Non-Intrusive Occupancy Monitoring using Smart Meters

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ABSTRACT

Detailed information about a home's occupancy is necessary to implement many advanced energy-efficiency optimizations. However, monitoring occupancy directly is intrusive, typically requiring the deployment of multiple environmental sensors, e.g., motion, acoustic, CO_2, etc. In this paper, we explore the potential for Non-Intrusive Occupancy Monitoring (NIOM) by using electricity data from smart meters to infer occupancy. We first observe that a home's pattern of electricity usage generally changes when occupants are present due to their interact with electrical loads. We empirically evaluate these interactions by monitoring ground truth occupancy in two homes, then correlating it with changes in statistical metrics of smart meter data, such as power's mean and variance, over short intervals. In particular, we use each metric's maximum value at night as a proxy for its maximum value in an unoccupied home, and then signal occupancy whenever the daytime value exceeds it. Our results highlight NIOM's potential and its challenges.

Categories and Subject Descriptors

J.7 [**Computer Applications**]: Computers in Other Systems—*Command and control*

General Terms

Design, Measurement, Management

Keywords

Energy, Electricity, Grid

1. INTRODUCTION

Based on recent estimates, commercial and residential buildings continue to account for 75% of the electricity usage in the United States [23], with residential buildings alone accounting for nearly 45%.[1] As a result, improving building energy-efficiency is becoming an increasingly important research area. One of the simplest ways to reduce wasted energy and improve energy-efficiency is to automatically regulate a building's electricity usage in real time based on its occupancy [2, 15, 19, 25]. Researchers have proposed many applications that use occupancy information to drive a variety of novel building management optimizations. For example, a building management system may save energy in unoccupied buildings by automatically i) disconnecting inactive electrical devices (or *loads*), such as televisions, gaming consoles, and cable boxes, to lower vampire power usage [11], ii) adjusting environmental setpoints and guardbands for air conditioners, heaters, and humidifiers to operate outside occupants' normal comfort level, thereby shortening the length of their duty cycle [2, 14, 24], iii) turning off or dimming lights aggressively to reduce energy waste [9], and iv) placing idle desktop computers and other IT equipment into low-power standby states, e.g., Suspend-to-RAM [3].

A key prerequisite for implementing these occupancy-driven applications is an accurate, inexpensive, and non-intrusive method for monitoring occupancy. While determining occupancy is possible using GPS information from smartphones, the approach requires active participation by all occupants: they must carry their phone at all times and integrate it with each building's occupancy-detection system. The approach is clearly not feasible if occupants do not own smartphones, as with many young and low-income users, or are unwilling to link their phones with building management systems due to privacy concerns. Thus, many systems monitor occupancy by strategically deploying one or more environmental sensors, including motion [2, 24, 26], door [1], acoustic [8, 17], camera [14, 15, 20], contact [26, 29], and CO2 [10, 31] sensors.

As this prior research shows, directly sensing occupancy using environmental sensors poses many challenges. For example, users must carefully place and calibrate motion sensors to prevent spurious detection from pets or events outside windows [24]. While CO_2 sensors are less sensitive to placement position and external events, users must precisely calibrate them based on a building's ventilation system. Furthermore, these sensors incur an inherent detection delay, as additional occupants cause CO_2 levels to increase slowly [14, 31]. Each of the other environmental sensing options above introduce their own similar types of domain-specific challenges. In general, such *direct* occupancy monitoring also requires purchasing and retrofitting buildings with many external sensors. As a result, these systems must address problems common to any large distributed system, including detecting, diagnosing, and correcting sensor failures and ensuring each sensor has a reliable network connection. Finally, since retrofitted sensors are typically not connected to the power grid, they require periodic battery replacement or recharging, which imposes a significant maintenance burden in distributed deployments that employ many sensors [18].

The limitations above have led researchers to study *indirectly*

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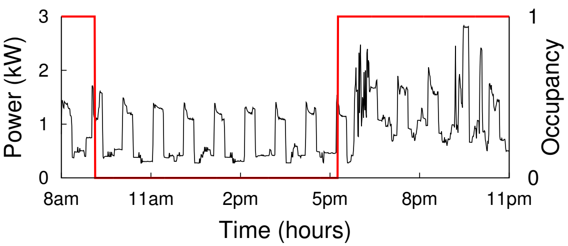
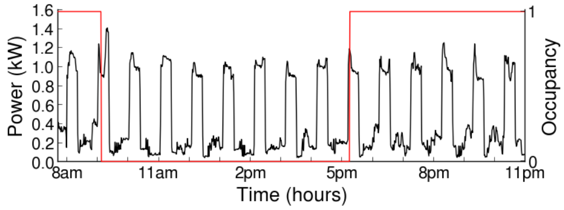
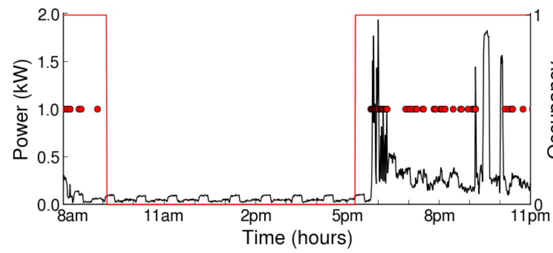


3
2
1
0
Power (kW)
1
0
Occupancy
8am
11am
2pm
5pm
8pm
11pm
Time (hours)



(a) Background Loads



(b) Interactive Loads with Event Labels

Figure 2: Power usage of background (a) and interactive (b) loads from Home-A for the same day as in Figure 1(a). We include event labels in (b) that indicate occupants' physical interactions with electrical loads.

which people manually control (e.g., by turning them on and off). We supplement our raw electricity data by using Insteon-enabled i) wall switches, ii) door sensors, and iii) thermostats. These sensors signal a computer whenever someone physically presses a wall switch, opens a door that triggers an electrical event, such as a freezer door that turns on an interior light, or adjusts a thermostat.

To asses NIOM's potential, we post-process this raw electricity and switch data to automatically generate an event trace of occupants' physical interactions with electrical loads. Examples of these events include occupants using a remote control to turn on a television, pressing a button to cook food in the microwave, or toggling a wall switch. Ultimately, the correlation between a home's pattern of electricity usage and occupancy derives from these physical interactions with electrical loads. Our goal is to learn the types of physical interactions occupants have with electrical loads, as well as their rate and frequency, to quantify the potential to monitor occupancy via smart meter data. For instance, if occupants are home and not interacting with any electrical loads, such as when reading a book, the correlation between electricity usage and occupancy may be weak. To extract events from our electricity data, we focus on circuits that power interactive loads and ignore those dedicated to background loads. Since each of these circuits only supports a small number of loads, we manually profile every load per circuit and derive power event detection rules tailored for each of a circuit's loads. In general, we find that a change in power greater than 30W indicates occupant interaction. We then augment these events with any events generated directly from the Insteon wall switch, door, and thermostat sensors to yield a final event trace.

Ground Truth Occupancy. In addition to automatically tracking occupants' interaction with electrical loads, we monitor ground truth occupancy via occupants' smartphones. This type of monitoring is feasible because the two primary occupants in each home reliably carry their phones at all times, and the occupants without smartphones are never home without the primary occupants also being home. We gather occupancy data by installing the Google Latitude mobile app on each phone. Latitude enables authenticated users to query a URL to retrieve a phone's current GPS coordinates (latitude and longitude), which we collect from a central server every 30 seconds and translate into a binary occupancy trace by considering locations within 500 meters of the home as 'occupied.' *Note that we only use the GPS data for deriving ground truth occupancy, and not when detecting occupancy from smart meter data.*

2.2 Analysis and Observations

Figure 1 (from §1) illustrates how a home's pattern of electricity usage changes whenever occupants are present. In both homes, the load profile reveals a number of attributes in the data that appear to correlate with occupancy, including a higher mean power usage, a higher minimum power usage, i.e., a raised power floor, a higher maximum power usage, and more bursty power usage. On this day, Home-B exhibits a drastic change in the pattern of power usage when occupants are present. Interestingly, for Home-A, which exhibits the weaker correlation between electricity usage and occupancy, there appear to be periods when occupants are present, but the load profile is similar to the profile when occupants are not present. For example, in Figure 1(a), the home is occupied between 8am and 9am, but the load profile at this time appears to be similar to the profile from 10am to 11am, when the home is unoccupied. As we show in §4, since occupants may not continuously interact with the electrical loads, any system that uses smart meter data to monitor occupancy has the potential to generate false negatives, i.e., by incorrectly determining that no one is home.

We use our event traces to examine the extent of occupancy's correlation with electricity usage, including the frequency of occupants' physical interactions with loads and its impact on home electricity usage. Here, we focus on Home-A, since it exhibits the weaker correlation. For Home-A, in Figure 2, we separate the electricity usage of the interactive loads and background loads for the same day as in Figure 1(a). Figure 2(a) shows the power usage of just the background loads, while Figure 2(b) shows the power usage of just the interactive loads, as well as our event labels that signify occupants' physical interactions. Since users do not interact with background loads, Figure 2(a) has no event labels.

Figure 2 illustrate multiple points about the potential for NIOM. First, note that the background loads in Figure 2(a) have a significant and highly variable load profile between 40W and 1.5kW. In total, on this day, the background loads contribute the majority (56%) of the home's electricity usage, while exhibiting a range in power usage of 1366W, e.g., a peak usage of 1413W and a minimum usage of 47W. As a result, we cannot simply assume that an unoccupied home has a low or constant power usage. However, the background loads do exhibit a consistent pattern of power usage regardless of occupancy. Second, Figure 2(b) indicates that occupants have near-continuous interaction with electrical loads while home, physically interacting with them at an average rate of 11.58 interactions per hour. In total, these interactive loads contribute 44% of the home's electricity usage, while exhibiting an even wider range of power usage than the background loads, e.g., with a peak usage of 1937W and a minimum usage of 21W. In addition, the longest observed "dead period"—when occupants are home but do not interact with electrical loads—is only 58 minutes (between 9pm and 10pm when they are watching TV). Unlike the background loads, the interactive loads only consume significant power when occupants are home. Since aggregate power is the combination of the interactive and background loads, we expect any change in the pattern of power usage to also indicate a change in occupancy.

While we only use one day's worth of data to illustrate the points above, Table 1 shows the number of events over 71 days starting

Category	*Count*	*Percentage*
Lights	3048	39.25
Kitchen	2882	37.12
IT	1374	17.69
Large Appliances	263	3.39
Miscellaneous	198	2.55
Total	**7765**	**100**

Table 1: Number of physical interactions with different types of electrical loads over a 71 day period.

in mid-April caused by different types of loads, including lighting, IT devices, e.g., computer, television, and gaming console), kitchen appliances, (e.g., toaster, microwave, and coffee maker), large appliances, (e.g., washing machine and dryer), and miscellaneous (e.g., vacuums and fans). In total, the occupants interacted with loads 7765 over this period at a rate of 109 events per day, and 10.08 events per hour when occupied. Not surprisingly, a large majority of events are due to lighting. As we discuss in §4, lighting is a particularly challenging load for NILM algorithms to detect.

While the observations above use one-minute average power data, they also hold for coarser data, although the correlations become more subtle as the data becomes coarser. For example, an occupied home may have 2X higher average power than an unoccupied home using average power data over five minutes, but only 1.1X higher average power using average power data over one hour. In general, as data becomes coarser, it averages out the "peaky" features of interactive loads in power data that imply occupancy.

3. NIOM ALGORITHM

Unlike the analysis in the previous section, where we use external sensors to establish ground truth and study the potential for NIOM, our NIOM algorithm uses only a home's smart meter data to infer occupancy. Below, we describe three statistical metrics we monitor in smart meter data to detect occupancy and our intuition for using them. We then propose a simple threshold-based NIOM algorithm that detects changes in each metric and then clusters them to generate a continuous trace of binary occupancy.

Average Power. As Figure 1 indicates, occupancy generally implies a higher average power usage. Intuitively, the correlation between high average power and occupancy is due to occupants turning interactive loads on, which increases the home's aggregate power. To detect changes in average power $N_{average}$, at time t, we simply average the previous consecutive data points over a window τ in the power time-series, and then signal potential occupancy at time t if the result exceeds a predefined threshold $P_{average}$. Both τ and $P_{average}$ must be jointly set. As τ becomes smaller, to prevent false positives, $P_{average}$ should increase such that it is always greater than the maximum power over τ data points when the home is unoccupied. Similarly, as τ becomes larger, $P_{average}$ should decrease to prevent false negatives.

Standard Deviation. Figure 1 also suggests that an occupied home has more variable power usage than an unoccupied one. Intuitively, the correlation between more variable power usage and occupancy is due to occupants toggling interactive loads on and off. To detect changes in standard deviation N_{stddev}, at time t, we also compute the standard deviation of the previous τ consecutive data points in the power time-series, and then signal potential occupancy at time t if the result exceeds a predefined threshold P_{stddev}. As above, both τ and P_{stddev} must be jointly set, since a larger τ determines P_{stddev}'s magnitude. Detecting changes in standard deviation in addition to average power is useful, since occupants may toggle loads on and off frequently, such that average power does not rise above the $P_{average}$ threshold, but the standard deviation does rise above the P_{stddev} threshold.

Power Range. Finally, Figure 1 suggests that occupancy implies a larger absolute range in power. We define the power range N_{range} as the difference between the absolute minimum and absolute maximum power over the previous τ consecutive data points. Intuitively, the correlation between a large power range and occupancy stems from our observation that occupants sometimes have few interactions with electrical loads. While minimal interactions with electrical loads may not increase the average power or standard deviation, they are likely to increase the power's absolute range, since any interaction will briefly raise the maximum power. As above, we signal potential occupancy if the power range over the last τ data points is above a threshold P_{range}.

Note that we only intend our threshold-based approach above to detect daytime occupancy, e.g., 6am to 11pm. Nighttime occupancy correlates less with electricity usage, since occupants are generally sleeping. As a result, nighttime occupancy is much harder to determine. One simple approach, we which use in this work, is to infer nighttime occupancy from daytime occupancy: if anyone is at home at during the previous evening then we assume the home is occupied throughout the night. This works well because people are usually home at night with high probability, unless they are out of town. However, the approach may not be appropriate in some cases, e.g., if all occupants work night shifts.

Changes in each of the metrics above result in a series of discrete time-stamped occupancy events. To generate a continuous occupancy trace, we cluster these events, such that if any two events are within $\tau_{cluster}$ time window, we label the intervening period as being occupied. As $\tau_{cluster}$ increases, the greater the likelihood of false positives, e.g., detecting someone is home when no one is home, while, as $\tau_{cluster}$ decreases, the greater the likelihood of false negatives, e.g., detecting no one is home when someone is home. After clustering, occupancy detection using each metric produces a continuous time-series of the home's binary occupancy. We then *combine* these time-series to generate a final solution by detecting occupancy if *any* of the metrics signal occupancy.

Of course, for each metric, accuracy is sensitive to τ and the metric's P threshold. If the power usage of the background loads is consistent, a static threshold works well. However, we investigated setting static thresholds based on training data and found that these thresholds did not work well over long periods, since the set of active background loads and their operation changed over time, e.g., as occupants turn them on and off and environmental conditions change. As a result, we set each metric's threshold dynamically based on its maximum value the previous night. Our premise is that a home's nighttime power usage and unoccupied power usage are dictated solely by its background loads. Thus, nighttime usage should provide a rough approximation of background load usage, and if any metric's value exceeds its maximum value using background loads, then the home is likely occupied.

One benefit of our approach is that it requires no training data that specifies the home's ground truth occupancy and electricity usage over an extended period. Training data is difficult to gather, since it requires deploying sensors to collect data during a training phase, which is exactly the problem NIOM is attempting to avoid. However, one drawback with our approach is that the nighttime power usage of background loads may not be an accurate indicator of background load power usage during the day. This is especially true for loads with daily cycles, such as air conditioners, which may use significantly more energy during the day. That said, our results indicate that nighttime usage performs well in our two test homes.

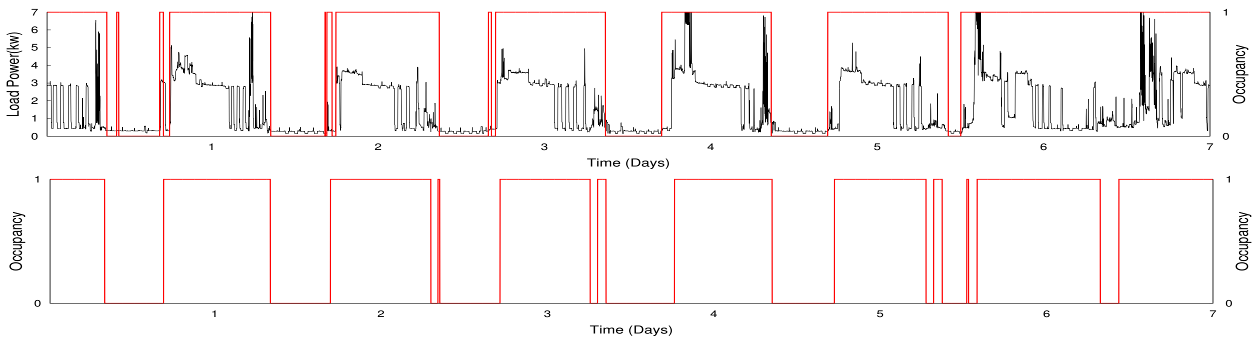


Figure 3: Home-B's load profile and ground truth occupancy over a summer week (top) and its detected occupancy using our NIOM algorithm (bottom), which combines results from all three metrics.

	True Positives	True Negatives	False Positives	False Negatives
Average Power	53.50%	24.84%	0.54%	21.12%
Standard Deviation	49.69%	24.69%	0.70%	24.93%
Power Range	37.15%	25.30%	0.08%	37.47%
Combination	**66.11%**	**24.52%**	**0.86%**	**8.50%**

Table 2: NIOM accuracy for Home-B over the same summer week as Figure 3 using nighttime-based thresholds.

4. EVALUATION

The previous section outlines a simple threshold-based NIOM algorithm. In this section, we quantify its accuracy in two homes to demonstrate the algorithm's performance. We set $\tau = 15$ data points for each metric and $\tau_{cluster} = 60$ for the clustering threshold, which means our approach will generate false positives if occupants frequently leave and return within an hour. Unless otherwise noted, we set thresholds for each metric based on the metric's maximum value at night (1am-4am). Below, we compare our results with both ground truth occupancy and a NILM-based approach.

4.1 Comparison with Ground Truth

Figure 3 plots Home-B's load profile and ground truth occupancy over a summer week (top) and its detected occupancy using our NIOM algorithm (bottom), which combines the clustered results from all three metrics. As the graph shows, the detected occupancy is nearly identical to the ground truth occupancy. Table 2 shows the full breakdown of the percentage of time each individual metric yields true positives (detects occupancy and the home is occupied), true negatives (detects no occupancy and the home is not occupied), false positives (detects occupancy but the home is not occupied), and false negatives (detects no occupancy but the home is occupied). The overall accuracy is then (TP+TN) / (TP+TN+FP+FN). As the table shows, each metric individually generates a significant number of false negatives, with average power having the highest accuracy at 78.34%. Interestingly, combining metrics significantly reduces the percentage of false negatives (by more than double in all cases) while causing only a slight increase in false positives ($<$0.5%), resulting in an overall accuracy of 90.63%.

The increased accuracy is due to an increase in the true positive rate (or *recall*), i.e., the detection accuracy given that occupants are present, from 0.72 using average power to 0.87 when combining metrics. The result demonstrates that, in this case, additional metrics beyond average power provide useful information. Since all metrics and their combination have low false positive rates, they all exhibit high *precision*, i.e., the probability that the home is occupied when the algorithm detects occupancy, with the combined algorithm having a precision of 0.99. Of course, since the home is occupied 74.61% of the time, an algorithm that always assumes occupants are present will have an accuracy of 74.61%. As a result, the *F-measure*—the harmonic mean of precision and recall—is often used instead of accuracy to assess a binary classifier's overall performance, with values closer to 1 indicating better performance. The F-measure from combining the metrics is 0.93, while the F-measure of the best individual metric (average power) is only 0.70.

Figure 4 and Table 3 shows similar results over a summer week from Home-A. Notice that Home-A's profile is significantly different than Home-B's, primarily due to its use of multiple window air conditioning units instead of a single large centralized system, as well as other high-power background loads (as shown in Figure 1(a)). In addition, the occupants in Home-A are less likely to turn off their air conditioning when they leave the home than Home-B because they own pets. As a result, occupancy detection is more challenging in Home-A. While combining the metrics still yields the best accuracy (at 79.09%) and F-measure (at 0.82), each individual metric is only slightly worse. Even so, Home-A's results maintain a low rate of false positives. Home-A also demonstrates how sensitive our algorithm is to each threshold. In this case, lowering the threshold to be the average of each metric over night (rather than the maximum) significantly improves the results, yielding an overall accuracy of 90.39% and an F-measure of 0.94.

Both experiments above examine summer periods. However, we expect the set of background loads to change each season. For instance, air conditioners have a significant influence on both load profiles above. As a result, we also examine a spring week from Home-A, which shows the weaker correlation between occupancy and electricity usage. Figure 5 and Table 4 show the results, which exhibit a higher percentage of false negatives than the summer results. The increase in false negatives is due largely to the lack of air conditioning, which narrows the difference in the load profile between an occupied and unoccupied home, as indicated in Figure 5(top). The narrowed difference makes occupancy detection more sensitive to the selection of thresholds. In addition, during the summer, occupants in both homes often manually control air conditioners—turning them on when they are home and turning them off when they leave—which makes them act more like high-

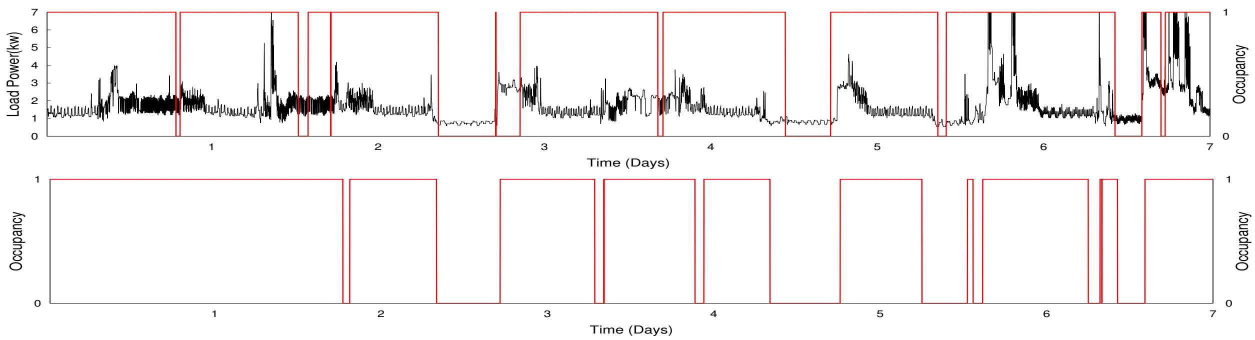


Figure 4: Home-A's load profile and ground truth occupancy over a summer week (top) and its detected occupancy using our NIOM algorithm (bottom), which combines results from all three metrics.

	True Positives	True Negatives	False Positives	False Negatives
Average Power	60.82%	11.91%	4.39%	22.88%
Standard Deviation	60.89%	14.39%	1.91%	22.81%
Power Range	62.68%	14.31%	1.98%	21.02%
Combination	**67.27%**	**11.82%**	**4.47%**	**16 .44%**

Table 3: NIOM accuracy for Home-A over the same summer week as Figure 4 using nighttime-based thresholds.

power interactive loads, rather than background loads that are consistently on regardless of occupancy. Thus, the algorithm is able to infer occupancy in the summer by detecting the presence of these loads in the aggregate data. Interestingly, in this case, the overall accuracy of 73.27% is slightly less than trivially assuming someone is always home, which yields an overall accuracy 75.3%. However, the true negative rate, i.e., the accuracy given no one is home (TN/(TN+FP)), is much higher (0.86 versus 0), since the false positives remain low.

4.2 Comparison with NILM-based Approach

Finally, we compare the results of our simple NIOM algorithm with an approach based on a modern NILM algorithm. NILM is a well-studied problem with the ambitious goal of disaggregating a home's aggregate time-series power data to obtain the time-series power data for each of its constituent loads. One obvious way to monitor occupancy is to first perform NILM, and then analyze the resulting power usage of the interactive loads to detect occupancy. As Figure 2(b) shows, interactive loads highly correlate with occupancy, and have nearly zero power usage when occupants are not present. For comparison, we obtain the interactive load profile using a NILM algorithm, and cluster events as in §3 to generate a continuous trace of occupancy. We then generate events in the interactive load trace from the NILM disaggregation using the same method as in §2 to detect occupants' physical interactions with loads based on the power usage of the interactive loads, e.g., any change in power >30W signals an interactive event.

We employ a NILM algorithm based on Factorial Hidden Markov Models (FHMM) used by Kolter and Johnson [22] to evaluate their Reference Energy Disaggregation Dataset (REDD), which is similar to a technique by Kim et al. [21]. FHMMs map well to NILM, since changes in building power reveal load state transitions, but not the actual state of each load. Figure 6 and Table 5 show the results. Note that our FHMM results are conservative, as we use the same data for training and disaggregation. Table 5 shows that with our standard clustering threshold of $N = 60$, the NILM-based approach simply predicts 100% occupancy. This behavior is due to the fact that while NILM tends to work well for identifying background loads with regular and consistent power usage, it has difficulty with interactive loads with no regular pattern of operation. Since interactive loads, such as lighting, do not exhibit many identifiable power features, have no regular usage patterns, and are often low-power, it is difficult for NILM algorithms to accurately extract them. As a result, as shown in Figure 6, NILM outputs large numbers of spurious events and obscures the clear periods of inactivity that signal occupancy. Lowering the clustering threshold corrects for this somewhat, as shown in Table 5, but barely improves (and eventually reduces) overall accuracy; In other words, the algorithm essentially does no better than the trivial approach of always predicting occupancy. Our comparison is only to demonstrate that the wealth of prior research on NILM does not directly apply to NIOM, and possibly other non-intrusive analytics.

5. CONCLUSION AND FUTURE WORK

In this paper, we explore the potential for NIOM, which analyzes electricity data from smart meters to infer occupancy, in two homes. Our intuition is that a home, when occupied, has a higher average power, standard deviation, and absolute power range over short intervals than when unoccupied. We develop a simple threshold-based NIOM algorithm based on this intuition and then empirically evaluate its accuracy. Our results show that the algorithm performs well, especially during the summer, although dynamically setting appropriate thresholds remains a challenge. In the future, we plan to apply more sophisticated methods for associating occupancy with power usage. For example, rather than using a binary classifier, we could assign a probability of occupancy based on recent electricity usage. In addition, machine learning techniques (using our metrics as features) may perform better than simply setting ad-hoc thresholds based on a home's nighttime power usage. However, these techniques have the drawback of requiring some form of training data, which is challenging and time-consuming to collect and our current approach avoids.

While researchers have focused heavily on the problem of NILM, NIOM represents another example of the type of simple and useful analytics possible with smart meter data. As we show in §4, directly applying a NILM algorithm to occupancy monitoring and other analytics may not be appropriate. Other potential examples of non-intrusive analytics that are distinct from NILM

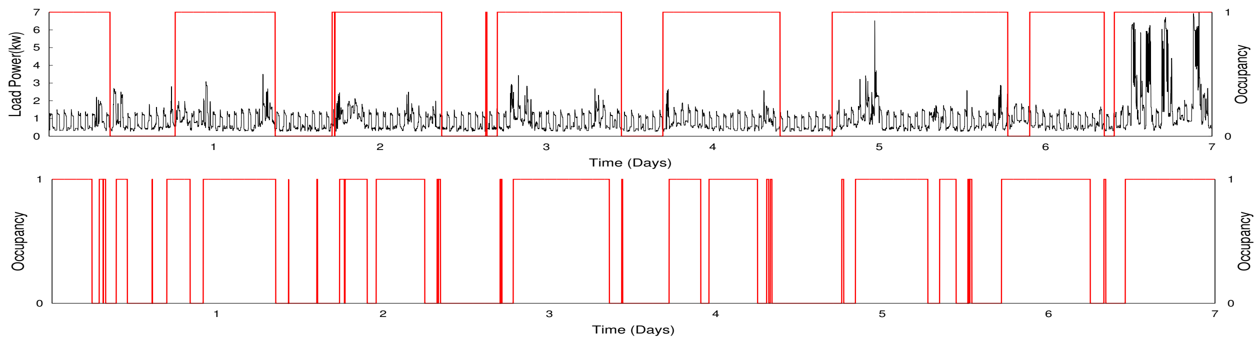


Figure 5: From top to bottom, Home-A's load profile and ground truth occupancy over a spring week, as well as occupancy detection based on the combination with thresholds for each metric set based on its maximum value at night from 1am to 4am.

	True Positives	True Negatives	False Positives	False Negatives
Average Power	50.17%	21.88%	2.81%	25.14%
Standard Deviation	38.49%	24.08%	0.61%	36.82%
Power Range	40.64%	23.24%	1.45%	34.68%
Combination	**52.09%**	**21.18%**	**3.52%**	**23.21%**

Table 4: NIOM accuracy for Home-A over a spring week using nighttime-based thresholds.

include include separating the temperature-dependent power usage from the temperature-independent power usage, or detecting different types of loads based on common power usage characteristics. For example, in recent work, we show that resistive, inductive, and non-linear loads each present highly identifiable characteristics—smooth power growth/decay, large power spikes, and rapid and random power fluctuations—in smart meter data [5]. As another example, converting smart meter data into the frequency domain can identify cyclical loads with semi-regular duty cycles. Each of these analytics, while useful, is simpler and likely more tractable than performing a complete disaggregation using NILM.

Even with the limitations of our current approach, NIOM has compelling applications given the widespread deployment of smart meters by utilities. For instance, prior work highlights that residential users often either i) do not program or ii) mis-program programmable thermostats [24]. While the NEST thermostat attempts to address the problem by automatically programming itself based on occupancy patterns it learns using a built-in motion sensor, it carries a significant cost (roughly $250). However, NIOM's potential to extract occupancy patterns from smart meters *en masse* enables utilities to automatically determine i) how much a programmable thermostat benefits each home and ii) suggest an optimal customized thermostat schedule. Utilities could include these results in electric bills or as part of routine energy audits to motivate consumers to upgrade to programmable thermostats and estimate their savings, or properly program their existing thermostat. While the applications above only require offline data, our algorithm could be run against real-time power data, although we do not evaluate its performance here. We expect future smart meters to enable customer's access to their data in real-time. Our algorithm's primary limitation in a real-time setting is its cluster threshold, which requires each metric being below its particular threshold for a certain time window before signaling occupancy. This clustering time window will dictate the system's detection latency.

Finally, our work only infers binary occupancy from smart meter data, i.e., whether anyone is home, and does not consider other dimensions of occupancy, such as the number of occupants or their location e.g.,, which room they are in. Our data suggests that the more people within a home, the more electrical events they produce, although the relationship is not linear since some activities are shared. Thus, accurately monitoring a home's occupancy count would likely require a technique more advanced than our simple threshold-based approach. Monitoring occupants' location might also be possible by detecting the operation of particular loads, such as kitchen appliances, and then associating these loads with room occupancy. However, such associations would likely require some knowledge of the mapping of devices to rooms, as well as higher resolution smart meter data, since one-minute average power does not reveal many identifiable load characteristics [5].

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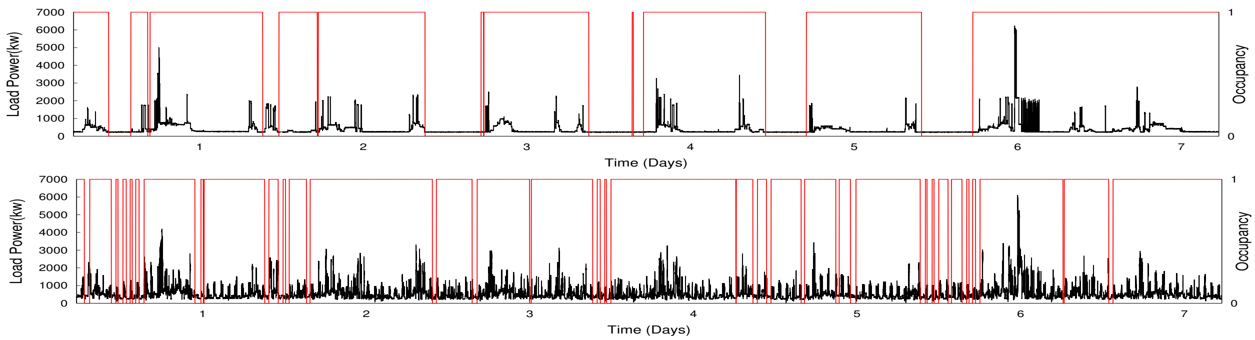

Figure 6: The power usage of the interactive loads from Home-A over the spring week (top), which highly correlate with occupancy, versus the usage of the interactive loads extracted using a NILM algorithm (bottom, $N = 30$).

Clustering Threshold	True Positives	True Negatives	False Positives	False Negatives
N = 60	78.61%	0.00%	21.39%	0.00%
N = 30	73.30%	6.36%	15.03%	5.31%
N = 15	62.58%	11.63%	9.76%	16.03%

Table 5: Occupancy monitoring accuracy using a NILM-based approach for a week in Home-A.

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