Appliance Usage Prediction for the Smart Home with an Application to Energy Demand Side Management

And Why Accuracy is not a Good Performance Metric for this Problem

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Abstract: Shifting energy peak load is a subject that plays a huge role in the currently changing energy market, where renewable energy sources no longer produce the exact amount of energy demanded. Matching demand to supply requires behavior changes on the customer side, which can be achieved by incentives such as Real-Time-Pricing (RTP). Various studies show that such incentives cannot be utilized without a complexity reduction, e. g., by smart home automation systems that inform the customer about possible savings or automatically schedule appliances to off-peak load phases. We propose a probabilistic appliance usage prediction based on historical energy data that can be used to identify the times of day where an appliance will be used and therefore make load shift recommendations that suite the customer's usage profile.

A huge issue is how to provide a valid performance evaluation for this particular problem. We will argue why the commonly used accuracy metric is not suitable, and suggest to use other metrics like the area under the Receiver Operating Characteristic (ROC) curve, Matthews Correlation Coefficient (MCC) or F_1-Score instead.

1 INTRODUCTION

With renewable energy sources, electric grid operators face a variety of new challenges. One being the highly variable amount of power produced, e. g. by wind turbines or photovoltaic systems. In order to guarantee the stability of the grid, the amount of energy in the grid has to be just right. Hence, supply and demand must match. Up to now, unexpected power fluctuations emerged on the demand side only (in particular industrial plants and private households), which could be balanced for example by gas engines. A wind turbine, however, generates energy in windy weather conditions, but not necessarily when the power is required on the demand side. In windless phases (or cloudy ones in terms of photovoltaic systems), the result is an undersupply of power in the grid. As power cannot be stored very efficiently, over-production is also a major problem for grid operators. Therefore, the problem to be solved is to balance demand and supply. One step in this direction is the smoothing of load peaks through load shifting, i. e., shifting parts of power consumption to other time periods, in which less power is used.

Our aim is to develop solutions for optimal load shifting for private consumers using artificial intelligence, and Real-Time-Pricing (RTP) as an incentive to integrate the customer into the balancing of supply and demand (see (Hassan et al., 2016) for a discussion of methodologies to assist grid operators in designing incentives for consumer participation in demand response management taking into account inconvenience for participating users). RTP are tariffs, in which electricity cost varies over time (e. g., the price changes every 15 min) (S.a., 2005a). Studies suggest that RTP models require a complexity reduction in order to be accepted by the end-user (S.a., 2005b), as well as that customers will respond with shaving instead of shifting of their peak demand (Schleich and Klobasa, 2013). We therefore combine such tariffs with the knowledge of a household's typical power consumption, which form the basis for an intelligent demand side management system. The system is then capable of shifting loads to better suited time periods through measures specifically tailored to user behavior. Simulations have already shown that such systems can effectively reduce the peak-to-average ratio (Mohsenian-Rad and Leon-Garcia, 2010). We aim to reduce the system's complexity sufficiently, in order to enable technically unversed persons to make use of it as well.

Smart meters are used for metering and billing;

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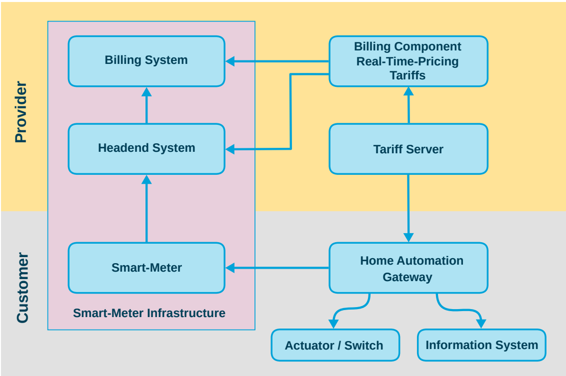


Figure 1: The big picture: the system for transmission and evaluation of tariff information is decoupled from the smart meter infrastructure. The customer has full control over the home automation gateway, therefore no privacy issues arise. This article's focus is on exploiting RTP tariffs on the home automation side using AI methods.

these devices are digital electricity meters that connect to the utility company over a communication network. The design of a system for residential smart grid applications is discussed, e. g., in (Viswanath et al., 2016). As shown in Fig. 1, the system being developed in our project for transmission and evaluation of tariff information is decoupled from the smart meter infrastructure. The evaluation of tariffs in the home automation gateway may be augmented by a large variety of additional information, for example: historical energy consumption data of single appliances or the entire household; the presence or absence of residents; or weather forecasts. With this data, using artificial intelligence methods, behavior patterns can be detected; combined with tariff information the optimal use of household appliances can be computed. Based on the results of these computations, appliances can be controlled directly using the home automation system. A main challenge is to avert that power cost minimization has negative consequences for the user. This requires appliance usage profiling.

Appliance usage profiling and prediction is already discussed in various publications, where, e. g., ON/OFF probabilities are used to build a non-homogeneous Markov Chain to model end-use energy profiles on appliance level (Kang et al., 2014); (Chang et al., 2013) propose a daily pattern based probability model. Decision trees and Bayesian network-based prediction are utilized in (Arghira et al., 2012) to discover behavior patterns within sequential data; (Heierman and Cook, 2003) propose using the ED (Episode Discovery) data-mining algorithm for this purpose. (Hawarah et al., 2010) predict the user behavior with bayesian networks and (Basu et al., 2013) compare the performance of different classifiers such as bayesian networks, decision trees and decision tables for predicting the future 24h power consumption of an appliance.

In this paper, as a first step, we present an approach for predicting appliance usage (e. g., for dishwashers, washing machines etc.), which allows the automation system to either control the appliances directly, or to give recommendations to the residents in which time period using the appliance would result in lower energy costs, based on the users' normal behavior patterns, which are learned from historical data automatically. This requires some kind of energy load prediction. Our prediction model is based on the appliance's usage cycles, thus requiring the extraction of appliance operation cycles (start/end time) from its electricity metering data (Stephen et al., 2014).

2 PREDICTION METHOD

Probabilistic Model. There are basically two main factors that need to be taken into account when computing the probability that an appliance will be used: The time elapsed since it was used last and the time of day it is usually used. For example, a dishwasher will typically be switched on in more or less regular intervals and only at certain times of day (e. g., normally not at 2 a. m.). We model these separately as probability distribution functions (PDFs), where in the following E will denote the event *elapsed time* and D the event *time of day*. To give recommendations to the user, the combined probability of these two events has to be calculated and must be above a defined threshold to initiate a recommendation:

$$\begin{aligned} P(E \cap D) &= P(E \mid D)P(D) \\ &\overset{\text{if independent}}{=} P(E)P(D) \quad . \end{aligned} \tag{1}$$

Statistical independence of E and D is assumed here; although strictly speaking not necessary, as the conditional probability $P(E \mid D)$ can be computed from the data if a sufficient amount of representative data are available. As this is quite often not the case (cf. Sect. 4 for details on typical data sets), the independence assumption results in more stable estimates of $P(E \cap D)$. That independence is valid can be checked on the data set by computing the product on the right and middle of (1), and checking that equality holds.

The probability $P(E)$ that the appliance is not used for a time period t (here measured in minutes) is modeled by an exponential distribution:

$$P(E) = P(E \leq t) = \begin{cases} 1 - e^{-\lambda t} & t \geq 0 \\ 0 & t < 0 \end{cases} \quad . \tag{2}$$

A maximum likelihood estimate of the parameter λ can be obtained from a sufficiently large data set by

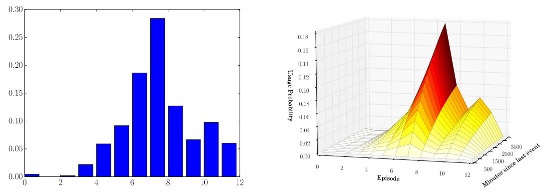


Figure 2: Example of estimates for $P(D)$ (discrete density of appliance usage throughout the day, left) and the combined cumulative distribution $P(E \cap D)$ (right). Episode length is 2h, resulting in 12 episodes per day.

computing the mean value of the time periods between consecutive appliance-switch-on events. A good estimate of λ will be obtained when the time between usage is fairly regular, resulting in a small value for the variance of the time periods.

In contrast to using a continuous distribution for E, a discrete PDF for the event D is estimated from the sample data by computing relative frequencies of appliance usage viewed over the 24 hour time period of a day. This period has to be divided into discrete intervals, which we will call *episodes* in the following. An episode must be sufficiently large, so that statistically valid relative frequencies (which are an estimate of the probability that the appliance is used in a particular episode) can be obtained. On the other hand, it has to be small enough to be of practical use. We found episodes having a length of 1h to 2h to be a good compromise. To avoid issues with episodes where no samples are contained in the data set, leading to density values of zero, the Parzen window approach (Parzen, 1962; Duda et al., 2000) can be applied, which is basically an interpolation and smoothing method, typically using Gaussians. Figure 2 shows an example of a discrete PDF computed from the GREEND data set (Monacchi et al., 2014).

Inactivity Detection. Most household appliances with non-homogeneous distribution in electricity consumption require the user's presence when starting the appliance. Thus, the prediction of a household appliance usage is often accompanied by a prediction of the home's occupancy; in some cases an appliance might even be directly linked to the presence of a specific person. Without ground truth on the occupancy, a strong indication that can be found in the historical electricity data is the usage of such appliances in the recent history. We therefore add knowledge of the events that occurred in recent history to the prediction by lowering the probability in case no appliance was used in recent episodes. We found that the past 12h to 24h are of specific interest and improve the prediction significantly. This approach may be replaced by more sophisticated occupancy detection algorithms, which are not the focus of this paper.

Threshold Estimation. Now that the usage probability can be computed at any time of day, a threshold has to be set that determines whether the home automation system turns on the appliance (or gives a recommendation to the user to do so). Note, that the absolute values of $P(E \cap D)$ depend heavily on the time interval chosen as episode duration. Obviously, longer episodes result in higher probabilities for appliance usage during this period; e. g., using 2h instead of 1h episodes would approximately double the probabilities (exactly for uniform distribution, less so for uni-/multi-modal densities). We propose to compute the threshold automatically from the training data by calculating $P(E \cap D)$ for each episode of the training set. Let p_i be the predicted probability at the i-th turn-on event of a total of N that occurs in the data, the threshold θ_p is computed as the mean: $\theta_p = \frac{1}{N} \sum_{i=0}^{N-1} p_i$. If extreme outliers are expected or more control over the threshold is desired, the Median or any other quantile may be used instead.

Extended Model. The model described above works well when appliances are typically used in fairly regular intervals, like dishwashers. There are scenarios, however, where it fails; e. g., a household may use the washing machine every Saturday, but not only for a single washing cycle but two or three times in a row. While the estimate for $P(D)$ will still be valid, the parameter λ of the exponential distribution will be invalid. This issue can be overcome by introducing an additional discrete random variable U, describing how many times an appliance has been used during the past n_e episodes. The parameter n_e can be adjusted to the appliance at hand; e. g., for a washing machine a 10h period may suffice. Generalization of (1) gives:

$$\begin{aligned} P(E \cap D) &= \sum_{i=0}^{\infty} P(E \cap D \mid U = i) P(U = i) \\ &= \sum_{i=0}^{n_m} P(E \cap D \mid U = i) P(U = i) + \\ &\quad P(E \cap D \mid U > n_m) P(U > n_m) \quad , \end{aligned} \tag{3}$$

where n_m is an upper limit for the number of times an appliance is used that can be derived from the training data (a washing machine may be switched on 3 or 4 times in a 10h interval, but not 20 times); from a certain value of i onwards, all probabilities $P(U = i)$ will usually be zero.

3 ACCURACY IS NOT A GOOD PERFORMANCE METRIC

In many publications on appliance usage prediction or energy load disaggregation the performance metric *accuracy* is chosen to evaluate the proposed classification methods. The accuracy A is defined as the proportion of data that has been classified correctly:

$$A = \frac{T_P + T_N}{n}, \tag{4}$$

where n is the total number of events, T_P is the number of positive events and T_N is the number of negative events that have been classified correctly (True Positives and True Negatives, respectively). For the problem at hand we get a true positive if the algorithm predicts that an appliance is running during a given time period and the appliance is actually doing so. In the same manner, for a true negative the prediction is that the appliance is off and this is truly the case. The denominator n is then the total number of episodes.

The main issue with this commonly chosen metric is that it is not meaningful for rare events; this is known as the *accuracy paradox* (Zhu and Davidson, 2007; Valverde-Albacete and Peláez-Moreno, 2014). Rare events, however, are in most[1] cases the standard when looking at the problem of appliance usage prediction! Consider, for instance, a dishwasher: this appliance is normally used quite regularly, say every other day, where it takes about 2h to finish its cycle. This means, though, that in 96% of the total time the dishwasher is off. Even if it is used twice as often, i. e., every day, it will still be off 92% of the time. Publications making use of accuracy, such as (Heierman and Cook, 2003; Barbato et al., 2011; Basu et al., 2013; Lee et al., 2013; Lachut et al., 2014), could therefore easily be outperformed for rare events by simply *always* predicting no occurrence (i. e., a Negative), which will result in an accuracy of 96% for the dishwasher example above.

The issue of selecting an appropriate metric has been addressed before by several authors from various fields (Cook, 2007; Hand, 2009; Powers, 2011; Makonin and Popowich, 2015). The overall performance of a binary classifier is usually captured using the Receiver Operating Characteristic (ROC), which is a plot of the true positive rate (TPR, also called sensitivity, recall, or detection rate) vs. false positive rate (FPR). These are given by:

$$\mathrm{TPR} = \frac{T_P}{P}, \quad \mathrm{FPR} = \frac{F_P}{N}, \tag{5}$$

where F_P is the number of negative events that have been classified incorrectly as positive ones, P is the total number of positive and N the total number of negative events, with $n = P + N$. Examples of ROC plots are shown in the experiments section in Fig. 4. A perfect classifier would show a rectangular curve, while the main diagonal indicates complete randomness. Any point on the curve can be selected for classification by choosing the classifier's parameters appropriately. Every point results in a different value for the accuracy A calculated as shown in (4). In publications, where only accuracy is presented, this will usually be the point on the ROC curve where the maximum value is obtained.

This is similar for the following two metrics, the F_1-Score and the Matthews Correlation Coefficient (MCC):

$$F_1 = 2 \cdot \frac{\mathrm{PREC} \cdot \mathrm{TPR}}{\mathrm{PREC} + \mathrm{TPR}}, \quad \mathrm{PREC} = \frac{T_P}{T_P + F_P}, \tag{6}$$

where PREC is called precision, and TPR is the true positive rate (recall) from (5).

$$\mathrm{MCC} = \frac{T_P T_N - F_P F_N}{\sqrt{PN(T_P + F_P)(F_N + T_N)}}, \tag{7}$$

with F_N and T_N being the number of false and true negatives, respectively. F_1 ranges from 0 to 1, the MCC, being a correlation coefficient, ranges from -1 to $+1$. In both cases zero indicates total randomness and one perfect classification. While the F_1-Score also suffers from a bias when sample sizes for positive and negative data are different, the MCC balances these. It is therefore much better suited for measuring classifier performance in cases, where events are rare.

In contrast to all these metrics, which measure performance for a single point on the ROC curve, the Area Under Curve (AUC) tries to capture the quality of the whole ROC in single numerical value by computing the area under the ROC:

$$\mathrm{AUC} = \int_0^1 \mathrm{ROC}\ \mathrm{dFPR}. \tag{8}$$

For a correctly evaluated classifier, the AUC will range from 0.5 (total randomness) to 1 (perfect). Although reducing two dimensions to a single one without losing information is not feasible, AUC is still a valid metric for overall performance, and much better suited than accuracy. Extensions of AUC can be found in literature, e. g. (Hand, 2009), who suggests a weighted AUC.

Unfortunately, knowledge regarding evaluation metrics does not seem to be widely spread in the energy usage prediction and disaggregation community. This has been criticized before by several authors like (Kim et al., 2011; Makonin and Popowich, 2015), alas with apparently little effect. We propose using AUC, F_1, and MCC, and will give results for all three metrics in this paper's experiments section.

[1]The possible exception being appliances like fridges or freezers.

4 EXPERIMENTAL RESULTS

Evaluating the proposed prediction method requires high resolution power consumption measurements of individual appliances. A few publicly available data sets already exists, usually containing the whole house and appliance level energy consumption data (see Table 1). We selected homes from the GREEND data set (Monacchi et al., 2014) to evaluate our prediction model. This set was chosen as it provides enough measurements to enable statistical analysis of events and is of sufficient data quality. Other data sets, such as REDD (Kolter and Johnson, 2011) or ECO (Beckel et al., 2014), do not provide enough data or the required quality (e. g., there are often long periods where data is missing). The GREEND data set provides measurements of eight homes with a varying amount of appliances and measuring periods ranging from 134 to 500 days. The data are sampled with a rate of 1 Hz and provide the power consumption in Watts per appliance.

Comparing our results to previous usage prediction publications proved to be infeasible as the results are not comparable due to the chosen data set or evaluation metric. Evaluations using artificially generated data (Heierman and Cook, 2003; Barbato et al., 2011) are not comparable as the amount of introduced randomness will dictate the result, especially for rare events such as dishwasher usage. We do not consider these evaluations as valid. Publications evaluating appliance usage prediction on short data sets, e. g. REDD (Truong et al., 2013a; Truong et al., 2013b), are also not comparable due to the insufficient amount of data in the set. REDD contains data for only up to 19 days, a duration that we consider totally inadequate for training and evaluation of rare events such as dishwasher usage.

Extracting Events. As the prediction is based on event occurrences, where an event is defined by the start and end of an appliance's usage cycle, in a first pre-processing step the events must be extracted from the continuous power consumption data stream. As the start and end of an event are not provided by any of the data sets listed in Table 1, the performance of the event extraction cannot be measured against ground truth. We first aggregate the data to $1/60$ Hz by averaging the power consumption. The start and stop of an event are defined by the rising and falling edge of the signal, which allows using a threshold method. In case an appliance's power consumption falls below the threshold during an event, this event will be partitioned, thus (incorrectly) generating multiple usage cycles instead of a single one. For the method proposed in this paper, the partitioning will not be an issue for computing the discrete estimate of $P(D)$ in (1); however, the estimate of λ of the exponential distribution $P(E)$ in (2) would be distorted. We overcome this problem by defining an individual threshold for each type of appliance, which minimizes the partitioning, and then only use events of sufficient length. Table 2 gives a statistical overview of the extracted events for appliances selected from the GREEND data set.

Results. The extracted events were split into two disjoint parts, 60% for training and 40% for evaluation. The training set is used to estimate λ in (2) by calculating the mean value between consecutive appliance-switch-on events. As an example, λ for the dishwasher in house 3 is 2274 minutes (≈ 1.6 days). An episode length of 360 minutes was chosen, which divides the day into four partitions. A smaller episode length leads to a more time precise prediction task, and vice versa. As we do not require high time precision, but rather a recommendation window that suites the user's behavior patterns, four partitions per day give a reasonable recommendation window.

The probability $P(D)$ from (1) for each episode is calculated by binning the appliance-switch-on event duration into the corresponding episode-bin. Figure 3 shows $P(E \cap D)$ for the dishwasher in house 3. It clearly shows the characteristics of $P(D)$: The appliance is not likely to be used in the morning, very likely during midday and medium in the evening. With this information we can define the user's preferred usage window and only recommend load shifts within this window. It also shows the effect of $P(E)$ on the combined probability, as the probability drops immediately after the appliance is switched on. This respects the mean duration between events, hence no load shift recommendation must be made until a significant probability is reached in the successive episodes.

For usage prediction performance comparison between the appliances in different homes we calculate the ROC and the area under the ROC curve (AUC) by changing the threshold probability at which the prediction will consider the appliances as being used; also the F_1-Score and MCC. The results are highly dependent on the house and appliance (cf. Table 2) The worst prediction result is obtained for the fridge in house 1, a MCC of 0.029, which is complete randomness. The reason is insufficient data: Table 2 shows that there were only 15 events available in the whole data set, therefore good performance cannot be expected.

Although very good results can typically be achieved for fridges, these are not ideal for load shifting; dishwashers, washing machines and dryers on the other hand are of special interest, as they are well suited for this purpose. ROC curves for these appli-

Table 1: Publicly available appliance and whole house energy consumption data sets.

Data set	Reference	Location	Duration/ house	# of houses	Appliance sample intvl	Aggregate sample intvl
REDD	(Kolter and Johnson, 2011)	MA, USA	3–19 days	6	3 sec	1 sec & 15 kHz
Smart*	(Barker et al., 2012)	MA, USA	3 months	3	1 sec	1 sec
AMPds 2	(Makonin et al., 2016)	BC, Canada	2 years	1	1 min	1 min
UK-DALE	(Kelly and Knottenbelt, 2015)	London, UK	3–26 months	5	6 sec	1–6 sec & 16 kHz
ECO	(Beckel et al., 2014)	Switzerland	8 months	6	1 sec	1 sec
GREEND	(Monacchi et al., 2014)	Italy & Austria	12 months	9	1 sec	–
Dataport	(Pecan Street Inc., 2014)	TX, USA	0–2.75 years	824	1 min	1 min
DRED	(Uttama Nambi et al., 2015)	Netherlands	2 months	1	1 sec	1 sec

Table 2: Statistics of extracted events of the GREEND data set, providing the days between first and last events as well as the total events count for six different homes. Also shown are resulting performance metrics using an episode length of 360 minutes.

H#	Appliance	Days	Events	AUC	F_1	MCC
0	coffee maker	308	676	0.703	0.708	0.498
0	dishwasher	306	143	0.684	0.389	0.348
0	fridge freezer	309	7353	0.999	0.999	0.972
0	lamp	307	215	0.701	0.524	0.344
0	television	117	445	0.567	0.852	0.251
0	washing mach.	309	256	0.591	0.378	0.190
1	bedside light	473	456	0.859	0.704	0.580
1	dishwasher	472	248	0.651	0.335	0.213
1	dryer	473	405	0.859	0.811	0.763
1	fridge	454	15	0.550	0.017	0.029
1	washing mach.	467	166	0.839	0.415	0.390
2	coffee maker	494	512	0.580	0.333	0.180
2	dishwasher	495	477	0.856	0.654	0.553
2	dryer	495	424	0.828	0.596	0.499
2	television	497	1446	0.770	0.786	0.618
2	washing mach.	497	794	0.809	0.728	0.634
3	coffee maker	456	250	0.719	0.397	0.349
3	dishwasher	456	211	0.843	0.414	0.394
3	fridge	460	1100	0.917	0.909	0.818
3	television	461	849	0.827	0.783	0.652
3	washing mach.	457	279	0.789	0.392	0.329
4	fridge freezer	282	137	0.802	0.471	0.451
4	television	280	2242	0.753	0.675	0.543
4	television 2	280	1657	0.657	0.706	0.332
4	washing mach.	263	81	0.641	0.198	0.168
5	fridge freezer	418	13054	0.734	0.985	0.665
5	lamp	416	322	0.627	0.420	0.193
5	television	417	1297	0.867	0.880	0.710
5	television 2	417	677	0.582	0.561	0.247
5	washing mach.	415	521	0.624	0.396	0.229

ances are shown in Fig. 4. The best prediction results for this type of appliance were achieved for the dryer in house 1 with an AUC of 0.859 and MCC of 0.763. The home with the most predictable dishwasher and washing machine usage is house 2, with AUC 0.856, MCC 0.553 (dishwasher), and AUC 0.809, MCC 0.634 (washing machine). On the other hand, the results for house 0 are AUC 0.684, MCC 0.348 (dishwasher) and AUC 0.591, MCC 0.190 (washing machine). The reason for the performance difference compared to other homes lies in behavior changes of the inhabitants of house 0, which can be shown by comparing the probability distribution $P(D)$ for training and evaluation data (see Fig. 5). While in the dishwasher's training data the first episode of a day has a probability of 0.37, in the evaluation data it is 0.08. The probability densities show that the events where moved to the last episode of the day, an episode with a low probability in the training data. The changes, represented as the mean square error (MSE), between training and evaluation are 0.0462 for house 0 and 0.0033 for house 2. Thus, the preconditioned behavior consistency is no longer given in house 0, a problem which could be overcome by analyzing recent behavior changes and adapting $P(D)$ accordingly. This is a topic for future research.

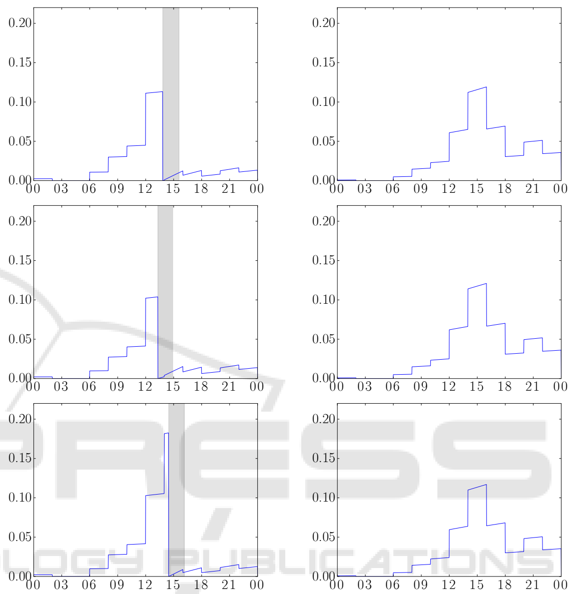
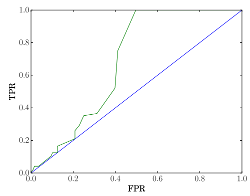
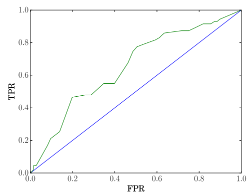


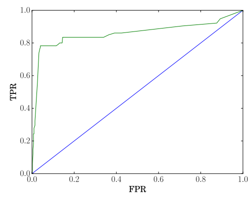
Figure 3: Usage probability prediction and real occurrence for each day of a dishwasher during 2015/2/1 to 2015/2/6 (l.r.t.b). The gray area marks the time the appliance is switched on, the curve the probability of the device being switched on at each minute. For a clearer demonstration, we chose an episode length of 120 minutes; the x-axis is labeled by the hour of the day.



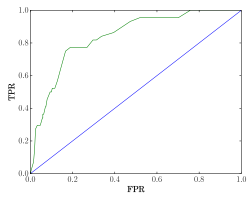
(a) H#0 – dishwasher



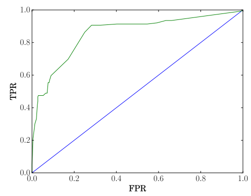
(b) H#1 – dishwasher



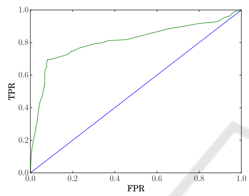
(c) H#1 – dryer



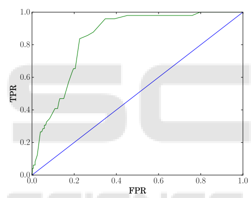
(d) H#1 – washing machine



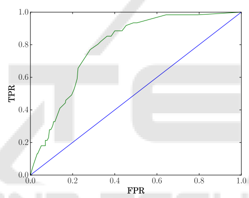
(e) H#2 – dishwasher



(f) H#2 – washing machine

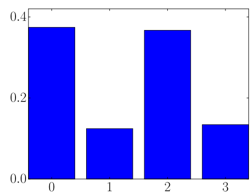


(g) H#3 – dishwasher

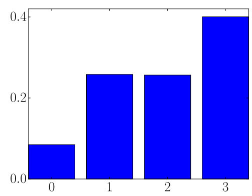


(h) H#3 – washing machine

Figure 4: Examples of ROC curves of the prediction algorithm on the GREEND data set. Dishwasher, washing machine, and dryer were selected as these appliances are particularly suited for load shifting. A perfect classifier would show a rectangular curve, while the main diagonal indicates complete randomness.



(a) training data



(b) test data

Figure 5: $P(D)$ of the dishwasher in house 0 shows significant difference between (a) training and (b) evaluation.

5 CONCLUSION

We presented probabilistic models for appliance usage prediction based on historical energy data. The application we have in mind is to give recommendations to the user (or home automation system), whether switching an appliance on would result in lower energy costs whilst taking into account the appliance's typical usage pattern in the particular household. An important topic for future work is to investigate how to handle long term behavior changes like those found in house 0 of the GREEND data set for the dishwasher, and how to adapt the model over time. The results on the GREEND data set look promising; there are currently no publications available providing results for this kind of application that we could use as a benchmark, as the evaluation method is often invalid due to the accuracy paradox, or the amount of data used for training is insufficiently low to provide reliable results. At the moment, it is not yet clear what the best and most meaningful performance evaluation metric for this sort of prediction problem would be, as in contrast to usual classification problems, the goal is not to predict the *exact* time an appliance is used, but rather give a recommendation at convenient times. We presented our results using the AUC, F_1 and MCC metrics to provide a comparable benchmark for future publications.

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