Building Virtual Power Meters for Online Load Tracking

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Many energy optimizations require fine-grained, load-level energy data collected in real time, most typically by a plug-level energy meter. *Online load tracking* is the problem of monitoring an individual electrical load's energy usage in software by analyzing the building's aggregate smart meter data. Load tracking differs from the well-studied problem of load disaggregation in that it emphasizes per-load accuracy and efficient, online operation rather than accurate disaggregation of every building load via offline analysis. In essence, tracking a particular load creates a *virtual power meter* for it, which mimics having a networked-connected power meter attached to the load, but notably does *not* require tracking every other load as well. We propose *PowerPlay*, a model-driven system for performing accurate, high-performance online load tracking. Our results from applying the system to real-world energy data demonstrate that PowerPlay (i) enables efficient online tracking on low-power embedded platforms, (ii) scales to thousands of loads (across many buildings) on server platforms, and (iii) improves per-load accuracy by more than a factor of two compared to a state-of-the-art load disaggregation algorithm. Our results point to the potential of replacing physical energy meters by "virtual" power meters using a system like PowerPlay.

CCS Concepts: • **Information systems → Information systems applications**; • **Applied computing → Computers in other domains**;

Additional Key Words and Phrases: Online load tracking, load modeling, smart meters, smart grid

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1 INTRODUCTION

Collectively, buildings consume significantly more energy (41%) than society's other broad sectors of consumption—industry (30%) and transportation (29%) (Kelso 2012). As a result, the design of "smart" buildings that are capable of automatically regulating their energy usage has become an important research area. However, one continuing impediment to improved building

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energy-efficiency is that, despite much prior research (Hnat et al. 2011), accurate online monitoring of individual electrical loads[1] remains problematic at scale. In particular, deploying and maintaining large numbers of embedded networked sensors in every building is prohibitively expensive, invasive, and unreliable. Unfortunately, timely and accurate knowledge of per-load energy usage is a prerequisite for implementing many energy optimization techniques (Barker et al. 2012b; Carpenter et al. 2012; Taneja et al. 2010).

Rather than relying on expensive instrumentation via embedded sensors to monitor loads, an alternative approach is to analyze electricity data from smart meters to infer a load's energy usage. This approach is becoming increasingly attractive due to the wide deployment of smart meters that monitor an entire building's energy usage at small intervals (e.g., minutes to seconds). Such meters are being widely deployed by electrical utilities and consumers (EIA 2017). In this article, we propose a new analysis technique, which we call *online load tracking*, that monitors the operation of individual building loads (i.e., when they turn on or off and their fine-grained energy usage) by analyzing smart meter data. In essence, "tracking" a particular load creates a *virtual power meter* for it, which mimics a network-connected energy meter attached to the load without needing any actual hardware beyond the building-wide smart meter.

Tracking loads *online* (i.e., in real time as a smart meter generates new data) is critical, since many higher-level energy optimization techniques require such real-time data. For example, an automated load scheduling policy that reduces a building's peak power demand by deferring one or more background loads must know the energy usage of each background load to determine which of them to defer and for how long (Barker et al. 2012b). As another example, a recommendation engine may monitor the energy usage of a building's interactive loads to push energy-efficiency recommendations to occupants' smartphones in real-time, directing them to take an immediate action to better optimize their energy usage, e.g., such as turning off an idle coffee pot (Banerjee et al. 2011). Essentially, online load tracking is useful for any application that requires attaching a power meter to a load that transmits its average power usage every pre-specified time interval in real time.

Our work builds on prior work, which has already developed a variety of analysis techniques for smart meter data, including load disaggregation (Armel et al. 2013; Hart 1992; Kolter and Johnson 2011; Zeifman and Roth 2011) and occupancy detection (Chen et al. 2013). Many startup companies are now combining such energy-based analytics with cloud-based, "big data" platforms (Bidgely 2018) to mine building smart meter data *en masse*. However, we argue that online load tracking differs from the well-studied problem of *complete load disaggregation*, often termed Non-Intrusive Load Monitoring (NILM) (Armel et al. 2013; Hart 1992; Kolter and Johnson 2011; Zeifman and Roth 2011), in two important respects:

Simplicity. Online load tracking is a simpler problem than complete load disaggregation—load tracking targets *individual* loads, while complete load disaggregation focuses on disaggregating an entire building by apportioning its total energy usage across *every* load. Clearly, if complete, accurate, and inexpensive disaggregation was feasible, it would subsume the problem of online load tracking. However, techniques for complete disaggregation continue to suffer from inaccuracy, especially when disaggregating small loads or scaling up to large numbers of loads (Armel et al. 2013). Thus, load tracking is better suited for scenarios where disaggregating *all* of a building's loads is either infeasible (due to the large number of loads) or simply not necessary.

Efficiency. Prior disaggregation techniques implicitly assume offline analysis and are often computationally expensive. In contrast, load tracking explicitly targets online monitoring in near real time. This leads us to focus on performance issues not addressed in prior research, such as

[1]We use the term electrical load, or simply *load*, to refer to any distinct appliance or device that consumes electricity.

enabling tracking to either (i) run on the low-power embedded platforms used in smart meters or (ii) scale to thousands of loads on server platforms.

To enable high performance, we take a model-driven approach to load tracking, which focuses on detecting a small number of identifiable load features in smart meter data. These features derive from a parameterized model of a load's energy usage profile over time, which is based on a small number of fundamental electrical characteristics, i.e., whether a load is resistive, inductive, non-linear, or cyclical. A detailed description of these load types, and their corresponding models, is described in prior work (Barker et al. 2013). We select a compact set of identifiable load features from the models and then design efficient online methods for tracking loads by detecting one or more of these features in smart meter data. In doing so, we make the following contributions:

Feature Selection. We describe a compact set of features that loads may exhibit, including power steps, spikes, growths, decays, oscillations, and cycles. We extract a load's features from its model and then choose a small set of identifiable features for tracking. Using only identifiable features to track loads increases efficiency, compared to using every feature, while maintaining accuracy.

Online Load Tracking. For each feature, we design efficient online methods to detect that feature in smart meter data. Since a load may exhibit multiple features, tracking a load may require using multiple feature detectors. Hence, we present an online tracking algorithm that combines multiple feature detectors to efficiently detect and track loads.

Implementation and Evaluation. We implement our load tracking system, called PowerPlay, and evaluate it "live" using a 1Hz power meter. We show that our approach enables efficient, online load tracking: on a 2.4GHz, single-core server, PowerPlay is able to track loads in smart meter data comprised of nearly 100 loads in real time each second—the same resolution of the building's power meter. We also show that PowerPlay improves per-load accuracy by more than a factor of two compared to a state-of-the-art disaggregation algorithm (based on Factorial Hidden Markov Models (FHMMs) (Kim et al. 2011; Kolter and Johnson 2011)) designed for offline analysis.

Section 2 formally defines the load tracking problem and the related (but distinct) NILM problem, and briefly surveys prior work to distinguish PowerPlay's approach. Section 3 describes the offline components of PowerPlay—namely, modeling an electrical load and extracting its most identifiable features to track. Section 4 describes the online components of PowerPlay—i.e., the core load tracking algorithm and the methods to detect the features detailed in Section 3. Section 5 details our prototype "live" implementation of PowerPlay within a real-world home. Section 6 evaluates the system's accuracy, scalability, and sensitivity, and compares its tracking performance to a FHMM-based NILM technique. Finally, Section 7 concludes.

2 BACKGROUND AND APPROACH

PowerPlay assumes a building equipped with a networked power meter that monitors its aggregate electricity usage over time. We refer to this building power meter as a *smart meter*. We assume smart homes employ automated energy management techniques, which require real-time operational knowledge of particular loads' energy usage, e.g., air conditioners (A/Cs), furnaces, or other appliances amenable to automated energy management. Rather than directly monitoring such loads using sensors, our goal is to provide a virtual power meter abstraction that tracks a load's energy usage and when it turns on and off from the home's smart meter data. Load tracking is useful in scheduling home loads or pushing alerts to users (e.g., to indicate that a laundry cycle is complete), or when exercising control over "large" loads (such as A/Cs) across many homes to smooth grid demand.

2.1 Problem Statement

Formally, we define the problem of online tracking for load p_i as inferring its average power usage $p_i(t)$ from a home's total power usage $P(t)$ recorded by its smart meter over the period $(t - \tau, t]$. Due to its online nature, computing each $p_i(t)$ must complete within $t + \epsilon$ for some value of ϵ. Observe that tracking a load's power usage $p_i(t)$ also indirectly reveals when it turns on and off. Load tracking targets individual loads and does not attempt a full disaggregation, as is common with NILM techniques, which try to infer $p_i(t)$ for *all* n building loads, such that $\sum_{i=0}^{n} p_i(t) = P(t)$. Further, to the best of our knowledge, no prior NILM technique addresses online operation with a timing constraint.

Of course, perfectly tracking all n loads would be equivalent to a complete and accurate disaggregation. Since load tracking values system performance, as well as the accuracy of a load's inferred power readings, its goal is to *both minimize* ϵ *and maximize accuracy*. In this case, we measure accuracy based on a load's *tracking error factor* δ, which is simply the error between a load's actual and inferred power usage, normalized by its total energy usage. If $\tilde{p}_i(t)$ denotes load p_i's actual power usage at time t and $p_i(t)$ denotes its inferred power usage from load tracking at time t, then we define the tracking error factor over T intervals as

$$\delta = \frac{\sum_{t=1}^{T} |\tilde{p}_i(t) - p_i(t)|}{\sum_{t=1}^{T} \tilde{p}_i(t)}. \tag{1}$$

Here, the numerator is the sum of the absolute errors at each data point, and the denominator is the load's total energy usage over T. Lower values of δ are better; an error factor of zero indicates perfect tracking. While there is no upper bound on the tracking error factor, an error factor of one indicates that the reading-to-reading errors are equal to the load's energy usage. In general, a tracking error factor near one is not considered good, since simply inferring a load's energy usage to be zero at each time t results in $\delta = 1$. Note that this metric is a load-specific variant of the "total energy correctly assigned" metric from prior work (Kolter and Johnson 2011).

We denote the meter's data resolution using the sampling time interval τ. A coarser (or longer) sampling interval "averages out" features in $P(t)$, eliminating identifiable attributes, while a finer (or shorter) interval reveals more attributes but also more data to process, as well as more noise. Our work specifically targets consumer-grade power meters, such as the TED (TED 2018), eGauge (Egauge 2018), and BrulTech (2018), which commonly provide a sampling resolution of one reading per second, e.g., τ = 1s. While today's utility-grade smart meters provide, at most, minute-level sampling, e.g., a reading once every 5–15min is common, there are indications the next generation of meters will provide second-level sampling. For example, a U.K. subcommittee defining future smart meter specifications recently released a report advocating a 5s sampling resolution (UK-Smart 2011).

2.2 Prior Work

Our focus on tracking individual loads, rather than complete disaggregation, stems from a recognition that (i) accurate disaggregation continues to be an elusive goal despite two decades of research, and (ii) the simpler load tracking problem is sufficient for many sensor-based applications and can be more efficient and accurate. Prior disaggregation approaches differ widely based on τ's value, which ranges from >100,000,000 samples per second (Patel et al. 2007) to one sample per hour (Kolter and Ng 2010). Interestingly, a recent survey (Armel et al. 2013) points out that, despite τ's importance, prior work often does not report it.

In addition, despite the plethora of prior work on disaggregation, the same survey (Armel et al. 2013) highlights the lack of research that targets second-level sampling. To the best of our

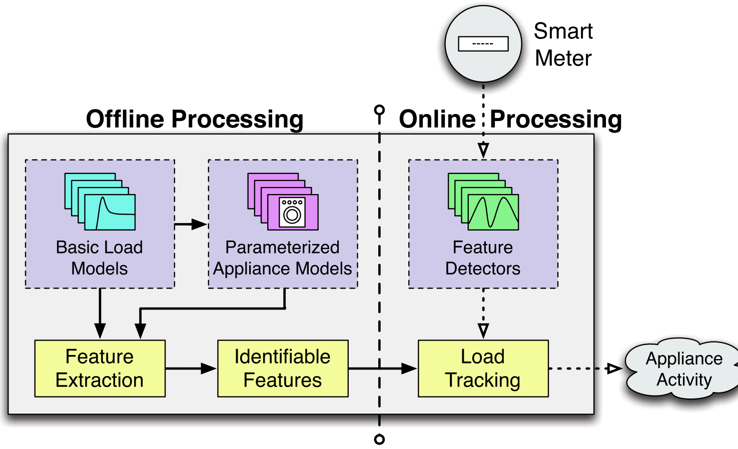


Fig. 1. PowerPlay uses offline modeling and feature extraction for online load tracking.

knowledge, only Hart's original work (Hart 1992) and two recent papers (Kim et al. 2011; Kolter and Johnson 2011), which both use an approach based on Factorial Hidden Markov Models (FHMMs), target data with second-level sampling resolution, albeit for full disaggregation. Since there is no prior work on online load tracking, we use a FHMM technique modified for online operation as a baseline for comparing PowerPlay's performance and accuracy, as described in Section 6.

2.3 Basic Approach

PowerPlay employs a model-driven approach for load tracking, which ensures accuracy and computational efficiency by decomposing tracking into multiple distinct subproblems. Note that prior work on complete load disaggregation typically conflates these subproblems. The subproblems include (i) empirically modeling a load, (ii) extracting features from the model, (iii) selecting the most identifiable features, and, finally, (iv) detecting and tracking a load based on these features. Figure 1 depicts the basic workflow of each subproblem, which we, in turn, outline briefly below.

1. Empirical Modeling. We first empirically model each load's energy usage based on properties of the four basic types of electrical loads, i.e., resistive, inductive, capacitive, and non-linear. Prior work describes how to derive such models and shows that such empirical models accurately capture the behavior of nearly every common household load (Barker et al. 2013). We assume a load's model accurately describes its energy usage when on.

2. Feature Extraction. After empirically modeling a load, we decompose it into a set of features. Each feature captures a subset of the load's pattern of energy usage within the model: The set of features collectively represents a concise description of how the load's operation manifests itself in power data. Intuitively, a load tracking algorithm must "search" for these features within a home's aggregate smart meter data to detect the presence of the load and track it.

3. Identifiable Feature Selection. PowerPlay optimizes load tracking efficiency by distilling a load's full feature set into a subset of its most identifiable features. Identifiable features are a load's most prominent (and unique) features, such that a tracking algorithm need only search for these identifiable features, rather than the full feature set, to detect and track a load with high confidence. Clearly, the smaller the set of identifiable features, the more efficient online detection.

4. Online Load Tracking. The final step is to design a tracking algorithm that detects a load's identifiable features in the smart meter data in an online fashion.

The first three steps above, namely empirical modeling, feature extraction, and identifiable feature selection, are one-time tasks performed offline, while PowerPlay's final detection and tracking step is continuous and online.

PowerPlay's model-based, feature-driven tracking differs from low-level time-series matching (Kelly 2011). In essence, the time-series approach takes either a trace or model of a load's raw power usage when on and "matches" it against a recent (sliding) window of time-series data from a smart meter to determine whether it is "embedded" in the data. Matching typically involves computing a time-series distance function, such as Euclidean distance or Dynamic Time Warping (Keogh and Pazzani 2001), between the load's raw power usage and the most recent set of smart meter readings of equal size; a match then occurs when the distance is less than a predefined threshold. Low-level time-series matching is more expensive and less robust than using higher-level features for load tracking.

3 OFFLINE FEATURE IDENTIFICATION AND SELECTION

We first describe the three offline steps in PowerPlay's approach, namely modeling a load, extracting a load's features, and then selecting a subset of identifiable features to track. As this process is a one-time step, we envision manufacturers profiling each load and supplying its model and features as part of its technical user manual. The information could also be crowd-sourced, such as in The Power Consumption Database, which already provides crowd-sourced information on maximum and idle power for a wide range of loads, indexed by type, manufacturer, and model number (TPCDB 2018).

3.1 Modeling and Feature Extraction

Electrical loads in an alternating current (AC) system fall into one of four basic types—resistive, inductive, capacitive, or non-linear. Informally, resistive loads include heating elements, such as a toaster; inductive loads include AC motors, such as fans or compressors; and non-linear loads include any type of electronic device, such as TVs or computers. Loads behaves differently based on their load type, but devices of the same type exhibit many common behaviors. Complex appliances that operate multiple internal loads, e.g., a refrigerator with a motor-based compressor and interior light bulb, exhibit a composition of these behaviors. Further details of how the four basic types map to real-world devices are provided in Barker et al. (2013). Below, we enumerate the identifiable features that PowerPlay tracks.

Stable Power Steps. The simplest feature is a discrete change in average power from one stable value to another stable value. Most disaggregation algorithms that analyze real power data, e.g., at sampling resolutions coarser than 60Hz in the U.S., consider stable power steps as the **only** identifiable feature. In reality, only a few low-power resistive loads, such as incandescent lights, exhibit only these simple steps when on.

Power Growth, Decay, and Spikes. Many loads experience smooth increases or decreases in power when turned on (e.g., due to decreasing resistance as a heating element warms), or abrupt and sudden spikes in power (e.g., when starting an induction motor). We consider power growths, decays, and spikes as distinct features: *spikes* capture an initial power surge, while logarithmic *growths* and exponential *decays* capture gradual increases or decreases in power.

Bounded Power Oscillations. Many non-linear devices based on electronic controllers (e.g., microwaves) draw a seemingly random amount of power within a fixed range when on. We consider bounded power oscillations between maximum and minimum power thresholds as a distinct feature resembling a random walk between thresholds.

Stable Power Oscillations. Some non-linear loads only have either an upper threshold or a lower threshold, resulting in oscillations from a stable power state (e.g., due to the variable draw

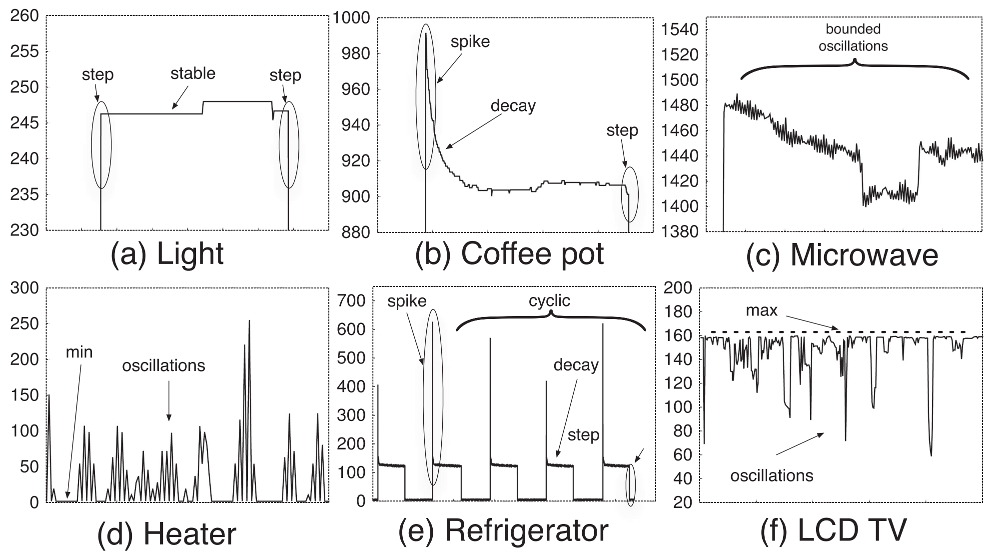


Fig. 2. Annotated features from representative loads.

of a switched mode power supply). Stable power oscillations are a combination of the *stable* power feature and power *spike* feature that captures frequent positive or negative random fluctuations from a stable power level.

Power Cycles. Many loads include timers that operate them periodically in a repeating pattern, e.g., a dehumidifier may include a timer that turns it on for two hours out of every 4h. A cyclic feature captures the interval and conditions at which the features repeat, and potentially their duration, e.g., the length of a stable power level.

Since essentially every electrical load is either an induction motor, heating element, non-linear electronics, or some combination thereof, every load exhibits one or more of the above features. Since the feature set is small, we only require a small set of detection techniques to identify these features in smart meter data, as described in Section 4. Note that the features above are parameterized for each specific load (e.g., the magnitude of a step or the rate of a decay), and may differ across two loads of the same type, e.g., two A/Cs from different manufacturers may require different features and parameters. Thus, PowerPlay's offline component not only extracts the features of a load but also determines the parameters for each feature. Figure 2 includes annotated features in power usage data for a variety of common loads.

3.2 Selecting Identifiable Features

Since basic loads only include a few features, an online load tracking algorithm can use all of their features to detect their presence. However, complex loads, such as a washing machine, may exhibit an excessively large number of features. Fortunately, searching for every feature is generally not necessary for accurate detection; it is often sufficient to select a subset of prominent features to uniquely identify the load. PowerPlay leverages this insight to only search for a small set of *identifiable features* to match complex loads, which improves both efficiency and scale.

Selecting identifiable features for a load is a one-time offline task, and presents a tradeoff between accuracy and performance. A smaller set of identifiable features improves the efficiency of detection, but decreases tracking's accuracy. At present, we construct a complex load's set of identifiable features experimentally by iteratively adding the next highest magnitude features, e.g., that include the largest changes in power, to the feature set and then executing our tracking algorithm on historical data until the tracking error factor is below a pre-defined threshold.

3.3 Automatic Feature Generation

The current version of PowerPlay relies on pre-generated (and parameterized) features to track a given device. This requirement may add significant manual overhead, particularly on complex devices requiring multiple features. While a public feature database such as proposed previously would largely solve this problem, without such a database, using PowerPlay to track any specific device requires first designing and tuning its model. The simplest approach is to design the features by hand, which is tedious and prone to human error.

Notably, however, there is no requirement that the feature generation process be manual. Recent work such as (Iyengar et al. 2016) proposes methods to computationally generate and parameterize feature-based models like those used in PowerPlay. With such techniques, the process of constructing the features may be largely automated, vastly simplifying the process of tracking new devices. The automated models generated in Iyengar et al. (2016) are reported to differ from manually constructed models detailed in Barker et al. (2014) by less than 1%, which is well within the margin of error needed for accurate tracking by PowerPlay.

4 ONLINE LOAD TRACKING

In this section, we first describe PowerPlay's online tracking algorithm and then describe the various feature detection techniques the algorithm uses to detect the features from Section 3. The right side of Figure 1 depicts this process.

4.1 Tracking Algorithm

PowerPlay's load tracking algorithm is shown in Algorithm 1 and detailed below.

The algorithm takes as static inputs a list of loads to track and a set of identifiable features for each of these loads. During operation, these inputs are combined with a continuous stream of aggregated data from a smart meter. Feature detectors for each load operate over a moving window of data points of size W, starting from the most recent data point in the time-series of a home's power readings (i.e., a sliding window ending with the most recent reading). This window represents the minimum time period over which a feature manifests itself. The output of the tracking algorithm acts as a set of virtual power meters providing device-level power data for each tracked load.

PowerPlay orders the list of all identifiable features across all loads into three sets, from most to least distinctive. The first set contains "noisy" features—specifically, all stable and bounded power oscillation features across all loads in the tracking set. The second set contains the remaining basic features: steps, spikes, and decay/growth features across all loads. The third and final set contains any cycle features for loads in the tracking set. Given these ordered sets, the tracking algorithm repeatedly executes its main loop (the first loop in Algorithm 1), which applies every feature detector (from all loads) in order. The behavior of each feature detector is described in Section 4.2.

The system buffers any smart meter data that arrives while executing the main loop, reading and appending it to the home's power data time-series on the loop's next iteration. The time taken to complete the main loop defines PowerPlay's online performance, i.e., the minimum ϵ it can support. For example, if the main loop takes 30s to complete, then the tracking algorithm can only output each load's inferred power usage every 30s. The exact value of ϵ depends on available hardware resources, as well as the number of virtual power meters to simulate—i.e., twice as many tracked loads will generally increase ϵ by roughly 2×, depending on the exact features involved.

ALGORITHM 1: PowerPlay's Load Tracking Algorithm

```
Inputs:
  list of loads to track;
  set of identifiable features per load;
  unprocessed, aggregated smart meter data (continuously);
Preprocessing:
  group all features based on "noise";
   1st group: stable min-max and bound oscillations;
   2nd group: spikes, growth/decays, and steps;
   3rd group: cycles;
while true do
    Read in new, unprocessed smart meter data from buffer;
    Append new data to existing (filtered) power data time-series;
    Execute every stable min-max and bounded oscillation feature detector on filtered data;
    if Match then
        Identify and label feature;
        Filter feature from power data time-series;
    end
    Execute each spike, growth/decay, and step detector on filtered data;
    if Match then
        Identify and label feature;
        Filter feature from power data time-series;
    end
    Execute each cycle detector across labeled features;
    if Match then
        Identify and label cycle;
    end
    for each load in the tracking set, ordered by load size do
        if features present (in model-specified order) then
            Identify load's presence;
            Reconstruct load's inferred power time-series;
            filtered load features and full model;
        end
    end
end
```

PowerPlay prioritizes detecting the "noisy" features (those containing significant power fluctuations) to filter them before detecting less pronounced features. These noisy features are detected, labeled, and filtered from the home's power data as described in Section 4.2. Doing so enables PowerPlay to more easily and accurately detect the remaining features, as the residual data has less noise after filtering. Subsequently, PowerPlay applies the remaining basic feature detectors (e.g., spikes, growth/decays, and steps) to identify and label those features in the data. Finally, PowerPlay runs the cycle feature detector over the list of labeled features to identify repeating patterns of features—the cycle feature detector is unique in that its input is a set of labeled features rather than raw time-series data, and as such is run last.

For each desired virtual power meter (i.e., each load in the tracking set), PowerPlay then examines the list of labeled but unassigned features found in the recent past (over a window W). If the identifiable features of the load are found in the window, then it assigns these features to the load and declares a load match. Upon assigning features to a load, PowerPlay removes them from the

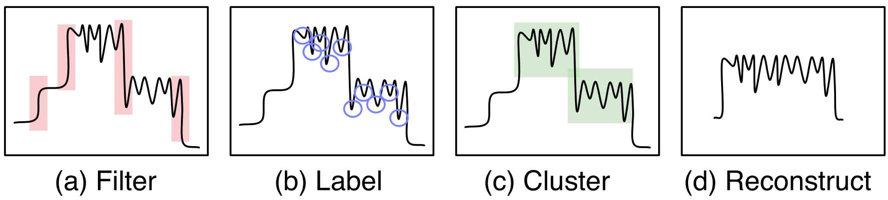


Fig. 3. Detection of a stable oscillation feature.

list of unassigned features. For composite loads, the set of features (over window W) may need to occur in a certain order (or within a certain time interval) to infer a load's presence. Finally, whenever PowerPlay detects a load based on its features, it updates the load's inferred power usage $p_i(t)$ using the filtered feature data and the load's model, which captures the load's full power usage behavior. The inferred power consumption constitutes the output from the load's virtual power meter.

Load Ordering. All loads are tracked using a single (i.e., shared) pool of features, and a detected load results in the removal of its features from the pool. As a result, the specific order in which loads are detected can have a impact on the performance of tracking other loads—either positive (if the removal of a load's features disambiguates other loads) or negative (if another load's feature is prematurely and incorrectly assigned). PowerPlay tracks devices in order according to their expected usage over a typical (e.g., 1 day) interval. For example, a dryer (which uses a large amount of energy on a day in which it is active) will be tracked before a toaster (which uses a much smaller amount of energy). This approach will tend to prioritize devices with longer active periods, larger energy steps, and more rapid cycles—all of which will generally correspond to more "recognizable" devices.

4.2 Feature Detection

PowerPlay's tracking algorithm relies on individual feature detectors to identify the features described in Section 3, including power steps, spikes, growth/decay, bounded oscillations, and stable min-max oscillations. As with other similar types of analyses, feature detectors first transform raw power readings into a series of changes in power, or *power deltas*, e.g., +50W, −30W, +25W, and so on, before processing them. PowerPlay associates each power delta with one and only one feature from a single load, removing it from further consideration by other feature detectors. We detail each of our feature detectors below.

Stable Oscillation Detector. This detector examines data for frequent power oscillations from a stable minimum or maximum power level, such that for every negative power delta (i.e., a power drop) there is a corresponding positive power delta in the near future. More formally, it identifies a stable power oscillation feature by scanning a recent window of data, while maintaining a stable power level p, which it updates only if power deviates from p by at least T watts for at least D seconds. The parameters T and D are specific to a particular device that exhibits this feature. Power changes that update p are considered background activity, which are excluded from the stable power oscillation feature, while any other oscillations within the window are flagged for consideration in the feature. Finally, we cluster nearby groups of labeled points to result in the time range (and flagged deltas) comprising the feature.

To filter the feature from the raw data, we remove from the data any oscillations that do not result in an update to p, and then use them to reconstruct the feature's second-to-second energy usage due to its stable oscillation behavior, as illustrated in Figure 3. In determining the D parameter for each load, the goal is to set it long enough to ensure changes in power are not random

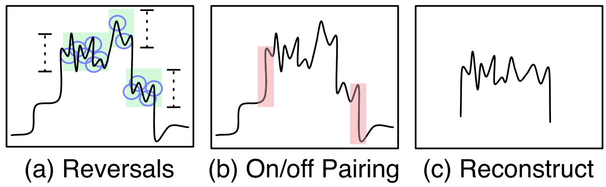


Fig. 4. Example of bounded oscillation detector.

oscillations due to some other load, but short enough to prevent filtering short-lived loads. For T, the goal is to select a value large enough to capture the expected oscillations without attributing the power usage of unrelated background loads to the feature.

Bounded Oscillation Detector. The bounded oscillation detector examines data for groups of deltas within a certain range that reverse themselves—change from positive to negative—frequently within a given minimum window size (e.g., 60s). In particular, the detector looks for a minimum proportion of reversals within the window (e.g., 50%), extending the window size until the minimum proportion is not met or several seconds have passed without a reversal (i.e., power use has stabilized, indicating the device is off). Within the resulting window, power deltas exceeding the bounded power range are filtered out, as these changes are presumably caused by other devices. As an example, we might parameterize a bounded oscillation feature for a particular microwave by dictating that at least 50% of reversals over its time window are within a 30W range. Thus, over an initial 15s window, there must be at least eight reversals to detect the feature, at which point the detector extends the window until (i) the minimum reversal percentage no longer holds, or (ii) a short period passes, e.g., 10s, without any reversals. This approach serves to extend the window as long as necessary without overly lengthening the window for long-running loads. To extract the feature, we pair active windows of reversals with matching on and off power steps of the approximate expected size for the feature (e.g., 1000W for a particular microwave), as illustrated in Figure 4.

Growth/Decay Detector. To detect a decay or growth feature, we identify positive steps near a feature's expected magnitude, representing possible "on" events. Since the expected decay or growth rate specifies a maximum per-second negative step (for a decay) or positive step (for a growth), the detector then scans forward, discarding all changes that exceed the expected maximum. The result of this process is a filtered time-series that, assuming the data actually represents a growth or decay, should approximately fit an exponential or logarithmic curve. The detector then performs the standard Levenberg-Marquardt Algorithm (LMA) (Levenberg 1944) to perform curve fitting. If the fit fails, or the derived decay/growth parameter is far from the expected value, then the detector moves on to the next possible "on" event. If the fit is successful, then the detector identifies the "off" event for the device, or, equivalently, the duration of the decay/growth. To do this, the detector gradually extends the fitted curve while looking for an "off" step of the expected magnitude, based on the magnitude of the "on" step plus the cumulative growth or decay of the fitted curve, which increases with the length of the curve. The detector then chooses the "off" step within a bounded interval most closely matching the expected value. In this case, bounding prevents a runaway search. After selecting the "off" step, the detector is able to trivially reconstruct the entire feature, based on the identified "on" and "off" events and the fitted curve between them. The process of fitting and filtering a decay feature is illustrated in Figure 5.

Spike Detector. Power spikes manifest themselves across multiple seconds, either due to variation in a load's exact activation time, i.e., when it activates within the 1s sampling interval, or due to a short ramp-up period, which is especially prevalent in high-wattage loads. Thus, the spike

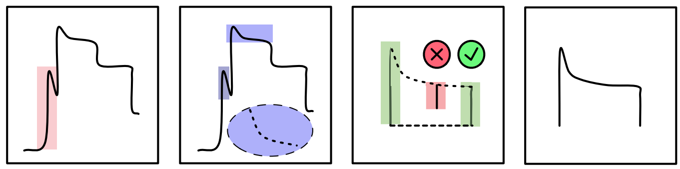


Fig. 5. Operation of the decay/growth detector.

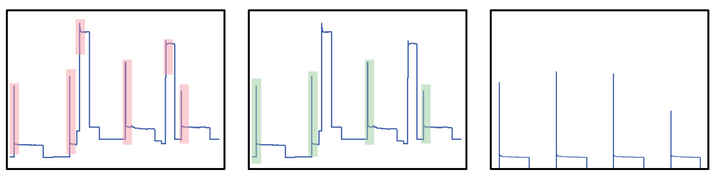


Fig. 6. Operation of the cycle detector.

detector collapses consecutive power steps in the same direction (up or down) into a single aggregate power step. Once collapsed, we identify spikes by a large positive step, followed *immediately* by a smaller, but still significant, negative step (currently, at least 30% of the positive step). Importantly, the spike detector separates the spike itself from its load's standard power step feature. For example, PowerPlay considers the series of changes in power [0, 0, +500, −400, 0, 0] both a +100W power step feature with a 500W power spike. Although the naïve step-only approach would output a +500W step and a −400W step, the spike detector recognizes that this time-series most likely represents a 100W inductive load, such as a 100W refrigerator. Since the magnitude of a spike is highly influenced by when a load turns on within the sampling interval, we represent the spike as a binary flag associated with the regular power step feature, e.g., the +100W step in our refrigerator example.

Step Detector. While power steps are the simplest feature, the trivial approach to identifying them (detecting second-to-second deltas of a certain magnitude) is often inaccurate due to the fact that loads turn on at different points within the sampling interval. Thus, similar to the spike detector above, we collapse multi-second power deltas in the same direction into a single aggregate delta before comparing the step's magnitude against a specific (i.e., parameterized) step feature. Deltas previously assigned to other features are excluded from consideration in this process.

Cycle Detector. Unlike the detectors above, the cycle detector operates on a series of labeled features (from the detectors above), and then (i) identifies each potential cyclic feature from the data and (ii) chooses a sequence of the features that most closely matches the cycle's expected period length. Figure 6 illustrates the process, where the cyclic feature is a spike. To determine the best sequence of cyclic features of a particular type, we chose an arbitrary cyclic feature of the type at time t_1, then the next one closest to time $t_2 = t_1 + period$, and so on for $t_k = t_{k-1} + period$. To account for features missed by its particular feature detector, we may also match t_k to $t_k = t_{k-1} + 2 * period$. The "error" of the resulting sequence of t_k is computed as $\sum_k |t_k - t_{k-1} - period|$, i.e., the amount the sequence differs from the expected period. This error is computed for all sequences starting from each possible t_1, and the detector selects as the predicted cycle the sequence with the lowest total error. After determining the sequence of cycle "on" events, we filter and reconstruct the feature's energy usage by filling in its corresponding load's model starting from each "on" event, as shown in the final step of Figure 6.

As an example, consider a refrigerator with a 30min period and a magnitude range between 80W and 120W for its spikes at startup. Now suppose the detector extracts all spikes (due to the refrigerator's compressor) from the data, and of those spikes, each one with a step between 80W and 120W occur at times [0m, 20m, 30m, 55m]. In this case, the detector labels events at 0m, 30m, and 55m as the "on" events of the refrigerator, while excluding the the event at 20m, as it is does not match the expected period. While this is a brute-force approach, the relatively small number of cyclic loads, ensures the process is not computationally expensive.

4.3 Load Tracking Complexity

Each feature detector operates over the most recent data window of size W. Within the window, most detectors make a single pass over the entire window to look for the relevant feature (e.g., a step feature looking for an expected step size, or a decay feature looking for descending steps matching the expected decay magnitude)—i.e., these detectors are expected to operate in $O(W)$ time. The cycle detector is an exception in that it operates on other features (rather than the data window itself), and considers possible cycles beginning with every labeled feature, resulting in $O(n^2)$ expected runtime for n features under consideration. However, in practice, the window size W will dominate the number of labeled features within the data, and therefore the impact of the cycle detector on overall performance is minimal.

Each load is modeled using a constant number of features, which varies from load to load but is a fixed parameter of the load's model. Thus, given a window size W and load count L, we can describe the overall complexity of the load tracking algorithm as roughly $O(W \times L)$. Importantly, this means that an increase in the number of tracked loads (or equivalently, the number of features) will not result in a loss of efficiency for tracking existing loads. Our empirical experiments in Section 6.1 support this result and demonstrate the scalability of the tracking algorithm.

4.4 Limitations

PowerPlay's load tracking algorithm is designed to mitigate many issues that hinder the perform of traditional NILM algorithms, such as difficulty when the number of loads in the building is scaled up. By focusing on identifiable features and loads, PowerPlay retains the ability to track devices even when disaggregating *every* load would be infeasible. However, we highlight a few notable limitations (which are largely experienced by NILM algorithms as well):

- Difficulty tracking loads with few features, or features that are not distinctive. A representative example of such a load is a typical 60W light, which might only have one feature (a 60W step) that cannot be isolated with high confidence from noisy smart meter data. PowerPlay's strength lies in tracking devices that have multiple distinctive features, such as dryers, washing machines, air conditioners, and so on. Importantly, however, almost all higher-consumption loads fall into this latter category, and thus PowerPlay is able to effectively track the most important devices in even a large home.
- Sensitivity to poorly tuned models. Since feature matching is dependent on tuned load models, a poorly tuned model that does not accurately describe load behavior may lead to PowerPlay failing to track the load. However, model tuning is an advance, one-time step, and may be assisted by automated techniques such as those mentioned in Section 3.3. Moreover, a poorly tuned model would not be expected to interfere with the tracking of other loads.

5 IMPLEMENTATION

We implement PowerPlay's feature detectors and tracking algorithm as a library in Perl. The input to the tracking algorithm is a continuous stream of new smart meter data, which PowerPlay buffers

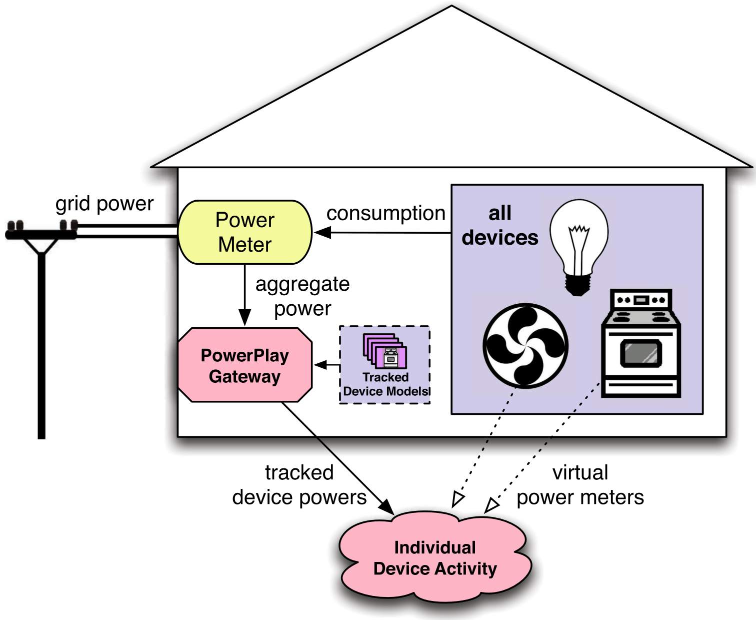


Fig. 7. When deployed in a home, PowerPlay simulates a virtual power meter attached to each tracked device.

while executing its main loop. Thus, if each iteration of the main loop takes ϵ time, then the next iteration will consider the set of data points that arrive and are buffered over the previous ϵ. The tracking algorithm also has, as input, the set of loads to detect and the corresponding set of identifiable features (parameterized separately for each load) extracted offline. The algorithm then outputs, for each load, its inferred per-second power usage over ϵ for each iteration of the main loop, resulting in a separate time-series of power data for each load in the tracking set.

Figure 7 depicts our system architecture deployed in a home environment. The sole hardware component of the system is the PowerPlay gateway, which consists of an unobtrusive, low-power machine that reads aggregate power readings and executes the load tracking algorithm. In conjunction with the device models stored on the gateway, the output of the gateway consists of power readings for virtualized power meters attached to each of the tracked devices. The home may also contain any number of untracked devices (e.g., the light in Figure 7), which are not included in PowerPlay's output.

We deploy PowerPlay in a real home following the setup shown in Figure 7. While our deployment home contains nearly 100 individual loads, we focus on five representative tracked devices: a freezer, a refrigerator, a dryer, a toaster, and a heat recovery ventilator (HRV). Untracked devices include other typical household appliances (e.g., coffeemaker, TV) as well as many small loads such as lights, chargers, and so on. Details on the home, its loads, and our instrumentation are provided in prior work (Barker et al. 2012a). Briefly, the home includes a Internet-enabled power meter installed in its electrical panel to monitor the second-to-second power usage of the home and each of its circuits. There are multitude of such meters now available, both commercially (TED 2018) and in recent research (Klingensmith et al. 2013), that record home-level and circuit-level data at 1Hz sampling resolution. We also record ground truth power data (or on-off events, which we correlate with the power meter data) for individual loads not connected to dedicated circuits using either Z-Wave Smart Energy Switches, Insteon iMeters, or Insteon SwitchLincs. In total, our deployment includes 92 sensors producing roughly four million data points per day. Such an extensive deployment is necessary to compare our results based the home's power data with ground truth power data from each individual load.

6 EVALUATION

We evaluate the accuracy and efficiency of PowerPlay's online load tracking algorithm in our home deployment. We first measure the computational overhead of load tracking to quantify PowerPlay's *efficiency*, which enables it to either track loads on low-power embedded platforms or scale to thousands of loads (across many homes) on server platforms. We then evaluate PowerPlay's *accuracy* by quantifying the tracking error factor δ for various loads. In both cases, since there is no prior work on load tracking, we compare PowerPlay to a complete disaggregation algorithm (based on FHMMs) modified for online operation. In this case, we use the same approach as Kolter and Johnson (2011) to evaluate their Reference Energy Disaggregation Dataset (REDD), which is similar to the technique by Kim et al. (2011).

Since PowerPlay relies on load models computed offline, we manually model the representative set of tracked loads in our deployment home that collectively cover each feature type. The set includes a toaster oven (steps, decays), a refrigerator and freezer (steps, spikes, cycles), a heat recovery ventilator or HRV (stable oscillations), and a dryer (bounded oscillations, cycles, steps, decays). PowerPlay then tracks these loads in real time using per-second power data for the entire home (operating nearly 100 distinct loads).

6.1 Tracking Efficiency

PowerPlay operates online by continuously receiving power readings each second and executing its main loop to perform feature detection on the most recent window of data. Since PowerPlay stores recent data in memory, I/O overhead is negligible and efficiency is solely a result of the computational overhead of the feature detectors.

The tracking efficiency of PowerPlay is determined by the computation overhead of the feature detectors in processing the most recent window of data. This overhead determines both (a) the tracking delay (ϵ from Section 2) of the system, where $\epsilon = 1$s is perfect (1 Hz) real-time tracking, and (b) the number of loads (and homes) that a platform can effectively track. Note that, since PowerPlay's main loop detects features across all loads, increasing the number of loads, ignoring parallelism, increases tracking delay across all loads. Thus, we measure the aggregate number of loads PowerPlay can track, while maintaining a low tracking delay.

We perform the following experiments on a single-core server running Ubuntu Linux (kernel version 3.2.0) with a 2.4GHz Xeon processor. We vary a common window size across all features, then observe the tracking delay (ϵ) achieved by PowerPlay. As seen in Figure 8, the tracking delay is modest across every load. For example, with an excessively long tracking window of 24h, PowerPlay completes in less than 3s per load. As expected, loads with more features (e.g., the dryer) result in a longer tracking delay. We also observe that the tracking delay effectively varies linearly with the tracking window size. As a result, shortening the window size linearly decreases the tracking delay. In practice, most features require significantly less than a 24h window to reliably detect.

Result: *PowerPlay is able to track multiple loads in real-time, or near real-time, on commodity servers.*

We also compare PowerPlay's scalability with a complete disaggregation algorithm based on FHMMs. Here, we assume a server must track loads across *many* homes, not just a single home. We quantify both PowerPlay's performance (with 24 and 4h tracking windows) and an FHMM approach following Kolter and Johnson (2011). Since disaggregation using the FHMM is exponential in the number of building power states (which is based on the number of loads and the

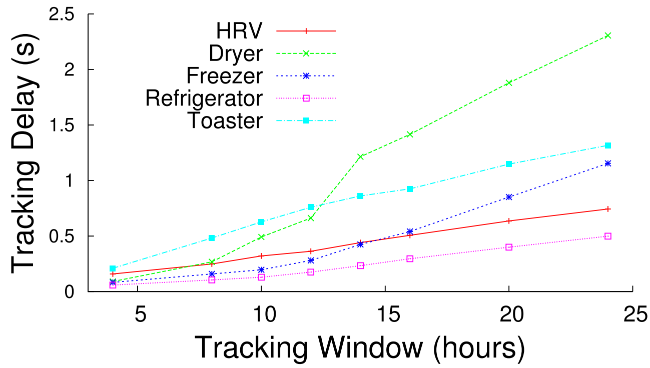


Fig. 8. PowerPlay's tracking algorithm is efficient, with tracking delays of at most a few seconds.

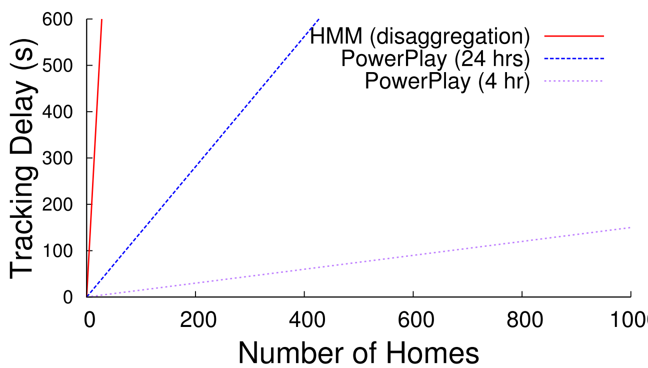


Fig. 9. PowerPlay efficiency enables it to scale to many homes, while maintaining a low tracking delay.

number of power states per load), the FHMM approach models each load as having only four power states and disaggregates at the level of circuits rather than individual loads. Since our home has only 25 circuits, but operates 92 individual loads, our FHMM performance numbers for a complete disaggregation are conservative.

Since the FHMM approach requires a sizable amount of data, e.g., 24h, for complete disaggregation, it cannot operate on a small window size. As a result, our modified FHMM executes a similar main loop as PowerPlay, but always disaggregates the most recent 24h of data. Our example online FHMM incurs an 86s tracking delay to track the loads in Figure 8 for a single home. In contrast, PowerPlay imposes only a 5.6 and 0.6s delay for the 24 and 4h tracking windows, respectively, for the same home. We also plot the scalability of each approach on a quad-core server running at 2.4GHz in Figure 9, where the number of independent homes we track is on the x-axis (each home is an independent tracking process that runs in parallel). We see that the FHMM approach does not operate in real-time: even tracking loads in a mere 10 homes imposes a tracking delay greater than 10min. PowerPlay performs much better with the same 24h time window, supporting roughly 100 homes with a tracking delay of 2.5min. The more realistic scenario, with a smaller 4h time window, scales even better: PowerPlay tracks each of the five loads in 1,000 homes (or 5,000 total loads) with a tracking delay of only 2.5min.

Result: *PowerPlay scales to support online tracking of many homes; in this case, tracking 5,000 loads across 1,000 homes with a tracking delay of only 2.5min.*

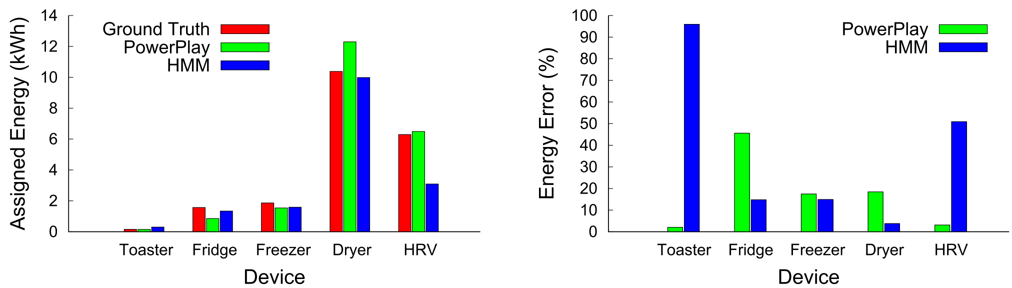


Fig. 10. Both PowerPlay and the FHMM approach accurately assign the energy used by most loads. Assigned energy shown as absolute values (left) and as an error percentage relative to ground truth (right).

Finally, we also consider PowerPlay's performance on embedded platforms that track a set of loads *within* a home, such as in an embedded energy monitoring and analytics platform (Klingensmith et al. 2013). To evaluate this case, we deploy PowerPlay on a low-power DreamPlug computer with a 1.2GHz ARM processor and 512MB memory, costing less than $100. Tracking the same five loads as above in our deployment home with a 4h tracking window, PowerPlay achieves a tracking delay of just 18s, with individual load tracking times ranging from less than a second for the refrigerator to 4s for the toaster.

Result: *PowerPlay is capable of online tracking of loads within a home on low-power embedded platforms.*

6.2 Tracking Accuracy

In addition to efficiency, load tracking must also be *accurate* to be useful. As before, we compare PowerPlay's accuracy in tracking multiple loads' real-time power usage with the FHMM approach, which performs a complete disaggregation. We take the conservative approach of training the FHMM on per-load data from the home that we disaggregate, although doing so is often not possible in practice, since disaggregation is typically only useful in homes where such training data is not available. As disaggregation often focuses on inferring a breakdown of per-load energy usage for a building over a long time period, e.g., an entire day or week. Figure 10 shows the actual energy usage over an entire day for five loads, as well as the inferred energy usage from both PowerPlay and the FHMM disaggregation. As seen in the left graph of Figure 10, most energy usage is accurately assigned over long periods (especially for larger devices), although the FHMM approach is less accurate for the heat recovery ventilator due to its stable power oscillations. Viewing the energy assignments in terms of error percentages from ground truth (the right graph of Figure 10) demonstrates larger errors, but these are mostly due to missed activity in smaller devices—e.g., the FHMM approach fails to recognize the toaster activity entirely. Our results are consistent with prior work on the FHMM approach, which performs as well, or better, than other prior approaches to disaggregation (Kim et al. 2011; Kolter and Johnson 2011).

Result: *The accuracy of PowerPlay's inferred energy usage for loads in the tracking set over long periods is comparable to that of complete disaggregation via a FHMM.*

Unfortunately, inferring energy usage over a long period is not appropriate for online operation, and does not take into account *when* a load uses energy. We use the tracking error factor δ from Section 2 to quantify per-load accuracy over time. In Figure 11, we first quantify accuracy as we scale up the number of non-tracked loads in a home, since more loads result in more (and less visible) features. In this case, the x-axis is a rough measure of the data's complexity, i.e., the number of power deltas >15W. By gradually adding circuits from our home deployment to the smart meter

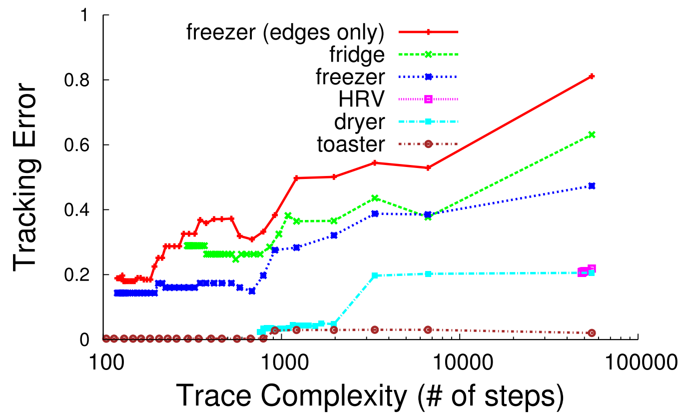


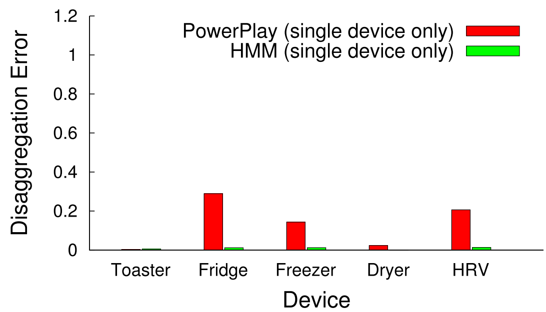
Fig. 11. PowerPlay error factors when scaling up to highly noisy and complex smart meter data.

data. For example, the far left side of the graph includes only one circuit (the one including the corresponding tracked load) and each data point to the right represents a dataset with one more circuit added to it. For each new circuit, we track the loads and compute the error factor per load on the new dataset. Figure 11 plots the results for our representative loads. Note that the x-axis is on a log scale, since a small number of loads contribute the majority of the power deltas. For comparison, we also include a second model of the freezer that only uses step features (i.e., simply edge detection), to illustrate the effect of removing all but the most trivial features present in PowerPlay.

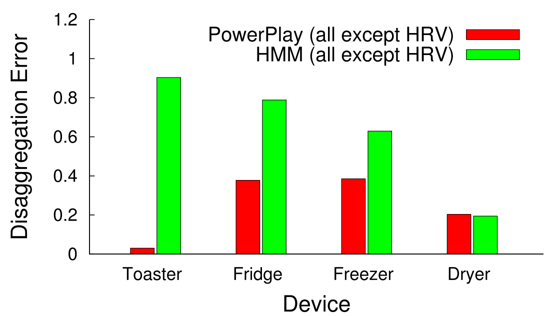
As expected, the error factors increase as we add more circuits and more complexity to a home's data. We also see that the freezer's accuracy is nearly a factor of two higher when including its full set of identifiable features, compared to restricting it to only step features. However, beyond a complexity of 1,000 power deltas, the error factors stay roughly constant (with the exception of the refrigerator), even when the complexity goes to 50,000 power deltas. The refrigerator's accuracy decreases significantly when adding a complex load, e.g., in this case a heat recover ventilator that exhibits stable power oscillations. The reason is that its cycle detector is unable to select spikes that correspond to the refrigerator, due to the heat recovery ventilator generating a large number of similarly sized spikes at various intervals.

Figure 12 then examines three specific points from the previous graph and compares them with the FHMM approach. In Figure 12(a), we use both PowerPlay and the FHMM approach to track a load from data that *only* includes that load. As shown, the FHMM approach is nearly perfect, since its model is trained on the actual data we disaggregate in this case. By comparison, PowerPlay shows some error due to the fact that our models, while accurate, only include offline features and not attributes based on when and how long the load operates. However, Figures 12(b) and 12(c) shows the error factor for the same loads if we include every circuit both with Figure 12(b) and without Figure 12(c) the complex heat recovery ventilator. Prior work on load disaggregation has generally evaluated their algorithms at small scales, e.g., 5–10 individual loads, that are not representative of the multitude of small and complex loads present in a modern home. Our results demonstrate that PowerPlay performs well even as the number and complexity of loads scales up.

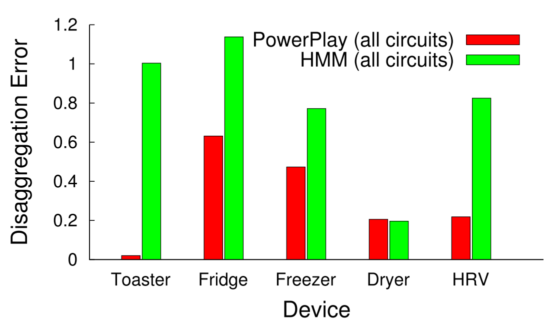
The result shows that PowerPlay is significantly more accurate than the FHMM approach for each load, with the exception of the clothes dryer. While PowerPlay is not more accurate than the FHMM approach at small scales, as in Figure 12(a), with less "noisy" data, it is significantly more accurate as complexity increases. For example, PowerPlay is nearly perfect at detecting the



(a) Self Input



(b) Aggregate Data minus HRV

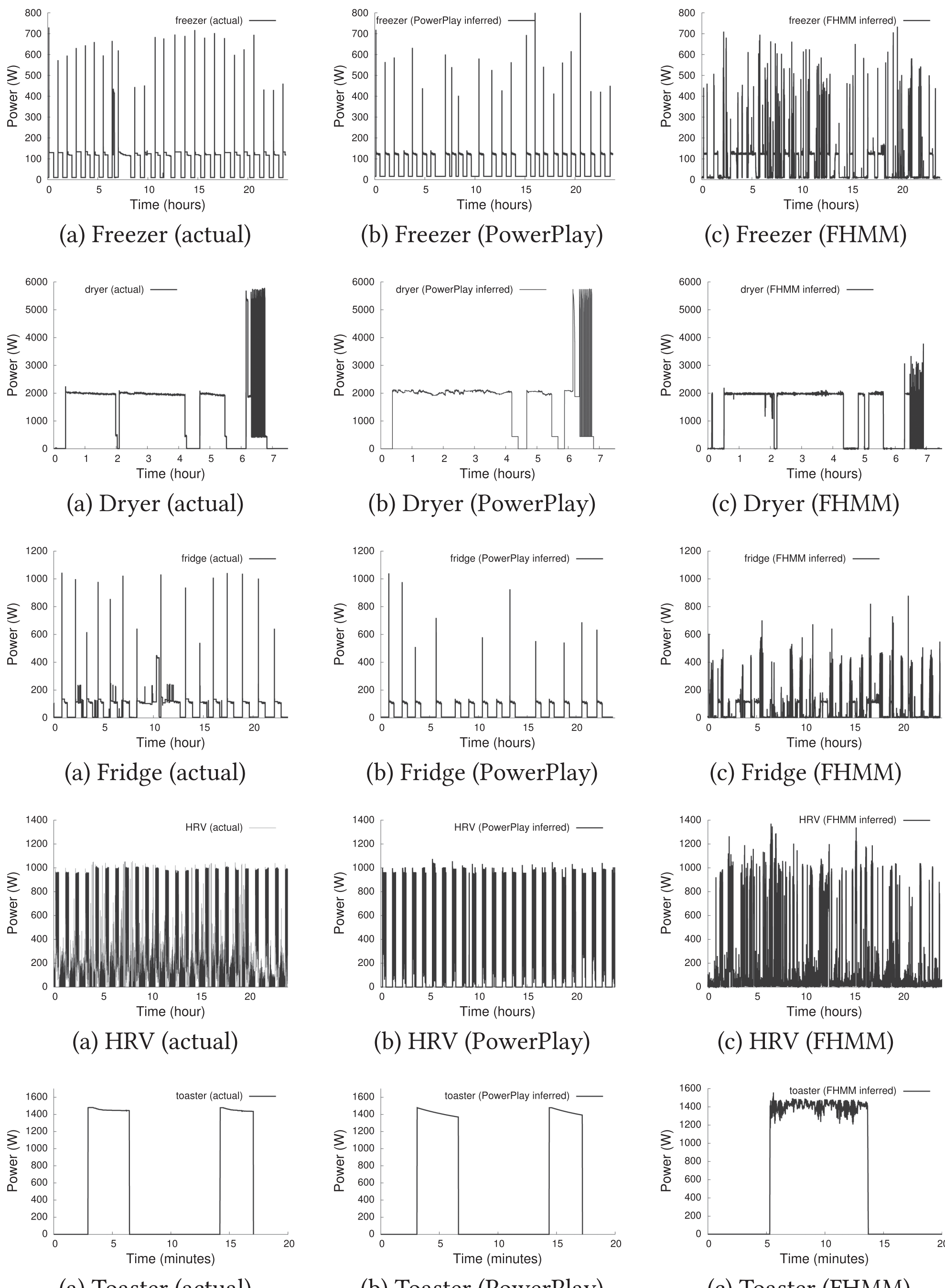


(c) Aggregate Data

Fig. 12. PowerPlay is more robust to noisy smart meter data than the FHMM-based approach.

second-to-second power usage of the toaster even within a highly complex trace, largely due to PowerPlay's highly accurate model of the toaster (as shown in Figure 12(a)). In general, the improvement in error factor for each load over the FHMM approach is greater than 2× (and over 100X in the case of the toaster). Both PowerPlay and the FHMM approach perform well on the clothes dryer, because it is large compared to the other loads (~6kW peak power versus ~1kW peak power), such that the added complexity does not affect detection.

The time-series power data corresponding to our representative loads is shown in Figure 13. For each of these devices, the ground-truth time-series data is shown, as well as the inferred time-series produced from (1) PowerPlay and (2) the FHMM-based approach. Visual inspection confirms that, in most cases, PowerPlay is more accurately able to track the true usage of the load. The difference



(a) Freezer (actual) (b) Freezer (PowerPlay) (c) Freezer (FHMM)

(a) Dryer (actual) (b) Dryer (PowerPlay) (c) Dryer (FHMM)

(a) Fridge (actual) (b) Fridge (PowerPlay) (c) Fridge (FHMM)

(a) HRV (actual) (b) HRV (PowerPlay) (c) HRV (FHMM)

(a) Toaster (actual) (b) Toaster (PowerPlay) (c) Toaster (FHMM)

Fig. 13. Inferred time-series generated from tracking the true power usage (left) of various loads using either PowerPlay (center) or the Factorial Hidden Markov Model approach (right).

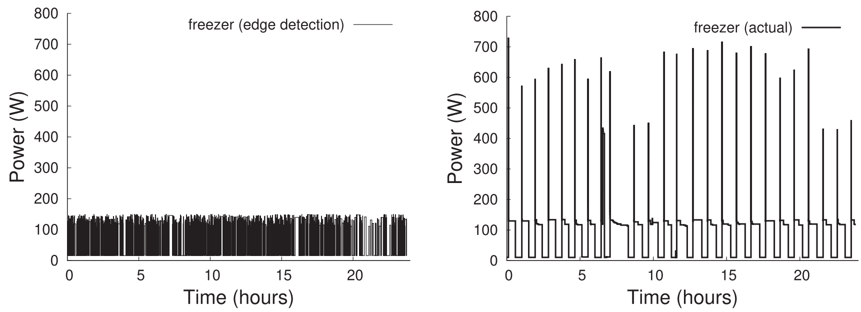


Fig. 14. Load tracking of a freezer using simple edge detection (left) is insufficient to accurately capture the true behavior of the freezer (right) in noisy aggregate data.

between PowerPlay and the FHMM approach is most notable in the case of the toaster, for which the FHMM is effectively unable to detect its actual active interval (versus PowerPlay, which tracks the toaster with near-perfect accuracy).

Finally, to illustrate the importance the importance of considering the variety of features used in PowerPlay, the time-series produced from simple edge detection on the freezer is shown in Figure 14, alongside the actual usage of the freezer. This edge detection time-series corresponds to the edges-only case previously depicted in Figure 11, and demonstrates that simple steps (the only feature considered by an edge detector) are not sufficient to track even a modestly complex device.

Result: *PowerPlay maintains a low per-load tracking error factor as the number of loads, and their complexity, increases in a home. For the loads in our tracking set, the error factor is generally a factor of two less than a state-of-the-art disaggregation algorithm based on FHMMs.*

6.3 Load Ordering

As discussed in Section 4, when tracking multiple loads, PowerPlay intelligently chooses their tracking order to maximize the accuracy of feature assignments to loads. A poor ordering of loads can result in reduced tracking accuracy for all devices, while a good ordering of loads can result in increased tracking accuracy for all loads. This effect will be most pronounced for devices exhibiting similar features that may be more difficult to correctly assign.

In the case of our representative loads, the two devices exhibiting the most similar features are the refrigerator and the freezer. Both are compressor-based devices that are active continuously throughout the day, and their models are thus compromised of similar features (e.g., spikes on compressor activation and a cyclic activity pattern). As can be seen in Figure 13, the primary difference between these two devices that is captured by their models is that the freezer has a more rapid duty cycle (i.e., is active more frequently). As a result, the freezer is expected to use more energy overall, and therefore is given priority by PowerPlay when assigning features to loads.

To illustrate the significance of this choice, we conduct an experiment in which we override PowerPlay's chosen tracking order such that features are assigned to the refrigerator *before* the freezer (representing an arbitrary ordering), and then track both loads again. Note that the tracking order is the only aspect of the system that we modify—the models and features themselves are left unchanged.

The resulting disaggregation errors for the refrigerator and freezer are shown in Figure 15, for both cases of excluding the HRV load (a) and including it (b). We see that the disaggregation error of *both* devices is improved by ordering loads by load size (which prioritizes the freezer over the refrigerator). This result is due to the freezer having a more rapid (i.e., distinctive) cyclic activity

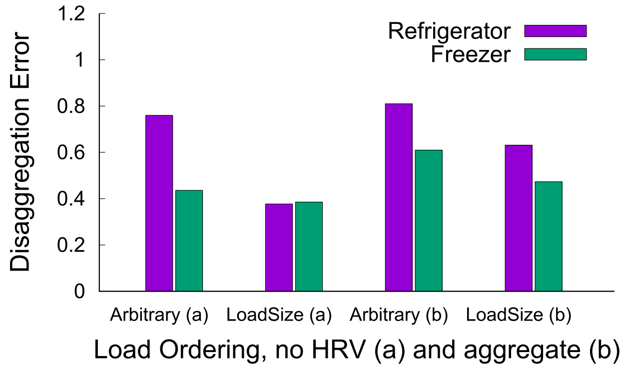


Fig. 15. A load tracking order based on load sizes leads to improved tracking accuracy for all loads.

pattern, which is easier for PowerPlay to extract from the aggregate power data. Once the freezer features are extracted from the aggregate data, the refrigerator is easier to identify. The inverse is also true—if the refrigerator is tracked first, then some freezer features are incorrectly assigned to the refrigerator load, resulting in lower accuracy both for the refrigerator and subsequently for the freezer. This effect is most pronounced for the aggregate-data case (b), since the addition of the HRV obscures some features that are otherwise easier to detect.

Note that a useful consequence of this behavior is that tracking additional devices using PowerPlay can improve the tracking accuracy of *existing* devices by removing distinctive features before they are erroneously assigned to other loads. In the particular instance of Figure 15, greater refrigerator accuracy is only achieved by first identifying and extracting the freezer features (tracking the refrigerator in isolation results in the lower accuracy of the "arbitrary" case).

Result: *PowerPlay achieves greater tracking accuracy across loads by tracking more identifiable loads first, and thus can increase overall accuracy as the total number of tracked loads is increased.*

6.4 Case Study: Demand Response Capacity

Last, we consider a real application of scalable, online load tracking, where a utility wishes to monitor aggregate demand response capacity across a neighborhood in real time. In this case, we assume the utility is only able to reduce demand by deferring customers' A/Cs, such that the demand response capacity at any point in time is the amount of power consumed by each active A/C. Thus, to estimate demand response capacity over time, the utility must know: (i) what percentage of its customers have active A/Cs, and (ii) how much power they are consuming.

We assume a utility server collects smart meter data from each home and runs PowerPlay to track the power usage of customer A/Cs. For our case study, we consider a 10-day period of our deployment home's smart meter data, including a central A/C. To simulate many homes across a neighborhood, we generate 100 virtual homes by randomly time-shifting the A/C's power usage within the smart meter data, which results in 100 distinct homes with different time-varying A/C power usage. PowerPlay then uses our model of the A/C (which includes a mix of the cycle, decay, and step features) to track each home's A/C power usage. Finally, we use PowerPlay's output to query the set of active A/Cs across homes over time. For example, at a random point in time, 34 of the 100 homes had an active A/C, with PowerPlay correctly identifying the status of each A/C with 96% accuracy. In particular, PowerPlay detected 30 out of 34 active A/Cs and all inactive A/Cs, demonstrating 88% recall and 100% precision. Of the 30 detected A/Cs, PowerPlay's second-to-second inferred power readings differed from the A/Cs actual power usage by an average of 104W (out of its 3kW peak and 2.6kW average power). PowerPlay estimated the total A/C power usage across the neighborhood, i.e., its demand response capacity, to be 78.1kW, which differs from the actual capacity of 87.9kW by 12%, with the difference primarily due to the four undetected active A/Cs. Excluding the undetected A/Cs, the total A/C power inferred by PowerPlay differed from the actual power by less than 1%.

Result: *PowerPlay enables new applications for online analytics on smart meter data—in this case accurate, online estimation of the grid's demand response capacity,*

7 CONCLUSIONS

This article presents PowerPlay, a system for online load tracking that emphasizes both efficiency and accuracy. In essence, "tracking" a particular load creates a *virtual power meter* for it, which mimics having a network-connected energy meter attached to it. PowerPlay takes a model-driven approach to online load tracking, which focuses on detecting identifiable load features in smart meter data. By focusing on a small set of identifiable features common across loads, PowerPlay employs models of specific devices to efficiently detect them even in the presence of many other (either tracked or untracked) devices. Using a higher-level feature abstraction allows PowerPlay to remain computationally tractable even on low-power machines and results in accurate load tracking in close to real-time. Our experiments on a set of representative loads in a real-world home demonstrate that PowerPlay improves per-load tracking accuracy by a factor of two compared to a FHMM-based disaggregation algorithm. These results point to the potential of using a system like PowerPlay to replace physical plug-level energy meters in a sensing deployment with software-based "virtual" energy meters.

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