Towards Bridging the Gap Between the Smart Grid and Smart Energy Consumption

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ABSTRACT

Smart meters report power usage at 15 minute intervals and, compared to monthly power bills, provide the users with a much finer resolution time series of energy usage. However, apart from identifying times of peak energy usage, these smart meters provide little actionable data for the user in terms of reducing their power costs. Our research involves the development of an intelligent metering system that uses non-intrusive appliance load monitoring (NIALM) to identify the largest energy usage appliances in a residence or small business. The signal processing algorithms employed separate the energy used by individual appliances from the total natural gas and electricity measured at the point where the utilities enter the residence. Utility ratepayers need detailed information to effectively identify and mitigate inefficient appliances and activities. The cost to operate each specific appliance is sent, via a secure home area network, to the user's computer and accessed via a web browser. An easy to use interactive tool has been developed to label appliances and present this data to the user. Tests have been performed in three residences to compare the performance of our load disaggregation system with that of isolated electrical power measurements from ten or more appliances. Disaggregating the total energy usage into appliance specific usage will transform ratepayers' ability to conserve energy. Inefficient appliances can be identified, usage patterns can be shifted to lower tariffs times, failing appliances can be detected before they fail, and energy efficient measures can be implemented based on a true cost-benefit calculation.

Introduction

Supplanting our current energy sources of coal, gas, and oil with renewable sources is a critical step toward curtailing human caused climate change. The timescale of this transition will be measured in generations. The 2009 domestic energy consumption projections, from the *U.S. Energy Information Administration* web site (www.eia.doe.gov), forecast that by 2035, coal, natural gas, and oil will still account for 78% of the nation's energy consumption versus the current share of 84% in 2008.

These projections may be altered by technical innovations in renewable energy; however the relative growth in carbon free energy sources is likely to only slightly outpace the nation's overall growth in energy consumption. Moreover, increasing demand from developing countries will drive up commodity prices of oil, natural gas, and coal. To improve the prospects of limiting carbon emissions, additional measures must be taken to accelerate the adoption of renewable energy sources and improve efficiency. Energy efficiency can be viewed as an additional carbon free energy source since the energy saved offsets the total energy demand.

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Homes and buildings account for ~40% of the total energy consumed in the U.S. (www.eia.doe.gov). A major obstacle to improved efficiency is the lack of relevant information ratepayers see when using energy and purchasing products. Monthly utility bills aggregate energy consumption over the billing period. Appliances and activities that are inefficient are hidden within any summary usage information provided in the bill. Additionally, utility ratepayers do not have a convenient way to accurately determine their payback for the costs associated with a specific efficiency measure. This lack of detailed feedback is a market barrier to improved energy efficiency and results in inaction on the part of utility ratepayers.

Non-Intrusive Appliance Load Monitoring

Residential monthly gas, electric, and water bills indicate the amount of utilities consumed; however this is an ineffective system for motivating consumers to conserve. Usage data arrives typically one month after the activities have occurred and there is no disaggregation to indicate what activities incur the greatest cost. To address this issue, (Hart 1992) created a Non-Intrusive Appliance Load Monitoring (NIALM) technique to record energy consumption data and determine the operating schedules of the various loads within a residential environment. His approach involved measuring the current and voltage on two legs at the service entry point into the residence (typically at the electric meter or breaker box). Using a series of mathematical transformations, NIALM determines which of the largest energy consuming appliances are on at any moment. In his original publication, Hart identified a number of limitations of his approach. Specifically, the technique is not suitable for detecting household devices using less than 100 W, the software is subject to confusion when new appliances are added, and multi-state appliances (e.g. dishwashers, washing machines, and heat pumps) appliances are not well defined by the software.

The ability of NIALM to resolve specific loads on electrical systems was enhanced by (Leeb, Shaw & Kirtley 1995) with the introduction of transient event detection. In this approach, signatures of appliances at startup are used to identify what appliance is being turned on. The selectivity of NIALM was also improved by using odd number harmonic coefficients of the real and reactive power to distinguish appliances.

Concurrent with the NIALM development, a proprietary software, the Heuristic End-Use Load Profiler (HELP), was developed using decision analysis techniques to distinguish appliances (Powers, Margossian & Smith 1991). Factors such as time of day and load duration were used to recognize various loads. In a similar approach (Farinaccio & Zmeureanu 1999), used a pattern recognition technique and rules to automatically detect a domestic water heater and refrigerator based on electrical current flow into the residence. The authors also tested their generic algorithms in a home and were able to achieve daily recognition rates between 84% and 90% for the two major appliances. Further refinement and the use of training datasets, acquired directly from individual major appliances, improved the recognition accuracy to greater than 90% (Marceau & Zmeureanu 2000).

In the late 1990s, a multi-household NIALM study was conducted for the purposes of predicting diurnal load profiles (EPRI, 1997; Drenker & Kader 1999). The NIALM system used in that study stored "edge" data (real and reactive power load changes between the transition from one steady state period to the next) and load profiles with one to fifteen minute resolution. The study found that the NIALM system accurately (< 5% difference) isolated the electrical power usage of water heaters, well or sewage pumps, and water bed heaters. Other appliances such as central air conditioners, heat pumps, clothes dryers, and refrigerators were recognized by the NIALM with measured and inferred cumulative power differences between 10% and 24%. However, some appliances such as furnace blowers, electrical space heaters, dishwashers, and range/ovens could not be automatically isolated and identified with the NIALM system.

The limits and resolution of NIALM were investigated by (Fuentes et al. 2003). In their analysis, electrical current datasets were collected at the distribution level and at 20 individual appliances varying in power from 7 W to 570 W. Tests were conducted in both a laboratory and at a residence. The authors concluded that it was not possible to consistently identify all loads individually even with the use of higher order harmonic coefficients. Since the previous studies have indicated recognition accuracies of ~90%, one would expect a limit of detection to be approximately 10% of the maximum single load on the system. In this case 10% of 570 W is 57 W which was larger than the load of 11 out of the 20 appliances on the circuit.

Innovations in NIALM methods have been published by (Baranski & Voss 2004; Berges et al. 2008; Lee et al. 2005; Patel et al. 2007; Pihala 1998). However, due to the potentially lucrative nature of products developed with this technology, many innovations remain trade secrets

The Utility Accountant

The Utility Accountant (UA), an energy management device developed at the Desert Research Institute (DRI), measures electricity and natural gas entering a building and applies a sophisticated advanced NIALM system to inform users how utilities are consumed by individual appliances within the building (Kuhns, Roberts & Nikolich 2008). The UA provides the consumer with a detailed energy bill (much like phone bills) so that the consumer may target efficiencies toward the activities that are most wasteful. Figure 1 shows an example of the detail feedback that is provided. In addition to monitoring the utilities, the UA monitors the indoor and outdoor temperatures, with this information, coupled with the disaggregated information regarding how much energy is used by the HVAC system, the UA is able to accurately calculate the buildings heating / cooling envelope. The computer algorithm separates individual appliance loads based on: the signals associated with appliances or systems turning on / off, the characteristic signature of the appliances while on, and the energy usage profiles of the appliances.

The UA is a significant innovation beyond commercially available remote energy displays, or smart meters, in that the system accurately determines the individual energy usage of each major load within a building by analyzing only the aggregate building load measured at the AC mains. Data from the UA is accessed via a Web page through the user's secure networked computer requiring no additional specialized software other than a Web browser. As well as monitoring their energy usage, users can target and repair/replace appliances or systems that are operating inefficiently. The UA uses a logic rules engine to identify the various appliances within the building.

Figure 1 - Example Summary Data from the Single Appliance Tests

HOME | TRAINING | ELECTRICITY | HVAC | SETUP | HELP

Data Analysis Period : - 12/03/2009 14:22:02 - 12/03/2009 15:56:10 House = Peter's, Circuit = Leg 2

Press to export this data

ID	Name	Location	Category	Known	Cost	Energy (kWh)	Ave Power (W)	Time On (S)
Filter: All	Filter: All	Filter: All	Filter: All	Filter: All				
0				U	$0.0090	0.0276	18	5,647.9
31	Main Furnace	Garage	Heating	K	$0.0053	0.0396	462	308.2
13	Oven top	Kitchen	Cooking	K	$0.0039	0.0291	1,546	67.8
24	Garage Furnace	Garage	Heating	K	$0.0027	0.0200	260	276.8
20				U	$-0.0026	-0.0196	-28	2,539.9
14	Oven Bottom	Kitchen	Cooking	K	$0.0019	0.0139	1,362	36.7
28	Garage door opener 1	Garage	Yard Work	K	$0.0016	0.0120	108	398.8
23	Jetted Spa Motor	Master Bathroom	House Keeping	K	$0.0011	0.0083	932	31.9
9	Outlet: S Wall W Microwave	Kitchen	Cooking	K	$0.0010	0.0071	1,345	19.1
10	Coffe Maker	Kitchen	Cooking	K	$0.0010	0.0071	904	28.1
4	Light: Overhead (2) (Entry)	Hallway	Lighting	K	$0.0008	0.0058	124	167.7
12	Light: Chandelier	Family Room	Lighting	K	$0.0008	0.0057	207	99.7
16	Computer	Office	Office	K	$0.0008	0.0062	105	212.4
2	Light: Entry	Outside	Lighting	K	$0.0005	0.0034	325	38.0
8	Light: Sink	Kitchen	Lighting	K	$0.0002	0.0013	62	78.5
	Base Line				$0.0056	0.0414		
	Total P120				$0.0289	0.2143		

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The 90 minute test attributes the costs of the $0.03 of energy consumed in one leg of the house #3 in Reno. When operated during a month-long interval, the result will be an itemized utility bill that will enable users to cost effectively target energy efficient activities.

Potential Savings

User savings associated with whole building energy monitors have been established in residential markets. One example (Mountain 2006), reported the results of a 2.5 year pilot study involving more than 400 households in Canada using wireless real-time energy display. During the study, the aggregate power consumption by all participants with the display was 6.5% lower than the control group without the display. This reduction did not decay during the study period, indicating that long-term efficiencies can be achieved through use of real-time displays. Positive results from this pilot study encouraged Hydro One (Ontario's largest electrical delivery company) to distribute displays to all of their customers free-of-charge upon request. This resulted in a contract to Blue Line Innovations, Inc to purchase 30,000 units.

The Salt River Project (in Phoenix) deployed more than 50,000 real-time energy displays that also incorporate a credit card based prepayment feature (ACEEE, 2007). Whole-house power consumption displays permit users to establish a baseline of consumption and experiment with usage behavior to achieve savings (Darby, 2006).

To date, there are no studies documenting energy conservation using NIALM systems. The most analogous study using intrusive load monitoring (Ueno et al., 2006) found that Japanese homeowners reduced electricity consumption by 18% and natural gas consumption by 9%.

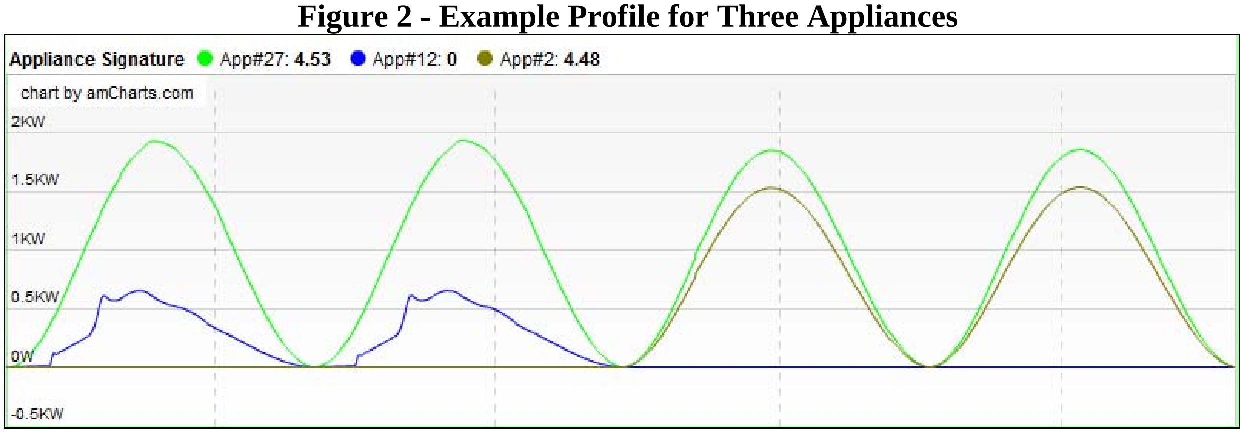
As reported on the *US Energy Information Administration* web site (www.eia.doe.gov) , in 2008, the average California residential customer consumes 7044 kW-hr per year at a rate of $0.138/kW-hr for an annual electric bill of $972; and consumes 46.6 Thousand Cubic Feet of natural gas at a rate of $12.75 per Thousand Cubic Foot for an annual gas bill of $594. Assuming the same benefits realized with the Japanese study, the average household could save 1267 kW-hr ($175) on the electric bill and $53 on the gas bill per year by using the Residential Utility Monitoring System.

With an estimated installed cost for the Utility Accountant to be $350 - $400, the device would pay for itself within 2 years for the average household. It is expected that larger residential consumers would realize cost benefits sooner since a proportional reduction in consumption translates into a large dollar savings. Installation of the Utility Accountant in small businesses is likely to have an even shorter return period since business owners tend to be more focused on the profitability of their businesses. As a retrofit for existing buildings, installation requires the user to remove the circuit breaker front panel and to clip the current sensors onto the building electrical mains. While this task can be performed in less than 15 minutes, it is a potentially dangerous activity for the average homeowner due to the risk of electrocution and requires the services of an electrician.

Utility Accountant Appliance Profiles

A unique feature of the UA is the way it automatically detects appliances in the home. It requires no a-priory knowledge of what is in the house nor does it require that each detected appliance exists as a model in its library. Once installed, the system discovers the main appliances in the home over a period of 1 to 3 days. It searches for key profile information that allows the appliances to be isolated from the combined electricity usage measurement. As time progresses the UA builds confidence in the appliances it has isolated and presents this information to the user. Appliances are detected as they are switched on / off. When they are first encountered they are added to the internal library of the UA. The UA uses various proprietary signal processing algorithms to extract unique profiles for the appliances being monitored. Figure 2 shows an example of three appliance profiles: Appliance #27 is a 240V a coffee maker; appliance #12 is a HVAC blower; appliance #2 is a refrigerator. The profiles allow the UA to isolate individual appliances from the total power values. Over time the UA generates an event time series for each isolated appliance. Figure 3 shows an example event time series for three isolated appliances, the red trace indicates the total power on one leg in the home, the green trace show the coffee maker that first turns on at 5:00am, the blue trace is the HVAC blower, and the brown trace is the refrigerator.

Figure 2 - Example Profile for Three Appliances



Three appliance profiles: 240V coffee maker (#27), HVAC blower (#12) and refrigerator (#2). The X-axis is the phase of the 60Hz voltage cycle, first half is leg1, second half is leg 2.

Figure 3 - Usage Time Series

Usage time series for the three appliances in Figure 2, coffee maker (#27), HVAC (#12) and refrigerator (#2)

Evaluating the Utility Accountant

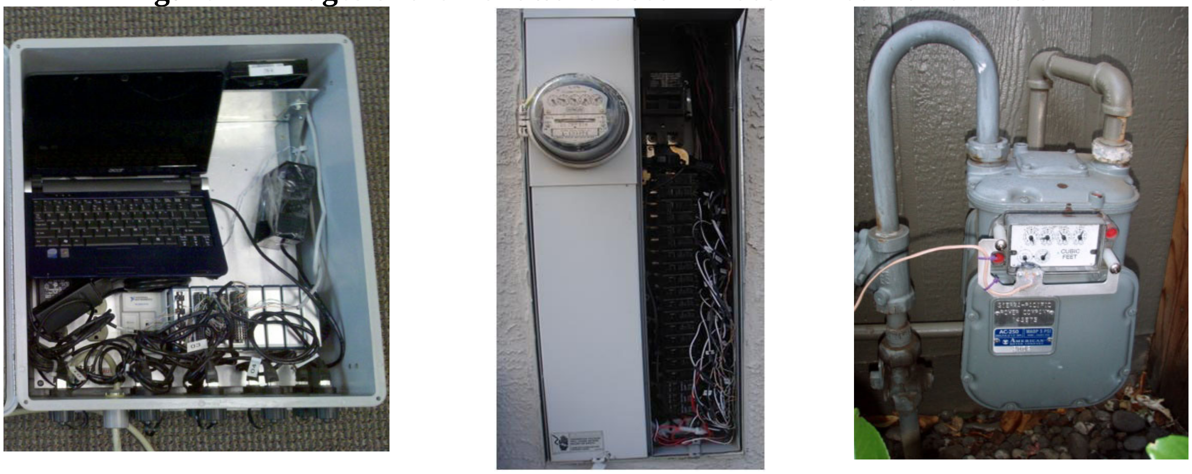
The NIALM components in the UA are under constant development. It would be neither an efficient nor cost effective method of evaluating improvements in the NIALM if field studies were required for each improvement. An alternative was to replicate field studies in the lab; by replaying back the previously collected raw data as input to the UA NIALM modules. Extensive field data was first collected from three residences, recording the power entering the residence on the two main legs and on each individual circuit breaker. This data was later replayed as the raw input to various versions of the NIALM to quantify the performance of the NIALM. The field data logger was part of an NSF SBIR phase I project to test the ability of the UA at isolating specific appliance energy usage from whole building energy consumption.

Data Acquisition

The primary data logging equipment assembled (Figure 4) was a National Instruments (NI) Chassis for Compact DAQ modules, a 4 channel 24-bit ADC module, and 3 x 16 channel 16-bit modules. A custom National Instruments LabView application was written to perform summary file averaging calculations and store all logged data on removable high capacity storage drives. The application runs on a netbook PC. Ten 1TB storage drives were used to hold the data and archive the original data sets.

The DAQ simultaneously logged: 1) the voltage and current on each of the two main power legs entering the building (4 channels); 2) the current on each of the individual circuits in the circuit breaker box (up to 28 channels); and 3) source and reflected signals from the optical gas meter sensor (4 channels). The equipment was housed in a weatherproof enclosure which also includes heating and cooling elements for year round outdoor deployment.

Figure 4 - Images of the Hardware Used in 2009 Three Home Trials



DAQ system (left) assembled to monitor energy flow on each circuit (center) & gas flow from the meter dial (right).

Two AC voltage sensors and 34 current transformer (CT) sensors were constructed. The CTs were calibrated using a specially built AC power supply capable of generating currents between 10mA to 150A (with 0.1% accuracy). A multiplexed gas sensor was assembled using an optical device that attaches to the gas meter and is capable of operating in conditions ranging from complete darkness to direct sunlight. Prior to deployment, the data acquisition system underwent calibration and testing using NIST certified voltage and current reference systems. Current sensors were calibrated with six standards logarithmically spaced measurements between 100 mA and 34 A. The minimum calibration r-square for any sensor through this range was 0.9998. The maximum standard errors of the calibrations were 0.8 W for the 24 bit sensors attached to the main legs, 7 W for the standard circuit current sensors (16 bit), and 20W for the larger sensors used on individual breaker circuits rated at more than 30 A (16 bit).

Residence installation. Three residences in Reno, Nevada, used for the sampling tests are described in Table 1.

Table 1. Description of Test Houses and Sampling Dates

	House 1	House 2	House 3
Zip	89512	89509	89511
Stories	2	1	1
Square Footage	2843	2447	2818
Year built	1997	1977	1992
Bedrooms/Bathrooms	4/3	4/2	3/2.5
Occupants (Adults/Children)	1/0	2/2	2/0
Number of Main Legs/Circuits	2/24	2/25	2/28
Number of appliances cataloged/tested	148/107	111/104	78/60

The data logger sampled the power flowing to each appliance at two points: the power flow through the individual circuit breaker and the power flow through one of the two main legs.

This provides an adequate basis to evaluate the accuracy of the NIALM software as each appliance needs to be seen at the circuit breaker and the appropriate main leg. Many circuits serve only one or two appliances, and the accuracy of the NIALM results measured on the main legs can be evaluated against the integrated power measurements on the individual circuits.

At each house, all appliances with a rated power >10 W were cataloged in a database. In addition, "single appliance tests" were conducted for as many of these appliances as possible. The procedure for the single appliance tests involved: 1) turning off every possible appliance in the home; 2) switching on an appliance; 3) wait approximately 20 seconds; 4) switching off the appliance; and 5) repeating steps (2) through (4) for each cataloged appliance. Some cataloged appliances could not be switched such as hard wired door bells, fire alarms, etc. Others such as dishwashers have several modes of operation and full cycles were not run for the single appliance tests.

Real-time data logging. All data were logged in the field on a 1 TB hard drive. Due to the high resolution and large channel count, ~4.2 GB of data was generated per hour. The storage format used was a self documenting Technical Data Management Streaming (TDMS) format that stores measured values as integers and retains a scaling factor to convert these values back into volts or amps. Reading and writing speeds for this data format are very fast making this format ideal for these types of data sets. Typical data volumes for seven days of sampling were 700 GB. After field sampling, an identical copy of the original hard drive was made for archival purposes. To facilitate data processing, all contiguous one hour files were merged into a single TDMS file on a 3rd hard drive. This had the additional benefit of defragmenting the files for efficient access of any record from the file. Logging all the data in this manner allows for both subsequent analysis and algorithm development in the lab.

Single appliance tests. The UA process contains multiple steps that are critical for the system to function accurately. Errors that occur at early stages in the process can result in a missed event that may result in power usage errors that are off by orders of magnitude (e.g., a blender that runs for a week instead of the actual 20 seconds). Moreover, the number and complexity of appliances in a building or on a circuit have a direct effect on system accuracy due to errors associated with mismatching.

Consequently, percentage performance metrics in units of power may appear very poor when in fact the system is only making a relatively small number of errors. To test the system, four types of data sets are available. In increasing order of complexity, these sets include: 1) single appliance tests on one circuit; 2) single appliance tests on one leg; 3) week-long, whole-house tests on one circuit; and 4) week-long, whole-house tests on one leg. The results obtained from these tests are currently being used to improve the NIALM algorithms.

With the single appliance tests, errors associated with multi-appliance events are minimized since all other appliances in the house are turned off. These tests evaluate how well the algorithm distinguishes between similar appliances on the same leg or circuit. During single-appliance tests, the timing and activity of each appliance is documented in the field. This information is extremely useful for the load reconciliation step to ensure that the assigned labels are accurate.

Results of the load reconciliation process for the 28 circuits in house #3 were analyzed in detail. One circuit had an issue with a computer and four peripherals turning on simultaneously while turning off at separate times. After that point, the unknown fraction of power became negative due to a missed "on" event. Other circuits performed very well with all power attributed to a baseline load or the appliances tested. The NIALM system is unable to attribute power to appliances that are part of the baseline (constantly on appliances) since there are no events associated with this lowest power level seen. Overall in individual circuit monitoring single-appliance tests, the algorithm was able to learn 245 Wh out of a possible 250 Wh (known + unknown) while the baseline accounted for 58 Wh out of 340 Wh of total energy.

The same single appliance test analysis for leg 2 generated 33 profiles of which three were combination profiles. After reconciliation, 19 unique profiles remained and the resulting profiles were linked to 32 individual appliances tests from the field notes. The reason why 19 profiles were associated with a larger number of appliances is that four of the profiles mapped onto the usage of profiles of several different appliances. In all cases, the appliances were light fixtures with purely resistive profiles. The algorithm was not be able to differentiate between the light fixtures associated with these four profiles (e.g., utility room light 1 can't be distinguished from utility room light 2). This is not a significant drawback as the algorithm correctly apportions energy uses to lighting, and the wattages apportioned are correct.

Many electrical appliances are comprised of several distinct (elemental) electrical sub-systems. Test house #3 had two furnaces, which both had three elemental sub-systems. The algorithm was unable to distinguish between the two startup elemental sub-systems of the furnaces, but was able to distinguish between the third elemental sub-system of each furnace. Each time the furnaces turns on, the three sub-systems operate in sequence - thus we are confident that by using higher level sequencing rules we will be able to differentiate among all sub-systems of the two furnaces.

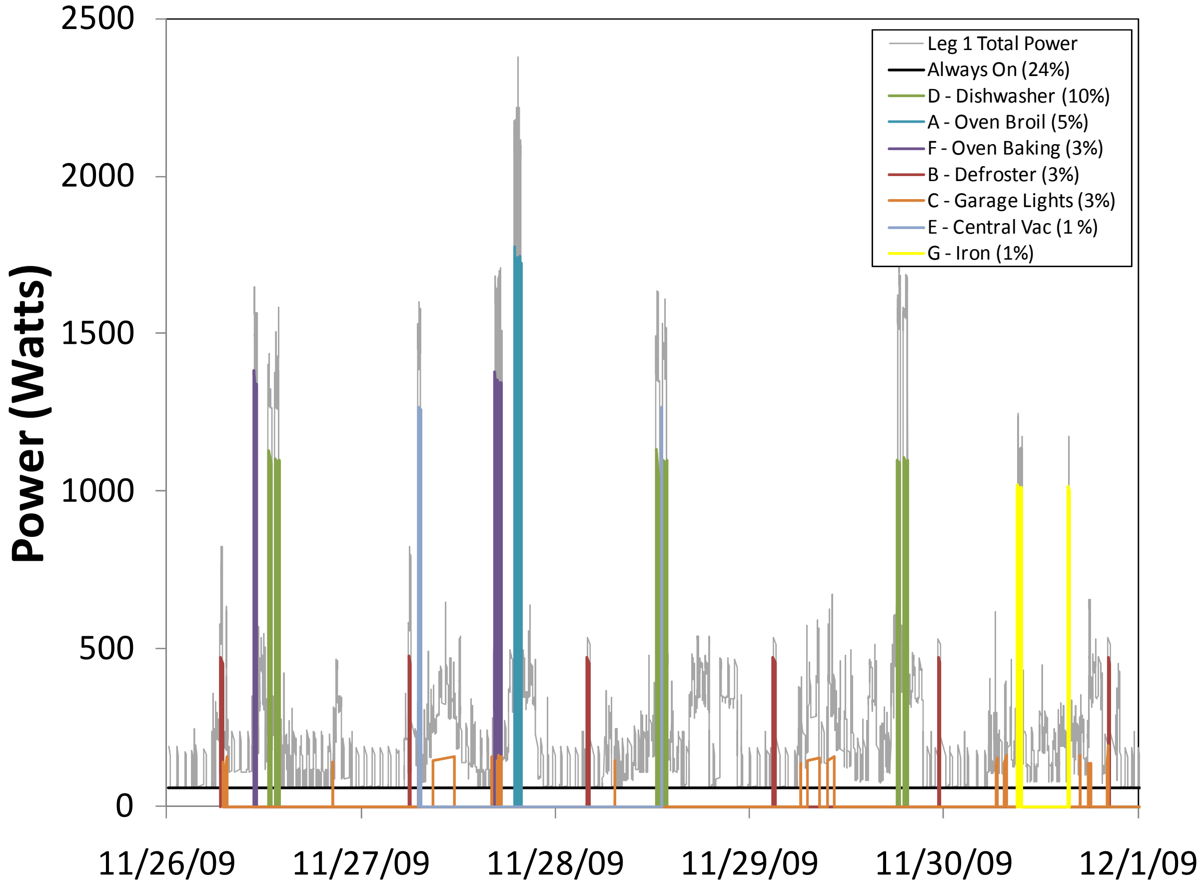
One area that needs improvement is in detection of the computer and its associated peripherals. Analysis of the data shows that an "on" transition was missed by the algorithm resulting in a negative figure for the "unknown power" being generated when the corresponding "off" transition was detected. This was the only appliance on the leg for which the load reconciliation phase was not completely successful. To overcome the missed "on" transition, the user manually grouped the computer and associated peripherals as one appliance. Apart from the computer peripherals, the algorithm was able to detect and attribute power to all appliances to which it was exposed on this leg; ranging from 25 W light bulbs to a 1.4 kW oven.

The initial results of the Utility Accountant system indicated that parameter tuning was needed to resolve some appliances that used less than 25W. Other appliances were found to have significantly different "off" and "on" profiles. These were accommodated by changing the criteria or the weighting of some of the fitting parameters used in the NILAM algorithms. Tuning the parameters is a relatively fast process since the program is simply rerun on the reduced steady state files with the modified parameters.

Whole house multi-day test. Figure 5 shows some of the appliances that the UA isolated from a main circuit leg during five days of normal use of the home. In this test the UA does not make any use of the data seen in the earlier single "on" tests, nor any of the data being simultaneously recorded on each of the individual breaker circuits. However, that data is used by the researchers to check how well the individual loads are being isolated from the total load on the main leg.

Figure 5 shows the total power usage on the main leg with each of the seven colored plots indicating an appliances isolated by the UA. There were a total of 3500 appliance transitions (appliances turning on / off) during this 5 day sampling period. The seven appliances shown had a total of 200 transitions and the UA picked up all the transitions for these seven appliances with no errors or omissions. The UA is able to isolate significantly more appliances than those shown; the appliances shown are the appliances for which no error (i.e. missed on or off transition) occurred. The NIALM algorithms are currently being analyzed and improved to overcome the missed transitions for the other appliances.

Figure 5 - Time Series of Allocated Power



Five day time series of allocated power for one leg of a residence in Reno, NV

Future Work

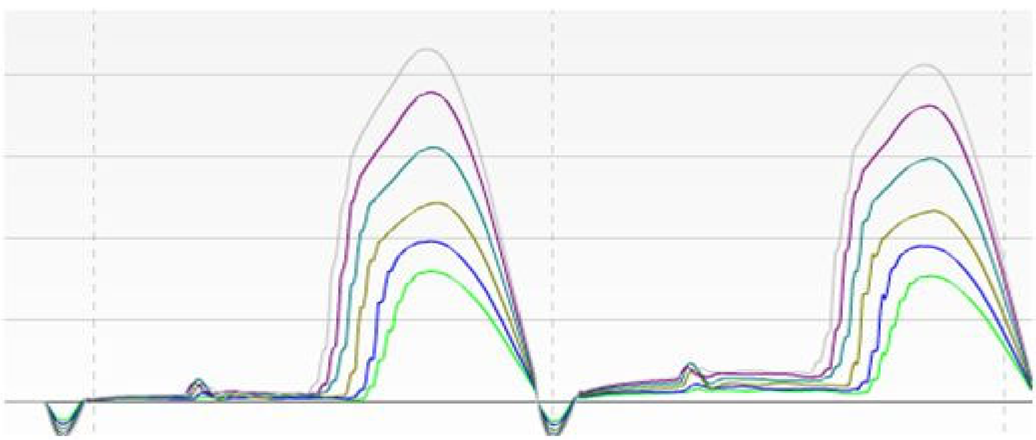
Data from controlled single appliance tests were analyzed and showed promising results; indicating that the system can distinguish and attribute power for 85% of the power used during a single appliance tests. Moreover, the fact that all data analyzed here are archived means that the algorithm can be modified and reapplied to improve upon this initial performance measure. Transparency of the data processing system is another major advance resulting from this project. When the Utility Accountant produces inaccurate results, the data may be probed at each step to determine where the error is being produced.

The results from combined appliances on the individual legs is also encouraging, however some particular issues that need to be addresses have been identified. Many electrical appliances are comprised of several distinct (elemental) electrical sub-systems. For example, a microwave oven is composed of a magnetron, turntable, light, fan, and electronic controls. As the microwave is used, its power usage profile varies as the elemental sub-systems are energized.

The UA is able to isolate the elemental sub-systems but a mechanism needs to be developed that links those elemental profiles and recognizes them as a single appliance.

If an appliance is found to turn on and then turn on again without first turning off, the NIALM algorithms recognize this as an inconsistency. The inconsistency can be caused by missed events, but could also be caused by two identical version of that appliance at the home (e.g. two furnaces). We are currently developing additional analyses to properly handle such apparent inconsistencies. Variable load appliances, such as a front loading washing machine, can generate numerous distinct profiles (Figure 6). A characteristic of the washing machine is that when the washing cycle first starts, the power usage increases with time as the clothes become heavier due to the weight of the water absorbed. As the load increases, the new power profile will not match the previous power profile. The temporal relationships between these profiles are currently being analyzed in the order to recognize these profiles as belonging to one appliance.

Figure 6 - Six Sequential Profiles for the Washing Machine



As the clothes in the washing machine get wetter (heavier) the profiles increase. There are several common characteristic features present in each profile. X axis = the phase of the 60Hz voltage cycle, Y axis = power.

While several significant challenges remain, the UA has shown promising results in its ability to isolate key appliance from the combined electrical signal entering the home. Combining the electrical data with measurement taken for other utilities, e.g. gas and water, will provide a more robust disaggregation module.

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