Mining Sequential Patterns for Appliance Usage Prediction

Mathieu Kalksma[1], Brian Setz[2], Azkario Rizky Pratama[2], Ilche Georgievski[3] and Marco Aiello[2]
[1]*Quintor B.V., Ubbo Emmiussingel 112, 9711 BK Groningen, The Netherlands*
[2]*Distributed Systems, Johann Bernoulli Insititute, University of Groningen, Nijenborgh 9, 9747 AG, Groningen, The Netherlands*
[3]*Sustainable Buildings, Nijenborgh 9, 9747 AG, Groningen, The Netherlands*

Keywords: Appliance Usage Prediction, Energy Consumption Prediction, Sequential Pattern Mining.

Abstract: Reducing the energy consumption in buildings can be achieved by predicting how energy-consuming appliances are used, and by discovering their usage patterns. To mine patterns, a smart-metering architecture needs to be in place complemented by appropriate data analysis mechanisms. These usage patterns can be employed to optimize the way energy from renewable installations, home batteries, and even microgrids is managed. We present an approach and related experiments for mining sequential patterns in appliance usage. We mine patterns that allow us to perform device usage prediction, energy usage prediction, and device usage prediction with failed sensors. The focus of this work is on the sequential relationships between the state of distinct devices. We use data sets from three distinct buildings. The data is used to train our modified Support-Pruned Markov Models which use a relative support threshold. Our experiments show the viability of the approach, as we achieve an overall accuracy of 87% in device usage predictions, and up to 99% accuracy for devices that have the strongest sequential relationships. For these devices, the energy usage predictions have an accuracy of around 90%. Predicting device usage with failed sensors is feasible, assuming there is a strong sequential relationship for the devices.

1 INTRODUCTION

Electric appliances are responsible for a significant portion of a household's energy consumption, having a strong impact on a household's carbon footprint. In fact, according to the U.S Energy Information Administration (EIA), the energy consumption for household appliances, electronics and lighting is responsible for 37% of the total energy consumed by households in 2016 (EIA, 2016). This is an increase of 10% compared to 1993. Since household appliances and other electronics are responsible for an ever-increasing share of a household's consumption, it is important to focus on energy usage optimization efforts in order to meet global greenhouse gases emission goals.

Smart-metering architectures are essential to gain insight into the way energy is used and to predict the future energy consumption. These predictions enable the optimization of energy production and management by smart scheduling of renewable resources and devices. At the consumer end of the spectrum, this means measuring and monitoring the way appliances are utilized and predicting their future usage patterns. With the emergence of the Internet of Things, we expect an increasing number of appliances to be connected to the Internet. These appliances shall be able to provide real-time information on their energy usage as a service. Till then, we can use commercially available electric plug monitoring devices to collect consumption information. The collected information can then be exploited to make predictions about future device utilization and energy consumption. For example, in previous work, we investigated device recognition by means of an aggregated power consumption observed at a single point measurement (Pratama et al., In Press). This type of information is essential for home and building energy management systems, and also has potential for use in smart and micro-grid applications.

In this work, we focus on mining patterns from household appliances and propose an approach based on high-order Markov models to predict: 1) the usage of devices, 2) the expected energy footprint, and 3) the usage of a device with a failed sensor. We focus specifically on the sequence of device states over time, and the patterns that exist there. The model we propose is based on a modified version of

Kalksma, M., Setz, B., Rizky Pratama, A., Georgievski, I. and Aiello, M.
Mining Sequential Patterns for Appliance Usage Prediction.
DOI: 10.5220/0006669500230033
In *Proceedings of the 7th International Conference on Smart Cities and Green ICT Systems (SMARTGREENS 2018)*, pages 23-33
ISBN: 978-989-758-292-9

the Support-Pruned Markov Model (Deshpande and Karypis, 2004) that utilizes a relative support threshold. The results of our experiments demonstrate the viability of the approach, especially for device usage predictions. To verify the validity of the model and the prediction algorithms, we consider three distinct datasets coming from real-world installations. Two data sets are from actual households, and one data set is from an office building functioning as a living lab. We use these data sets to train our model and to evaluate the quality of the predictions.

The remainder of the paper is organized as follows. In Section II, we provide a formal definition of the proposed model and describe the algorithms behind our designed solution. Section III describes the experimentation on three distinct data sets. Section IV presents related work, while concluding remarks are presented in Section V.

2 APPROACH AND PROPOSAL

We aim to discover sequential patterns in the state changes of devices over time, in order to forecast the future state changes and energy footprint. A Markov Model (MM) enables the prediction of future states based on the current state. In MM terms, the current state refers to the current state of the set of devices. The future state represents the predicted state changes for a set of devices, given the current state.

A high-order MM considers more historical actions to predict the future state. In other words, the kth-order MM considers the sequence of the previous k states when predicting the next state. The All-Kth-Order Markov model (Pitkow and Pirolli, 1999) addresses the issue of reduced coverage by looking for a sequence in the k^{th}-order and, if not found, it continues searching the lower orders. The disadvantage of All-Kth-Order Markov models is that the state space expands drastically, as all models from 1 to k have to be trained and stored.

The Support-Pruned Markov Model (SPMM) is based on the All-Kth-Order Markov model (Deshpande and Karypis, 2004). It introduces the concept of pruning in order to reduce the large state space of All-Kth-Order models. The state pruning relies on the observation that a state with low support often has a low prediction accuracy associated with it. Pruning these states increases the overall accuracy and reduces the state-space complexity. States with low support are identified by applying an absolute frequency threshold, ϕ. The frequency threshold is the minimum absolute number of instances in the training set required for a state to be included in the model. If there are less than ϕ instances, the support for the state is too low and it is pruned. As higher-order states often have less support in the training set, these are more likely to be removed, dramatically decreasing the state-space complexity.

2.1 Model Definition

We propose an adapted version of the SPMM in which, instead of an absolute frequency threshold ϕ, a relative support threshold r is applied, inspired by the method described in (Agrawal et al., 1993). Using a relative threshold, we ensure that we do not prune subsequences with a strong relationship. We employ the following definitions:

Devices: Let $\mathcal{V} = \{v_1, \ldots, v_n\}$ be a set of devices. At any given time t, a device has a binary state s, where $s = 1$ and $s = 0$ are equivalent to the device being turned on or off, respectively. The historical data of a device v_i is defined as a set $\mathcal{S}_{v_i} = \{< t_1, s_1 >, \ldots, < t_m, s_m >\}$, where $s_1, \ldots, s_m$ are the historical states and $t_1, \ldots, t_m$ are their corresponding timestamps.

Transaction: A *transaction* τ is defined as a set of devices for which $s = 1$ at a given time t, thus $\tau(t) = \{v_i | \forall i : \mathcal{S}_{v_i}(t) = 1\}$. A set of transactions $\mathcal{T}$ is an ordered set of transactions such that $\forall i, j : i < j, \mathcal{T}_i < \mathcal{T}_j$; all transactions in the set $\mathcal{T}$ are ordered by time in ascending order.

Sequence: Given a set of transactions $\mathcal{T}$, a sequence *seq* is defined as the transitions in time between the transactions $\tau \in \mathcal{T}$. The maximum timespan between the first element in $\mathcal{T}$ and the last element $(\mathcal{T}_0 - \mathcal{T}_{|T|})$ is referred to as m. In this work, m is always denoted in minutes. To further reduce the state space, next to the relative support threshold, a maximum length of a sequence is enforced. Let $|seq| \leq k$, where k is the maximum length of a sequence.

For example, consider the set of devices to be $\mathcal{V} = \{A, B, C\}$, $\tau_1 = \{A\}$, $\tau_2 = \{B, C\}$ and $\tau_3 = \{A\}$, and τ_1 transits to B and C via τ_2 and to A via τ_3. Thus, according to our definitions, the transaction set $\mathcal{T} = \{\tau_1, \tau_2, \tau_3\}$ encompasses all of the following sequences: $\{ABA\}, \{ACA\}, \{AB\}, \{AC\}, \{A\}, \{B\}$, $\{C\}$, $\{AA\}$, $\{BA\}$ and $\{CA\}$.

Support: The relative support of a sequence seq_i is defined as $supp(seq_i) = w(seq_i)/w(seq_i^p)$, where w is a function returning the number of times a sequence occurs in the transaction set $\mathcal{T}$ and seq_i^p is the parent sequence of seq_i. For example, given a sequence $\{A, B, C\}$, the parent sequence is $\{A, B\}$. A sequence is supported if, and only if, the support for that sequence is above r, the minimal support threshold. We use a relative support threshold instead of an absolute support threshold to prevent the pruning of sequences that have a low initial support but a strong relationship with its child sequences.

To illustrate the difference between absolute and relative thresholds, let there be three sequences: $seq_0 = \{A\}$, $seq_1 = \{AB\}$, and $seq_2 = \{ABC\}$. We assume the following number of occurrences after 100 measurements: seq_0 occurs a 100 times, seq_1 occurs 10 times, and seq_2 occurs 9 times. We set the threshold to be $r = 0.1$. The absolute support for seq_2 is 0.09 ($r = 9/100$), whereas the relative support $supp(seq_2)$ equals 0.9 ($r = 90/100$) as seq_2 follows seq_1 90% of the time. If the absolute support were used, seq_2 would have been pruned ($0.09 < 0.1$) despite having a very strong relationship with seq_1. Thus, we choose to use the relative support to prevent the pruning of strong relationships between (sub)sequences.

2.2 Predictive Algorithms

We utilize algorithms to solve the problems of device state prediction, energy consumption prediction, and device state prediction with a failed sensor. We describe each of the algorithms in the following subsections, while a complete definition of the pseudocode for each individual algorithm can be found in (Kalksma, 2016).

2.2.1 Device State Prediction

The device state prediction is a prediction of which devices will be used in the next m time units. To predict the state of devices in the next m time units, we take a stream of real-time transactions and store the last x transactions, such that the time span between $\mathcal{T}_0$ and $\mathcal{T}_x$ is less than m time units. All possible sequences are determined based on the cached transactions. When the model is trained, it predicts which devices will be in the "on" state for the next m time units.

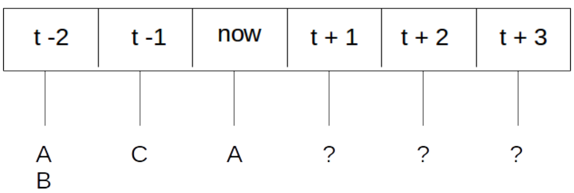


Figure 1: Illustration of a transactions time line.

Figure 1 provides an example of a time line with $m = 3$ time units. The transactions that occurred at $t-0$, $t-1$ and $t-2$ have been cached. At $t-0$ device A is in the on state ($s_i = 1$), at $t-1$ device C is on, and at $t-2$ both device A and B are on. In this case, the possible sequences based on the cached transactions are $\{ACA\}$, $\{AC\}$, $\{A\}$,$\{BCA\}$,$\{BC\}$,$\{B\}$, $\{AA\}$,$\{BA\}$,$\{CA\}$ and $\{C\}$.

For each device a *certainty* $\mathcal{P}$ is determined, which is the probability for a device to be in use given a certain supported sequence. The certainty $\mathcal{P}$ can be defined in two ways: average certainty and weighted average certainty. The average certainty, $\mathcal{P}_{avg}$, is the sum of all probabilities of the supported sequences, divided by the total number of supported sequences. The weighted average certainty, $\mathcal{P}_{wavg}$, is the sum of all probabilities of the supported sequences times a weight w, divided by the number of supported sequences. The methods used to calculate $\mathcal{P}_{avg}$ and $\mathcal{P}_{wavg}$ are referred to as *avg* and *wavg*, respectively. If $\mathcal{P}$ is greater than 0.5, the device is considered to be used ($s = 1$) in the next m time units.

2.2.2 Energy Consumption Prediction

Next, we predict the energy consumption, also referred to as the energy footprint, of a set of devices. The prediction of energy consumption is based on an extension of the state prediction algorithm. The output of the state prediction is used as input for the energy consumption prediction. When a device is predicted to be in use for a given time interval, we predict the energy consumption for this interval. In order to perform these predictions, a second Support-Pruned Markov Model is trained. The model predicts the transitions between the energy consumption levels of a device. The energy consumption levels for each device are defined in bands. For example, an energy consumption band could be $\{0W, 5W, 10W, 30W\}$, where 0, 5, 10, and 30 are the levels we identified for this specific device. The actual consumption measurements are rounded to the nearest band. From these measurements, a Markov chain is created based on the energy consumption measurements of the last $m = 3$ time units.

To predict the future energy consumption of a device, we follow a similar approach to training as we did for the energy consumption model. First, the observed energy consumption measurements are rounded to the nearest band and a sequence is created from the last three measurements. When the state prediction indicates that a device will be used, the energy consumption model is used to retrieve the predicted energy consumption for the given device. Using the current consumption sequence as input, the model predicts the future energy consumption by selecting the most probable sequence. When the input sequence is not available in the model, the algorithm will select the last known consumption as the predicted energy consumption. If the state prediction al-

Table 1: Properties of the data sets used in the evaluation.

Properties	Data sets		
Name	RUG	ECO1	ECO2
Number of devices	5	4	7
Measurement Period	195 days	237 days	245 days
Coverage ($\frac{N_{records}}{N_{minutes}}$)	77.84%	99.64%	98.58%
Training set ($N_{records}$)	131,386	211,619	175,679
Validation set ($N_{records}$)	86,066	120,960	169,860

gorithm concludes that the device will not be used, the lowest consumption band is selected as the predicted energy consumption.

For example, given a device with bands defined as $\{0W, 5W, 10W, 30W\}$, and an actual consumption history of $\{1.2W, 4.3W, 12W, 19W\}$. The historical consumption will be rounded to the nearest band, resulting in the following measurements: $\{0W, 5W, 10W, 10W\}$. The first three measurements ($m = 3$) of the consumptions for this device are $0W$, $5W$ and $10W$. Thus, the state sequence $0-5-10$ is trained with a future state of $10W$. Once the model is trained on a data set, it enables the prediction of the most likely energy consumption for the next time interval for each sequence per device.

2.2.3 Device State Prediction with Failed Sensor

Finally, we predict the state of devices while one of the sensors has failed. The algorithm for this prediction is also based on the algorithm used for state prediction. To verify if the model is still capable of predicting device states when a device is removed or a sensor has failed, the sequences that contain the selected device are ignored when retrieving supported sequences. This simulates the same behaviour of a sensor (or device) failing.

3 EVALUATION

We evaluate our approach on real-world data sets by performing experiments for each type of predictive model: device state, energy consumption, and device state with failed sensors.

3.1 Data Sets

Table 1 shows the properties of the three different data sets from real-world buildings considered in this work: RUG, ECO1, and ECO2. All data sets are adjusted by reducing the original data sets to one measurement per minute. The data sets are further split into a training set and a validation set.

The RUG data set is composed of data collected in our own office building at the University of Groningen, originally set up for the research presented in (Georgievski et al., 2012). It contains power consumption data from five devices, namely a boiler, coffee maker, printer, microwave and TV-screen. The original data set has six power consumption measurements per minute for each device.

The ECO1 and ECO2 data sets are collected from two Swiss households, which are part of the Electronics Consumption Occupancy (ECO) data set (Beckel et al., 2014). ECO1 is the data set of the first household and contains power consumption measurements of four devices: a fridge, washing machine, dryer, and freezer. ECO2 is the data set of the second household and contains power consumption measurements of seven devices: a dishwasher, air exhaust, fridge, freezer, dimmable lamp, TV, and stereo. ECO2 is created from the original household data set by selecting records of seven out of twelve available devices to maintain a trainable density of our data set.

Both RUG and ECO datasets are collected using commercially available Plugwise[1] measurement devices which have a measurement error of about 5%. The missing data in the ECO dataset is handled by replacing a missing value with the last known measurement if there are less than a 100 missing data points (Beckel et al., 2014). In the RUG data set, the missing data is replaced with the value of -1. The RUG dataset uses a sample rate of 10 seconds for each of the sensors. On the other hand, the ECO data sets are both sampled at 1 second intervals. For our experiments, we downsample the RUG, ECO1 and ECO2 data sets to 1 minute intervals in order to provide a fair comparison.

3.2 Experiments & Parameters

In order to optimize our models we have to employ the correct parameters. This section provides a description of the experiments and parameters used for evaluating each of the three different types of predictive models. If the parameters for a certain model type

[1]https://www.plugwise.nl/

Table 2: Bands defined for each device per data set.

Device	Bands
RUG data set	
Screen	$\{0, 100, 200\}$
Microwave	$\{0, 100, 200, \ldots, 1100, 1200\}$
Printer	$\{0, 100, 200, \ldots, 1300, 1400\}$
ECO1 data set	
Fridge	$\{0, 5, 10, 30, 40, 60, 100, 200, 400, 600, 800, 1000\}$
Dryer	$\{0, 5, 50, 300, 350, 400, \ldots, 900, 950\}$
Washing machine	$\{0, 100, 200, \ldots, 2100, 2200\}$
Freezer	$\{0, 5, 10, \ldots, 75, 80\}$
ECO2 data set	
Dishwasher	$\{0, 100, 200, \ldots, 1500, 1600\}$
Air exhaust	$\{0, 5, 10, 30, 40, 60, 100, 200, 400, 600, 800, 1000\}$
Fridge	$\{0, 5, 10, 30, 40, 60, 100, 200, 400, 600, 800, 1000\}$
Freezer	$\{0, 5, 10, 30, 40, 60, 100, 200, 400, 600, 800, 1000\}$
Lamp	$\{0, 10, 20, \ldots, 190, 200\}$
TV	$\{0, 2, 5, 140, 150, 160, 170\}$
Stereo	$\{0, 10, 20, \ldots, 190, 200\}$

are not explicitly given, the parameters from the previously discussed model are reused.

3.2.1 Device State Prediction

We derive a near-optimal configuration by tuning the following parameters: the relative support threshold (r), time-unit length (m), and sequence length (k). We test the impact of each of these parameters in isolation by changing one parameter while keeping the rest constant. The fine-tuning of the parameters was performed on the RUG data set.

The number of supported sequences per threshold value r influences the model complexity; the more supported sequences, the higher the complexity. With only a small threshold ($r < 0.3$), the number of supported sequences drops significantly (to about 355). If trained sequences also include devices that are turned off, the number of supported sequences grows drastically (to about 15,290). The drop in the number of supported sequences has a minimal effect on the accuracy of predictions for all $r < 0.4$, which means the most important sequences are not dropped. When tuning the time-unit length m, we note that the accuracy is best when using either a small value ($m = 5$), or a large value ($m \geq 20$). We test the impact of the maximum sequence length k on the accuracy by using *avg* with $m = 10$ and $r = 0.3$. The test results indicate acceptable accuracy when $2 \leq k \leq 10$ within which range the accuracy stabilizes at $k \geq 5$ with a value of 45%.

To summarize, our configurations consist of $m = 5$ and $k = 5$, and either $r = 0.2$ or $r = 0.4$ depending on the data set. Since there is hardly any difference in the accuracy of predictions between the *avg* and *wavg* methods, we choose to use *wavg*.

3.2.2 Energy Consumption Prediction

We define bands for all of the devices in each data set in order to discretize the measurements. For example, for the screen device in the RUG data set, we specify $\{0, 100, 200\}$, for the freezer in ECO1 and the dishwasher in ECO2, we use $\{0, 5, 10, 30, 40, 60, 100, 200, 400, 600, 800, 1000\}$ and $\{0, 100, 200, \ldots, 1500, 1600\}$, respectively. Only the boiler and coffee maker (RUG data set) are not configured because they are never predicted to be on, thus having empty ($\emptyset$) bands. Table 2 shows the bands for the rest of the devices in all three datasets.

To compare the predicted energy consumption with the actual one, we look for patterns in small fragments of energy consumption data. We use the following standard Mean Absolute Error (MAE) measurement to see how close predictions are to the actual observed value.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |f_i - y_i| \quad (1)$$

where f_i is the prediction at point i and y_i is the actual observation at that moment.

In addition, we also employ the following standard Mean Absolute Percentage Error (MAPE) measurement to observe the accuracy of prediction in percentage.

$$MAPE = \frac{MAE}{\frac{1}{n} \sum_{i=1}^{n} y_i} * 100\% \quad (2)$$

where y_i is again the observed value at point i.

For each device in the data sets, a table is provided which shows the MAE, the average energy consumption, and the MAPE. Lower MAE and MAPE values indicate better results.

3.2.3 Device State Prediction with Failed Sensor

Sensor failures can severely impact the accuracy of certain state prediction methods. Since our approach uses the states of all devices to predict the state of a given device, we expect to be able to handle sensor failures in some cases. Thus, to verify this we dedicate experiments to device state predictions with failed sensors. To simulate a sensor or device failure, we retrieve all supported sequences except those that contain the device being predicted for. Since we know the actual state of the device, we can validate the predictions that were made when excluding this device from the supported sequences. Except for filtering supported sequences, this experiment is performed in the same way as the experiment on device state predictions, allowing us to directly compare the results of both experiments.

3.3 Results

In this section, the results for each of the predictive models are given. First, the results for device state predictions are presented, followed by the energy consumption prediction results. Finally, the results for device state prediction with a failed sensor are given. In several occasions, we use the following statistic parameters:

- Correct: the algorithm predicts a correct state.
- Correct off: the device is off and the algorithm predicts it as off, sometimes abbreviated as Corr. off.
- Correct on: the device is on and the algorithm predicts it as on, sometimes abbreviated as Corr. on.
- Wrong: the algorithm predicts a wrong state.
- Device off: time that a device is in the off state, sometimes abbreviated as Dev. off.
- Device on: time that a device is in the on state, sometimes abbreviated as Dev. on.
- On coverage: the algorithm predicts the device as on and it is on, sometimes abbreviated as On cov.
- Off coverage: the algorithm predicts the device as off and it is off, sometimes abbreviated as Off cov.

3.3.1 Device State Prediction

Table 3 shows comparable results for state prediction on each data set with an overall accuracy of almost 90%. The accuracy for predicting that a device will not be turned on ($> 90\%$) is better than the accuracy for predicting that a device will be turned on (between 65% and 77%). This difference in accuracy can be explained by the amount of time devices are turned on – the longer devices are turned on, the higher the accuracy of predicting devices ‘correctly on’. In general, devices in our data sets spend more time in the ‘off’ state.

Table 3: Overall comparison of the state predictions results.

Statistic	RUG	ECO1	ECO2
Correct	0.8978	0.8892	0.8786
Correct off	0.91	0.9458	0.9628
Correct on	0.6492	0.7707	0.7179
Wrong	0.1023	0.1109	0.1215
Device off	0.8838	0.7145	0.7289
Device on	0.1163	0.2856	0.2712
On coverage	0.2617	0.8713	0.9098
Off coverage	0.9815	0.8964	0.8671

Table 4 shows the state prediction results specific to each device in each data set. At first glance, we notice a high accuracy for the RUG data set, especially for the screen, microwave and boiler. However, when looking exclusively at the ‘on coverage’, the results are not as high. The microwave is the only device whose ‘on coverage’ is greater than 50%, while for the boiler and coffee maker the coverage is 0%.

The results for ECO1 are significantly better. The device with the lowest accuracy, the freezer, has an accuracy of almost 72%. The dryer and the washing machine have an accuracy of 99% and 97%, respectively, which is achieved by the ‘off coverage’ being nearly 100% for both devices, and a decent ‘on coverage’ of 82% and 74%, respectively.

Except for the fridge and freezer, the results for ECO2 also report high accuracy. The issue with the fridge and freezer is their ‘off coverage’ (only 52% for the fridge and even 30% for the freezer), which negatively affects the detection that they will not be used. On the other hand, the air exhaust has a low ’on coverage’, possible caused by the fact that the device is turned on for only 1.2% of the time. Interestingly, the dishwasher is turned on 1.6% of the time, but does have a high ‘on coverage’ of 60%.

Table 4: State predictions results per device for all data sets.

Device	Correct	Corr. off	Corr. on	Wrong	Dev. off	Dev. on	On cov.	Off cov.
RUG data set								
Screen	0.9998	0.9998	0.9334	0.0003	0.9996	0.0005	0.3889	1
Microwave	0.967	0.9734	0.9084	0.0331	0.8861	0.114	0.7895	0.9898
Boiler	0.9691	0.9691	0	0.031	0.9691	0.031	0	1
Coffee maker	0.8077	0.8077	0	0.1924	0.8077	0.1924	0	
Printer	0.7564	0.79	0.4588	0.2548	0.7564	0.2437	0.2544	0.9034
ECO1 data set								
Fridge	0.8764	0.9082	0.8303	0.1237	0.6063	0.3938	0.8621	0.8856
Dryer	0.9922	0.9928	0.9738	0.0079	0.9606	0.0395	0.8238	0.9991
Washing machine	0.971	0.9749	0.9209	0.0291	0.9104	0.0897	0.7397	0.9938
Freezer	0.7173	0.7198	0.7167	0.2828	0.3806	0.6195	0.8993	0.4213
ECO2 data set								
Dishwasher	0.9929	0.9935	0.9364	0.0072	0.9842	0.0159	0.5908	0.9994
Air exhaust	0.9898	0.9903	0.7716	0.0103	0.9886	0.0115	0.1475	0.9995
Fridge	0.6662	0.7733	0.6053	0.3339	0.532	0.4681	0.8244	0.527
Freezer	0.6586	0.6948	0.651	0.3415	0.409	0.5911	0.9106	0.2943
Lamp	0.9852	0.9854	0.9846	0.0149	0.8247	0.1754	0.9303	0.9969
TV	0.8851	0.9962	0.7024	0.115	0.732	0.2681	0.991	0.8463
Stereo	0.9728	0.9914	0.943	0.0273	0.6321	0.368	0.9855	0.9653

3.3.2 Energy Consumption Prediction

Table 5 shows the results of the accuracy of predicting energy consumption. For the RUG data set, the MAPE is 90% of the total average consumption. This is due to the dependency of energy consumption predictions on the state predictions, meaning that the state prediction errors impact the accuracy of energy consumption predictions. Since the state prediction always fails for the coffee machine and boiler, the energy consumption prediction for these is always close to zero. When in use, the coffee machine and boiler use over $2500W$ and $2000W$, respectively. Only these two devices already cause an error of $4500W$ in the predictions when both turned on at the same time. Thus, both, the coffee maker and the boiler, have an MAE which is almost the same as their average consumption values. For ECO1, each device has a MAPE less than 50% of the average consumption with an overall MAPE of 29% of the total average consumption. For ECO2, the air exhaust has a MAE of $3W$, which is an error of 278%. In this case, the MAE of $3W$ should serve as an indication rather than the percentage error because of the low average consumption, which makes even a small MAE to causes a big MAPE. The most interesting results are for the lamp, TV and the stereo with a MAE of only a few Watt and a MAPE of around 10% (notice that these devices have an 'on coverage' in the order of 90%). This indicates that only a few errors are passed on from the state prediction to the energy consumption prediction.

3.3.3 Device State Prediction with Failed Sensor

First, we evaluate how many times the state prediction with a failed sensor is the same as the state prediction. These two types of predictions are in fact the same for about 95% (RUG), 80% (ECO1) and 90% (ECO2) of the time. Next, we evaluate the device state prediction with a failed sensor for each device separately, as shown in Table 6. The results show that predicting device states when a sensor has failed is impossible with the RUG data set; for all devices, our approach is unable to predict the 'on' state correctly. This is due to the very weak sequential relationship between devices in this data set. The results with ECO1 are better. Our approach is capable of predicting the fridge and freezer to be used while the measurement of their power consumption is disabled (simulating a failed sensor). Although the accuracy of their state predictions with a failed sensor is lower than the original state predictions (87% versus 60% for the fridge, and 71% versus 49% for the freezer), the results show that our approach is capable of predicting device states correctly as long as a strong sequential relationships between devices exist. As for ECO2, there are varying results for different devices of which the TV and stereo have the most interesting outcomes. The TV has the same accuracy with a failed sensor, as it has with the original state prediction for 99.98% of the time with an overall accuracy of 88.5%. The stereo has even more accurate results, with an overall accuracy of 89%, and 92% of the predictions simulating a failed sensor are the same as the original state predic-

Table 5: Errors in predicting energy consumption.

Device	MAE (W)	Average Consumption (W)	MAPE
RUG data set			
Screen	0.92	2.1	43.81%
Microwave	28.75	27.67	103.90%
Boiler	35.75	37.22	96.05%
Coffee maker	149.08	152.08	98.03%
Printer	20.58	32.15	64.01%
Overall	227.62	251.23	90.60%
ECO1 data set			
Fridge	9.88	25.74	38.38%
Dryer	3.67	29.59	12.40%
Washing machine	19.89	40	49.73%
Freezer	5.23	18.86	27.73%
Overall	33.48	114.15	29.33%
ECO2 data set			
Dishwasher	11.16	18.01	61.97%
Air exhaust	3.26	1.17	278.63%
Fridge	33.99	48.04	70.75%
Freezer	33.56	49.74	67.47%
Lamp	3.55	27.09	13.10%
TV	2.55	42.22	6.04%
Stereo	1.91	19.48	9.80%
Overall	79.32	205.71	38.56%

tions. There is a strong sequential relationship between the TV and the stereo.

3.4 Discussion

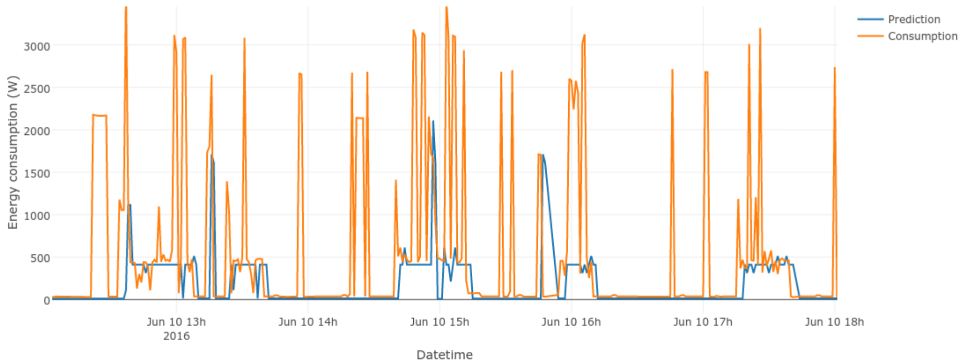
Looking at the results, the approach performs best on devices with *regular patterns*. For state predictions, devices with regular usage patterns are more suitable. For energy consumption predictions, devices with regular patterns of consumption, such as a TV, have higher accuracies. For devices that are rarely used, it is hard to predict their future states or their energy consumption, as a strong sequential relationship is usually not developed. For devices, such as a fridge, that have *cyclic patterns* – run on an automatic schedule instead of being triggered by a user – it is difficult to predict their state with an approach based on Markov chains, thus a different approach is required. Devices with *peak patterns* (e.g., fridge), which do not heavily depend on previous consumption records, have less accurate energy consumption predictions in our models.

For certain devices, it is more accurate to predict when a device will not be used than when it will be used. The reason for this is that such devices are not used most of the time (i.e. not used around 70% of the time), thus it is more likely to guess right. The accuracy of energy consumption predictions depends on the accuracy of the state predictions. This means that errors from state predictions are taken over by energy consumption predictions, which we observed for the coffee machine and boiler in the RUG data set). While we could have filtered the input of the energy consumption prediction model by removing incorrectly predicted states, we decided not to do so in order to create the most realistic scenario.

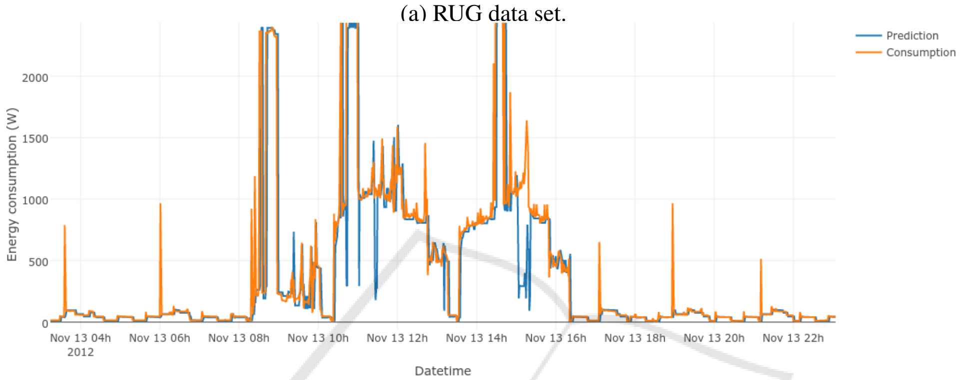
As the number of devices considered by the model increases, the complexity also increases dramatically. Furthermore, the density of data sets also influences the complexity of the model. To optimize the model for training, we prune infrequent sequences from the model. A consequence of pruning the model is that the devices used less often will be removed, making their prediction harder. To overcome the complexity of considering a large number of devices, we can partition the devices. By separating devices that have no relationship whatsoever in separate partitions which have their own models, we can drastically reduce the overall complexity.

4 RELATED WORK

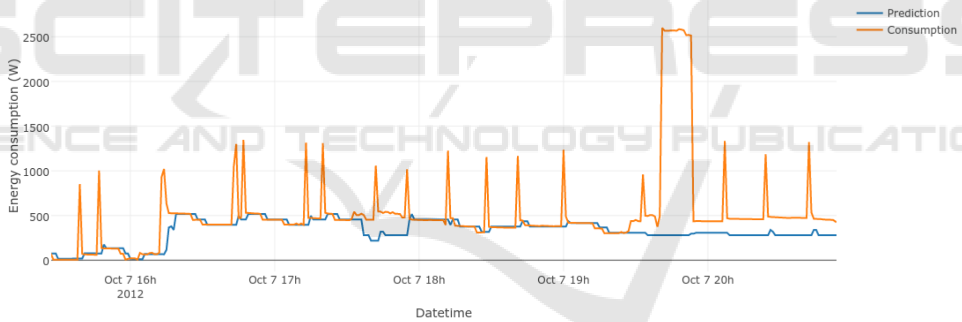
There are numerous studies that consider state and energy consumption prediction for devices. Basu et. al. (Basu et al., 2013) utilize a decision tree, a de-



(a) RUG data set.



(b) ECO1 data set.



(c) ECO2 data set.

Figure 2: Energy consumption prediction for all data sets.

cision table, and a Bayesian Network to predict the device usage for 1 hour and 24 hour intervals. While they report the overall accuracy over 90% for the REMODECE dataset (De Almeida et al., 2006), there is no algorithm that generalizes well for all appliances; the state prediction of lighting devices and oven appliances perform better with the decision table approach, while the state prediction for a washing machine is most accurate when using the decision tree approach.

In (Zhang et al., 2016), Zhang et. al. proposed a method using a weighted Support Vector Machine with a differential evolution algorithm. Their goal is to predict both the short-term and mid-term energy consumption. The results of their experiments show a MAPE of 5.843% for daily predictions and a MAPE of 3.767% for half-hourly predictions. The authors of (Jung et al., 2015) proposed an approach using a Least Squared Support Vector Machine technique for forecasting the daily energy usage of buildings. To optimize the parameters of the model, DSOR-CGA is applied, a hybrid of direct search optimization and real-coded genetic algorithm. They report an average Root Mean Square Error (RMSE) between 7.5994 and 11.1319, depending on the data set used. In (Wang and Ding, 2015), the authors describe an annual occupancy-based energy consumption prediction method for offices, combining a Markov chain and the Monte Carlo method. Their reported error rates vary from 0.99% to 3.95%, depending on the office. The authors of (Li et al., 2015) apply an Artificial Neural

Table 6: Results for state prediction with failed sensor per device for all data sets.

Device	Correct	Corr. off	Corr. on	Wrong	Dev. off	Off cov.	Same prediction
RUG data set							
Screen	0.9996	0.9996	0	0.0005	0.9996	1	0.9998
Microwave	0.8861	0.08861	0	0.114	0.8861	1	0.8932
Boiler	0.9691	0.9691	0	0.031	0.9691	1	1
Coffee maker	0.8077	0.8077	0	0.1924	0.8077	1	1
Printer	0.7564	0.7564	0	0.2437	0.7564	1	0.8649
ECO1 data set							
Fridge	0.598	0.607	0.4071	0.4021	0.6063	0.9563	0.636
Dryer	0.9606	0.9606	0	0.0395	0.9606	1	0.9623
Washing machine	0.9104	0.9104	0	0.0897	0.9104	1	0.9215
Freezer	0.4919	0.3835	0.623	0.5082	0.3806	0.5516	0.6754
ECO2 data set							
Dishwasher	0.9842	0.9842	0	0.0159	0.9842	1	0.9901
Air exhaust	0.9886	0.9886	0	0.0115	0.9886	1	0.9979
Fridge	0.544	0.5619	0.5156	0.4561	0.532	0.6489	0.7482
Freezer	0.5518	0.4458	0.612	0.4483	0.409	0.3952	0.8107
Lamp	0.8247	0.8427	0	0.1754	0.8247	1	0.8344
TV	0.885	0.9959	0.7025	0.1151	0.732	0.8464	0.9998
Stereo	0.8932	0.8763	0.932	0.1069	0.6321	0.9675	0.9177

Network (ANN) to perform hourly predictions of a building's electricity consumption. They apply an improved Particle Swarm Operation to adjust the ANN's structure, weights, and thresholds, ultimately resulting in a MAPE of 0.0162%. They also experiment with a Genetic Algorithm-ANN and report a MAPE of 0.00185%. These results improve the energy consumption prediction using a normal ANN that delivers a MAPE of 0.0211%.

The work of Barbato et. al. (Barbato et al., 2011) is closely related to our presented work. The authors take a probabilistic approach to device state predictions. Devices that were considered in their research include: an oven, TV, boiler, and computer. For these devices, they obtain a state prediction accuracy of 76%, 82%, 94%, and 88%, respectively. To compare our approach to Barbato's approach, we implement their approach and evaluate it on an ECO data set. We choose the ECO2 dataset, as it has the highest reliability: only 3% of the values are missing for the fridge, freezer, dishwasher, TV, and stereo (Cicchetti, 2014). The evaluation of the approach on the ECO2 data set is shown in Table 7. When compared to our approach (Table 4), we can see that in some cases the performance is similar, while in general our approach performs better. Barbato's approach fails to identify when the dishwasher and air exhaust are turned on. For the fridge and freezer the results are closer together, though our approach performs approximately 10% to 15% better. The accuracy of the predictions for the lamp come closest to ours, but once more their approach struggles with the accuracy of 'on' predictions. We observe a similar trend for the TV and stereo.

In Tang et. al. (Tang et al., 2014), the authors also consider the device states and estimate energy usage. Based on the predicted device states, the authors estimate power consumption using the rated power given by hardware vendors. Their main concern is to break the aggregated energy consumption to individual appliance for every timestamp, without learning the sequence of the device activation. Our work differs in the way how energy consumption is predicted, as we focus on individual devices instead of the aggregated consumption.

5 CONCLUDING REMARKS

We proposed an approach based on a modified version of Support-Pruned Markov Models to mine patterns of device usage. We designed experiments involving three data sets that represent real-world environments. We achieved 87% accuracy in device usage predictions over three different data sets. Moreover, the approach is very reliable for devices that exhibit a strong sequential pattern over time, achieving up to 99% accuracy in state predictions. For these selected devices, the expected energy footprint is predicted correctly with only a few Watts of error, resulting in an accuracy of around 90%. We also demonstrated that our approach can handle, to some degree, the us-

Table 7: State predictions results for Barbato *et.al.* approach (Barbato et al., 2011) on ECO2.

Device	Correct	Corr. Off	Corr. on	Wrong	Dev. off	Dev. on	On cov.	Off cov.
Dishwasher	0.9854	0.9854	0	0.0147	0.9854	0.0147	0	1
Air exhaust	0.962	0.9923	0.0155	0.0381	0.992	0.0081	0.0598	0.9693
Fridge	0.5004	0.6292	0.378	0.4997	0.6256	0.3745	0.5175	0.4902
Freezer	0.5146	0.4954	0.5281	0.4855	0.4817	0.5184	0.597	0.4259
Lamp	0.8987	0.9213	0.4768	0.1014	0.901	0.0991	0.2446	0.9706
TV	0.7156	0.835	0.4159	0.2845	0.7635	0.2366	0.501	0.7821
Stereo	0.6213	0.751	0.448	0.3788	0.6659	0.3342	0.5737	0.6452

age predictions of devices for which the sensor havew failed. This is accurate for devices that have strong sequential relationships amongst each other, that is, these devices are often used together, or one after the other. Cyclic and peak patterns, on the other hand, are harder to predict with the proposed approach. This is especially true when there is not a large quantity of data available, therefore cyclic and peak patterns will require a different set of techniques.

ACKNOWLEDGEMENT

Mathieu Kalksma thanks the Distributed Systems Group at the University of Groningen for the opportunity of and support while performing the presented research. The work is partially supported by the Dutch National Research Council Beijing Groningen Smart Energy Cities Project, contract no. 467-14-037.

REFERENCES

Agrawal, R., Imielinski, T., and Swami, A. (1993). Mining associations between sets of items in massive databases. In *Proceedings of the ACM-SIGMOD Int'l Conference on Management of Data*, pages 207–216.

Barbato, A., Capone, A., Rodolfi, M., and Tagliaferri, D. (2011). Forecasting the usage of household appliances through power meter sensors for demand management in the smart grid. In *2011 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pages 404–409.

Basu, K., Hawarah, L., Arghira, N., Joumaa, H., and Ploix, S. (2013). A prediction system for home appliance usage. *Energy and Buildings*, 67:668–679.

Beckel, C., Kleiminger, W., Cicchetti, R., Staake, T., and Santini, S. (2014). The eco data set and the performance of non-intrusive load monitoring algorithms. In *Proceedings of the 1st ACM International Conference on Embedded Systems for Energy-Efficient Buildings (BuildSys 2014). Memphis, TN, USA*, pages 80–89. ACM.

Cicchetti, R. (2014). Nilm-eval: Disaggregation of real-world electricity consumption data. Master's thesis, Swiss Federal Institute of Technology Zurich.

De Almeida, A., Fonseca, P., Schlomann, B., Feilberg, N., and Ferreira, C. (2006). Residential monitoring to decrease energy use and carbon emissions in europe. In *International Energy Efficiency in Domestic Appliances & Lighting Conference*.

Deshpande, M. and Karypis, G. (2004). Selective markov models for predicting web page accesses. *ACM Trans. Internet Technol.*, 4(2):163–184.

EIA (2016). How is electricity used in u.s. homes? https://www.eia.gov/tools/faqs/faq.php?id=96&t=3. Accessed: 29-12-2017.

Georgievski, I., Degeler, V., Pagani, G. A., Nguyen, T. A., Lazovik, A., and Aiello, M. (2012). Optimizing energy costs for offices connected to the smart grid. *IEEE Trans. Smart Grid*, 3(4):2273–2285.

Jung, H. C., Kim, J. S., and Heo, H. (2015). Prediction of building energy consumption using an improved real coded genetic algorithm based least squares support vector machine approach. *Energy and Buildings*, 90:76–84.

Kalksma, M. (2016). Mining household appliances patterns by monitoring electric plug loads. Master's thesis, University of Groningen.

Li, K., Hu, C., Liu, G., and Xue, W. (2015). Building's electricity consumption prediction using optimized artificial neural networks and principal component analysis. *Energy and Buildings*, 108:106–113.

Pitkow, J. and Pirolli, P. (1999). Mining longest repeating subsequences to predict world wide web surfing. *Proceedings of USITS '99: The 2nd USENIX Symposium on Internet Technologies \& Systems*, pages 139–150.

Pratama, A. R., Widyawan, Lazovik, A., and Aiello, M. (In Press). Power-based device recognition for occupancy detection. In *Service-Oriented Computing - ICSOC 2017 Workshop*.

Tang, G., Wu, K., Lei, J., and Tang, J. (2014). Plug and play! A simple, universal model for energy disaggregation. *CoRR*, abs/1404.1884.

Wang, Z. and Ding, Y. (2015). An occupant-based energy consumption prediction model for office equipment. *Energy and Buildings*, 109:12–22.

Zhang, F., Deb, C., Lee, S. E., Yang, J., and Shah, K. W. (2016). Time series forecasting for building energy consumption using weighted Support Vector Regression with differential evolution optimization technique. *Energy and Buildings*, 126:94–103.