional combination based solution such

TABLE IX
IDENTIFICATION RATE VERIFICATION

Appliance Name	Actual operation times	Correctly identified operation times	False identified operation times	Identification accuracy(%)
Chest Freezer	178	163	2	90.5
Fridge	213	203	4	93.4
Furnace	185	172	1	92.4
Stove/Oven	16	16	0	100
Microwave	23	22	0	95.7
Kettle	12	11	0	91.6
Toaster	6	6	0	100
Washer	3	3	0	100
Dryer	4	4	0	100

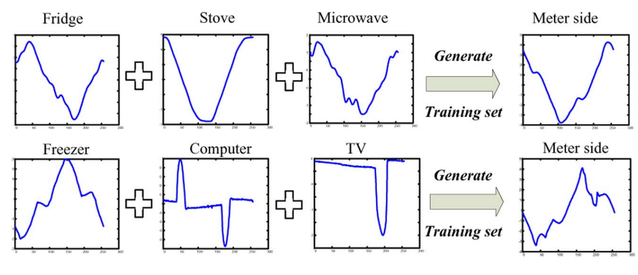


Fig. 15. Examples of generated training sets based on harmonic (waveform) signatures of appliances.

as discussed in [8], [9]. According to [9], a two-layer feed-forward network is adopted here for comparison. Other similar solutions are not discussed here.

Firstly, specific appliances were measured in the lab and their harmonic signatures were collected. Not like in the proposed approach, no process related signatures is considered by neural networks. Harmonic contents of aggregated signal are used as input layer while appliance composition list as output layer. Since both magnitude and phase of a certain harmonic order are considered, the input layer has 16 nodes of up to 15th harmonic content (odd ones). Hidden nodes are set to be 20. As shown in Fig. 15, according to [9], numerous training sets are generated mathematically by adding up harmonic contents (waveforms) of designated individual appliances. Also, to make training more reliable, a less than 10% deviation is added to original magnitude as noises.

For test stage, a bottom-up based aggregating program turns on/off each load according to their regular behavior. The aggregated meter side signal is formed this way. Then both of the two approaches were tested to decode the overall meter signal and their performances are discussed as below.

Comparison is firstly conducted when there are only single-state type loads. This is because single-state type loads only have a steady-state harmonic content. The results are shown in Table X.

As can be seen, for a system composed of only single-state type loads, proposed approach has a performance similar to NN based approach. This is because there is no change in each appliance's operation process. However, results are heavily changed when complicated loads are brought in.

In Table XI,as can be seen, NN based approach is significantly affected by the introduction of multi-stage loads (furnace and washer) and continuous varying loads (fridge and freezer).

TABLE X
COMPARISON FOR ONLY ON/OFF TYPE LOADS

Loads	Identification accuracy(%)	
	NN based approach	Proposed approach
Microwave	97.9	99.9
Monitor	98.3	98.3
TV	99.2	98.1
Vacuum	97.6	98.6
Monitor	99.9	98.5
Incandescent light bulb	98.9	98.5
Fluorescent light bulb	99.0	99.2

TABLE XI
COMPARISON WITH COMPLICATED LOADS

Loads	Identification accuracy(%)	
	NN based approach	Proposed approach
Microwave	92.3	99.9
Monitor	93.6	94.9
TV	84.4	94.2
Vacuum	85.0	96.3
Monitor	79.8	97.7
Incandescent light bulb	97.5	98.5
Fluorescent light bulb	95.6	99.2
Fridge	63.7	97.9
Freezer	68.5	95.3
Washer	73.4	97.1
Furnace	57.2	98.4

This drawback is actually discussed in [9] due to the lack of a steady-state harmonic content in those appliances. Their harmonic contents can vary tremendously with time. Sometimes, harmonic contents of different operational stages of the same load cannot even be comparable such as in furnace. To cope with this problem, NN based approach has to average the harmonic contents and use the average value for training. This will introduce not only large error to those complicated loads themselves but also to those single-state loads if they are turned on at the same time. For example, for a given point, if the aggregated waveform is composed of fridge and microwave, identification of microwave may fail due to error from fridge. In contrast, proposed approach captures event window and utilizes process signatures to identify. In theory, the more complex the process is, the more unique its window can be and the easier it can be identified. This is the reason proposed approach has a much better performance. In the meanwhile single-state appliances will not be affected by complicated appliances since they have different edges.

Another obvious advantage of proposed approach is it only identifies loads users are interested in and willing to register. In contrast, NN based approach's training process has to cover all major appliances. Also, once user purchases another heavy load such as a stove, the accuracy of identification will become not reliable at all. This is because the trained network itself has been changed due to the newly added element. As shown in Table XII, any aggregated signal that has stove on at the same time will become unidentifiable (this is especially severe for other kitchen appliances). However, stove hardly has any impact to identification of registered loads using proposed approach since proposed approach is based on searching relevant edges of registered appliances. Those nonrelevant edges from stove will be ruled out of the window candidates of registered loads.

TABLE XII
COMPARISON WHEN STOVE IS NOT TRAINED OR REGISTERED

Loads	Identification accuracy(%)	
	NN based approach	Proposed approach
Microwave	78.0	94.5
Monitor	77.8	94.3
TV	76.6	94.2
Vacuum	65.2	96.1
Monitor	95.8	95.8
Incandescent light bulb	64.1	95.1
Fluorescent light bulb	38.6	95.8
Fridge	51.3	96.1
Freezer	56.3	90.6
Washer	45.4	92.7
Furnace	44.3	95.6
Stove	---	---

To conclude, the proposed approach has the following obvious advantages:

- Process based signatures and event window make identification of complicated loads possible. However, combination based approaches such as NN cannot effectively identify those loads.
- Composition of appliances is not only judged by an independent point of meter side signal but also events before and after this point. Association of load states is much more strengthened. A load's OFF event can only be confirmed if its ON event is found within a time window.
- Training process does not need to cover all major appliances any more. Users only need to register their interested loads they want to track down.
- Nearly no additional effort if load inventory is partially changed.

VII. CONCLUSIONS

This paper has presented a new method to identify and track home appliance loads using the smart meter data. The main idea of the proposed method is to model the entire operating cycle of a load and make identification based on event windows. A set of algorithms has been developed for this purpose. Another contribution of this paper is the proposition of a novel method for creating signature databases tailored for individual houses. Tests conducted in two houses have shown that the rate of successful identification is above 90% for all types of appliances. Although through detailed comparison with traditional neural network based solution, several advantages of proposed approach are revealed. It is believed that the proposed technique makes nonintrusive monitoring more applicable for complicated loads; it can also reduce ordinary house owner's efforts to apply NILM.

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