Recent Approaches to Non-intrusive Load Monitoring Techniques in Residential Settings

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***Abstract*—The concept of Smart Grids is closely related to energy conservation and load shedding concepts. However, it is difficult to quantify the effectiveness of energy conservation efforts in residential settings without any sort of end-use energy information as feedback. In order to achieve that, load monitoring methods are normally used. In recent years, non-intrusive load monitoring (NILM) approaches are gaining popularity due to their minimal installation requirements and cost effectiveness. For a NILM system to work, only one sensor at the entry point to a home is required. Fluctuations in the aggregate power consumption signals are used to mathematically estimate the composition of operation of appliances. This approach eliminates the requirement of installing plug-meters for every appliance in the house.**

In this paper, we provide a review of recent research efforts on state-of-the-art NILM algorithms before concluding with a baseline and overall vision for our future research direction.

I. Introduction

With the increased usage of electricity across the globe due to rapid urbanization, energy cost, and concerns about the climate change due to the carbon emissions into the atmosphere, there is an increased interest for energy conservation. An integral part of this is the accurate measurement of individual energy consumption of household appliances and provision of real-time feedback to the consumer. Various studies show that availability of this information to the households stimulates the energy conservation efforts [1], and reduces the reliance on trial and error approach which often leads to inaccurate decisions on what should be turned off to save energy [2] [3]. In addition, the value of end-use data is not just limited to the consumer benefits. It allows governments to accurately evaluate the effectiveness of their existing energy policies and devise new energy saving programs with better efficacy [4]. Also, the availability of this data will allow utilities to introduce dynamic pricing schemes according to energy used by different load classes or in particular to deter operation of certain loads in residential settings to manage peak consumption periods [5]. This issue, called "Demand Response" (DR), is one of the key components of the Smart Grid concept. DR allows loads to be curtailed during peak periods of electricity demand while giving incentives to consumers in the form of reduced pricing. However, load shedding via DR is built on a trust model between utilities and consumers [6]. It is assumed that when *Load Shed Instructions* are sent to an appliance, its state is changed accordingly. Here, the problem is verification, does the appliance in fact perform the expected state change? For example, if the appliance is tampered to ignore the load shed instruction, the consumer would have a free ride on the reduced pricing while spoofing the real operation state of the appliance. The solution to this problem without incorporation of plug-meters is *Non-Intrusive Load Shed Verification (NILSV)* which monitors the state of the appliance of interest using only information from the residential meter at the entry point and replies to the utility via the *Advanced Metering Infrastructure (AMI)* with a *Load Shed Verification* messages if the verification is valid [6]. Overall, this shows the importance of end-use data to not just the average consumer but to the realization of a practical Smart Grid implementation.

Traditionally, energy breakdown information of appliances is obtained by streaming energy information from sub-metering-sensors attached to each appliance in the house to a central metering point (via a home area network). This approach is called "intrusive load monitoring (ILM)". Even though the installation of the devices in a house is simple, there are reliability problems due to the existence of multiple sensors in the system and hence the associated occurrence of any one sensor failure increases [7]. If the system's objective is to obtain a complete energy profile of the whole house, any one sensor breakdown would constitute a system failure [8]. In addition, it is not scalable. For instance, when a nation-wide energy information sharing scheme is to be deployed for Smart Grid purposes, enormous amount of sensors are required to be installed in all consumer premises. This is clearly cost prohibitive in terms of labor and capital.

On the other hand, *Non-Intrusive Load Monitoring (NILM)* aims to rectify this by requiring only aggregate energy information from one sensor attached to the service entry point. This sensor is used to estimate the composition of appliances that are turned on. This provides significant value for energy auditors because no additional devices are needed and the method does not introduce any inconvenience to consumers. The idea of NILM was pioneered by Hart [9] in the 1980s. Recently this method has gathered significant interest due to the improved computational power of embedded devices and growing climate change concerns.

In general, two components define a given NILM system –

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the appliance signature and the inference/classification algorithm. Once both are defined, an implementation of a NILM system starts with acquisition of electrical signals, then, the features of interest are extracted from the samples, and finally the core NILM algorithms are applied to classify the appliances (Figure 1).

Fig. 1: Three stages of the NILM process.

There are already a number of commercial NILM products in the market [10]–[13]. But, they are new and no performance test data was made public unfortunately. Still, for some products at least, their limitations are obvious. For example, Enetics [10] uses Hart's steady-state step change algorithm [9] whose performance is only limited to identification of loads which have rapid level changes.

In this paper we provide an overview of the recent research efforts on NILM algorithms. We divide the presentation in two key sections. First, we offer the detailed characteristics of appliance signature approaches. Then, we provide a summary of the algorithms. In closing, we discuss briefly the current state of research and our current research focus on improving the NILM accuracy.

II. Appliance Signatures

Before classification of an appliance using NILM is possible, a unique feature that characterizes its behaviour is required [9]. An example would be an appliance's active power consumption when it is turned on.

There are two main classes of appliance signatures that all identification efforts rely on. They are either steady-state or transient signatures. A significant number of research work uses a combination of both, and utilizes mathematical transforms of time-series features.

A. Steady-State Signatures

One of the most commonly used signature is the change in steady-state power as it is easy to obtain from metering devices and does not require fast sampling rates. It is first used by Hart [9] to prove the NILM concept. In Hart's work, real power P and reactive power Q are both acquired over one second intervals. This is followed by the normalization of the power metrics defined by Equation 1:

$$P_{\text{norm}} = \left(\frac{120}{V}\right)^2 P \tag{1}$$

where V is the measured line voltage and 120 is the nominal line voltage of one phase with respect to neutral in typical American homes. This normalization is required to prevent ambiguities that arise from fluctuations of the voltage signal that may cause misleading appliance events. By feeding the edge detection procedure with normalized power metrics, segments of steady-state changes are then mapped to a two-dimensional signature space as normalized P and Q before classification is performed. Although this prototype worked well for tracking the behaviour of appliances, the normalization did not take non-linear loads into account and also had issues with multi-state appliances and variable loads.

Following Hart's work, Cole and Albicki [14] explored the association of steady-state P and Q change sequences with appliance identities. Their work was built on the Zero Loop-Sum Constraint concept defined by Hart [9]. What this means is that the collection of edges that defines the steady-state changes for a given appliance as seen from the metering point must have its total power change equal to zero. For example, in Figure 2, edges A and D belong to an appliance while edges B and C belong to another. The confidence of the association is evaluated by how many said sequence of edges are observed over a training period.

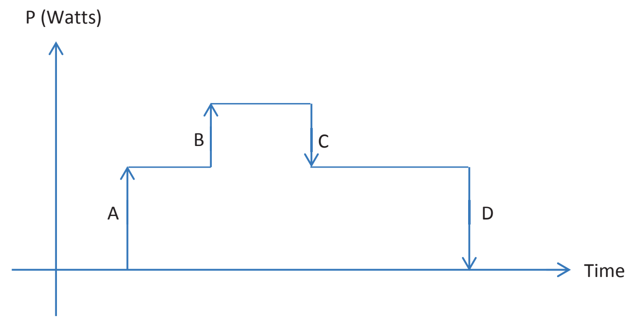

Fig. 2: Edges corresponding to changes of the states of appliances.

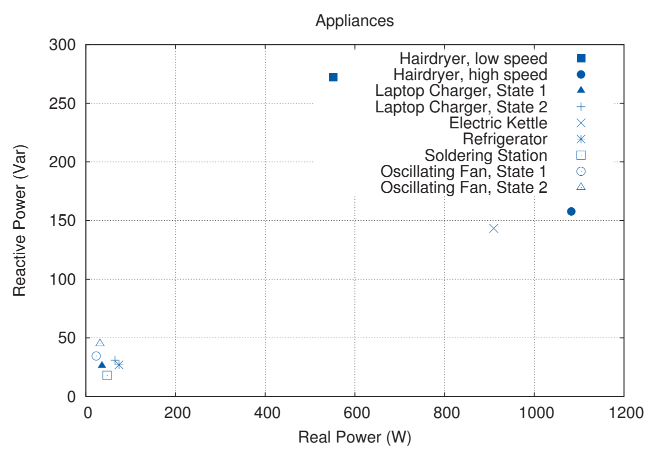

Fig. 3: Plot of the steady state power consumption of a number of household appliances. Real power is plotted against reactive power.

Although most research efforts related to steady-state signatures revolve around the use of both P and Q to reduce the aliasing problem in which two different appliances share the same signature, Bijker [15] explored the possibility of using only steady-state P changes. Bijker's approach works by incorporating time information (duty cycle and cyclic characteristics) to distinguish different appliances with similar power usage. This is attractive from the point of view that it allows NILM to be used on metering devices with limited monitoring capabilities (particularly true for existing smart meters). Apart from that, steady-state changes of power factor was also shown to work well as an appliance signature [16], [17].

Overall, steady-state signatures are simple exploitable features that require minimal hardware requirements. However, despite the additional information from investigating both P and Q, signature ambiguities could still occur in certain circumstances. As an example, consider the appliances shown in Figure 3. Appliances in the lower left corner in the figure are hardly distinguishable from one another. This shows a need for additional signature dimensions (See Section II-C) and strengthen the opinion that different signature types could be used to identify different class of appliances [18], [19]. For example, different classes of appliances are identified using different signature types according to how good the separation performance in a given signature space. Another problem is the natural limitation of poor tracking of Variable Speed Drive (VSD) appliances [8].

B. Transient Signatures

Associated with any turn-on events are momentary fluctuations in power or current before settling in to a steady-state value. These short-term fluctuations are called transients. As the nature or type of a given appliance is closely tied to its transient characteristics [20], it can be used as a decent appliance signature. In fact, transients were utilized by numerous works in the past [7], [20]–[24].

One of the first prominent works in this area was done by Leeb [20], [21]. In Leeb's work, a multi-scale prototype transient event detector for NILM was developed to map transients and the associated progression of spectral envelope of current with time to the corresponding appliances. The key benefit is the multi-scale (tree-structured decomposition) approach as the amount of training needed for each appliance is reduced because only one appliance signature is needed to summarize the operational characteristics of a class of appliance. For instance, the general transient shape of various induction motors are similar; the magnitude and duration are just a scale version of one another. Using this observation, it was shown that applying a transient exemplar of a motor to identify a motor (not recorded in the database) of different type is possible.

As an extension to the aforementioned work, Cox and Leeb [22] built upon the existing detector to investigate the transients related to line voltage distortion when appliances change states. In contrast to their previous work, the spectral envelope of both live-to-neutral voltage and neutral-to-ground (instead of current) are computed before any detected transient features are classified. A plus point here is the use of only voltage features, putting away the need of any sort of current transducers and simplifying installation efforts.

Chang [23] later followed up with the transient work by introducing their own turn-on transient energy detector. The detector is based on an iterative algorithm that computes the energy associated with a transient event. One concern is the repeatability of the transient signatures as the transient shape might change depending on which phase the voltage signal is currently at when the switch is turned on. To prove that transient is a fairly repeatable feature, he showed that the variability is less than 1% [23].

Despite the richness of information afforded by transient analysis, the problem with transients is that turn-off events are hard to classify as they are not as obvious as their turn-on counterparts. Also, there is the inevitable additional requirement for using high sampling rates to capture the salient transient features [17]. Unless a separate, more capable add-on device is to be installed at the metering point, this remains as a problem as most existing smart meters are designed to only output power metrics at up to a rate of once every second.

C. Hybrid Approaches

Some features are more prominent for one class of appliances but not others. To understand this, we must consider the type of appliances that are commonly found in residential settings. Sultanem [19] posits that there are generally six major categories of appliances: Resistive, pump-operated, motor-driven, electronically-fed, electronic power control, and fluorescent lighting appliances. Depending on the appliance to be detected, different signatures can be used for different categories. For example, resistive appliances do not commonly show distinctive transient characteristics. Therefore, it is difficult to separate a set of resistive appliances with transient features alone. However, transients can be successfully used to distinguish appliances that belong to different classes. Consider the case where we were given a mixed set of resistive appliances, pump-operated appliances and motor-driven appliances. Using transients as a discriminator during the first-pass, the mixed set could be classified into resistive appliances and non-resistive appliances. Then, separation within the resistive appliances class can be based on other signature types such as steady-state P and Q values.

The use of multiple signatures is certainly promising. It was shown by Chang [18], [23], [25] that given different appliances with the same steady-state P and Q values, disaggregation with the addition of transient features triumphs disaggregation with steady-state P and Q alone.

Another interesting development was done by Liang [26], [27]. In this work, the value of reaching a more accurate conclusion from multiple but less accurate conclusions is shown. Specifically,

- Current waveform,
- Active and reactive power,
- Harmonics,
- Instantaneous admittance waveform,
- Instantaneous power wave,

- Eigenvalues, and
- Switching transient waveform

are extracted from the raw data to perform each feature-disaggregation separately before combining the results using a "Committee Decision Mechanism" to produce the best final estimation. In the paper three different committee decision mechanisms are outlined – Most Common Occurrence, Least Unified Residue and Maximum Likelihood Estimation. All methods outperformed any algorithm that only utilizes one feature [27].

All in all, one feature may have larger similarity between different appliances and consequently when used for disaggregation, may perform badly. The idea of using other features with less significant similarity in combination of the former might probably be the only reliable solution for appliance aliasing problem in NILM. However, evaluating every single-feature single algorithm before combining with a committee decision mechanism may be computationally intensive and not feasible in real-world applications such as smart meters currently are in use.

D. Other Approaches

There are a few approaches which do not use the steady-state or transient appliance signatures. In this section we provide an overview of these methods.

1) Frequency Analysis - Harmonics: In [8], current harmonics are used as a feature to disaggregate among appliances that are similar in the ΔP-ΔQ signature space. It is shown that by keeping track of multiple harmonics, it is possible to form a relationship between harmonics and the fundamental component. Through the variation in harmonics, contribution of variable speed drive appliances can be subtracted from the fundamental component so that the subtracted metric can be used to accurately disaggregate among non-variable speed drive appliances. In addition to this, [28] also uses a preprocessing stage incorporating Fast Fourier Transform to compute the harmonic features that would be fed into a Support Vector Machine (SVM) [29] classifier.

Another closely related approach is Wavelet Transform [30]. Su [31] did a comparison between features extracted from Short-Time Fourier Transform and Wavelet Transform of the raw current signal drawn by an appliance. Consistent with the theory, Wavelet Transform features are more granular in terms of time resolution and scale, allowing a more accurate localization of the appliance when it is turned on and the onset of time of the steady-state operation. Coupled with that are the Wavelet Transform Coefficients that characterize the rich information of the transient event.

2) Basic Power Consumption Unit: A "basic power consumption unit" can be defined as building blocks of a power consumption curve [32]. In [32], Wang uses these basic consumption units in addition to steady-state and transient signatures. The basic power consumption units are attributed to fast switching events and steady working events. Together, they are both represented as basic unit of triangle and square respectively with respect to the power consumption curve. As a system, the original power consumption curve is first decomposed into basic units of triangle and square. Associated with the basic units are parameters such as start, peak and end times, and peak value for triangle, start and peak times, peak value, and steady time and steady value. The frequency of occurrence of the basic units are then taken into account as working styles. With these parameters and the working styles, non-parametric classification is performed to identify the category of appliance the detected event corresponds to according to a set of rules. Interestingly, the concept of power decomposition is also used by Cole [33] to segment the power consumption curve into slopes and edges as features of appliances.

3) V-I Trajectories: Apart from the usual electrical features, Lam [34] explored the construction of signatures using voltage-current (V-I) trajectory. In this work, as a start, one cycle of the voltage waveform and the current waveform for each appliance are acquired. They are then normalized and plotted on a V-I plane. From the V-I trajectory, the following shape features are extracted:

- Asymmetry,
- Looping direction,
- Area,
- Curvature of mean line,
- Self-intersection,
- Slope of middle segment,
- Area of left and right segment, and
- Peak of middle segment.

From the taxonomy studies conducted by Lam [34], the grouping of appliances based on shape features can capture the similar operational characteristics of different appliances better than the traditional features such as power metrics. This may provide significant value to NILM systems that aim to reduce the amount of training required as it might be possible to obtain a generalized set of signatures from the V-I trajectories to represent a subgroup of related appliances.

E. Extensions

The robustness of appliance signature can in generally be improved in four ways:

1) Including more features in the appliance signature,
2) Dependencies between appliances,
3) Incorporation of time information, and
4) Correlation between additional sensor information (for example, light sensors and temperature sensors) and appliance states.

Adding more features is akin to increasing the dimensions of the appliance signature space. This may or may not be beneficial depending on the type of appliances in the monitored system. The obvious advantage is similar to the hybrid approaches (Section II-C) to appliance signature design in which the overlapping appliance features in one dimension can be resolved by investigating other dimensions. However, the training procedure gets more complex as more features are included. Moreover, the number of dimensions may be detrimental to the computational performance of the disaggregation process. This is vital especially when the disaggregation algorithms are preferred to be run on the smart meter itself. However, dimensionality reduction methods like Principal Component Analysis [35] can be used to determine the optimal features to be retained without throwing away useful information.

It is well known that operational states of appliances are not entirely independent in nature. For example, it is more likely that a game console would be in the on-state while the television is turned on. Similarly, the extractor hood is more likely to be turned on when the induction stove is turned on. This information can be exploited for improving the accuracy of identification [36].

Last but not least, time information can also convey important information to augment the robustness. The works reported in [37] and [38] use modified versions of Viterbi algorithm [39] to take into account history state information and estimate the most likely sequence of system states. Additional time information can be taken from the appliance state duration distribution [36], [37]. For example, one might ask "Given the refrigerator has turned on for T minutes, what is the likelihood that it will remain in the on-state at this moment?".

III. Event Detection

Most existing NILM methods can be categorized as either event-based or non-event-based. The former generally starts with event detection by using edge detection algorithms on the total power consumption curve. Captured features around the neighborhood of the event point are then classified according to a set of rules using machine learning methods (See Section IV). Figueiredo's approach [17] is an example of this. First, steady-state step changes are detected, then the features are classified using Support Vector Machine and k-Nearest Neighbour methods. Jin [40], [41] also proposed a probabilistic way to detect edges using goodness-of-fit χ^2 test to compare between two windows of samples from the total power consumption curve. The method is distribution agnostic. In other words, the distribution of the samples in the two windows does not matter. It is shown that the method performed better than the common generalized likelihood ratio test used by earlier works [42], yielding correct detection rate and false detection rate of 98% and 1% respectively compared to 94% and 14% [40].

Non-event-based methods do not rely on edge detection schemes before classification. Instead, every sample of aggregate power is taken into account for inference. Examples include works related to Hidden Markov Model [36], [43].

Between the two, event-based methods are more computationally efficient as inference and classification is only needed for detected events. However, the misdetection and false detection of edges could occur as opposed to the non-event-based approach where every sample is taken into consideration for classification. The comparison is summarized in Table I.

TABLE I: Comparison between event based and non event based methods

Event Based	Non Event Based
Event detection is performed on every sample but inference is done only on detected edges. It is more computationally efficient.	No event detection is performed. Inference is performed for each sample. Example includes those which utilize Hidden Markov Models (HMM) [36], [43].
Problem related to misdetection or false detection may arise.	Errors caused by wrong estimation for a given sample can be corrected.

IV. Classification

Given a stream of samples, matching is performed between the extracted features and features stored in the database to estimate the associated appliances which contribute to the aggregate power as seen from the metering point. Various machine learning techniques have been used in previous works and they can be broadly categorized in two groups – supervised learning and unsupervised learning [44].

A. Supervised Learning

Supervised machine learning techniques require an offline training stage to build the a priori class information for future prediction. Among others, artificial neural networks (ANN) [18], [23], [45]–[47], support vector machines (SVM) [17], [28], naive bayes classifier [48] and k-nearest neighbour (kNN) [17], [49]–[51] have been used to solve NILM problems.

B. Unsupervised Learning

In contrast, unsupervised learning as its name implies does not require any sort of training procedure before the system goes online. In fact, prior information which must otherwise be obtained offline are inferred from the test data on the fly. This reduces the intrusiveness of the training steps required to build the appliance database. From the practical point of view and the goal of wide deployment, unsupervised learning is more appealing than its supervised counterpart. One of the staple methods of unsupervised learning is clustering. [32] and [52] both use variations of clustering methods to automatically group together similar points in the signature space. The grouping of points form a cluster and it is normally followed by labelling of that cluster with meaningful appliance name that end-users could relate to.

V. Conclusions

In a nutshell, most of the algorithms in the literature require enormous offline training that would not be practical for real-world wide deployments across residential homes. Although there are a few works related to unsupervised learning in recent years, there are still no complete universal NILM algorithms that work across all kinds of appliances. Also, previous works do not build NILM algorithms around prospective integration with Smart Grids and the computational performance of running NILM on devices with limited capabilities such as embedded systems.

In this paper, we have presented the four key areas that need to be fine-tuned. Therefore, to move forward with the research, we need to make a choice between the following key aspects that define a NILM system:

- Appliance signature,
- Intrusiveness,
- Event-based vs non-event-based, and

- Classification algorithms.

Table II summarizes the requirements for our future system. The parameter of focus would be training intrusiveness and we feel more work is be needed here to integrate with existing approaches. Until a more robust automated training NILM system is devised, NILM would not be practical for large scale deployments. Nevertheless, existing works have built a strong foundation and further research and innovation in this area should continue the drive for a complete robust system that could be integrated with Smart Grids.

TABLE II: Parameters that need to be defined for a given NILM implementation

Parameters	Description	Comments
Appliance Signatures	Unique identifier for a given appliance	Largely depends on the capabilities of the monitoring hardware. More than one dimension should be used.
Training Intrusiveness	Amount of work needed to train the system	Unsupervised learning methods should be employed.
Event Detection	Event-based or non-event-based	For performance reason, we will used event-based methods. (See Table I)
Classification Algorithms	Machine learning techniques for classifying features	It should be simple and computationally efficient. An example is k-NN which is shown to work particularly well [42].

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