# Disaggregated End-Use Energy Sensing for the Smart Grid

*This article surveys existing and emerging disaggregation techniques for energy-consumption data and highlights signal features that might be used to sense disaggregated data in an easily installed and cost-effective manner.*

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Imagine an energy feedback system that displays not only total power consumption and cost, but also suggests specific cost-effective measures to improve energy efficiency. Such a system could report, for example, "Based on your energy consumption patterns, you could save US$360 per year by upgrading to a more efficient refrigerator, which would pay for itself after 21 months." The challenge in this scenario is how to sense end uses of energy to provide feedback at the individual device or appliance level. Emerging smart meters promise a tighter temporal coupling between energy usage and feedback (down to 15-minute sampling intervals). However, the focus still is on aggregate consumption, making it difficult for consumers to ascertain which devices or appliances are responsible for their energy usage. Disaggregated end-use energy data promises to transform the way residents, utilities, and policy makers think about and understand how energy is consumed in the home.

Our research team and many others worldwide are working toward a new generation of electricity, water, and natural gas measurement systems that are low cost, easy to install, and most important, capable of providing disaggregated data about consumption at the individual appliance or device level. Our team's contributions are focused on approaches for obtaining this disaggregated data from a single sensing point. Our vision is to provide high granularity resource-sensing systems for homes and businesses that will fundamentally transform how electricity, water, and natural gas are understood, studied, and ultimately consumed. This article focuses on electrical energy, but we've also developed systems for disaggregating water and gas usage (see the "Water and Gas" sidebar). All three of our systems share a common approach: they monitor side effects of resource usage that are manifest throughout a home's internal electricity, plumbing, or gas infrastructure.

Although our techniques should function in commercial and industrial sectors, we've concentrated so far on validating our methods in the residential sector, which presents many challenges. In addition to the significant amount of energy use and $CO_2$ emissions in the residential sector,[1,2] there's a higher degree of decentralized ownership. Also, levels of self-interest and expertise in reducing energy consumption vary, compared with the industrial and commercial sectors. Perhaps more compelling, however, is that energy consumption can vary widely from home to home based simply

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## Water and Gas

In addition to sensing disaggregated uses of electrical energy from a single point, our lab has also been investigating the disaggregation of water and gas consumption using similar approaches. We rely on conducted pressure waves in the plumbing infrastructure generated as side effects of appliance or fixture usage to identify and classify events to their source. The goals here are the same: create easy-to-install sensors that provide disaggregated data to better inform residents about their consumption practices and to enhance use models for utilities and policy makers.

Like electrical energy, individual behavior also plays a significant role in water usage; residential water use accounts for 50 to 80 percent of public water supply systems and 26 percent of total use in the US.[1] Although some municipalities have been successful in curtailing water use, overall residential water use is still increasing in many North American cities.[2] In addition, the US Environmental Protection Agency estimates that more than 1 trillion gallons of water are wasted in US households alone ("Fix a Leak," *WaterSense*; www.epa.gov/watersense/pubs/fixleak.html). To better inform residents about their water consumption and to provide automatic leak detection, we developed HydroSense, a pressure-based sensing solution capable of tracking water usage to the fixture level from a single installation point.[3] HydroSense works by identifying the unique pressure wave signatures generated when fixtures are opened or closed. This pressure wave is propagated throughout the home's plumbing infrastructure, enabling the single-point sensing approach. So far, we've tested HydroSense in 12 homes and three apartments by performing more than 5,000 controlled experimental trials (for example, by repeatedly opening and closing each water fixture in the home). Our results indicate that we can classify water usage to the individual valve level with 70 to 95 percent accuracy.

Unlike electricity and water usage, which often are the result of direct human actions such as watching TV or taking a shower, gas usage is dominated by automated systems like the furnace and water heater. This disconnect between activity and consumption leads to a lack of consumer understanding about how gas is used in the home and, in particular, which appliances are most responsible for this usage.[4] This misunderstanding can lead to wasteful behavior (for example, heating empty rooms) and using inefficient settings (for example, unreasonably high thermostat settings on the hot water heater). Our gas-sensing approach uses a single sensor that analyzes the acoustic response of a home's government-mandated gas regulator, which provides the unique capability of sensing both the individual appliance at which gas is currently being consumed as well as an estimate of the amount of gas flow. Our approach provides several appealing features, including the ability to be installed easily and safely without requiring a professional. We tested our solution in nine different homes, and initial results show that GasSense has an average accuracy of 95 percent in identifying individual appliance usage.[5]

It's interesting to note how all three resources are interconnected. One of the largest uses of water is in electricity production. For example, to produce one kilowatt-hour of electricity requires 140 liters of water for fossil fuels and 205 liters for nuclear power plants.[6] Large amounts of energy (both electricity and gas) are also used to treat, pump, distribute, and heat water. Our energy infrastructure is tied intrinsically to water and vice versa; water is used to produce electricity that, in turn, supplies consumable water.

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on differences in individual behavior. Indeed, studies have consistently found that energy use can differ by two to three times among identical homes with similar appliances occupied by people with similar demographics.[3,4]

We believe that disaggregated data presents an enormous opportunity for households to better understand their consumption practices, determine easy and cost-effective measures to increase their energy efficiency, and ultimately reduce their overall consumption. Even a 10 to 15 percent reduction in electricity use among homes in the United States would be substantial, representing nearly 200 billion kWh of electricity per year. This reduction would be equivalent to the yearly power output of 16 nuclear power plants or 81.3 million tons of coal. Such statistics have led a growing body of scientists, utilities, and regulators to view energy efficiency as the most accessible and cost-effective form of alternative energy.

## The Value of Disaggregated Data

Before discussing specific techniques for sensing disaggregated energy data, it's useful to highlight why we think this level of sensing is valuable to residents, utilities, policy makers, and appliance manufacturers. With regard to residents, for example, research in environmental psychology has uncovered some profound misconceptions about energy usage in the home. In 1982, Barbara Mettler-Meibom and B. Wichmann interviewed 52 households in Munich, West Germany, and asked them to estimate the proportional energy cost of specific uses.[5] They then compared these responses to actual usage. Consumers vastly underestimated the energy used for heating and overestimated the energy used for appliances, lighting, and cooking. Mark Costanzo and colleagues had similar findings.[6] Willett Kempton and Laura Montgomery found that consumers often estimate an appliance's energy use by its perceptual salience (for example, TV and lighting are often overestimated) and overestimate energy used by machines that replace manual labor tasks (for example, dishwasher, clothes washer).[7] Consumer estimates of aggregate energy usage are also poor. In multiple studies spanning a total of 700 people, R. Winett, M. Neale, and H. Grier found that only 1 to 2 percent knew how many kWh they used per month or per day; most didn't even know where their electricity meter was located.[8]

These misunderstandings of how energy is used in the home are reflected in the steps that consumers believe they can take to conserve it. People tend to overestimate the effectiveness of conservation measures that depend on changes in short-term behavior such as turning off the lights when leaving a room. They underestimate technical or building innovation solutions such as deciding to replace an inefficient appliance or upgrading a home's insulation.[7] Others have shown dramatic misunderstandings of the benefits of weatherization, retrofits, and tax breaks.[9] These results suggest the need for more accurate and specific information about how actions in the home affect energy consumption. Disaggregated data could be used by energy eco-feedback systems to provide both pertinent information about energy usage as well as tailored feedback at opportune times.[10,11] For example, an eco-feedback interface could provide information about the most convenient and cost-effective measures to reduce energy consumption based on the specific appliances and devices in a home as well as the way in which those systems are used. The feedback interface might make specific recommendations about retrofit solutions and appliance upgrades, or focus on curtailing particularly wasteful behaviors. Disaggregated data could also be used to inform residents about malfunctioning equipment or inefficient settings (for example, "the water circulation pump appears to be operating continuously rather than being triggered by a thermostat").

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From a policy perspective, knowing how much energy is being consumed by each class of appliances or devices is critical to the development and evaluation of evidence-based energy-efficiency policies and conservation programs directed at reducing capital expenditure on additional capacity.[12] Disaggregated data would enable utilities to accurately assess and prioritize energy-saving potentials of retrofit or upgrade programs. Equipment manufacturers and governments could compare energy measurements performed under controlled test conditions to measure actual home usage conditions. These comparisons would result in more realistic test procedures and, ultimately, more energy-efficient designs as use cases are better understood.

In addition to providing utility companies with an evidence-based method of evaluating their own conservation programs, disaggregated data presents opportunities for power system planning, load forecasting, new types of billing procedures, and the ability to pinpoint the origins of certain customer complaints. For demand response, utilities would be able to improve the quality of demand forecasting by having better models of usage (for example, the number of households with energy-efficient air conditioning). With real-time eco-feedback displays in the home, utilities could also suggest specific appliances to turn off or recommend other actions to conserve energy during peak load times. Finally, although some utilities currently utilize different pricing schemes depending on usage (for example, tiered pricing based on overall usage or time-of-use pricing, which is based on the time of day when energy usage occurs), future pricing models could consider the type of usage and charge accordingly. For example, heating, ventilation, and air conditioning (HVAC), refrigeration, and lighting could have different pricing models.

## Existing Techniques to Measure Disaggregated Energy Usage

Field surveys traditionally have provided the most common approach used to acquire details on occupant behaviors and appliance penetration levels.[13] Survey data is used for conditional demand analysis (CDA), a modeling technique that attempts to disaggregate individual end uses of energy.[1] CDA compares the time-dependent load profiles of households with known appliances to those without, enabling statistical characterization of consumption behavior. CDA accuracy is limited because of the diversity of devices and appliances in homes and because many users share temporal load profiles, causing aggregate load profiling to be relatively inaccurate. CDA traditionally has relied on self-report surveying for load disaggregation, which provides a relatively sparse dataset that contains various self-reporting biases.

In contrast to survey-based methods, automated methods for sensing disaggregation don't rely on self-reporting and potentially can provide extremely rich use datasets. However, no commercially available disaggregation method currently exists that's easily deployable, highly accurate, and cost-effective. There are two primary techniques for automatically measuring disaggregated energy usage to the individual appliance or device: distributed direct sensing and single-point sensing. These approaches are differentiated by their varying degree of hardware and software complexity, whether they require installation by a homeowner or a licensed professional, their calibration (or training) requirements, and their potential cost.

### Distributed Direct Sensing

Distributed direct sensing requires a sensor at each device or appliance to measure consumption. Although conceptually straightforward and potentially highly accurate, direct sensing often is expensive because of time-consuming installation and the requirement for one sensor for each device or appliance. In addition, appliances that tend to consume the most electricity are frequently hard-wired (for example, electric water heaters or lighting) or difficult to reach (behind a refrigerator or dryer), making installation and maintenance difficult and costly. Finally, because these sensors are distributed in the house, a communication protocol must be devised that can communicate sensor information to a local repository using, for example, multi-hop radio or power-line communication. Direct sensors have the potential to both sense and control the operation of various devices and appliances because they can be co-located (for instance, turning off a light when an occupant leaves a room; see, for example, iControl [www.icontrol.com]). This dual capability isn't possible with single-point sensing unless the sensing system communicates with a distributed control system. An additional benefit of direct sensors is that the calibration process typically requires no more than providing a label for each sensor. This label corresponds to the device or appliance connected to the sensor.

### Single-Point Sensing

In response to limitations with the direct sensing approach, researchers have explored methods to infer disaggregated energy usage through a single sensor. Pioneering work in this area is nonintrusive load monitoring (NILM), first introduced by George Hart in the 1980s.[14] In contrast to direct sensing methods, NILM relies solely on single-point measurements of voltage and current on the power feed entering the household. NILM consists of three steps: feature extraction, event detection, and event classification. The raw current and voltage waveforms are transformed into a feature vector—a more compact and meaningful representation that might include real power, reactive power, and harmonics. These extracted features are monitored for changes, identified as events (for example, an appliance turning on or off), and classified to the appliance or device category level. A pattern recognition algorithm is used for classification, which compares the features to a preexisting database of signatures. In its simplest form, the NILM feature vector can contain only one value, a step change in measured power to disambiguate between devices. More advanced NILM features can contain measures of power differentiated by frequency and temporal patterns.[15] Leveraging recent advances in device and appliance power supplies, our lab has extended the NILM approach for electrical disaggregation by using high-frequency sampling of voltage noise.[16,17] Voltage noise provides an additional feature vector that can be used to distinguish more accurately between energy usage signatures that would otherwise appear very similar.

Most single-point sensing approaches rely on pattern matching, which presupposes the existence of a database of appliance and device usage signatures. For example, Mario Berges and colleagues[18,19] and M. Roberts and H. Kuhns[20] are investigating how to build databases of these signatures for the NILM architecture. In the ideal case, these signatures would be similar among homes and could be preloaded on the sensing device or uploaded and examined in the cloud. In the worst case, however, a training example of each appliance or device must be produced per home, which would greatly increase installation complexity.

An additional benefit of direct sensors is that the calibration process typically requires no more than providing a label for each sensor.

### Intermediate Sensing Methods

Some sensing systems function somewhere between direct and single-point sensing. *Smart breaker* devices, such

TABLE 1. The various features, algorithms, and technologies used to disaggregate use energy data from single-point sensors. The AC subscript indicates that features were extracted using only the 60-Hz component.

| Extractable features / Comparison criteria | Real/reactive power (watts vs. VARs) | Apparent power from $\|I_{AC}\|$ | Harmonics of $\|I_{AC}\|$ | Startup of $I_{AC}$ | $\|V_{AC}\|$ | Transient voltage noise signature | Continuous voltage noise signature |
|---|---|---|---|---|---|---|---|
| **Sensing hardware** | Smart meters capable of medium-rate sampling | Current clamps or inductive sensors | Current clamps or ammeters | Current clamps or ammeters | Voltmeter | High-sampling-rate voltmeter | Medium-sampling-rate voltmeter |
| **Disaggregation level** | Device category | Large load category | Large load category | Large load category | Large load startup detection | Individual devices with mechanical switches | Individual devices utilizing SMPS, or other electronic load controls |
| **Example devices that can be disaggregated** | Fans, motors, HVAC systems, forced air heaters | Stove, dryer, electric heaters | Fans, dryers, compressors | CFLs, motors | Motor appliances, dryers, electric heaters | Any switched load | Continuously switched devices: CFLs, TVs, DVD players, charging units |
| **Algorithm** | Clustering of watts and VARs | Step change in magnitude | Magnitude of harmonics | Pattern matching of startup transients | Magnitude | Pattern matching on transient pulses | Pattern matching on features of resonant frequency |
| **Installation** | Breaker or meter: inline ammeter with voltmeter | Breaker or meter: inline ammeter, or affixed outside | Breaker or meter: in line, or affixed outside | Breaker or meter: in line, or affixed outside | Plug-in anywhere | Plug-in anywhere | Plug-in anywhere |
| **Ease of physical installation excluding calibration** | Very difficult | Current clamps: difficult; inductive sensors: easy | Difficult | Difficult | Very easy | Very easy | Very easy |
| **Ease of calibration** | Very easy | Difficult | Difficult | Easy | Very difficult | Easy | Very easy |
| **Cost (including cost of installation)** | Very high | Low | Medium | Medium | Very low | Very high | High |
| **Advantages** | Automatic categorization of certain loads, works well for appliances | Simple, enables central database of signatures, reduces per-home calibration | Discriminates among devices with similar current draw | Discriminates among devices with similar current draw and startup | Simplicity and cost | Nearly every device has observable signature, independent of load characteristics | Stable signatures among homes and devices, independent of load characteristics |
| **Limitations** | I and V must be sampled synchronously, few devices with diverse power factor | Few devices with diverse power draws | Limited to large inductive loads that distort AC line, loads must be synchronous to 60 Hz | Limited to loads with diverse, long duration startup characteristics like motors and some CFLs | Few devices affect VAC line, susceptible to line variations | Requires per-home calibration, requires fast sampling (1–100 MHz) | Requires medium sampling rate (50–500 kHz) |

as the Powerhouse Dynamics eMonitor (www.powerhousedynamics.com), are installed by an electrician inside a home's circuit breaker panel to provide a circuit-by-circuit analysis of energy consumption. Depending on the design of a home's circuit layout, each circuit might feed only one appliance. So, an approach like that of eMonitor could be used to acquire use consumption data. If multiple devices or appliances share a circuit, the smart breaker approach doesn't offer use disaggregation at the individual appliance or device level. Multiple-sensor approaches often are cost prohibitive, especially when the cost of professional installation is included.

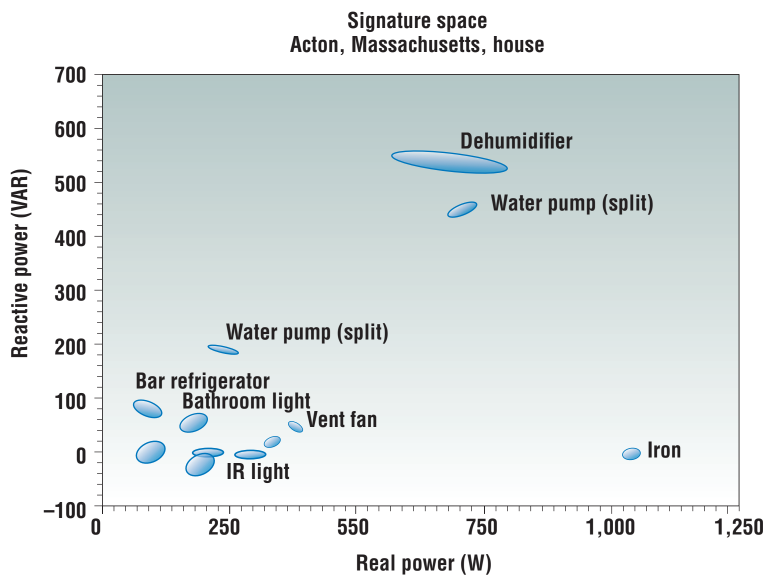


Figure 1. An example power-based signature space based on one home.[14] Note that resistive appliances (iron, electric water heater) appear on the real power axis and that motors have a reactive component.

## Observable Features for Single-Point Energy Disaggregation

Single-point sensing has advantages over direct sensing in terms of cost, ease of installation, and overall intrusiveness. However, single-point sensing is limited fundamentally by the amount and quality of information that can be sensed from a single point in the home's electrical infrastructure. The approaches to appliance- and device-level use monitoring can be subdivided into three groups: approaches based on aggregate power consumption, current consumption and startup characteristics, and voltage signatures. Table 1 provides a complete summary.

### Approaches Based on Aggregate Power Consumption

Perhaps the most obvious starting point to discriminate automatically between devices is to use the total power consumed by each device. As different devices tend to draw different amounts of power, and these power draws tend to be consistent over time, total power is a reasonable feature to use for classification (for example, a lamp typically uses less than an iron, which uses less than a microwave). Most devices have predictable current consumption and all are comprised of a mixture of resistive and reactive components, which are expressed as real or true power (watts) and reactive power (volt-ampere reactive, or VAR). Many devices can be categorized according to the magnitude of watts and VARs consumed (see Figure 1). For example, a refrigerator might consume 400 ±10 W and 450 ±20 VARs. This approach, commonly referred to as load monitoring, was used originally to categorize high-power devices, such as refrigerators and HVAC systems.[21] However, load monitoring is more difficult to apply to devices that consume little instantaneous power such as radios and small fans because the overlap in the feature space is considerable.[14] It's also important to note that although load monitoring categorizes devices, it can't disaggregate two similar devices in the same home (such as lights in separate rooms).

A significant disadvantage of this method is the need to install sensing components that are capable of measuring watts and VARs. Measuring real and reactive power requires knowing the phase angle between the main-line AC voltage and current. This measurement requires that a system synchronously sample the voltage (VAC) and current (IAC) waveforms either at the meter or directly before the breaker box. Most commonly, clamp-type current transformers measure IAC indirectly. Building codes typically require that a licensed electrician install these devices. The process involves dismantling the breaker box and clamping magnetic sensors around the main power feed conductors. To gather electrical current features in a consumer-installable manner, we developed a contactless current sensor that can be mounted to the outside of the breaker box. The sensor infers current from the magnetic fields generated by the feed conductors inside the box.[16] Although this configuration eliminates the need for professional installation and greatly reduces the complexity and safety concerns of the installation procedure, sensor placement and calibration become critical for high accuracy. In the future, smart meters could provide electrical current information, but it's unclear

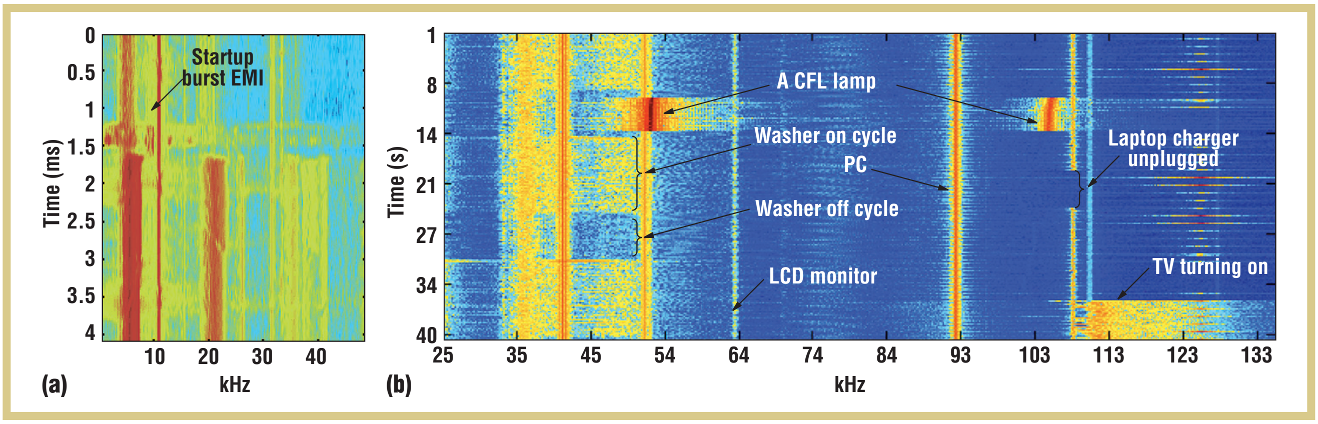


Figure 2. Spectrogram. (a) Transient voltage noise signatures of a light switch being turned on. Colors indicate amplitude at each frequency. (b) Steady-state continuous voltage noise signatures of devices during various periods of operation.

when this data will be available and whether the temporal resolution will be sufficient for disaggregation (current smart meters are typically configured to report consumption data with 15-minute granularity).

### Approaches Based on Current Consumption and Startup Characteristics

Synchronously sampling both the voltage and current waveforms can add considerable cost to the sensing unit and installation. Consequently, many newer sensing algorithms attempt to classify electrical device end use by using only the magnitude of IAC or the magnitude of IAC over long durations (on the order of one second) when a device is first actuated (startup), which eliminates the need to sample voltage and reduces the sampling rate for the current waveform (most designs use approximately 600-Hz sampling).

Many electrical devices such as heaters, fans, and compressors exhibit current waveforms with significant energies in the 60-Hz harmonics. We can find distinct features in the current waveforms by isolating each harmonic and analyzing the spectral envelope over a fixed duration during the device startup (typically 100 to 500 ms). A. Cole[22] and S. Leeb[23] were able to use these startup features together with load monitoring to categorize residential appliances. These approaches usually require some form of template matching on a known library of startup features to classify unknown loads. C. Laughman and colleagues showed that this feature space is less susceptible to overlapping categories and therefore able to separate many devices with similar load characteristics compared to approaches based on aggregate power consumption.[15] For example, two motors with similar real and reactive power consumption can exhibit significantly different startup features, making them easy to differentiate. This approach is limited primarily to devices that consume large current loads, which exert significant harmonic distortion on the current waveform. Even so, some switching mode power supply (SMPS) devices exhibit continuous harmonic signatures in the current waveform (not just distortions during startup, but constant signatures embedded in each harmonic).[24] These signatures, however, are modeled more effectively using voltage, where the features have considerably less overlap.

### Approaches Based on Voltage Signatures

Using voltage-domain measurement for electrical device disaggregation at first seems counterintuitive. The incoming power feed to a home is often assumed to be a well-regulated 60-Hz pure sine wave AC source. Of course, this power might be true at the point of generation but not true in a home. Instead, appliances conduct a variety of noise voltages back onto the home's power wiring. In an attempt to limit interference among devices, US Federal Communications Commission (FCC) rules restrict the noise voltage that each device can conduct back onto the power line. Researchers have found, however, that devices that comply with the FCC's limits still yield measurable noise signatures that are easily detectable using appropriate hardware. These signatures occur at a broad range of frequencies, not just 60 Hz and its harmonics. Gen Marubayashi categorizes three types of voltage noise: on-off transient noise, steady-state line voltage noise (generated at 60 Hz and harmonics), and steady-state continuous noise (generated outside 60 Hz).[25] Past work on electromagnetic compatibility focused largely on ensuring that this noise doesn't adversely affect power distribution or interfere with radio or television reception. Since 2007, we've been developing methods for characterizing these voltage noise signatures and using them to classify the operation of electrical appliances and devices in the home.

An important advantage of voltage noise signatures is that any electrical outlet inside the home can be used as a single installation point because the line voltage is sampled in parallel with the incoming AC line. This installation contrasts to electrical current sensing solutions that require professional installation of sensors around power feed conductors. A second advantage is that, unlike both of these approaches, voltage noise signatures can be used not only to categorize energy usage but also to identify the specific source of usage. In other words, this approach can discern not only that a lightbulb was turned on but which lightbulb.

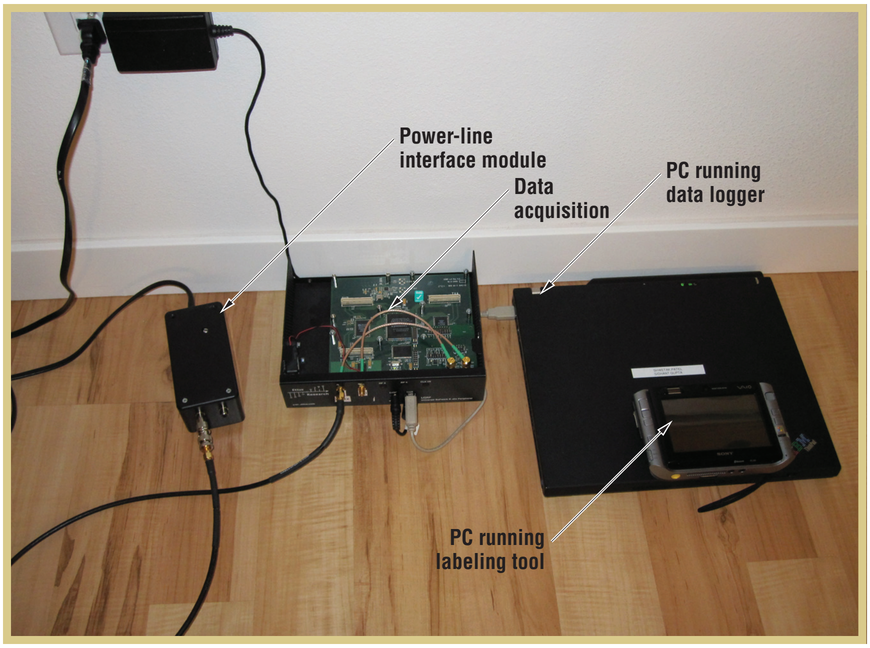


**Figure 3. Prototype. The single-point disaggregated energy-sensing system consists of a single plug-in module, acquisition hardware, and the supporting software.**

***Transient voltage noise signatures.*** Any mechanically switched device, such as a light switch, induces a short duration (transient) pulse when making or breaking an electrical circuit. This pulse is the result of a rapid series of switch contact openings and closings due to the physical nature of the switch itself through bouncing, sliding, rocking, and surface contaminants.[26] These *contact bounces* create impulse noise, which typically lasts only a few microseconds and consists of a rich spectrum of frequency components ranging from a few kHz up to 100 MHz. The transient voltage noise is filtered by the home's electrical infrastructure (the transmission line's path) and the switch's internal structure, so the transient noise generated by each switch is unique. This unique transient noise enables per-device identification but usually prevents generalization among homes.

Figure 2a shows a spectrogram of a light switch being turned on in a home. Note the rich spectrum of frequency components and the relative strength of each frequency component. Through empirical observation, we've found that these transient signatures are relatively stable over time.[16]

***Continuous, line-synchronous voltage signatures.*** Unlike transient voltage noise, which is present only for an instant when a device is turned on or off, steady-state noise exists as long as a device is powered on. Motor-driven devices such as coffee grinders, fans, and hair dryers create continuous voltage noise synchronous to the frequency of AC power (60 Hz in the US) and its harmonics. The magnitude of the 60-Hz harmonics can be used to detect the presence of large motor loads. Given that the steady-state noise signal is continuously generated, systems utilizing this feature have the ability to classify the signal even if the device activation/deactivation event is missed. So, steady-state signals in some ways are more attractive than their transient counterparts.

***Continuous, high-frequency voltage signatures.*** Because of their higher efficiency, smaller size, and lower cost compared to traditional power supplies, an increasing number of devices in the home use SMPS. These devices, which include laptops, charging units, and TVs, exhibit continuous voltage signatures at the resonant switching frequencies of the SMPS hardware and usually are operated in the range of 5 kHz up to 1 MHz with a bandwidth of a few kHz. With the wide variety of manufacturing processes and power requirements of SMPS devices, there's a minimal amount of overlap in the frequency spectrum, making the resonant frequency an attractive feature for classification.

A similar switching mode characteristic is also seen in compact fluorescent lights (CFLs) and dimmer switches. A CFL power supply uses the same fundamental switching mechanism to generate the high voltages required to power the lamp. Dimmers also produce continuous signatures because of the triggering of their internal TRIAC, which can be used to detect and identify the incandescent loads that they control. In contrast to the narrowband noise produced by SMPS, a dimmer produces broadband noise spanning up to hundreds of kHz.

Figure 2b shows a frequency domain waterfall plot indicating a variety of devices and appliances. When a device or appliance is turned on, we see a narrow-band continuous noise signature that lasts for the duration of the device's operation. The excitation of a switching device can be considered a series of periodic impulses. The electrical lines of the household (the house's transfer function) act as filters, affecting the magnitude and bandwidth of the resonances and the corresponding harmonics. Some features can be generalized among homes. Others can be used in homes to disaggregate similar appliances in different rooms or used to track the outlet to which a particular mobile device is connected.[17]

## Implementing Electrical Energy Disaggregation Using Voltage Noise

Our prototype voltage noise-based system consists of a single custom powerline interface plug-in module that can be plugged into any electrical outlet in the home (see Figure 3). The output of the plug-in module is connected to a high-speed data acquisition system that digitizes the analog signal and streams it over a USB connection to data collection software running on a PC. The PC then samples and conditions the incoming signal. Although we tested our system on a 120-V, 60-Hz electrical infrastructure, our approach could easily be applied to an electrical infrastructure that utilizes different frequency and voltage ratings with little change to the hardware and no change to the software. For homes that have split-phase wiring (two 120-V branches that are 180 degrees out of phase), high-frequency coupling at the breaker box between the two branches typically enables us to continue to monitor at a single location and capture events occurring on either branch.

To detect and classify the transient voltage noise, we utilize a simple sliding window algorithm (one microsecond in length) to identify substantial changes in the input line noise (both beginning and end). A real-time signal processing system running on the PC creates a feature vector of frequency components and their associated amplitude values by performing a fast Fourier transform on the sliding window sample. A Euclidean distance measure compares contiguous examples; when the distance first exceeds a predetermined threshold, the start of the transient is marked. The window continues to slide until there's another drastic change in the Euclidean distance, which indicates the end of the transient. The feature vectors that comprise the segmented transient are then sent to a support vector machine (SVM) for classification. Note that the SVM must be trained using three to five labeled transient voltage noise signatures from the home in which it is to be used.

To detect and classify steady-state noise, we also utilize a frequency-based analysis. The incoming time domain signal stream from the data acquisition hardware is buffered into 4-ms windows. Using Welch's method,[27] we create frequency-based feature vectors, which then are fed into our event detection and extraction software. When the system begins, it creates a snapshot of the baseline frequency signature. Thereafter, new vectors are subtracted from the baseline signature to produce a difference vector. Our feature extraction algorithm finds new resonant peaks using the difference vector and extracts quantities related to center frequency, magnitude, and bandwidth of the resonances. We build templates of known devices and use nearest neighbor search in Euclidean space to classify the feature vectors into their source device or appliance.

To evaluate the feasibility and accuracy of our approach, we conducted several staged experiments on 14 homes of varying styles, ages, sizes, and locations. In two of these homes, we also examined the temporal stability of voltage noise signals by conducting longitudinal deployments. To reduce confounding factors, we performed transient and steady-state noise experiments independently of each other. For transient voltage noise analysis, we tested our system in one home for six weeks and in five homes for one week each to evaluate the system performance over time and in different types of homes. Results indicate that we can learn and classify various electrical events with accuracies ranging from 80 to 90 percent with recalibration being unnecessary even after six weeks of installation. We were able to disaggregate events to single light switches and were even able to distinguish between two different switches that had the same load characteristics (for example, both switches were connected to a 100-W lightbulb).

We tested the steady-state voltage signatures approach in one home for a period of six months and in six other homes using staged experiments in a fixed setting. Results indicate that we can classify devices with accuracies ranging from 89 to 97 percent in individual homes. This classification includes the ability to disaggregate the same model and brand of LCD televisions in the same home as well as differentiate individual CFLs. We also investigated the feasibility of using our method to train general templates for four electrical devices at one home and then classify the devices in six other homes. In five of the six homes, we were able to classify the devices with 100 percent accuracy, and in the final home, we were able to classify three of the four devices with 100 percent accuracy (the single failure case was a laptop power adaptor whose noise characteristic is dictated by the charging state). Unlike transient voltage noise, whose characteristics result from a random distribution, SMPS steady-state noise is predictable between similar hardware

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designs. In a follow-up study, we acquired ten 20-inch Dell LCD monitors and created a single noise signature using one random monitor. We obtained near 100 percent classification accuracy when using a single learned model to a random installation of the nine other monitors in the various homes.

Our noise-based approaches enable us to identify when and what devices or appliances are used. However, these approaches don't provide power consumption data. The last step in our approach is to sense changes in whole-home, aggregate power consumption and map these power changes to the identified events. Any of the discussed current sensing approaches allow for this, including those that leverage contactless sensing.[28]

We believe that disaggregated energy usage data is considerably more valuable and actionable than aggregate energy usage data at the whole-house level. However, several open problems must be solved for single-point sensing to become a viable energy disaggregation sensing method. Many of these open problems are well suited for investigation by the pervasive computing research community, including the development of probabilistic classification approaches and new methods for ground-truth labeling of energy usage data, as well as algorithms for calibrating and training the sensing apparatus itself.

The cost and ease of installation, including any required training or calibration, must be considered in terms of the likely impact on large-scale adoption of energy disaggregation solutions. Although the ease with which a given disaggregation device can be physically installed is important, the ability for that device to function out of the box or with a small number of calibration steps is perhaps of even greater importance. We pursued two complementary disaggregation approaches that utilize fingerprinting for classification—that is, a database of labeled signatures must exist for the method to perform well. The calibration process requires that a user walk around the home, activating and deactivating each device or appliance at least once (to create an appliance signature) and to provide a familiar human-readable text label for each device. Although initially burdensome, the calibration process would be performed only once or when a new device or appliance is installed. In either case, mobile phone software could guide the user in this process and serve as an interface for collecting text labels.

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Of course, this level of calibration is required only if the device or appliance's disaggregation signature is different among homes. In the case of transient voltage noise, we found this level of calibration to be required. In other words, transient voltage noise alone isn't portable enough to enable a shared database of signatures to take the place of in situ calibration. In contrast, we found that steady-state noise signals from SMPS and CFLs have a large degree of signal similarity among homes and devices.[17] This degree of signal similarity is likely because these signatures are shaped largely by the device's particular circuit design and electronic components rather than its position on the home's internal powerline infrastructure. Given this signal invariance, a distributed system based on the deployment of single-point sensors across many homes could use a crowd sourcing approach for signature labeling that shares signatures and their labels among homes via a common backend database.

Future work could also look at the feasibility of automatically clustering and classifying unknown signals in an unsupervised fashion. That is, an unsupervised learning system need not require a human-labeled database of signatures and labels. Instead, such a system would learn these signatures over time and then acquire the labels later. A carefully designed user interface could then present a list of these unknown signals to the homeowner and ask for a semantic label. For example, the eco-feedback system might state, "The second most power-consuming appliance in your home has yet to be labeled. We think it's a hot-water heater. Is this correct?" In this way, the calibration effort is amortized over a longer time. Roberts and Kuhns are in the early stages of evaluating their sensing system, which requires no a priori knowledge of devices or appliances in the home, nor does the system require that each detected device or appliance exist as a model in its library.[20] Although the sensing system can learn unique signals over time, it still requires user intervention to provide semantic labels for these signals.

In addition to unsupervised learning, we're also studying the benefits of exploiting contextual cues and temporality of device usage (a strategy exploited by CDA). For example, many devices have predictable usage duration or are commonly used with other devices. Many devices also have predictable states of electrical usage, such as washing machines, dryers, and HVAC systems. Dynamic Bayesian networks (DBNs) are well suited to exploit this kind of a priori information. DBNs also have the added benefit of seamlessly integrating multiple feature streams, such as those measured from voltage and current—essentially providing a high-level method to integrate all the features mentioned previously.

Finally, one of the primary research challenges in investigating energy disaggregation techniques is evaluation. Although computer simulation and laboratory-based testing are useful in evaluating an approach's feasibility, it's difficult to replicate the complexity and nuance of device and appliance usage in these artificial environments. The problem with in-home evaluation is the difficulty of establishing a method to acquire ground-truth labeling about when and which devices and appliances are used. For our own evaluations, we largely relied on manual labeling of electrical device activation and deactivations using staged in-home experiments with custom-built labeling software. However, this approach is labor intensive, making it difficult to conduct experiments among a large set of homes. It's also unclear how effectively these controlled activation/deactivations mimic naturalistic energy usage. For example, some disaggregation techniques are affected by the number of appliances or devices that are active simultaneously. Such dependencies must be reflected in the staged experiments.

The labeling of appliance and device usage could be handled by distributed direct sensing or hybrid methods that monitor power draw on each electrical branch of a home. Here, a sensor or a set of sensors is installed at each device/appliance location to monitor use. An automated validation system could use these distributed sensor streams to evaluate the single-point solution's efficacy (for example, by comparing both outputs). Fully instrumenting a house with direct sensors on each outlet and for each appliance, device, and hard-wired system (for example, lighting) is extremely resource intensive both from an installation and a maintenance perspective. It's unlikely that any preexisting direct sensing system would be capable of providing per-device usage information, so new direct sensors must be custom designed, which presents its own challenges. Finally, system designers must ensure that direct sensors don't distort the signal features used by the disaggregation algorithms (for example, by adding additional noise to the power wiring). So, although a direct sensing approach clearly would have benefits (for example, this approach could be used to collect naturalistic ground-truth data over long periods), major challenges remain in making direct sensing practical.

One of the primary research challenges in investigating energy disaggregation techniques is evaluation.

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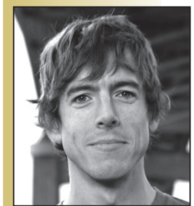

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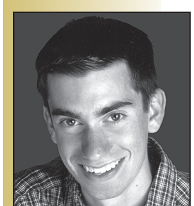

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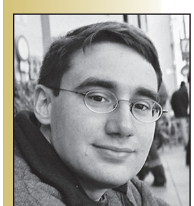

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