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The Cognitive Power Meter: Looking Beyond the Smart Meter

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***Abstract*—The smart meter is often heralded as the key component supporting energy displays that can notify home occupants of their energy usage. But, a smart meter is only a digital power meter with enhanced communications capabilities – it is not actually smart. We need to look beyond the smart meter and define what intelligence is needed to actually make a meter smart. One area with promise is load disaggregation. Load disaggregation can be used to determine what loads contributing to the consumption reading at the smart meter. A smart meter incorporating load disaggregation intelligence can be seen as going beyond the traditional smart meter – what we call a cognitive power meter (c-meter). However, using load disaggregation, in its current form, is not feasible. We critically review the requirements for a c-meter and provide insights as to how load disaggregation research needs to change to make the c-meters a reality.**

***Index Terms*—Power Meter, Smart Meter, Load Disaggregation, Cognitive Analysis, Demand Response, Energy Conservation**

I. Introduction

Currently much of the world is focused on reducing electricity consumption; our increase in consumption is neither economically nor environmentally sustainable. Additionally, there is a growing consensus that environmental and economical sustainability are inextricably linked. As the cost of power rises, we must find technological solutions that help reduce and optimize energy use. For homeowners and occupants, one way to achieve this goal is to monitor their power consumption through an effective display mechanism.

At the same time, utility companies around the world are replacing electro-mechanical power meters with new smart meters. These smart meters are simply digital power meters with enhanced communications capabilities – they are not actually *smart*. Coupled with an in-home display (IHD) home owners can receive real-time whole-house power and energy readings. Unfortunately, whole-house readings do little to inform customers how their individual appliances affect the aggregate power reading value. Furthermore, with initiatives such as time-of-day usage charges (peak charges) and demand response (DR) [1] homeowners are left with little to no information about their energy consumption to work from.

A. Demand Response Example Scenario

Let us propose an example scenario (**S1**) that will be revisited throughout the paper.

> A DR sign comes through a smart meter and is displayed on an IHD. The IHD notifies the occupant that if they immediately cut their consumption by 5kW they will receive a financial intensive. To opt-in occupant must cut power consumption within the next two minutes. The occupant who is interested in participating looks at his IHD and sees that his current demand is 15kW. The occupant concludes that he may be using too much power and is interested in participating. The occupant now has the challenge of discerning what appliance is consuming what amount of power. The occupant only has a real-time whole-house power reading to work from.

It is doubtful that the occupant knows which appliance(s) to turn off to meet the 5kW request without walking through the whole house and examining what appliances are on. Then the occupant would then need to turn off each appliance one at a time and go back to the IHD to observe the power demand to see if it meets the 5kW request. During this time consuming process, the occupant could easily miss out on the opt-in DR request. The smart meter has not done anything to help the occupant, it has just acted as a communication gateway.

B. Cognitive Power Meter Definition

What if we look beyond the smart meter to a meter that has the intelligence to help the occupant in **S1** participate in the 5kW opt-in DR request. One way to help is to have intelligence that can discern what appliances are running from examining the whole-house power reading. This is called *load disaggregation*; first developed by Sultanem [2] and then Hart [3]. A smart meter with load disaggregation intelligence can be seen as going beyond the smart meter – what we call a *cognitive power meter* (c-meter) (see Figure 1).

With a c-meter, the IHD can display a list of appliances or combination of appliances that the occupant can choose from to meet an opt-in DR request in a timely and confident fashion. *So why is there no c-meter?* Load disaggregation in its current form is not feasible, although some initial attempts in devices such as the TED-5000 have allowed use in restricted contexts[1]. There is an optimization problem (having the algorithm fit

[1] See the "I want to view more than my overall usage. How can I monitor an individual appliance?" FAQ question at http://www.theenergydetective.com/faq (last accessed January 26, 2013).

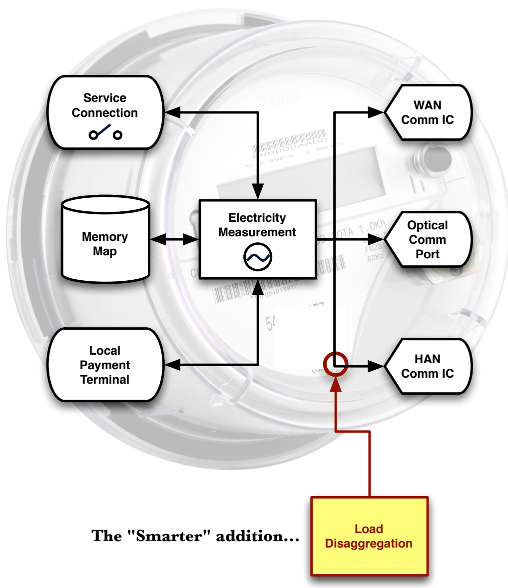


Fig. 1. The anatomy of a smart meter. To address privacy concerns the load disaggregation module should be placed on the Home Area Network (HAN) side and only communicate with devices on the HAN.

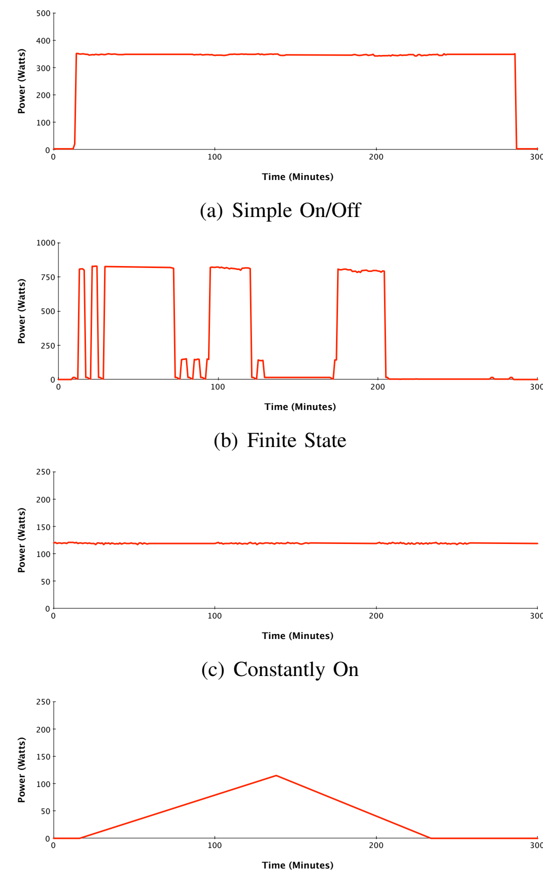
on an embedded MCU) and a generalization problem (having the algorithm disaggregate accurately on different houses with considerable retraining). We critically review these issues for the remainder of our paper.

II. Defining Load Disaggregation

In the computational sustainability research field, load disaggregation goes by many names and acronyms, including non-intrusive load monitoring (NILM) and nonintrusive appliance load monitoring (NIALM or NALM). Load disaggregation researchers have proposed many strategies to disaggregate loads from the whole-house power reading [2], [3]. However, recently researchers have focused on using smart meter data as a more realistic solution [4]–[12]. Other research which proposes specialized expensive equipment to disaggregation using high-frequency readings (e.g. 10kHz [13], 15kHz [14]), measurements not supplied by a smart meter (e.g. reactive power, harmonics [15]), or customer built measurement tools (e.g. measuring EMI [16]) are out of the scope of this paper and will not be reviewed.

A. Zeifman's Requirements

Zeifman [2] has identified six solution requirements that further restrict the solution space for applying load disaggregation in a home and should be considered. *Feature selection* constrains power measurement to those of a smart meter (real power and a frequency no greater then 1Hz). *Accuracy* is acceptable to occupants when it is greater then 80%. *Little-to-no training* is needed to reduce the burden on occupants setting up such a system. *Near real-time capabilities* is needed so that feedback is provided in time for occupants to respond. *Scalability and robustness* is needed to accommodate the recognition of new loads. *Various load types* need to be recognized and detected when running (see Figure 2).



(a) Simple On/Off

(b) Finite State

(c) Constantly On

(d) Continuously Variable

Fig. 2. The four load types [3], [11]. Power was monitored for 5 hours (at per minute readings) showing: (a) a set of six 65W light bulbs being turned on and then off, (b) a dishwasher cleaning a full load of dishes, (c) the HVAC fan which runs constantly for air circulation, and (d) a variable load such as a light dimmer where the knob is continuously turned creating a ramp-effect.

There are two issues with Zeifman's requirements. First, we believe that accuracy needs to be much higher than 80%. Any inaccuracies in the load disaggregation system would ultimately cause a loss of confidence in the system by occupants. We believable that accuracy needs to be at least 95% because opt-in DR requests may be of a critical nature (e.g. avoid a grid brownout) and commitment without action due to inaccuracy will hinder the power utility's avoidance strategy. Second, having the four load types (Figure 2) complicates the load disaggregation system being designed. *Simple on/off* loads and *constantly on* loads are just special cases of *finite state* loads, so they need to be combined into one type–finite state. Or, finite state loads need to be decomposed into multiple simple on/off loads. *Continuously variable* loads usage is often by appliances/tools/equipment that consumes small amount of power. So we question whether the disaggregation of such loads is really needed.

B. A Complex Problem

There are five key problems that we have identified which further challenge the success of a load disaggregation system.

1) Multiple, Simultaneous Load Events: Multiple, simultaneous load events (switching on/off or changing states) can cause a system to incorrectly identify active loads. For example, if we have two 100W lights and one 200W hand blender, then turning on two lights simultaneously could be mistakenly classified as the hand blender being used.

2) Noisy Power Signals: Electrical systems are inherently noisy. Causes of noise include harmonic distortions, small fluctuations in appliance consumption, electronics that are constantly on, and appliances turning on/off with consumption levels too small to detect. Less noisy a power readings will result in a more accurate load disaggregation system.

3) Dynamic & Changing Usage: Over a period of time, the number of appliances within a home can increase and decrease. They can also be replaced (e.g. an old dishwasher breaks down and replaced with new, more energy efficient model). These chagnes are coupled with the fact that occupant-home interaction varies greatly from one home to another, or over a long period of time [17], [18]. So it can be difficult for a load disaggregation system to generalize over data from other homes or other periods of time.

4) Computational Cost & Complexity: Practicality demands systems that process data online and react in real-time to changes in the power being monitored. Some systems, depending on the machine learning technique, can have a computational cost of $O(n^m)$. To reduce the computational cost, approximation algorithms can be used but at the cost of reduced accuracy. This results in an optimization problem when wanting to implement load disaggregation on an embedded processor.

5) Privacy: There are many privacy concerns that involve load disaggregation which centre around utility companies being able to tell what appliances a homeowner is using, and having the utility company turn off appliances without a homeowner's consent. Our opinion is that the intelligent load disaggregation part of the c-meter needs to exist on the Home Area Network (HAN) side of the meter as we noted in Figure 1. If the load disaggregation module only communicates with devices on the HAN then privacy concerns should be alleviated.

III. Load Disaggregation Anatomy & Review

Figure 3 depicts a summary of the different strategies used for load disaggregation systems which are discussed in the four subsections below. The depicted resulting benefits are discussed in Section IV-A.

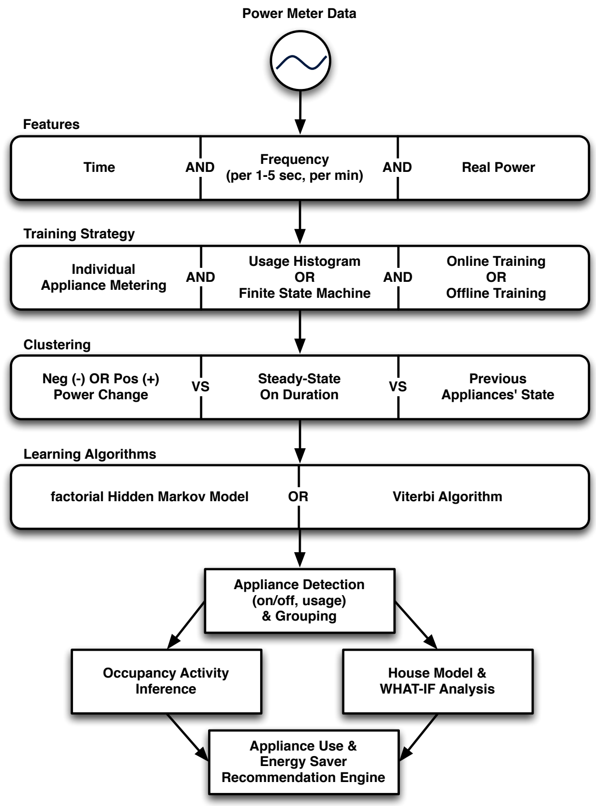


Fig. 3. An overview block diagram of strategies (rounded rectangles) different researchers have used to implement their load disaggregation system and the resulting benefits (cornered rectangles) that can be seen for such a system.

A. Power & Time Features

Smart meters can communicate real power (kW) and energy (kWh) readings every 1–5 seconds (0.2–1Hz) [19]. Researchers are limited in what measurements they can use. So different time-power based and power change measurements are used.

Zeifman *et al.* [10], [11] distinguished between negative power changes and positive power changes at 1Hz sampling. For positive power changes they measured the initial power spike when an appliance was turned on. Building a histogram of past appliance usage, they calculated duration time on, as well. However, only appliances that were simple on/off could be detected and power data was disaggregated offline.

Kim *et al.* [4] collected power data at 1Hz sampling. Frequency of use was measured and compared to wattage. The appliance percent used during time-of-day and day-of-week was generated from historical data. These features disaggregated well when the whole-house power reading had little to no noise. This problem impacts the generality of being able to use their systems in most homes because home homes have noisy power signals.

Kolter *et al.* [7] collected power data at 1Hz sampling as well. They tracked the duration at different levels of power demand which they called snippets. These snippets where then used to train their load disaggregation system.

Parson *et al.* [8] collected power data at one minute intervals (16mHz sampling). Sampling at such a low resolution was problematic because power spike readings from appliance usage where missed.

B. Training Strategy

Due to the *Dynamic and Changing Usage* problem we identified, researchers use training strategies that train the load disaggregation system to identify loads specific to that house. Current load disaggregation systems cannot generalize across different houses. So with each new house a phase of individual appliance metering is needed to generate the histograms and finite state machines needed for learning.

Zeifman *et al.* [10], [11] used the REDD dataset [6] to develop a histogram of appliance-on durations, negative power changes, and power-on spikes. They chose nine simple on/off appliances that were individually metered from one home for 26 days. There were two problems: (1) the whole-house power readings were measured in apparent power (VA) while the appliances were measured in real power (W), and (2) one of the appliances used was a dishwasher that had 2 power states which they tried to convert to one simple on/off appliance.

Kim *et al.* [4] gathered 6 months of data from 7 homes which they used as a dataset to develop histograms of on/off durations. Individual appliances were metered from each home. Appliances that were finite state where decomposed into multiple simple on/off appliances. This decomposition increases the number of appliances being tracked. They found that as they increase the number of appliance to disaggregate the accuracy of their system was severely impacted by about 20%.

Kolter *et al.* [7] used their REDD dataset [6] to analyze the power snippets and calculate the probability that one snippet caused the likelihood of another snippet. They did this for seven appliances that they used for testing. They found that if the on off events for the appliances where short enough they where able to snippets of that just contained a single appliances data. We find this claim interesting, because of the two problems we identified: *Multiple, Simultaneous Load Events* and *Noisy Power Signals*. Both problems mean there would be a lot of data that would not be of use and would need to be discarded.

Parson *et al.* [8] used the REDD dataset [6] for initial accuracy testing. Later they used six live homes for testing. A general appliance finite state machine was developed using a probabilistic graphical model based on the metered appliance data. They were able to tune a general appliance finite state machine to a specific appliance make and model across the six different homes they tested.

C. Clustering

Clustering involves the grouping of loads based on different dimensional measurements (e.g. time *vs* power). Based on the training strategy, clustering results in a set of probabilities that is then used by the learning algorithm.

Zeifman *et al.* [10], [11] clustered negative power changes by ΔP and the hourly presents/absence of the appliance running. They clustered positive power changes by ΔP and time duration of the power spike. An ISODATA algorithm [20] was used to create the clusters. If clusters were too close they were merged, and if a cluster contained multiple appliances it was split.

Kim *et al.* [4] chose not to perform clustering but to calculate the distribution shape of each appliance. They used a gamma distribution of each appliance-on duration. They also calculated the conditional probability of each pair of appliances.

Kolter *et al.* [7] used the snippet probabilities to cluster loads together using k-Nearest Neighbour and spectral clustering algorithms. They were able to distinguish nine separate signatures that occurred frequently. Each signature corresponded to a different appliance.

Parson *et al.* [8] did not use clustering, instead relying on the generalized probabilistic appliance finite state machines (FSM) they developed. These generalized FSMs where build from prior knowledge of how a type of appliance operated. They were then tuned to specific models in the house by using an EM algorithm on multiple small chunks of whole-house power data.

D. Learning Algorithms

Learning algorithms use the set of probabilities created during clustering to determine what loads are running and in what state, based on the current and past whole-house power reading.

Zeifman *et al.* [10], [11] ordered the lists of appliances by power demand and used a modified version of the Viterbi algorithm called VAST [21]. VAST considered the state of the each appliance with its 2 neighbouring appliances. Zeifman *et al.* used this modification to reduce the computational cost that would have been produced by using a large state change table. The reduction in computational cost outweighed the reduction in appliance detection accuracy. They achieved accuracies with mixed results from one appliance at 41% to two appliances at 100% of the nine appliances tested.

Kim *et al.* [4] used four variants of the factorial Hidden Markov Model (FHMM) [**?**], [22] which fed into each other. The distribution shape and additional time features where used as inputs. Due to the computational complexity of their approach, it is doubtful that the system could scale down to use an embedded processor. They were achieving accuracies of between 69%–98%, but as appliances were added accuracies decreased.

Kolter *et al.* [7] used a combination of two FHMM variants, *additive FHMM* and *difference FHMM*. Additive FHMM was used for finding the aggregate observed load. Difference FHMM was used to find the difference in the load from the previous time step and the current time step. Using the difference, they performed state estimation using an Additive Fractional Approximate MAP algorithm (which they developed). Their algorithm had issues disaggregating load with similar power demand. They achieved an average accuracy of about 71% based on the classification of seven appliances.

Parson *et al.* [8] used the difference FHMM as well. Generic appliance finite state machines and an extended Viterbi algorithm [21] were used for hidden state estimation. Viterbi was extended to ignore small joint probability observations and all sequences with joint probability were evaluated. The mean normalized error results they reported were very mixed, from 21% to 3469%.

IV. Broader Issues

Given our survey of the recent literature on load disaggregation using smart meters in the previous section, and our identification of specific problems or limitations with the current approaches, we can now discuss broader issues concerning load disaggregation.

A. Energy Conservation Benefits

The bottom of Figure 3 shows activities that benefit from a load disaggregation system that is accurate and timely. Once appliances are disaggregated we can begin to *group* the appliances together by different attributes (e.g. location in a home, likelihood of being on/off together). These groupings can further be extrapolated into systems that can *infer occupant activity* as well as construct *models of the home* to understand occupant-home interaction. Adding a system that can perform a *what-if analysis* can lead to the ultimate goal of developing a system that can *recommend strategies and activities* to homeowners and occupants on how to reduce their energy consumption. These recommendations would be unique to each home, based on that home's usage.

B. Deferrable & Non-deferrable Actions

We believe that load disaggregation only be highly accurate to identify appliances that have deferrable actions (e.g. clothes washer and dryer, HVAC, dishwasher, kitchen oven). Such loads are large consumers of power and more easily identifiable. This means that the high accuracy is achievable. A deferrable action is an action that an occupant does not necessarily need to perform now. For example, having the dishwasher run during periods of the day with the charge per kWh is less – resulting in a reduced power bill. Delaying actions that are non-deferrable would cause an inconvenience and discomfort to occupants – as is most often the case with home automation systems [23].

C. Adding Smart Plugs to the Mix

Do we need to disaggregate everything? Continuously variable loads, small loads, and loads that are continually on are not suited for disaggregation algorithms [3] and ultimately cause noise so a different approach is needed. For these loads we might want to investigate using *smart plugs* or plug-level meters to monitor these loads. The readings from these individual smart plugs can then be used by the c-meter to remove noise from the whole-house power reading. This would further increase the accuracy of any load disaggregation algorithm.

V. Conclusions

We have presented the need for a power meter that is more than a smart meter – a cognitive power meter. We also reviewed the current research on load disaggregation (the intelligence of the cognitive power meter) and discussed the short comings of this research. Now it is time to look ahead and focus on solving these short comings. We are hoping that other researchers refocus their researcher goals to solve these issues and provide a load disaggregation systems that meets the needs of homeowners and occupants – much like what we are currently doing.

Acknowledgments

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