Load Signature Study—Part I: Basic Concept, Structure, and Methodology

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***Abstract*—Load signature is the unique consumption pattern intrinsic to each individual electrical appliance/piece of equipment. This paper focus on building a universal platform to better understand and explore the nature of electricity consumption patterns using load signatures and advanced technology, such as feature extraction and intelligent computing. Through this knowledge, we can explore and develop innovative applications to achieve better utilization of resources and develop more intelligent ways of operation. This paper depicts the basic concept, features of load signatures, structure and methodology of applying mathematical programming techniques, pattern recognition tools, and committee decision mechanism to perform load disaggregation. New indices are also introduced to aid our understanding of the nature of load signatures and different disaggregation algorithms.**

***Index Terms*—Artificial neural network, committee decision mechanism, electric-load intelligence, load disaggregation, load signature, smart metering.**

I. Introduction

ELECTRICITY is one of the most common and important commodities we use everyday. Electric power is typically sold on a per-unit consumption basis, namely, x dollar per kilowatt-hour (kWh). With mounting concerns on climate change and competitive pressures, utilities need to devise innovative means to increase/create value beyond the $x/kWh. We proposed a concept called electric-load intelligence (E-LI) in 2006 and proposed how to derive new information and value from studying the consumption patterns of load entities [1]. The impetus of our research program is to develop load signature disaggregation capabilities at the metering point and explore potential applications. One of these applications is the ability to recognize individual appliances from a composite load signal measured at the meter. By doing so, we could add new services to customers. The objective of this paper is to define a universal platform on which we believe could help us further enhance the value of electricity by knowing more on how it is used.

Intuitively and, in fact, traditionally, it is possible to insert an intermediate monitoring device between the socket and the appliance and then record its operation. This method is generally called "intrusive" monitoring. One has to acquire such a recording device for all sockets or pay more for an appliance implicitly installed with these. This method is still considered inconvenient and expensive for large-scale deployment. With today's technology and the increasing deployment of smart meters and advanced metering infrastructure (AMI), the "non-intrusive" load disaggregation method presented in this paper presents an attractive alternative because it can be performed at the metering point (without the need to have access to individual sockets).

This paper first explains the concept of E-LI and defines what we regard as "micro" and "macro" level-load signatures. We then introduce the "snapshot" and "delta" forms of signatures. Based on a typical appliance-based dataset, key features of individual load signatures are presented and illustrated. The methodology of using computational tools to disaggregate a composite load into identifiable appliances is then presented. A multifeature and multialgorithm approach, called Committee Decision Mechanism (CDM), is proposed to consolidate the results from different single-feature, single algorithm disaggregation methods and then render the best answer possible. New assessment tools in terms of indices are defined to help us better understand the accuracy of the disaggregation process and the nature of load signatures.

II. Concept and Definitions

A. Electric-Load Intelligence (E-LI)

E-LI is an umbrella term we use to describe a concept of studying detailed usage pattern of electric loads and developing intelligent applications using technology to ultimately enhance the value of electricity [1], [2]. In other words, E-LI is not only about collecting consumption data of load entities, but also includes detailed analysis and intelligent applications of these data for innovative uses.

B. Load Signature (LS)

An LS is defined as the electrical behavior of an individual appliance/piece of equipment when it is in operation. Similar to any human's signature, each electrical device contains unique features in its consumption behavior. Of course, this behavior is limited to what can be monitored at a point of interest (e.g., at the meter). These variables normally include voltage, current, and power measurements. LS is the basic unit and the most important means we are using to develop the knowledge in E-LI. In mathematical form, we define a generic LS, $\Psi_i(\mathrm{t})$, for appliance i, as in (1)

$$\Psi_i(t) = \{f_{i,1}(\vec{v},t), f_{i,2}(\vec{v},t), \ldots, f_{i,M}(\vec{v},t)|\Delta t = T\} \tag{1}$$

Manuscript received August 28, 2008; revised May 25, 2009, August 28, 2009. First published November 17, 2009; current version published March 24, 2010. This work was supported by the CLP Research Institute. Paper no. TPWRD-00653-2008.

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Digital Object Identifier 10.1109/TPWRD.2009.2033799

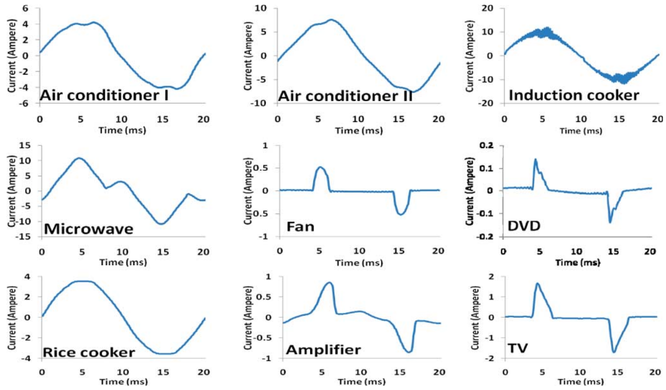

Fig. 1. Examples of micro load signatures.

where $\vec{v}$ is a vector of basic electrical measurements w.r.t. time (t); $f(\vec{v}, t)$ is a feature extracted from $\vec{v}$; M is the total number of features; and T is the sampling interval of $\vec{v}$. We use T to differentiate different levels of LS, and this will be elaborated in more detail later.

C. Composite Load (CL)

A CL refers to the net behavior of more than one appliance operating simultaneously and their collective behavior measured at an upstream position (e.g., at the meter). In mathematical form, it can be described as

$$\Omega(t) = \left\{ \sum_{i=1}^{R} \Psi_i(t) | \Delta t = T \right\} \tag{2}$$

where R is the total number of simultaneously-operating appliances. In general, CL is more complicated in nature because the unique features from individual appliances are mixed and sometimes certain features may even be masked or lost. However, this is generally the easiest accessible signal from the utilities' perspective.

D. Micro Level

Any load signature or composite load collected using a sampling interval (T) that is faster than 1 sample per cycle is considered at a micro level in our study. Fig. 1 shows some selected appliances depicted in their micro level. These are the current waveforms of different appliances with a sampling rate of 12 000 samples per second. It is easy to see that under this microscopic view, different appliances have very distinct waveshapes and amplitudes. This is the level of LS which was studied extensively in [1]–[5].

E. Macro Level

Any load signature or composite load collected by using a sampling interval that is slower than 1 sample per cycle is considered at a macro level. Fig. 2 shows a 24-h profile of the voltage, current, and power values collected from an apartment. The sampling rate is 1 sample/s. The current and power are the composite load readings and they are all considered macro-level signatures. It is apparent that the detailed waveshapes as shown in Fig. 1 are not observable here. However, other patterns, such as the duty cycles, are quite noticeable. This is the level of load signatures investigated by EPRI of the U.S. [6], [7] and MIT [8].

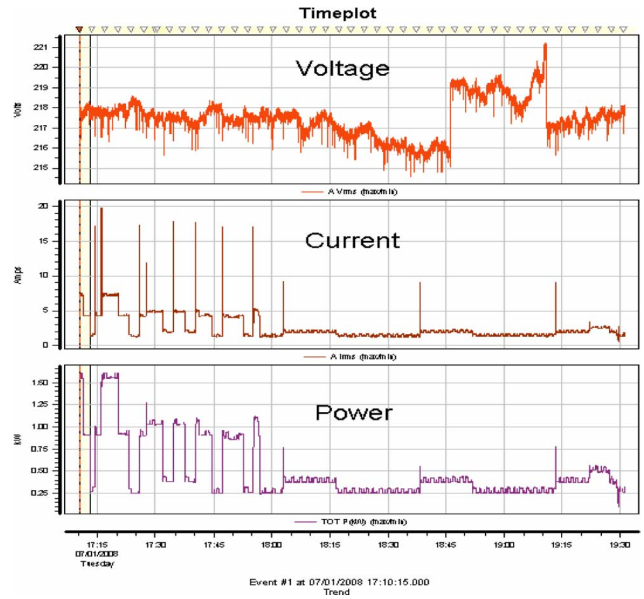

Fig. 2. Example of the macro-load signatures.

F. Snapshot Form

We further define two forms of signatures (which could be a load signature or a composite load). The first one is a snapshot form. In this form, the signature is the instantaneous snapshot of the load behavior taken at any fixed time intervals. This signature is generally a composite load with many load signatures mixed in it.

G. Delta Form

A delta form signature makes use of the difference between two consecutive snapshots form signatures. If the snapshot interval is made small enough, we can assume that only one appliance is switched on/off between the snapshots. Therefore, the delta form signature will behave more like a load signature (single appliance switching) instead of a composite load. In [6]–[9], 1 s has already been widely used as the snapshot interval.

III. Features of Load Signature

Millions of electrical appliances are in operation today. With an increasing number of electronically controlled and automated devices (e.g., washing machines), it is infeasible and impractical to obtain a complete and "personalized" database for all equipment. Therefore, we focus on developing a set of generalized and critical features that can be extracted from conventional measurements (e.g., current and voltage waveforms). In the past decade, researchers at MIT and EPRI have already demonstrated that using the real and reactive power (P and Q) features can track appliance usages [6], [7]. P and Q can also be used with higher harmonics for load identification [8]–[10]. In this paper, we propose a number of additional features on top of the P and Q and through them, we can improve the recognition capability.

Our multifeature approach covers transient and steady-state behavior spanning multiple domains. These features include: current waveform (CW), active/reactive power (PQ), harmonics (HAR), instantaneous admittance waveform (IAW), instantaneous power waveform (IPW), eigenvalues (EIG), and switching transient waveform (STW).

In general, there are two kinds of methods to build the database [6]. The first method is to record an individual appliance load signature manually, while the second is to develop an algorithm to classify them automatically. In this paper, the first method is adopted. Once the database is built, it can be assume that all of the appliances have been included and there is no new/unknown appliance being operated during the disaggregation process. An appliance database containing typical household equipment is used here to illustrate all of these features. The database includes 27 typical appliances with a total of 32 operating modes. If all of these appliances are switched on, the total consumption will reach approximately 10 000 W (the typical single household rating is about 11 000–13 200 W). Details of the database are shown in the Appendix.

A. Feature-Additive Criterion

We propose that all features being considered for a load signature analysis should preferably meet the feature-additive criterion, stated as follows.

Let $f_{i,j}$ be feature j from appliance i, and $\Omega_j(t)$ be the aggregation of feature j from a composite load made of K appliances operating simultaneously at time t. If appliance l is switched on at time $t+\Delta t$, and

$$\Omega_j(t+\Delta t) = \Omega_j(t) + f_{l,j} = \left(\sum_{i=1}^{K} f_{i,j}\right) + f_{l,j} \quad (3)$$

is satisfied, feature $f_{i,j}$ is said to have met the feature-additive criteria.

Thus, if a feature can meet the feature-additive criterion, it can be used in snapshot and delta forms for load disaggregation purposes. The individual features of an aggregated/unknown signature can then be compared directly with the known features in the database. However, if the feature does not meet the feature-additive criterion, it could only be analyzed individually in the delta form (e.g., comparing directly with the specific feature of an appliance in the database).

B. Current Waveform (CW)

The current waveform (CW) in the time domain provides one of the most complete sets of information to describe load behavior. Its main advantage lies in the high resolution of the signal which can reflect detailed characteristics of the appliance. Fig. 3 shows the CWs of several typical appliances. It is noted that some appliances have unique features in their CW. For example, the water boiler (resistive element) has a sinusoidal waveshape, the air conditioner (motor-driven) has a slightly warped sinusoidal shape, a TV (electronics) has a non-sinusoidal waveshape, and the induction cooker has high-order harmonics.

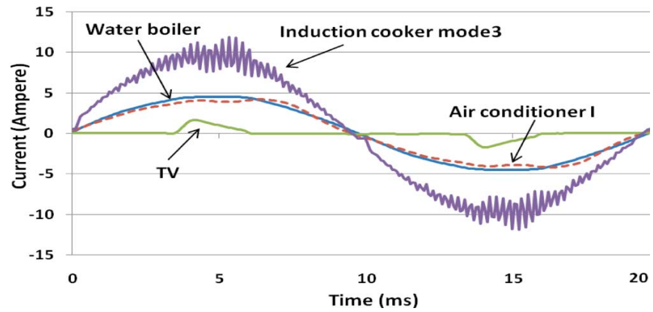

Fig. 3. CW feature.

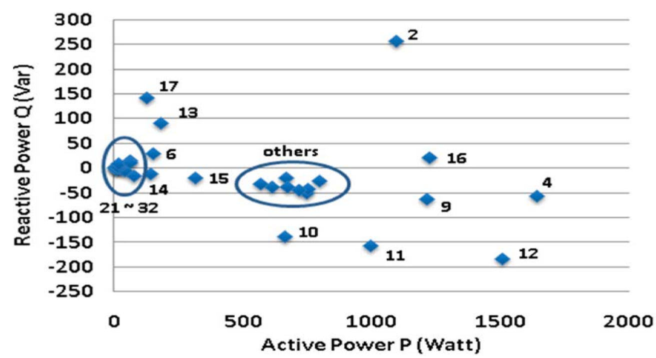

Fig. 4. PQ diagram of all appliances in the appliance database.

C. Active and Reactive Power (PQ)

Active and reactive power are the most frequently used measurements for load behavior. To guarantee the PQ feature meeting the feature-additive criteria, the following formula as shown in (4) and (5) which are based on [11] are utilized:

$$P = \sum_{k=0}^{\infty} P_k = \sum_{k=0}^{\infty} V_k I_k \cos(\phi_k) \quad (4)$$

$$Q = \sum_{k=0}^{\infty} Q_k = \sum_{k=0}^{\infty} V_k I_k \sin(\phi_k) \quad (5)$$

where V and I are the magnitude of voltage and current, respectively, ϕ is the phase angle between voltage and current, and k is the harmonic order.

A PQ diagram of all appliances is shown in Fig. 4. The numbers shown in Fig. 4 are the Appliance IDs listed in the Appendix (e.g., ID 4 is the column heater which consumes up to 1600 W and 52 var). It is interesting to note that for appliances with low power consumption (ID 21–32 as shown in Fig. 4), their PQ features tend to cluster around the origin and, hence, would be difficult to be identified based on PQ alone. This situation also applies to certain appliances with active power around 500–700 W.

D. Harmonics

Using fast Fourier transformation (FFT), the harmonic contents (or features in the frequency domain) can be obtained. It is noted that the rectangular form $(\mathrm{a} + j\mathrm{b})$ in the frequency domain satisfies the feature-additive criterion, but not the polar form $(\mathrm{A}\angle\theta)$. Therefore, if the snapshot form is used, we should use the rectangular form instead of the polar form to present

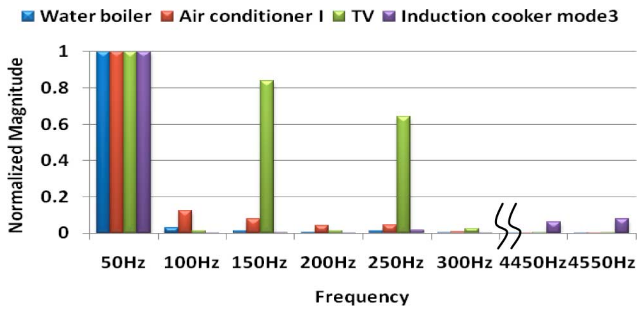

Fig. 5. Harmonics feature.

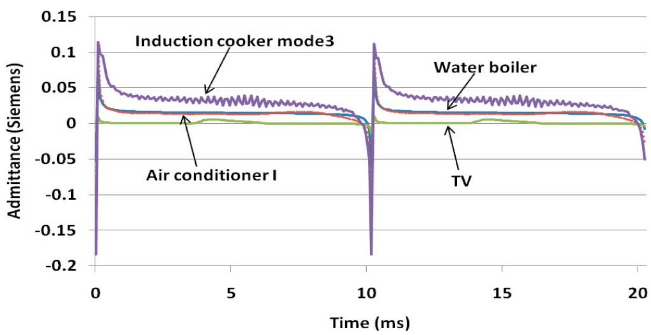

Fig. 6. IAW feature.

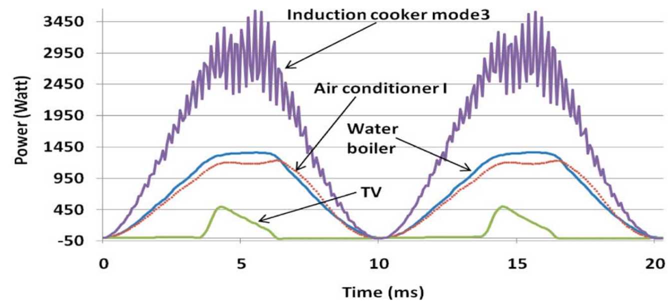

Fig. 7. IPW feature.

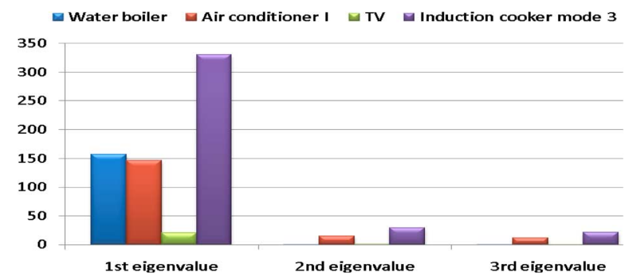

Fig. 8. Eigenvalues feature.

the harmonic feature. However, if the delta form signature is given, rectangular and polar forms can be used as we assume there is only one appliance existing in a delta form signature. Fig. 5 shows the harmonics feature of several appliances with their magnitude normalized. It is found that TV and the air conditioner have a strong low-order harmonics feature. But for the induction cooker, the high-order harmonics are more distinct.

E. Instantaneous Admittance Waveform (IAW)

IAW is defined as the quotient between the instantaneous current and voltage waveforms as in

$$\mathrm{IAW}(t) = \frac{i(t)}{v(t)}. \tag{6}$$

This is, in fact, the instantaneous admittance. The reason for choosing instantaneous admittance instead of impedance is because most household appliances are connected in parallel and, therefore, the equivalent admittance meets our feature-additive criterion. Fig. 6 shows the IAW of four appliances within a cycle. It can be seen that the IAW of the water boiler and air conditioner are quite similar (the same as in their CW feature). For TV, its IAW is generally flat except that it has a couple of distinct hums at around 5 ms and 15 ms. For an induction cooker, its high-frequency fluctuations are easily observed. IAW usually has sharp spikes at points where the voltage approaches zero (around 0 ms, 10 ms, and 20 ms in Fig. 6). This could introduce some numerical instability (division by zero) problems for the feature extraction and assessment. In this context, we discard the values of IAW if the corresponding instantaneous voltage is within the range of ± 3.5 V. The tradeoff is that we ignore about 8%–10% of the sampling data.

F. Instantaneous Power Waveform (IPW)

IPW is defined as the product of instantaneous current and voltage waveforms as

$$\mathrm{IPW}(t) = i(t) \times v(t). \tag{7}$$

This is also known as the instantaneous power. Fig. 7 shows the IPW of four appliances. It is apparent that the TV shows a uniquely nonsinusoidal shape; the water boiler and air conditioner are more distinguishable against each other and the high harmonics of induction cooker are quite dominant.

G. Eigenvalues (EIG)

For dynamic loads, such as air conditioners, their current waveforms could vary from cycle to cycle. In order to capture these dynamics, we can rearrange the time series of the current waveform into a matrix form so that we can perform an eigenvalue analysis of the time series. Singular value decomposition (SVD) is used to extract the principle component of the current envelope waveform [12]. After decomposing a cycle-by-cycle current matrix into three matrices, only the diagonal matrix, which contains the eigenvalues, is retained for load signature analysis. It is noted that the eigenvalues do not satisfy the feature-additive criterion and, hence, it can only be used for delta-form signature analysis. Fig. 8 shows the EIG features of four appliances. We note that the power-hungry appliances usually have a high 1st EIG. Therefore, it can be used to correlate with the power consumed by the appliance. For dynamic loads, such as the air conditioner and induction cooker, they have either an envelope effect or high harmonics, the second and third EIG also show good correlation. For other appliances, such as TV and the water boiler, their corresponding EIGs beyond the 1st EIG are very small.

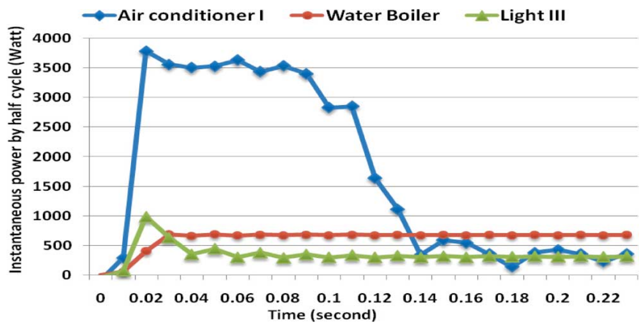

Fig. 9. Switching transient waveforms.

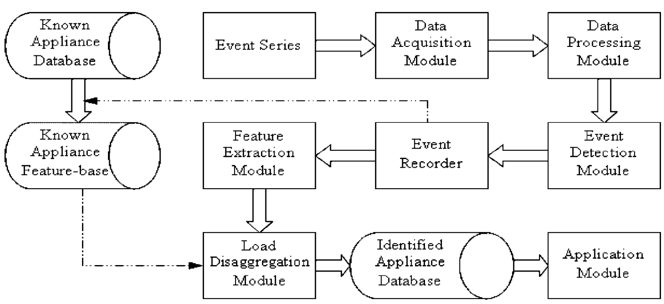

Fig. 10. Structure of the load disaggregation platform.

H. Switching Transient Waveform (STW)

So far, all of aforementioned features are derived from steady-state conditions. In fact, switching transients are also a good signature to use. In our study, we calculate the instantaneous power for every half cycle and use the resulting waveform as an STW. Fig. 9 shows the STW of three appliances. It is easy to observe that the water boiler will increase from a zero to steady-state value gradually without any overshoot. However, the air conditioner and normal light bulb will have a sharp rise to a peak value and then drop to the steady-state value with different settling times.

IV. Load Disaggregation Structure

Based on the multiple features developed so far, we have designed a load disaggregation platform as shown in Fig. 10. The aim is to use this to systematically identify and track appliance operations from any composite load signals. The following section explains the structure and function of individual modules of the platform.

A. Data-Acquisition Module

This module is to capture steady-state and transient signals. For the steady-state signal, a fix-interval sampling rate is set (e.g., every other second or minute). For the transient signal, a trigger threshold (e.g., $I_{rms} \geq 10$ A) is used to capture the waveforms during switching.

B. Data-Processing Module

After the raw data are captured, a series of data conditioning and processing will include: 1) resampling to align the current signal with respect to the voltage signal (act as a reference) to guarantee proper phase relationship; 2) normalization to normalize the data for the standardization purpose and to compensate for certain power-quality-related issues [11]; 3) filtering to extract specific harmonics features up front for later use.

C. Event Detection Module

Since it is neither efficient nor practical to store and process all captured data, our load disaggregation platform will detect when there is an actual appliance being switched (on/off). In our case, we use a simple triggering threshold (i.e., any power variation of 100 W or more between two snapshots is considered an event). Of course, other more sophisticated threshold can be used which may include changes in root-mean-square (rms) value, harmonics, and/or transient values.

D. Feature Extraction Module

For each detected event, different features as mentioned in Section III are extracted (i.e., including pre and postevent conditions). We will then submit these features to different algorithms to perform disaggregation.

E. Load Disaggregation Module

With a known appliance database and the extracted features, this module will identify from the detected event list which appliance has been switched and when. In comparison to other load disaggregation techniques, this paper proposes an innovative load disaggregation framework, in which different features and different disaggregation algorithms are applied. More details are given in Section V.

F. Application Module

Once the appliance state changes have been identified, this module will carry out an on–off matching operation for each appliance. Based on the individual appliance tracking results, the operation pattern and energy consumption of each appliance within the operation period can be estimated as well as the greenhouse gas (GHG) emission. In addition, other energy services, such as equipment health monitoring, may also be provided.

V. Disaggregation Methodology

A. Problem Formulation

The general load disaggregation problem can be described as follows: Given a known appliance database and an unknown composite load signal, we need to breakdown the unknown composite load into a set of identifiable load signatures belonging to the database. Mathematically, we can formulate this as in

$$\begin{aligned} \text{Given } \Psi &= [\Psi_1, \Psi_2, \ldots, \Psi_P]^T, \\ \Psi_i &= \{f_{i,1}, f_{i,2}, \ldots, f_{i,M}\}, \\ \Phi &= \{\phi_1, \phi_2, \ldots, \phi_M\}, \vec{x} = [x_1, x_2, \ldots, x_R]^T. \\ \min_{\vec{x}} \varepsilon_j &= g_j(\Omega, \Phi) = g_j((\vec{x}^T \Psi), \Phi) \\ &= g_j\left(\sum_{i=1}^{R}(x_i \times \Psi_i), \Phi\right) \\ &= g_j\left(\sum_{i=1}^{R}(x_i \times f_{i,j}), \phi_j\right) \end{aligned} \tag{8}$$

where Ψ is the set containing the entire appliance load signature database, $f_{i,j}$ is feature j of appliance i, extracted from the basic electrical measurements w.r.t. time (t) (e.g., voltage and current). M is the maximum number of available features in the database. Φ is the unknown composite load with M features $\{\phi_1, \phi_2, \ldots, \phi_M\}$. x_i represents the operation status of appliance i (0 indicates "OFF" and 1 indicates "ON"). The function $g_j(\Omega, \Phi)$ is to measure the fitness between the estimated appliance combination and the unknown composite load in terms of feature j, and R is the maximum number of appliances in the database. All seven features derived in Section III can be utilized in the fitness function $g_j(\Omega, \Phi)$. It should also be noted that the unknown composite load (Φ) in our study is made up entirely from the known appliance database.

B. Disaggregation Algorithms

To solve the aforementioned disaggregation problem, two different approaches are proposed in this paper (i.e., optimization and pattern recognition).

1) Optimization: The load disaggregation problem as shown in (8) is well suited to be solved as an optimization problem. This is accomplished by defining the objective function as a minimum residue while comparing the unknown CL with a set of candidates extracted from the known database. Mathematically, the objective function can be written as

$$\begin{aligned}\min_{\vec{x}} \varepsilon_j &= g_j\left(\sum_{i=1}^{R}(x_i f_{i,j}), \phi_j\right) \\ &= \sum_{k=1}^{N}\left(\hat{y}_{(k|j)} - y_{(k|j)}\right)^2 \end{aligned} \tag{9}$$

s.t.

$$\begin{aligned} A_j^T \vec{x} &= \hat{y}_j \\ C \le B \vec{x} &\le D \end{aligned}$$

where $\hat{y}_j$ is the feature j extracted from the estimated CL derived from the known LS in the database, and y_j is the feature j extracted from the unknown CL. N is the total number of points of feature j (e.g., $N = 2$ for the PQ feature and $N = 256$ for the CW feature). The matrix A is derived from all database items with respect to feature j, Matrix B, C, and D are specific features which can be used to constrain the searching space (e.g., certain features are limited to certain appliances only).

It should be noted that the complexity of solving (9) is highly dependent on whether the unknown signal (y_j) is a snapshot form or a delta form. In the simplest case in which only one appliance is switched on as in most delta forms (i.e., $x_i = 1$ and $x_k = 0$ for $k \neq i$), a one-to-one comparison with the known database can be performed. This is accomplished by directly computing the residue between the unknown and the individual appliance load signature in terms of feature j. The appliance with the minimum residue can then be considered as the targeted solution. This process is calleed the least residue (LR) algorithm in this paper.

However, when the unknown is a composite load in a snapshot form, it will contain more than one appliance's signature. The optimization problem becomes complicated and it will get worse if the database gets larger. However, integer programming (IP) [4] or genetic algorithms (GA) can still be applied to solve this problem. In our previous study, the snapshot form has been investigated and the results have been reported as in [2]. This study mainly focuses on the delta form.

2) Pattern Recognition: We can also use pattern recognition methods, such as artificial neural networks (ANN), to identify the appliance by simply teaching the ANN to learn specific features of different appliances [13]–[15]. Mathematically, we can define the input and output data of the ANN as in

$$\begin{aligned} &\vec{y_j} \to \vec{x} \\ &\vec{y_j} = \sum_{i=1}^{R}(x_i f_{i,j}) \text{ and } \vec{y_j} \in \Re^N \\ &x_i \in \{0,1\} \text{ and } \vec{x} \in Z^R \end{aligned} \tag{10}$$

where $\vec{y_j}$ (unknown CL) and $\vec{x}$ (database index) denote the input and output data of ANN, respectively. Through the training process, the structure and parameters of the ANN will be built to capture different features of appliance j using a function as defined

$$\vec{x} = h(\vec{y}_j, \vec{w}, \vec{b}) \tag{11}$$

where $h : \Re^N \to Z^R, \vec{w}$ and $\vec{b}$ are the weighting and bias factors of ANN, respectively. In our study, we have tested two types of ANNs (i.e., backpropagation ANN (BPANN) and radial-base-function ANN (RBFANN) [16]). After comparing the disaggregation performance for both algorithms, BPANN is selected for presentation here due to its better accuracy.

C. Single-Feature Single-Algorithm Disaggregation

We can then use any single algorithm (e.g., optimization or pattern recognition) for load disaggregation based on any single feature (e.g., current waveform). In general, the solutions provided by most of the disaggregation approaches are the right solution. However, if the load signature has high distortion, the solutions from different approaches may vary. Table I gives an example of the solutions provided by different single-feature single-algorithm approaches when a rice cooker is actually operated. It can be seen that different approaches have different solutions. It is also noted that from more trials similar to this that no algorithm can always get the right solution. However, if we pool all of the solutions together and consider them simultaneously, we could improve the accuracy much better as proposed in the following section.

D. Committee Decision Mechanism

Given the capability of extracting different features, such as CW, PQ, HAR, IAW, IPW, EIG, and STW, different disaggregation methods using single and/or combinations of algorithms could provide a group of candidates. We call this a "candidate pool." The key difference between a CDM and an individual disaggregation algorithm is that CDM always starts with a group of candidates while an algorithm always starts with only one or more features. CDM is then used to evaluate these potential solutions and render the best final solution [17]. This can be accomplished by using different decision-making paradigms,

TABLE I
COMPARISON OF CORRECT/ESTIMATED SOLUTIONS FROM DIFFERENT DISAGGREGATION ALGORITHMS

Alg'm	Correct Ans.	CW-LR	PQ-LR	IAW-LR	EIG-LR	HAR-LR
Sol'n	**Rice Cooker**	Hair dryer	**Rice Cooker**	Hair dryer	Air-con I	**Rice Cooker**
Alg'm	IPW-LR	CW-ANN	IAW-ANN	EIG-ANN	HAR-ANN	IPW-ANN
Sol'n	Hair dryer	Coffee maker	**Rice Cooker**	**Rice Cooker**	**Rice Cooker**	Hair dryer

such as consolidating information, balancing different aspects, building consensus, and/or through competition. The following sections describe three CDMs we have developed and tested.

1) Most Common Occurrence (MCO): This CDM chooses the most commonly occurred candidate within the pool. This is the least computational demanding mechanism because we only have to count the total number of votes within the pool. However, the chance of having a tie is relatively higher because the decision index is always an integer. For instance, appliance ia and ib could both have a total vote of 4. Therefore, MCO may provide nonunique solutions.

2) Least Unified Residue (LUR): This CDM selects the best candidate which has the least unified residue (LUR). A LUR is a measure between an unknown signature compared with the known data base items and it is defined as follows: First, we define an individual residue $(\mathrm{IR}(i,j))$ of an unknown which has a feature signal $(y_{(k\,|\,j)})$ and it is compared to feature j of appliance i, $(\hat{y}_{(k\,|\,(i,j))})$ as in (12)

$$\mathrm{IR}_{(i,j)} = \frac{\sum_{k=1}^{N}\left(y_{(k\,|\,j)} - \hat{y}_{(k|(i,j))}\right)^2}{\sum_{k=1}^{N} y^2_{(k\,|\,j)}} \tag{12}$$

where N is the total number of points in feature j. Note that the IRs are normalized. We then multiply the IRs of different features and form a unified residue (UR) for a candidate as

$$\mathrm{UR}_i = \prod_{j=1}^{M} \mathrm{IR}_{(i,j)} \tag{13}$$

where M is the total number of features considered. Finally, the LUR is defined as

$$\mathrm{LUR} = \min \quad (\mathrm{UR}_i| \quad \forall i \in \Theta) \tag{14}$$

where Θ is the pool of candidates.

With the LUR, we can identify an appliance in the candidate pool which has the least matching residue while all of the extracted features are taken into consideration. This mechanism is more computationally demanding than MCO and the chance of having a tie is relatively lower because the decision index is a real number. LUR will always provide a solution and most often unique.

3) Maximum-Likelihood Estimation (MLE): MLE is based on a statistical learning methodology in which an *a-priori* accuracy measure is used to help estimate the best possible solution [18]. In the present contest, we first conduct a series of random simulations (e.g., 5 000 random trials) and then estimate a set of probabilities reflecting different accuracies of various combinations. We define a series of conditional probabilities denoted as $p(\theta_{ia,ib,j,l})$, which represents the conditional probability of having appliance ib as the true answer while algorithm l using feature j gives the best solution as appliance ia. A set of likelihood indices is then calculated by using

$$\rho(ib) = \prod_{j=1}^{M}\prod_{l=1}^{L} p(\theta_{ia,ib,j,l}|ia = K(l,j), \forall ib) \tag{15}$$

where L is the total number of algorithms, and $K(l,j)$ is the function to give the best candidate using algorithm l and feature j. The maximum likelihood $\Lambda(\rho)$ is defined as

$$\Lambda(\rho) = \max\{\rho(ib)|\forall ib \in \Theta\}. \tag{16}$$

MLE is the most computational intensive method as it involves quite a bit of simulation as a prerequisite.

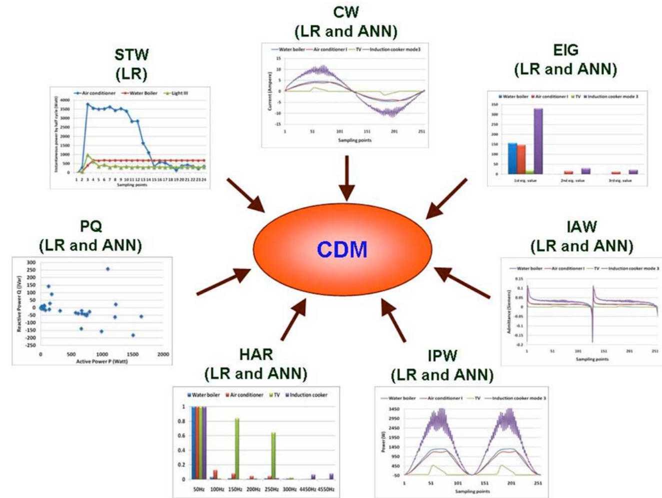

Fig. 11. CDM diagram [least residue (LR), artificial neural network (ANN)].

VI. ASSESSMENT TOOLS

In this section, we derive three kinds of accuracy measures, and then present some indices which can help us better quantify the nature of different load signatures and the effectiveness of different disaggregation algorithms. We pose the following questions: How do we measure the accuracy in a universal load disaggregation platform? Given a known database, what is the disaggregation accuracy for a particular type of appliance? How do we quantify similarity between two appliances? How do we know that the solutions provided by two disaggregation algorithms are mutually exclusive, complementary, or identical?

A. Accuracy Measures

Appliance switching could be wrongfully detected by the detection module at times. For instance, depending on the fluctuation of dynamic loads and the detection threshold (100 W in our case), Type I error (i.e., no appliance is actually operated but a detection is recorded) or Type II error (i.e., the appliance is operated but the detection module misses it) could result. Therefore, we propose three kinds of accuracy measures. First, we define the total number of detected events N_{det} as

$$N_{\text{det}} = N_{\text{true}} + N_{\text{wro}} - N_{\text{miss}} \tag{17}$$

where N_{true} is the true number of events that actually occurred, N_{wro} is the number of wrongfully detected events, and N_{miss} is the number of missed events. Second, we define the accuracy measures as follows.

1) Detection Accuracy (η_{det})*:* This is to measure the accuracy including the effects of wrongfully detected events

$$\eta_{\text{det}} = \frac{N_{\text{dis}}}{N_{\text{det}}} \tag{18}$$

where N_{dis} is the total number of events that is accurately recognized by a disaggregation algorithm.

2) Disaggregation Accuracy (η_{dis})*:* This is to measure the accuracy of disaggregation excluding the effect of wrongfully detected events

$$\eta_{\text{dis}} = \frac{N_{\text{dis}}}{N_{\text{det}} - N_{\text{wro}}}. \tag{19}$$

3) Overall Accuracy (η_{dis})*:* This is to measure the accuracy considering the effects of wrongfully detected and missed events

$$\eta_{\text{all}} = \frac{N_{\text{dis}}}{N_{\text{tru}}} = \frac{N_{\text{dis}}}{N_{\text{det}} - N_{\text{wro}} + N_{\text{miss}}}. \tag{20}$$

B. Appliance-Based Accuracy

This is the overall accuracy as in (20) but on an appliance basis. In other words, it is the accuracy of correctly identifying a specific appliance given that we know it is indeed operating. Mathematically, we can express this as

$$\eta_{\text{all}}^{i} = P\{\hat{x}_i = 1 | x_i = 1\} \approx \frac{N_{\text{dis}}^{i}}{N_{\text{true}}^{i}} \tag{21}$$

where $x_i = 1$ represents appliance i actually operating while $\hat{x}_i = 1$ represents the disaggregation algorithm which has identified that appliance i is operating. From the simulation results, we can estimate η_{all}^{i} by the ratio of the total number of correctly identified events attributed to appliance i (N_{dis}^{i}) by an algorithm to the total number of truly operating appliances i in a trial (N_{true}^{i}).

C. Similarity

The similarity index $(s_{(ia,ib)}^{j})$ is used to quantify the differentiability between any two appliances within a given database, which is defined as

$$s_{(ia,ib)}^{j} = \frac{\sum_{k=1}^{N} y_{k|(ia,j)}^{2}}{\left[\sum_{k=1}^{N} y_{k|(ia,j)}^{2} + \sum_{k=1}^{N} \left(y_{k|(ia,j)} - y_{k|(ib,j)}\right)^{2}\right]} \tag{22}$$

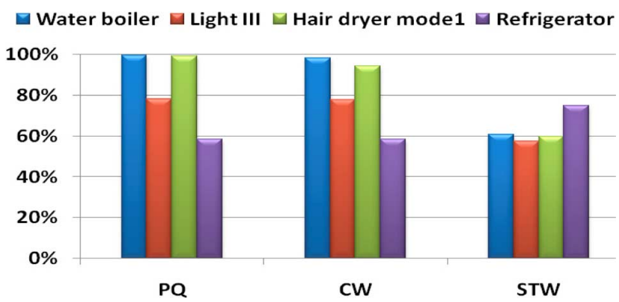

Fig. 12. Similarity analysis based on different features.

where ia and ib correspond to any two appliances in the database, $y_{k|(ia,j)}$ is a point k of feature j from appliance ia, and N is the total number of points of feature j.

With (22), the closer $s_{(ia,ib)}^{j}$ approaches unity (100%), the more the two appliances are similar to each other with respect to feature j. Therefore, by calculating this index for different features, the differentiability of each appliance with respect to each feature can be observed. Fig. 12 shows the similarity between air conditioner I compared to several other appliances, including the water boiler, light III, hair dryer mode1 and the refrigerator in terms of PQ, CW, and STW features. From Fig. 12, based on the CW feature, the similarity between air conditioner I, water boiler, and hair dryer was more than 95%. This means that by using CW alone, it will be very difficult to separate these three appliances. If we look at the transient feature (STW), the similarity indices were generally lower (except for the refrigerator). That would mean that by using this feature (STW), we can probably exploit the differences among these four appliances. Overall, this index helps us visualize the pros and cons of using specific features in disaggregation.

D. Complementary Ratio (CR)

To quantify the complementary effect of any disaggregation algorithm (Z_b) to a selected algorithm (Z_a), a complementary ratio $\text{CR}_{(Za,Zb)}$ is proposed

$$\text{CR}_{(z_a,z_b)} = \frac{P\{Z_a = \text{false} | Z_b = \text{true}\}}{P\{Z_a = \text{true}\}} \tag{23}$$

where $P\{Z_a = \text{true}\}$ is the probability of the disaggregation algorithm Z_a provides the correct solution, while $P\{Z_a = \text{false} | Z_b = \text{true}\}$ is the probability that Z_a provides a false solution since Z_b provides the correct solution. In simulations, $\text{CR}_{(za,zb)}$ can be estimated by the corresponding statistics pertaining to the conditions required.

If this ratio is zero, this means that there is no complementary effect between algorithm Z_a and Z_b. On the contrary, if the ratio is high, it means the solutions from both algorithms are complementary. Therefore, if the solutions are combined, we may improve the overall accuracy. Fig. 13 gives an example of the CR of CW-LR with other disaggregation algorithms. It can be seen that CW-LR had the highest CR with IPW-ANN.

Through the aforementioned similarity and complementary analyses, we can postulate that a CDM-based solution could al-

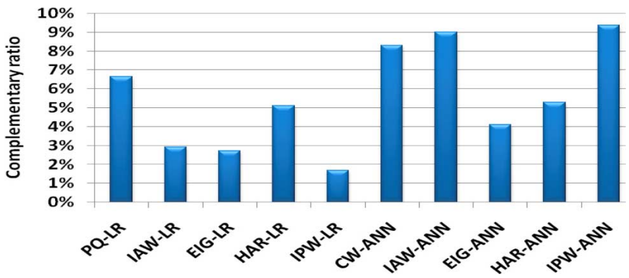

Fig. 13. Complementary ratio of CW-LR to other disaggregation algorithms.

TABLE II
APPLIANCE DATABASE IN A TYPICAL HOUSEHOLD

ID	Name	Power (kW)	ID	Name	Power (kW)
1	Air conditioner I	0.669	17	Refrigerator	0.126
2	Air conditioner II	1.094	18	Rice Cooker	0.568
3	Column heater mode1	0.796	19	Toaster	0.752
4	Column heater mode2	1.642	20	Water Boiler	0.716
5	Coffee maker	0.671	21	Amplifier	0.058
6	Dehumidifier	0.150	22	DVD	0.024
7	Hair dryer mode1	0.612	23	Fan	0.040
8	Hair Dryer mode2	0.748	24	Modem	0.014
9	Hair Dryer Mode3	1.213	25	Massager	0.009
10	Induction cooker mode1	0.660	26	Phone charger	0.005
11	Induction cooker mode2	0.993	27	Radio	0.002
12	Induction cooker mode3	1.507	28	Router	0.007
13	Light I	0.178	29	Stereo	0.011
14	Light II	0.141	30	Woofer	0.014
15	Light III	0.345	31	TV	0.074
16	Microwave oven	1.224	32	PC	0.060

ways perform better than any other single-feature/single-algorithm load disaggregation because it utilizes the characteristics of different features and algorithms to the maximum extent.

VII. CONCLUSION

In this paper, we defined the concept and key features of load signatures. Based on different features spanning different domains and including different behavior (steady state and transient), a structural and systematic platform of load disaggregation was proposed. This platform includes a problem formulation of the disaggregation process (such as at the meter) and the development of two distinct approaches to solve the problem, namely, via optimization and pattern-recognition algorithms. We further demonstrated that the solutions from any single-feature, single-algorithm disaggregation approaches could be combined under a committee decision mechanism to render the best solution. Different accuracy and assessment indices were finally proposed to help gauge the effectiveness of different algorithms and the level of difficulty in differentiating similar signatures.

APPENDIX
APPLIANCE DATABASE

The appliance database consists of 27 appliances in a typical household with a total of 32 modes. Their steady-state power consumption is shown in Table II. Both transient and steady-state signals of the voltage and current are acquired during the appliance startup and operating periods. The data-collection instrument is a Dranetz-BMI PX5 model which has a typical sampling rate of 256 points/cycle (1.28×10^4 Hz).

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