ABSTRACT

Heating control is of particular importance, since heating accounts for the biggest amount of total residential energy consumption. Smart heating strategies allow to reduce such energy consumption by automatically turning off the heating when the occupants are sleeping or away from home. The present context or occupancy state of a household can be deduced from the appliances that are currently in use. In this study we investigate energy disaggregation techniques to infer appliance states from an aggregated energy signal measured by a smart meter. Since most household devices have predictable energy consumption, we propose to use the changes in aggregated energy consumption as features for the appliance/occupancy state classification task. We evaluate our approach on real-life energy consumption data from several households, compare the classification accuracy of various machine learning techniques, and explain how to use the inferred appliance states to optimize heating schedules.

Categories and Subject Descriptors


General Terms

Algorithms, Measurement, Performance

Keywords

Energy Disaggregation, Heating Control

1. INTRODUCTION

The main goal of our study is to provide a framework for heating control and scheduling which considers the occupancy states of residential homes. Since most solutions for occupancy state identification involve complex sensor infrastructure and costly hardware which cause high usage barrier [4, 10, 15, 16], we aim to use given information from available electricity smart meters. We propose to employ energy disaggregation to infer appliance usage which is, as we will show, beneficial to occupancy state identification. In the following we briefly introduce the value of appliance usage information, before we explain how we use this information for the purpose of heating control.

In the context of domestic environments, consumers vastly underestimate the energy used for heating and overestimate the energy used for appliances that replace manual labor tasks [5]. Numerous studies have identified that consumers get a better understanding of their energy use by clear, concise, and direct feedback about appliance-specific consumption information [14, 18, 22].

In regard to power grid operators and power suppliers, knowledge about the energy consumption on appliance level is critical to the development of power system planning, load forecasting, billing procedures, and pricing models [5, 18]. In addition, the identification of electric appliances in domestic environments is important, because the increasing number of renewable energy sources in the power grid requires electric utilities to be able to quickly react to changes in supply and demand [17].

The growing need for accurate and specific information about domestic energy consumption on device level has led to numerous studies on appliance load monitoring [2, 5, 11, 21, 22]. Existing solutions for appliance load monitoring can be classified into two primary techniques [5, 20]: distributed direct sensing and single-point sensing.

Distributed direct sensing typically requires a current sensor to be installed in-line with every device and is therefore often referred to as intrusive load monitoring. Although intrusive load monitoring easily achieves a consumption breakdown, deploying a large number of sensors in the residential environment quickly leads to high cost and discouraging high usage barrier [20].

Single-point sensor systems are easier to deploy and are typically subsumed under the concept of non-intrusive load monitoring (NILM) [20]. Energy disaggregation is the task of using an aggregated energy signal, such as that coming from a single-point sensor or rather whole-home power monitor, to make inferences about the different loads of individual appliances [11]. However, single-point sensor systems require knowledge about the household devices and their electrical characteristics [20]. The challenges in energy disaggregation are mainly due to appliances with similar energy...
consumption, appliances with multiple settings, parallel appliance activity, and environmental noise [18]. Recent studies [9, 11, 12, 13, 14, 19] have shown that machine learning techniques represent a suitable solution to recognize appliances in such dynamic and unpredictable environments.

In this work we consider energy disaggregation techniques to derive occupancy states from appliance usage data in order to use this information in smart heating control strategies [10]. Heating control is of particular importance, since heating accounts for the biggest amount of total residential energy consumption and recent studies have shown that up to 30% of the total energy can be saved by turning the heating off when the occupants are asleep or away [15]. Existing work on the inference of occupancy states in residential environments includes statistical classification of aggregated energy data [10], hot water usage [4] as well as human motion and activity [16]. Our own approach to infer occupancy states differs in that we consider appliance usage, which gives more detailed information about the present context in a household and the devices which suggest user activity. Furthermore, our proposed framework does not require any additional infrastructure, and, therefore, is more likely to be accepted by residents.

For the evaluation of our approach we consider the REDD data set [11], which consists of whole-home and device specific electricity consumption for a number of real houses over the period of several month. In our experiments we compare the performance of different models for the appliance/occupancy state classification task. We use cross-validation (training on all houses and leave-one-out for testing) to evaluate how well the different models generalize. Our results suggest that the Naive Bayes classifier is suitable for the prediction of occupancy/appliance states and fits the problem of real-time heating control.

The rest of the paper is structured as follows. In Section 2 we give some background on recent advances in energy disaggregation. Section 3 introduces the formal notation of our appliance state classification task. Our proposed framework for heating control and scheduling by means of energy disaggregation techniques is described in Section 4. The experimental design and results on our approach are presented in Section 5. Eventually, we conclude our study and give an outlook on future work in Section 6.

2. BACKGROUND

Energy disaggregation, also referred as non-intrusive load monitoring, is the task of using an aggregated energy signal, such as that coming from a whole-home power monitor, to make inferences about the different individual loads of the system [11]. This approach is seen as an intermediate between existing electricity meters (which merely record whole-home power usage) and fully energy-aware home appliance networks, where each individual device reports its own consumption [17].

For a thorough evaluation of various energy disaggregation mechanisms under real-world conditions, a comprehensive collection of power consumption data is needed [17]. Most approaches to energy disaggregation have been supervised, in that the model is trained on individual device power signals [22]. The vast majority of supervised disaggregation approaches have evaluated the trained models on the same devices but in new conditions [2]. Research on energy disaggregation has been encouraged by publicly available data sets such as REDD [11], which contains information about the power consumption of several different homes on device level, and, therefore, allows cross-validation for individual appliances. Experiments on the REDD data set have shown that the Factorial Hidden Markov Model (FHMM) is able to disaggregate the power data reasonably well [11]. In that case, the disaggregation task is framed as an inference problem and the performance of energy disaggregation is evaluated considering the percentage of energy correctly classified.

Although FHMMs have shown to be a powerful tool [6] for learning probabilistic models of multivariate time series, the combinatorial nature of distributed state representation makes an exact algorithm for inferring the posterior probabilities of the hidden state variables intractable. Approximate inference can be carried out using Gibbs sampling or variational methods [6]. Recent work [9] on energy disaggregation presents different FHMM variants which incorporate additional features and better fit the probability distribution of the state occupancy durations of the appliances.

Another work [18] proposes Artificial Neural Networks (ANNs) for appliance recognition, because they (i) do not require prior understanding of appliance behavior, (ii) are capable of handling multiple states, and (iii) are able to learn while running. The results show that after training the ANN with generated appliance signatures, the proposed system is able to recognize the previously learned appliances with relatively high accuracy, even in demanding scenarios. To tune the ANN, the authors suggest to use the generated signatures to create a training data set with all possible combinations of appliance activity. Comparing the disaggregation performance for different ANN algorithms, additional work [12] suggests to employ back-propagation rather than the radial-base-function.

In another study [20] the authors propose a disaggregation algorithm that consists of several consecutive steps including normalization, edge detection via thresholding and smoothing techniques, extraction of power level and delta level consumption, matching of known appliances from a signature database with extracted delta vectors, and labeling of recognized devices. The proposed system does not require setup or training, because the user is able to label appliance signatures via her smart phone. In that case, the appliance signatures are based on apparent, reactive, real, and distortion power measured by the smart meter.

The classification of household items based on their electricity usage profile over a fixed time interval is discussed in yet another study [14]. The authors consider the time series classification problem of identifying device types through daily or weekly demand profiles. The proposed approach concentrates on bespoken features such as mean, variance, kurtosis, skewness, slope, and run measures. The experiments show that classification using the bespoken features performs better than classification using the raw data. However, the nature of similarity captured strongly depends on the features extracted.

In a similar work [17] the authors present an appliance identification approach based on characteristic features of traces collected during the 24 hours of a day. The extracted features include temporal appliance behavior, power consumption levels, shape of the consumption, active phase statistics, and noise level characteristics. Each resulting
feature vector is annotated by the actual device class and used to train the underlying model of the selected classifier. Among various tested classifiers the Random Committee algorithm perform best in categorizing new and yet unseen feature vectors into one of the previously trained device types. Additional work [12] demonstrates that the solution from any single-feature, single-algorithm disaggregation approach could be combined under a committee decision mechanism to render the best solution.

Yet another work [19] presents a non-intrusive appliance load monitoring technique based on integer programming. Since the overall load current is expressed as a superposition of each current of the operating appliance, the monitoring problem can be formulated as an integer quadratic programming problem by expressing the operating conditions as integer variables. Besides that the proposed method does not require relearning when a new appliance is installed in the house, it is furthermore able to distinguish between different device modes and some-type appliances that operate simultaneously.

To monitor the states of multiple appliances via electricity consumption measurements, another work [13] introduces the Bayes filter approach, which computes the posterior distribution over the current state given all observations to date. Since the state transition of an appliance is a continuous process, the authors employ a sliding window to take the temporal factor into consideration and extract the past records of data to be features. The estimated states are represented as binary strings, where each bit denotes the on/off state of one individual appliance. According to the results, the Bayes filter outperforms the KNN, Naive Bayes, and SVM classifier.

Leveraging recent advances in device and appliance power supplies, another series of studies [5, 7] extends the energy disaggregation approach by using high-frequency sampling of voltage noise, which provides an additional feature vector that can be used to distinguish more accurately between energy usage signatures. Appliances conduct a variety of noise voltage back onto the home’s power wiring, yielding measurable noise signatures that are easily detectable using appropriate hardware. An important advantage of voltage noise signatures is that any electrical outlet inside the home can be used as a single installation point.

3. NOTATION

Since different devices tend to draw different amounts of power, which are consistent over time, total power is a reasonable feature to use for classification [5]. Most devices have predictable current consumption and can be categorized according to the magnitude of real/reactive power. Given a household with $N$ devices, the power consumption of an individual appliance $i \in \{1, \ldots, N\}$ over a period of $T$ time points can be expressed as: $y_i(t) = \{y_i^1(t), y_i^2(t), \ldots, y_i^T(t)\}$. Usually we only observe the sum of all power outputs at each time: $\bar{y}_t = \sum_{i=1}^{n} y_i(t)$, with $t = 1, \ldots, T$.

Given the aggregated power signal most research on energy disaggregation [2, 21, 22] aims at inferring the individual device consumption. Since we aim to infer the context or rather occupancy states in residential environments in order to optimize heating control, we are mainly interested in the ON/OFF states of individual appliances $s_i(t)$, where $s_i(t) = 1$ if device $i$ is turned ‘on’ at time point $t$, and $s_i(t) = 0$ otherwise. The appliance state identification task can be framed as an inference problem. Given an aggregated power signal $\bar{y}_1, \ldots, \bar{y}_T$, we intend to compute the posterior probability $p(s_i(t) | \bar{y}_t)$ of individual appliance states $s_i(t)$ for each device $i = 1, \ldots, N$ and each time point $t = 1, \ldots, T$.

Due to the fact that the aggregated power signal is superimposed and unnormalized, and, therefore, unsuitable for the appliance state identification, we consider the changes in power consumption as features, which can be derived by the first-order difference of the power signal: $\Delta y_i(t) = y_i(t) - y_i(t-1)$ for $t = 2, \ldots, T$. Thus the appliance state identification task could also be formulated as a classification problem, where a certain change in power consumption categorizes a device into either ‘ON’ or ‘OFF’ state.

4. FRAMEWORK AND ALGORITHMS

Figure 1 shows a flowchart of our proposed framework for heating control and scheduling by means of energy disaggregation. The input for our heating control framework is an aggregated energy signal, such as that coming from a smart meter in a residential home. In the first step (i) we extract features from the energy signal, i.e. changes in consumption, which can be used to categorize the individual electrical devices. Subsequently (ii) we use the extracted features as input for the appliance state classification. For
the sake of simplicity, Figure 1 assumes that the individual appliance models were trained on other households prior to the classification task. Given the classified ON/OFF states for each appliance, we can eventually (iii) infer the occupancy state of the respective household and recommend optimized heating schedules.

In the following subsections we describe the (i) feature extraction, (ii) appliance state classification and (iii) inference of occupancy in more detail.

4.1 Feature Extraction

Given the overall energy consumption of a household and the energy consumption of the individual appliances in this household, we aim to build a model for each appliance in order to estimate its ON/OFF states in a previously unknown environment or household. Since an appliance can be either turned ON or OFF, the device state identification can be formalized as a two class problem. For the training of an individual appliance model we consider the changes in power consumption that classify the respective device states. In our approach the input for the classification model are two distributions of power changes, which represent the features that characterize one or the other class.

Figure 2 illustrates the feature extraction process on the basis of real-life measurements from the REDD data set, in particular the energy consumption of (a) House1 and (b) its Refrigerator for a sample time frame of 8 hours. We can see that (a) the overall energy consumption is the sum of (b) the Refrigerator’s energy consumption and the energy consumption of other appliances. Given this information, we can derive the changes in energy consumption by the first-order difference of the power signals. This step is often referred to as edge detection, since the stable periods in the signal are filtered out. The edges or changes in power consumption of the overall energy signal and the Refrigerator signal are shown in Figure 2 (c) and (d) respectively. Knowing which edges specify (d) the activity of the Refrigerator, we can easily separate the changes in energy consumption that categorize other devices by considering all the edges in (c) the overall energy signal which do not belong to the Refrigerator. The distribution of the edges that classify the Refrigerator’s ON/OFF states are illustrated in Figure 2 (e) and (f). These distributions can serve as training input for most probabilistic models.
4.2 Appliance State Classification

In this study we aim at evaluating the appliance state classification task by means of various machine learning techniques, including Naive Bayes (NB) classifier, Factorial Hidden Markov Model (FHMM), Classification Tree (CT), and One-Nearest-Neighbor (1NN) classifier.

We selected these models based on their complementary characteristics and degree of popularity regarding the energy disaggregation task. Table 1 shows typical characteristics of the considered machine learning techniques [1], although the characteristics strongly depend on the underlying algorithm and the problem. Therefore, Table 1 should be considered as a guide for an initial choice of models.

<table>
<thead>
<tr>
<th></th>
<th>NB</th>
<th>FHMM</th>
<th>CT</th>
<th>1NN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fitting Speed</td>
<td>Fast</td>
<td>Fast</td>
<td>Fast</td>
<td>Fast</td>
</tr>
<tr>
<td>Prediction Speed</td>
<td>Fast</td>
<td>Fast</td>
<td>Fast</td>
<td>Medium</td>
</tr>
<tr>
<td>Memory Usage</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Easy to Interpret</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

Table 1: Characteristics of Algorithms.

The NB classifier is a simple probabilistic model based on applying Bayes’ theorem with strong independence assumptions, which has been applied for appliance and occupancy recognition in various studies [10, 13, 14, 17]. Speed and memory usage of the NB classifier are good for simple distributions, but can be poor for large data sets [1].

The FHMM is a statistical model in which the system under study is assumed to be a Markov process with unobserved or hidden states. FHMMs have been successfully applied to the energy disaggregation problem [9, 11, 22], however their complexity increases with the number of states and the length of the Markov chain [6, 9].

CTs map observations about an item to conclusions about the item’s target value, meaning the predicted outcome is the class to which the data belongs. Decision tree learning has been proven to be applicable to appliance identification on metering data in a couple of recent studies [2, 17].

The 1NN classifier is often regarded as the simplest straw man or baseline approach [8], and has been considered for the energy disaggregation task in several studies [13, 14, 22]. 1NN usually has good performance in low dimensions, but can have poor predictions in high dimensions. For linear search, 1NN does not perform any fitting [1].

4.3 Inference of Occupancy

We assume that there exists a direct relationship between appliance usage and occupancy states in residential homes. For instance, if the lighting is turned on we usually know that the residents are at home, unless someone forgot to turn it off the lighting. Hence, lighting may be a straightforward indicator for occupancy states, enabling us to verify manually adjusted heating schemes and recommend optimized heating schedules.

However, heating control is much more complex, because the usage of certain appliance actually requires to decrease the temperature. For example, when residents turn on the oven or stove the temperature in the kitchen rises automatically, and we can reduce heating to save energy, instead of just opening the window. In case the heating control system would have knowledge about the installation points of all devices, one could even use the appliance states to control the temperature in individual rooms.

The knowledge of individual appliance states furthermore allows us to infer devices that are unrelated to occupancy. For instance, the refrigerator automatically switches between on and off state every few minutes, no matter if the residents are at home or not. The same is true for devices in standby mode or appliances such as the smoke alarm or electronic panels which are constantly drawing power. Therefore, by just looking at the overall energy consumption of a household it is impossible to distinguish between occupancy states.

The accuracy of the appliance state classification and the implications for heating control will be scrutinized in the following section.

5. EMPIRICAL EVALUATION

The goal of our evaluation is twofold: (i) we investigate which of the considered machine learning models is most accurate for the appliance state classification task; and (ii) we assess the use of the identified appliance or rather occupancy states for heating control.

5.1 Energy Data

We consider the REDD data set [11], which comprises electricity consumption measurements from six household at the granularity level of individual devices, and represents to date one of the largest and richest publicly available collections of power consumption data [3]. There are approximately 20 consecutive days of measurements available for each house, providing data from the two main phases and each individual circuit at 1Hz frequency rate. Measured appliances include main consumers such as Air Conditioning, Dishwasher, Disposal, Electrical Heating, Microwave, Oven, Refrigerator, Stove, Washer/Dryer as well as other miscellaneous electronics and outlets (see Table 2).

5.2 Experimental Design

In our empirical evaluation we compare the classification accuracy of the introduced machine learning models (see Table 1) on the REDD data set. Strictly speaking, we assess the appliance state classification accuracy for all considered models on a granularity level of individual devices.

The training of the respective models is done on appliance-specific consumption measurements of one particular device for all households but one. The aggregated electricity consumption signal of the left-out household is then used for testing the performance of the trained models for each individual device. This evaluation principle is also commonly known as cross-validation with leave-one-out.

5.3 Classification Accuracy

Table 2 illustrates the classification accuracy per (a) household and (b) appliance for all examined models, including Naive Bayes (NB), Factorial Hidden Markov Model (FHMM), Classification Trees (CT), and One-Nearest-Neighbor (1NN) classifier. The classification results present the performance
of the trained models in an unknown environment or rather before unseen household.

The results in Table 2 (a) show the classification accuracy of device states per household averaged over all appliances. For instance, the NB model achieved an accuracy of 0.8429 for House1, meaning that the model was trained on House2-6 and tested on the previously unknown House1, where 84.29% of all device states were classified correctly. However, as illustrated in Table 2 (a) the classification accuracy of each model varies with the household, which is due to the fact that the examined households use appliances of different manufacturers with dissimilar energy profiles.

Table 2 (b) presents the classification accuracy of device states per appliance averaged over all households. For example, the results show that the NB model is able to classify the device states of the Air-Conditioning with an average accuracy of 93.15%, taking the mean of House1-6. In general, all models achieved a relatively high classification accuracy for appliances with distinctive energy profiles, such as the Dishwasher or Oven, but performed less well on appliances with changes in consumption that can be easily be confused with other devices, like the Refrigerator or Lighting.

By taking the mean over all results for (a) each household and (b) each appliance per model, shown in the bottom row of Table 2 (a) and (b) respectively, we can easily see that on average the NB model achieved the highest classification accuracy, closely followed by FHMM and CT. Although the INN classifier shows relatively high classification accuracy for several individual appliances, it is unable to correctly classify the device states of others, and, therefore, achieved the lowest average classification performance.

5.4 Heating Control

In this subsection we discuss how the classified on/off device states can be used for heating control and scheduling. Since the Naive Bayes (NB) model achieved the highest average accuracy on classifying device states of appliances in an unknown household (see Table 2), we will consider the NB approach in our following exemplification.

Figure 3 shows the (a) observed and (b) estimated on/off states for the Washer/Dryer in House1 over a period of four weeks, where every quarter of an hour aggregates the device activities that occurred during the same weekday and time of day. By illustrating the (a) observed activity of the Washer/Dryer, which constitutes our ground truth, we see that this appliance is mostly used on Fridays and weekends. The (b) estimated activity of the Washer/Dryer, inferred from the overall energy consumption of House1 by the trained NB model, shows similar behavior patterns for weekends, but predicts false on states for Mondays.

By taking a closer look at the confusion matrix of observed and estimated on/off device states for the Washer/Dryer in House1, shown in Table 3, we are able to gain a better understanding of the estimated appliance activity. Table 3 reveals the percentage of true positives (TP) or true on states, true negatives (TN) or true off states, false positives (FP) or false on states, and false negatives (FN) or false off states. Although the NB model achieves a high classification accuracy [(TP+TN)/(TP+TN+FP+FN)=96.83%], the percentage of falsely classified states [FP+FN=3.17%] is not negligible, explaining the mistaken Washer/Dryer activity estimated for Mondays (see Figure 3(b)). The FP and FN estimates imply heating during absence and cooling during occupancy respectively.

The cause of falsely classified states can also be explained with help of Figure 2. By examining the distribution of on and off states of the Refrigerator in House1, shown in Figure 2 (e) and (f) respectively, we can see there is a significant overlap of changes in power consumption that are caused by both the Refrigerator and other devices. According to Figure 2 (e) and (f), changes in power consumption that range from around 1 to 50 Watt occur at times when the Refrigerator is turned on as well as when its is turned off, leading to an inaccurate appliance model.

In order to decrease the number of FP and FN device states one could orchestrate the trained appliance models or

\[
\begin{array}{|c|c|c|c|c|}
\hline
\text{House} & \text{NB} & \text{FHMM} & \text{CT} & \text{INN} \\
\hline
1 & 0.8429 & 0.8144 & 0.8319 & 0.7615 \\
2 & 0.9310 & 0.9300 & 0.9224 & 0.8062 \\
3 & 0.9275 & 0.9200 & 0.8908 & 0.7213 \\
4 & 0.8545 & 0.8616 & 0.8746 & 0.7938 \\
5 & 0.9864 & 0.9854 & 0.9839 & 0.7638 \\
6 & 0.8131 & 0.7873 & 0.7752 & 0.6050 \\
\hline
\text{MEAN} & 0.8942 & 0.8870 & 0.8798 & 0.7260 \\
\hline
\end{array}
\]

\[
\begin{array}{|c|c|c|c|c|}
\hline
\text{House} & \text{Air Conditioning} & \text{Bathroom GFI} & \text{Dishwasher} & \text{Disposal} \\
\hline
1 & 0.9315 & 0.9248 & 0.9300 & 0.9138 \\
2 & 0.9328 & 0.9275 & 0.9324 & 0.9134 \\
3 & 0.9541 & 0.9493 & 0.9551 & 0.9134 \\
4 & 0.9955 & 0.9818 & 0.9970 & 0.9919 \\
5 & 0.8863 & 0.8856 & 0.8620 & 0.8895 \\
6 & 0.8875 & 0.7970 & 0.7404 & 0.9991 \\
\hline
\text{MEAN} & 0.8875 & 0.8211 & 0.7924 & 0.5216 \\
\hline
\end{array}
\]

\[
\begin{array}{|c|c|c|c|c|}
\hline
\text{House} & \text{Furnace} & \text{Kitchen Outlets} & \text{Lighting} & \text{Microwave} \\
\hline
1 & 0.7902 & 0.7915 & 0.7070 & 0.1757 \\
2 & 0.7751 & 0.7737 & 0.8066 & 0.7611 \\
3 & 0.9516 & 0.9473 & 0.9526 & 0.9279 \\
4 & 0.9982 & 0.9995 & 0.9997 & 0.9996 \\
5 & 0.9754 & 0.9804 & 0.9815 & 0.9811 \\
6 & 0.7834 & 0.7872 & 0.7952 & 0.7898 \\
\hline
\text{MEAN} & 0.9315 & 0.9248 & 0.9300 & 0.9138 \\
\hline
\end{array}
\]

\[
\begin{array}{|c|c|c|c|c|}
\hline
\text{House} & \text{Electronics} & \text{Electrical Heating} & \text{Electronic Heating} & \text{Lighting} \\
\hline
1 & 0.9982 & 0.9995 & 0.9997 & 0.9996 \\
2 & 0.9754 & 0.9804 & 0.9815 & 0.9811 \\
3 & 0.9516 & 0.9473 & 0.9526 & 0.9279 \\
4 & 0.9982 & 0.9995 & 0.9997 & 0.9996 \\
5 & 0.9754 & 0.9804 & 0.9815 & 0.9811 \\
6 & 0.7834 & 0.7872 & 0.7952 & 0.7898 \\
\hline
\text{MEAN} & 0.9315 & 0.9248 & 0.9300 & 0.9138 \\
\hline
\end{array}
\]

\[
\begin{array}{|c|c|c|c|}
\hline
\text{House} & \text{Refrigerator} & \text{Smoke Alarm} & \text{Smoke Alarm} \\
\hline
1 & 0.9729 & 0.9629 & 0.9738 & 0.6234 \\
2 & 0.9346 & 0.9288 & 0.9363 & 0.8330 \\
3 & 0.9729 & 0.9629 & 0.9738 & 0.6234 \\
4 & 0.9346 & 0.9288 & 0.9363 & 0.8330 \\
5 & 0.9729 & 0.9629 & 0.9738 & 0.6234 \\
6 & 0.9729 & 0.9629 & 0.9738 & 0.6234 \\
\hline
\text{MEAN} & 0.9729 & 0.9629 & 0.9738 & 0.6234 \\
\hline
\end{array}
\]

\[
\begin{array}{|c|c|c|c|}
\hline
\text{House} & \text{Washing Machine} & \text{Washing Machine} & \text{Washing Machine} \\
\hline
1 & 0.8330 & 0.8275 & 0.8330 \\
2 & 0.8330 & 0.8275 & 0.8330 \\
3 & 0.8330 & 0.8275 & 0.8330 \\
4 & 0.8330 & 0.8275 & 0.8330 \\
5 & 0.8330 & 0.8275 & 0.8330 \\
6 & 0.8330 & 0.8275 & 0.8330 \\
\hline
\text{MEAN} & 0.8330 & 0.8275 & 0.8330 \\
\hline
\end{array}
\]

Table 2: Cross-validation of trained models.

Table 3: Confusion matrix of observed and estimated on/off device states for the Washer/Dryer in House1, where Accuracy=TP+TN=96.83%.
consider additional features that distinguish the appliances more accurate. However, this goes beyond the scope of this study, but could be part of future work.

A more thorough evaluation of the heating schedules would require datasets that comprise information about actual occupancy states in the residential homes and preferences of the residents in regard of temperature settings.

6. CONCLUSION AND FUTURE WORK

In this work we reviewed recent advances in energy disaggregation and adopted established appliance identification strategies to infer occupancy states for smart heating control and scheduling. Our proposed approach to appliances state identification considers the changes in power consumption as characteristic to classify the individual devices. In our evaluation we have shown that the Naive Bayes classifier is able to achieve relatively high accuracy on the appliance state identification task, even in unknown environments or households. Furthermore, we explained how to use the information about identified appliances to infer occupancy states in residential homes. We exemplified the idea of occupancy-based heating schedules and discussed the problem of falsely identified appliance states.

The main advantage of our proposed framework for heating control and scheduling is its simplicity in that we refrain from implementing new infrastructure in residential homes, but use given information from available electricity smart meters. This approach will eventually lead to higher acceptance rates among residents and provides alternative avenues for novel heating control strategies.

Since our appliance state identification strategy can replace sensing infrastructure that is used to identify occupancy states in residential homes, it would also be interesting to compare the energy savings provided by our approach with the performance of existing frameworks, such as the smart thermostat [15]. However, this would require datasets that comprise information about actual occupancy states in the residential homes and preferences of the residents in regard of temperature settings.

Our proposed approach to appliance state identification can furthermore be beneficial for other applications. Recent studies [3] have shown that the availability of smart meter data alone is often not sufficient to achieve high load disaggregation accuracies. Future work could combine the knowledge of total energy consumption with additional information about sequences of events, such as ON/OFF states for each individual appliance, to improve the accuracy of certain disaggregation algorithms [3] that use such events along with smart meter data.

7. REFERENCES


