Christoph Klemenjak

# On the Modelling, Monitoring, and Detection of Electrical Appliances

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**Evaluator:**
Univ.–Prof. Dr. techn. Wilfried Elmenreich
Alpen-Adria-Universität Klagenfurt
Institut für Vernetzte und Eingebettete Systeme

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## Zusammenfassung

Aus Informationen über den Energieverbrauch eines Haushaltes lassen sich Rückschlüsse auf die vorhandenen elektrischen Haushaltsgeräte als auch auf das Benutzerverhalten der BewohnerInnen ziehen. Besonders das Erfassen von nicht-elektrischen Größen wie z.B. des Verlaufes der Raumtemperatur bietet zusätzliche Einblicke in die Tagesabläufe von Mensch und Maschine. Zu diesem Zwecke wird ein Messsystem benötigt, welches sowohl den Energieverbrauch als auch eine Vielzahl von nicht-elektrischen physikalischen Größen aufzeichnet. Durch die Analyse dieser gewonnenen Daten lassen sich Abläufe optimieren und Kosten reduzieren.

Diese Arbeit umfasst folgende Forschungsbeiträge: Erstens, eine neuartige Klassifizierung von elektrischen Geräten, welche Geräte neben der Anzahl von Zuständen auch anhand der Vorhersagbarkeit deren Verhaltensmustern bzw. deren Verbrauchsprofilen unterscheidet. Zweitens, werden Anforderungen für die jeweiligen Messeinheiten eines verteilten Messsystems wie zum Beispiel Schnittstellen, Messfrequenz, oder Sicherheitsmaßnahmen ermittelt. Im Verlauf dieser Arbeit wird eine Implementierung eines solchen verteilten Messsystems vorgestellt, welches aus einem vernetzten Stromzähler, mehreren Smart Plugs, und einigen vernetzten Umgebungssensoren besteht. Drittens, wird der Matchmaker Detektor vorgestellt, ein Algorithmus zur Geräteerkennung, der neben der Korrelation nach Pearson auch einen in dieser Arbeit entwickelten Tracking-Window Mechanismus anwendet. Um die Performance des Matchmaker Detektors zu eruieren, wird dieser auf Datenreihen des Energieverbrauchsdatensatzes GREEND angewandt. Diese Datenreihen beinhalten Messungen des Energieverbrauchs ausgewählter Haushaltsgeräte über mehrere Monate hinweg. Die Resultate dieser Untersuchung bestätigen eine hervorstechende Performance für Haushaltsgeräte mit vorhersagbaren Verbrauchsprofilen, wie sie zum Beispiel bei Kühlschränken, Geschirrspülern oder auch bei Waschmaschinen auftreten. Im Gegensatz dazu zeigen die Resultate der Auswertung eine unzureichende Performance für Haushaltsgeräte mit nicht-vorhersagbaren Verbrauchsprofilen. Für diese Klasse von Elektrogeräten werden Maßnahmen vorgestellt, um die Performance des Matchmaker Detektors zu verbessern.

Im Großen und Ganzen resultiert aus der Kombination der Beiträge dieser Arbeit ein Messsystem, welches eine kostengünstige Alternative zu kommerziellen Messeinrichtungen darstellt. Im Besonderen wird dies durch den Einsatz von maschinellem Lernen zur Geräteerkennung und durch Anwendung von Techniken der Load Disaggregation ermöglicht.

## Abstract

To analyse user behaviour and energy consumption data in contemporary and future households, we need to monitor electrical appliance features as well as ambient appliance features. For this purpose, a distributed measurement system is required, which measures the entire power consumption of the household, the power consumption of selected household appliances, and the effect of these appliances on their environment.

This thesis contributes to the state of the art with a novel taxonomy for electrical appliances, a distributed measurement system that records and monitors electrical household appliances, and an algorithm, the Matchmaker detector, for appliance detection that utilises correlation filters. The presented appliance taxonomy distinguishes beside the states of operation also, if the shape of a certain appliance feature is predictable or not. Thereby, the consumption behaviour of electrical appliances can be described more precisely. The distributed low-cost measurement system integrates the YaY smart meter, a set of smart plugs, and several networked ambient sensors. The Matchmaker detector utilises a particular appliance feature to detect the respective appliance in consumption data. Therefore, the Matchmaker follows a specific procedure, which exploits the Pearson product-moment correlation. The performance of the Matchmaker detector was assessed on the energy consumption data provided by the GREEND data set. As the results approve, the detector shows a good performance for appliances with predictable consumption patterns such as refrigerators, dishwashers, or washing machines. For non-predictable consumption patterns we introduce a detection policy in order to maximise the performance.

Taking every finding of this thesis into account, the combination of the presented measurement system and the Matchmaker detector provides an efficient low-cost alternative to commercial energy monitoring systems by surpassing them with machine learning techniques, appliance identification methods, and applications based on load disaggregation.

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# Chapter 1

# Introduction

## 1.1 Motivation

At the present day we face the trend of changing housing situations due to demographical developments in our society. Until the year 2100 the European population is expected to decrease continuously [13]. Furthermore the percentage of single-person households is expected to grow in all OECD countries, especially in European countries[45]. As a consequence, innovative forms of compact one-person households are on the rise in order to provide an alternative to larger, expensive rental flats for future households. Of interest will be how this development will influence human biorhythm, consumption habits, presence at home and many other factors. In order to record and identify these changes, a specific measurement system is required that monitors the resident's habits and the consumption behaviour. Data of interest in this kind of instrumentation is the consumed power of day-to-day used household appliances such as domestic appliances, kitchen utensils, and consumer electronics as well as the entire energy consumed by the household. Furthermore, the measurement system should be able to detect present household appliances and their state of operation. By means of this detection, feedback as well as suggestions can be generated in order to achieve energy savings.

## 1.2 Problem definition

The design of a measurement system depends on the type of application and the requirements that follow from it. The objective of this thesis is to introduce a measurement system for households that is able to record electrical and ambient appliance features at several levels of the household's power distribution network and to detect present electrical appliances in the household by means of the recorded appliance features. In order to record the energy consumption of the household, a measurement system can follow three different approaches: A distributed approach, a central approach, or a combination of these. A distributed approach measures consumption at device level, as presented in [34]. To create a consumption profile of a household, several networked measurement units spread across the household are required, as discussed in [42]. Some appliances can't be monitored at device level such as water heaters or stoves. In order to overcome this issue, the analysis of the aggregate power consumption provides an opportunity to monitor such appliances by application of load disaggregation algorithms. A second solution for this problem is the utilisation of ambient sensors, which measure the impact of electrical appliances on their environment. For this reason, a measurement system that aims to record changes in user habits as well as consumption behaviour, has to comprise networked meters, ambient sensors, and device-level measurement devices. To measure the energy consumption and forward the gathered data several smart sensors and smart metering units were designed, as presented in [26], [38], [37], and [8]. All these smart devices integrate a processing unit, a metering unit, and one or multiple networking modules. Furthermore, measurement systems in [29] as well as [35] were applied to record the power consumption behaviour of households. Whether the introduced smart metering units nor the measurement systems in household measurement campaigns were designed to record electrical appliance features such as energy consumption and ambient features such as noise emission at the same time, although the combination of these appliance features may allow to analyse the usage history of devices, number of times a person washes his or her hands, cleaning habits and further more. On account of this, we identify the need for a distributed low-cost measurement system for the monitoring as well as the detection of electrical appliances in households.

## 1.3 Outline of the Thesis

This thesis is organised as follows:

Chapter 2 presents the fundamentals of appliance models. This comprises a novel taxonomy for electrical appliances in Section 2.1, the concept and the different types of appliance features in Section 2.2, learning approaches in Section 2.3, and the Pearson correlation coefficient in Section 2.4.

Chapter 3 presents design aspects, the elements of a distributed measurement system for households in general, and our implementation of a distributed measurement system, and depicts areas of application. The presented design aspects in Section 3.1 include functional and non-functional requirements. Section 3.2 discusses the required elements of a distributed measurement system. Section 3.3 presents our implementation of a distributed measurement system, which integrates a smart meter, smart plugs, and networked sensors. Section 3.4 proposes areas of application for our system.

Chapter 4 presents the concept and the implementation of correlation filters in Section 4.1, introduces and compares different kinds of power consumption patterns in Section 4.2. Finally, the Matchmaker detector and the tracking window mechanism for the detection of electrical appliances is presented.

Chapter 5 presents the evaluation of the Matchmaker detector on an energy consumption data set and summarises the key findings. First, a set of recorded power consumption patterns is examined for noise resilience in Section 5.1. The impact of noise on the detection rate for these recorded power consumption patterns is evaluated in Section 5.2. Section 5.3 presents the findings of the evaluation on consumption data from single appliances and aggregate consumption data.

Chapter 6 concludes the thesis and identifies the key challenges for future research and development.

# Chapter 2

# Fundamentals of Appliance Modelling

This chapter outlines the fundamental principles required for the modelling, monitoring, as well as for the detection of electrical appliances.

First, *appliance models* are introduced. These models classify the power consumption behaviour of electrical appliances by means of their operational states as well as their predictability.

Second, the concept of *appliance features* is presented and selected methods for appliance identification based on voltage, current, and power measurements are discussed.

Third, basic *learning approaches* are presented. Applying machine learning to consumption data of households allows to study the behaviour of inhabitants and present electrical appliances and to generate recommendations and predictions about the monthly energy consumption can be made.

Finally, we explore the *Pearson correlation* as a method to perform detection of electrical appliances.

## 2.1 Appliance Models

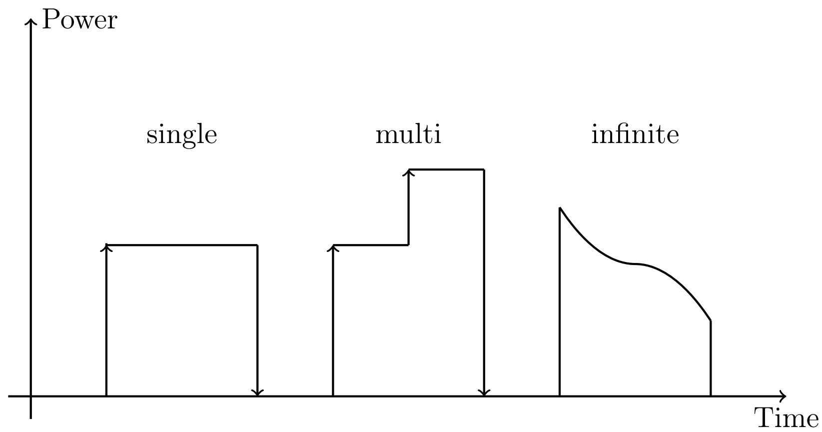



Figure 2.1: Sample power consumption patterns of different appliance types

### 2.1.1 Single-State Appliances

The first appliance model is the *single-state* model. With this model, the power consumption behaviour of household appliances can be described. For example toasters or light bulbs can be modelled within this category of appliances. Such appliances consume one specific amount of power during their operation. For the large part, single-state appliances are purely resistive. The fact that electric power is additive, is exploited when describing a set of single-state appliances. The total amount of power consumed at time-instant $t$ is the sum of all power signals $P_i(t)$, where $P_i(t)$ represents the power consumption of appliance i at time t. The power value is modified by a switching signal $a_i(t) \in \{0, 1\}$ is introduced. Therefore, the switching signal describes which appliances contribute to the total power consumption. The product of the switching signal and the power signal defines the power consumption of a certain appliance. The total power $P_{total}(t)$ can therefore be determined by:

$$P_{total}(t) = \sum_{i=1}^{N} a_i(t)P_i(t) + e(t) \tag{2.1}$$

The additive term $e(t)$ describes the deviation between the actual sum of the modulated power signals and consequently the measured total power. To estimate the state of operation for the respective appliances, the deviation $e(t)$ has to be minimised. In general, the problem with this is that the complete set of power signals $P_1(t)...P_N(t)$ is not known. A second issue is that a high measurement uncertainty in estimating the total power $P_{total}(t)$, can lead to a wrong estimation of the switching signals. A possible bad interpretation may be the assumption, that many appliances turned on or off at the same time. In order to prevent such wrong interpretations, the *Switch Continuity Principle* was introduced in [22]. It states that in a small time interval the number of appliances changing their state is also small. Consequently, we assume that in a small enough time window the number of state transitions is 0 or 1. The sampling frequency of the acquisition unit should be high enough to capture time windows without switching events. Between two such intervals, in which the total power consumption is steady, appliances which change their state can be identified.

### 2.1.2 Multi-State Appliances

A special approach of appliance modelling is represented by the multi-state models. Multi-state models describe the power consumption of electrical appliances by means of finite state machines (FSM). In order to mimic the power consumption behaviour of the appliance, the shape of the power over time is approximated with a finite number of states. At a given moment in time the state machine is in one of these states. Each of these states represents a specific amount of power that the appliance consumes. Depending on the amount of consumed power in this state, the output of the model adjusts the power consumption.

The graphic rendition of such an FSM consists of several circles, each corresponding to a specific state of operation with a well-defined power consumption. At the transition from one state to the other, visualised by an edge, the power draw increases or decreases by the difference in consumption between the two states of operation. For example, let there be a finite state machine model of an electric fire. This model comprises two states of operation, as illustrated in Figure 2.2. State A represents a power consumption of 500 W and state B a power consumption of 750 W. At the transition from state A to state B the power consumption of the appliance increases with an amount of 250 W. Respectively, the power consumption decreases by 250 W from state B to state A. This is analogous to Kirchhoff's law, as the sum of the power changes is zero.

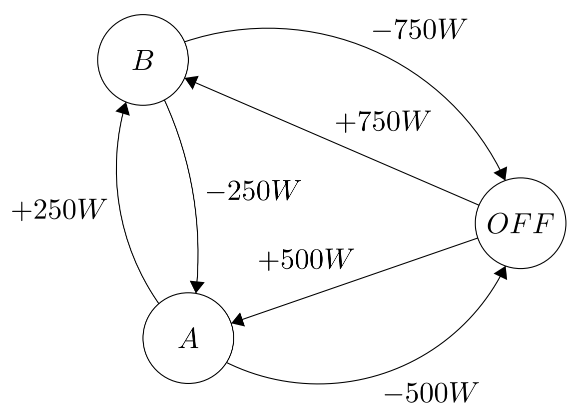



Figure 2.2: Multi-state model of an electric fire

### 2.1.3 Infinite-State Appliances

There exists a third category of appliances beside single-state and multi-state appliances: The infinite-state appliances. The basic difference between this category and the previous ones is the number of states that the model contains. In contrast to single-state and multi-state the number of states in this category is not finite. A telling example for an infinite-state appliance is a light-dimmer. A light-dimmer continuously changes its power consumption with no consistent step change. This characteristic makes it complicated to model and identify this type of appliances. Figure 2.1 shows the power consumption of such a continuously-varying power consumption. Whilst single-state appliances as well as multi-state appliances change their power consumption in one clear and observable step, the power consumption of infinite-state appliances show smooth transitions in the pattern. These transitions may be the result of processes within the appliances such as a discharging capacitor or transient oscillations. These transitions can be approximated by the application of mathematical expressions. The approximation by mathematical expressions represents the first approach to built infinite-state models. The second approach is to generate appliance models from measurement data. Therefore, a measurement device records the power consumption over time and generates an infinite-state model. The power values, which form the model, descend from an infinite set of states. A subclass of infinite-state appliances represent appliances with continuously consuming power consumption such as fire detectors. For this subclass, the power consumption pattern does not define a turn-on or turn-off point in time.

### 2.1.4 Predictable and Non-Predictable Appliances

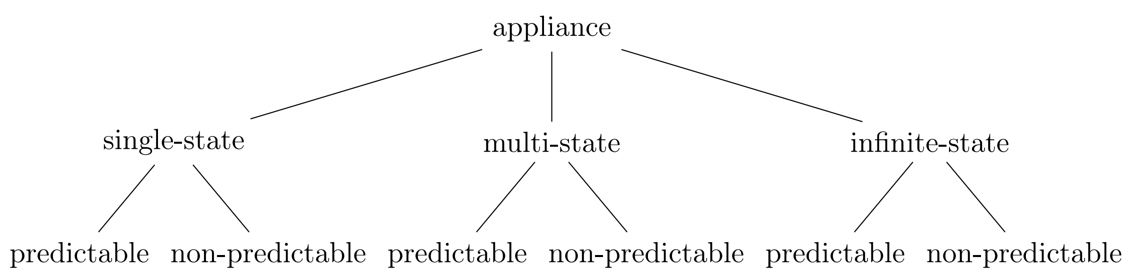



Figure 2.3: A novel taxonomy of appliances

As noted above, appliances can be categorised in single-state, multi-state, and infinite-state appliances. These categories describe the power consumption behaviour of a certain appliance for a single operation. The shape of the power consumption over time for a single operation is referred to as the power consumption pattern. Therefore, the power consumption pattern states the amount of consumed energy as well as the duration of the operation. Furthermore, a power consumption pattern models the behaviour of the respective appliance for a specific programme over time.

For some appliances the power consumption pattern will vary for two operations of the same programme. Such appliances belong to the category of *non-predictable* appliances.

Neither the amount of consumed energy during the operation nor the duration of the operation can be predicted. On the contrary, for a specific group of appliances the power consumption pattern is reproducible. These appliances execute pre-defined programmes with well-defined durations of operation. For this reason this category is referred to as *predictable* appliances.

This distinction in terms of reproducibility i.e. predictability applies to all three appliance models, as Figure 2.3 shows. Single-state, multi-state as well as infinite-state appliances can be further compartmentalised in predictable and non-predictable appliances.

### Predictable Behaviour

The group of predictable appliances represents a specific category of electrical appliances, since the power consumption pattern for every possible programme can be predicted. This means that every predictable appliance comprises a set of programmes, which it is able to execute. This set consists of a finite number of power consumption patterns. Each pattern describes an unique power consumption behaviour i.e. programme of the respective appliance. From this follows that the behaviour of the respective appliance can be described entirely. Furthermore, every possible power consumption pattern can be predicted.

Common household appliances such as dishwashers or washing machines belong to this category. For the sake of an example, let there be a dishwasher with a set of five programmes. If all five power consumption patterns are known, then it is possible to predict the energy consumption for all possible programmes. Furthermore, since all possible programmes are known it is likely that it is possible to detect this appliance.

**Examples** for such appliances are washing machines, dishwashers, tumblers, refrigerators, freezers, coffee brewers.

### Non-Predictable Behaviour

A vast number of appliances does not define a fixed operation duration. This means that neither the energy consumption nor the shape of the power consumption pattern can be predicted. Therefore, such appliances belong to the category of non-predictable appliances. The length of non-predictable power consumption patterns highly varies between two operations. For this reason, the behaviour of such an appliance can't be described by a finite set of power consumption patterns since every operation of the respective appliance results in a novel pattern.

A high number of household appliances is controlled by the inhabitant. For instance the filling level of a water kettle depends on the amount of water that the inhabitant fills into the kettle. The filling level will influence the amount of energy, which the water kettle requires to bring the water to boil. For this reason, the power consumption pattern of each heating process will highly vary from the previous ones.

**Examples** for such appliances are microwave ovens, water kettles, hair dryers, TVs, or lighting.

## 2.2 Appliance Features

Appliance features represent appliance-specific characteristics, which can be utilised for identification as well as classification. In general, appliance features can be seen as measurable parameters, which provide device-specific information extracted from physical quantities. Existing feature taxonomies distinguish features by their voltage-current characteristic [46] or divide features into non-intrusive and intrusive features[22]. Another approach of classification represents the division of features according to their origin. The origin of the feature describes the phase of operation as well as the physical quantity, which evoked this characteristic behaviour.

Features obtained in a steady level of operation are counted among *steady-state features*, features extracted in transition phases between steady states of operation belong to the category of *transient-state features*, and features that describe the impact of appliances on the environment are referred to as *ambient features*.

### 2.2.1 Steady-State Features

Steady-state features comprise extracted characteristics from appliances, which operate at a steady level of power consumption. More specifically, a steady-state feature is the result of analysing the difference in certain characteristics between two steady states of operation. An example for such a characteristic represents the change in power consumption, as was depicted in Figure 2.2. Steady-state features can further be categorised into the following groups:

- **Power Change:** Real and reactive power are physical quantities of great interest, since they provide very characteristic information about appliances. The proportion between real and reactive power that an appliance consumes represents a common metric to detect appliances. In order to perform detection, the power consumption is first determined and then plotted in a P-Q plane, as shown in Figure 2.4. The major difficulty associated with the detection by means of this method is the fact that certain power signatures may *overlap*. This results in a bad detection rate, especially for appliances with a low power consumption. The presented system in [25] utilises this method. With the aid of additional information about the respective appliance, the problem of overlaps can be eliminated. Appliances with a similar power consumption i.e. overlapping points on the P-Q plane can be distinguished by means of analysis of their V-I characteristics. For instance the analysis of the root-mean-squared values of voltage and current provides such vital information.

- **V-I Trajectory:** Another method based on analysis of current and voltage signals is the V-I trajectory. Appliances are classified by means of extracted features from their current and voltage signals. In particular, the shape of these trajectories show highly characteristic features such as asymmetry, looping direction, and enclosed area. An application that utilises this method can be found in [23].

- **Harmonics:** Fourier Analysis provides additional information about the several characteristics of an appliance [22]. Furthermore, the analysis of the current waveform reveals precise details. In particular, it was found that some non-linear ap-

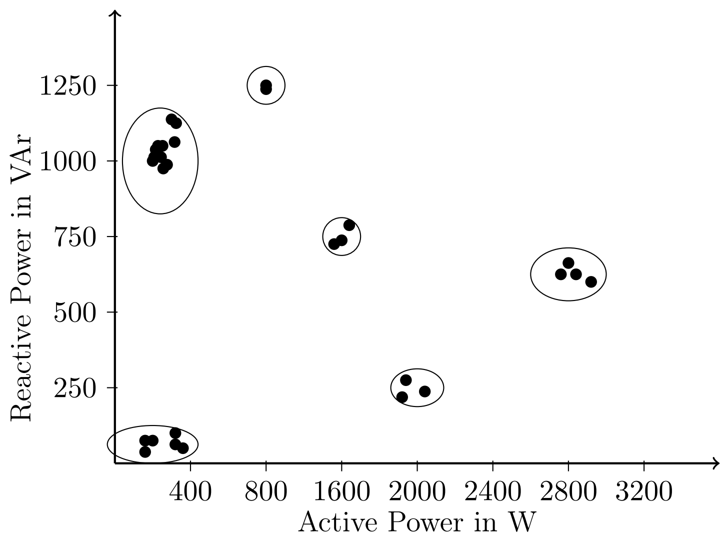



Figure 2.4: Distribution of appliances in a traditional P-Q plane

pliances such as motors or light-dimmers produce current waveforms containing a specific set of harmonics, which can further aid in classification.

Extraction of such steady-state features does not necessarily demand for high-end metering hardware. RMS values of current and voltage as well as frequent power readings provide a good basis to extract steady-state signatures. Already low-cost hardware such as introduced in [26] can be utilised to identify steady-state features.

### 2.2.2 Transient-State Features

Appliances may exhibit familiar steady-state signatures. This may result in identification problems such as discussed for the power change method. Features extracted from transitions between two states of operation provides information to distinguish between appliances. Moreover, transient-state features can reveal unique characteristics of a certain appliance. This may comprise specific turn-on characteristics of the current waveform or an unusually long transient phase. The transient signature is strongly influenced by the physical task the appliance performs [30]. For instance the turn-on current of a computer system differs greatly from a lighting system due to the integrated charging capacitors.

### 2.2.3 Ambient Appliance Features

Both steady-state as well as transient-state features are extracted from the distinct operational phases of an appliance. Transient-state features origin in turn-on, turn-off, or characteristics of transitions between two states. Steady-state features describe characteristics while an appliance operates in a specific state. In contrast to these features, ambient appliance features describe the impact of appliances on their environment. This means that the characteristics are obtained from environmental, ambient, or behavioural sources.

Examples for ambient features represent heat-dissipation or light-emission. Moreover, emitted sound waves (noise) of appliances likewise serve as ambient features. Such ambient features are suggested to be correlated with energy consumption characteristics of appliances in order to perform identification [21]. Environmental sensors serve as collectors of these features [7]. An application that utilises ambient features was proposed in [6]. In this application electromagnetic field detectors (EMF) were deployed. The obtained appliance features were combined with information about energy wastage and power-consumption profiles.

In contrast to information provided by sensors about appliances directly, there exists also the paradigm of Context-Aware Power Management (CAPM) [14]. CAPM techniques typically examine signatures not necessarily extracted from appliances themselves, but from their environment, users or usage behaviour. For instance, [28] explores behavioural patterns including duration of use and time of day. In [28] and [3] it is stated that such contextual information may also include location or even weather patterns. Furthermore, [41] studies appliance-user interaction to facilitate load-disaggregation. The behaviour and presence of human beings is traced by a set of motion sensors in the building and combined with other load monitoring techniques. To gather such ambient data, a wireless sensor network can be applied as demonstrated in [14].

## 2.3 Learning Approaches

Learning approaches for load monitoring can fundamentally be divided into *supervised* and *unsupervised techniques*. The distinction between a supervised and an unsupervised algorithm is whether or not ground-truth data about individual appliance features is available to train the algorithm. If such device-specific information is present, meaning that the algorithm knows *a priori* about the appliances it is monitoring, the learning approach is limited to disaggregation only. On the other hand, an unsupervised algorithm needs not only perform load-disaggregation, but additionally deduce which appliances exist in the circuit it is monitoring.

### 2.3.1 Supervised Learning Approaches

Supervised approaches feed the system with existing device-specific information, such as its power consumption profile. This data may either already exist, such as in the case of the REDD dataset [29], or is the result of an initial training phase, in which a database of appliances and their signatures is collected [1]. All supervised approaches can be divided into:

- **Optimisation**: Obtaining the solution for such problems is well-researched and builds on a simple concept. The extracted appliance features are compared to an existing database consisting of appliance features. When the deviation between the database's entry and the extracted feature can be minimised, the best match is obtained [1]. For a small number of appliances, this approach may very well be feasible. However, as discussed in [16], the performance of this method deteriorates with an increasing number of loads, while the complexity increases. Another weak point of this approach is that it may have significant difficulties in distinguishing between loads with overlapping signatures.

- **Pattern Recognition**: This approach detects appliances by means of clustering and mapping state-changes to a feature space [48]. An example of such clustering is given in Figure 2.4. As outlined by Hart in [22], the identified appliance features in the PQ plane are divided into clusters. Given this initial separation, the clusters are compared to those already known to the supervised system. In further detail, there exist two main approaches: Bayesian classifiers and heuristic methods. For the former, it is assumed that two operating states of an appliance are independent of each other. While research has shown promising results for the Bayesian approach, we note that the independence of states is an ideal but not practical model. For example, an oven may gradually step through lower temperature stages to reach some target value.

### 2.3.2 Unsupervised Learning Approaches

Supervised learning approaches require an initial training phase and input of external, labeled data. Practically speaking, for the average household, such data does not exist. Therefore, unsupervised learning approaches, which are able to operate without a priori information, are a promising alternative. Unsupervised disaggregation techniques are required not only to perform load-disaggregation, but must further train themselves *online*. This means that appliances need to be identified and extracted from the aggregate power signal and their models added to the database of existing devices. The quality of the load-disaggregation is thus additionally dependent on the ability of system to correctly identify existing devices.

Methods of probabilistic analysis such as Hidden Markov Models (HMMs) and extensions thereof are especially suited to this task [1]. An HMM is a probabilistic graphical model that differs from standard Markov models in that the states are not directly observable, but can only be estimated probabilistically given certain observations. For load monitoring purposes, an appliance can be described as an HMM with $n$ hidden states $S = \{s_1, ..., s_n\}$ representing the appliance's states of operation. Also, we define an observation or emission matrix describing the probability for the appliance to be in a certain state $s$ at time slice $t$ given the observation (emission) of an aggregate power consumption signal. Lastly, there exists a transition matrix $T = \{a_{i,j} \leq i, j \leq n\}$ where $a_{i,j}$ represents the likelihood for a transition of the appliance from state $s_i$ to state $s_j$ between two time slices $t$ and $t + 1$. More specifically, $a_{i,j} = P(x_{t+1} = s_j | x_t = s_i)$ with $a_{i,j} > 0$ and $\sum_{j=0}^{n} a_{i,j} = 1$ [27].

Factorial Hidden Markov Models (FHMM) are an extension of the basic HMM. An FHMM models not only a single but many independent hidden state chains in parallel, with the emission (the aggregate power consumption) being thus a function of all states combined. In [16] it is stated that this can help reduce the number of parameters maintained by the system.

## 2.4 Pearson correlation coefficient

The Pearson product-moment correlation provides information about the strength of association between two variables [40]. In particular, in order to test two variables for linear associations the Pearson correlation coefficient is of interest. This coefficient is a measure of the strength of the linear relationship between two variables x and y. The Pearson correlation transforms the two variables into standard scores, which makes it possible to test distinct physical quantities for correlation. The coefficient is defined for a population as well as for a sample. For a given population the Pearson correlation is denoted by $\rho$ and is defined as the ratio between covariance and the product of the standard deviations of the respective variables.

$$\rho = \rho_{x,y} = \frac{cov(x, y)}{\sigma_x \sigma_y} = \frac{E[(x - \mu_x) \cdot (y - \mu_y)]}{\sigma_x \sigma_y} \tag{2.2}$$

By means of substitution of the means $\mu_x$, $\mu_y$ with the sample means $\overline{x}$, $\overline{y}$

$$\mu_x = \overline{x} = \frac{1}{N} \cdot \sum_{i=1}^{N} x_i \quad \text{and} \quad \mu_y = \overline{y} = \frac{1}{N} \cdot \sum_{i=1}^{N} y_i \tag{2.3}$$

as well as the introduction of the summing notation for the standard deviations $\sigma_x$, $\sigma_y$

$$\sigma_x = s_x = \sqrt{\frac{1}{N-1} \cdot \sum_{i=1}^{N} (x_i - \overline{x})^2} \quad \text{and} \quad \sigma_y = s_y = \sqrt{\frac{1}{N-1} \cdot \sum_{i=1}^{N} (y_i - \overline{y})^2} \tag{2.4}$$

we obtain the Pearson correlation for a sample, denoted by r.

$$r = r_{x,y} = \frac{1}{N-1} \cdot \sum_{i=1}^{N} \left( \frac{x_i - \overline{x}}{s_x} \right) \cdot \left( \frac{y_i - \overline{y}}{s_y} \right) \tag{2.5}$$

The Pearson correlation coefficient r is a real number and takes values in [-1,1]. For $r > 0$ the coefficient indicates a positive association, from which follows that an increasing variable x results in an increasing variable y. On the other hand, the Pearson coefficient indicates a negative association for $r < 0$, which describes that the variable y decreases for an increasing variable x. If and only if the coefficient is equal to zero, then there is no linear association between the two variables x and y. The stronger the association between the variables is, the closer to 1 will be $r$. In many applications a decision is made on basis of the correlation‘s strength. The authors of [18] propose a categorisation for the strength of the Pearson correlation: For $|r| = 1$, we declare the correlation **perfect**, for $0.8 \leq |r| < 1$, we declare the correlation **high**, for $0.6 \leq |r| < 0.8$, we declare the correlation **medium**, and for $|r| < 0.6$, we declare the correlation **low**. This categorisation of the strength of correlation will be applied throughout the thesis.

A second correlation method is the Spearman’s rank correlation. The Spearman correlation coefficient represents a non-parametric measure of monotone association. The coefficient states to which degree a monotonic function is able to describe a relationship between two variables [24]. This kind of correlation utilises ranks to compute the correlation coefficient. In contrast to the Pearson correlation, the Spearman correlation does not assume a linear dependency between the input variables. For continuous input data, the authors of [12] report that the Pearson correlation coefficient may have significant advantages over the Spearman’s rank correlation. For this reason, the Pearson product moment correlation is utilised throughout the thesis.

# Chapter 3

# Monitoring of Appliances

The previous chapter introduced appliance models, appliance features as well as other fundamentals related to electrical appliances. For the generation of appliance models as well as for the detection of appliance features measurements have to performed. In order to perform this measurements, a measurement system comprising several instruments is required. In the context of electrical appliances, a wide variety of physical quantities can be monitored since appliances impact the overall power consumption of the household as well as their environment in a specific manner.

This chapter first discusses the design aspects of a distributed measurement system. Such a system aims to monitor the power consumption as well as ambient features of electrical appliances at several levels in the household.

Second, the required elements of such a distributed measurement system are introduced. In particular, the tasks of these elements as well as the expected benefits of their utilisation are presented.

Third, our implementation of a distributed measurement system is presented. The system comprises a smart meter, several smart plugs, as well as networked sensors.

Fourth, areas of application are depicted. These areas comprise the application of the system as an energy advisor in order to provide direct feedback to the residents. A second area of application is to apply the system to generate consumption patterns from measured appliance and ambient features. These consumption patterns serve as templates for appliance detectors such as correlation filters.

Finally, the introduced measurement system is evaluated by means of the presented design aspects. These aspects include non-functional features such as safety, security, and expandability as well as functional features such as measurement requirements, communication interfaces, as well as processing units.

## 3.1 Design Aspects

The design of a distributed measurement system comprises several aspects. These aspects involve the key features it requires to monitor a household's energy consumption as well as environmental impacts of electrical appliances. All these aspects can be divided into two kinds of aspects.

On the one hand, the design aspects include *non-functional* features such as safety, security, and expandability. These aspects include behavioural properties and constraints, which the system has to fulfil.

On the other hand, *functional* features belong to the design aspects as well. Functional requirements describe functionalities, which should be provided by the system. These features involve measurement requirements, communication interfaces, as well as processing units such as embedded linux platforms.

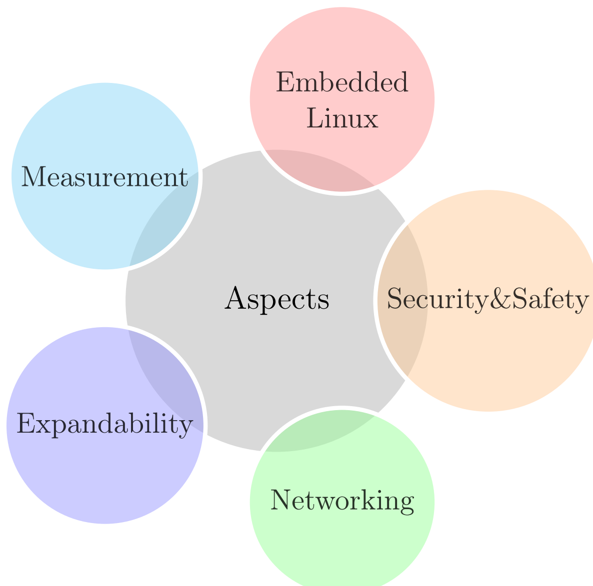



Figure 3.1: Design aspects at a glance

### 3.1.1 Measurement requirements

In order to provide a detailed overview of the household, it is obligatory for a distributed measurement system to measure the energy consumption at several levels in the internal power distribution network as well as characteristic ambient features in the household.

A conventional household provides several levels, at which the power consumption can be determined: At aggregate level, at the level of distribution boxes, and at appliance level.

The aggregate level represents the top level, which equals the feed point of the household. At this level, a measurement device is able to obtain the total power consumption of the household. Therefore, the application of a measurement device at this feed point is of crucial importance since the total power consumption as well as other characteristic physical quantities can be determined. Such characteristic physical quantities comprise parameters that provide information about the state of the grid such as the voltage level or the power line frequency.

Several distribution boxes are located in the household's power distribution network. At this level in the distribution network, a measurement device can determine the power consumption of the respective subnetwork and therefore the accumulative power consumption of several household appliances. This is of special interest whenever a certain appliance is not accessible such as water boilers and for this reason no measurement device can be attached to the appliance in order to measure the power consumption.

The household appliances represent the terminal points of the distribution network. Measurements at this level are referred to as appliance-level measurements since the obtained data describes exclusively characteristics of the respective appliance.

A wide variety of monitored physical quantities allows the generation of precise appliance as well as household models. As a consequence of these precise models, a deep behavioural analysis is possible. From the output of this analysis, predictions as well as recommendations are created in order to decrease the power consumption of the household i.e. to save costs, predictions about the energy consumption can be made, as well as the runtime schedule of household appliances can be optimised. In order to be in the position perform this optimisations, a wide variety of physical quantities at the several levels of the household's power distribution network have to be measured.

- Aggregate level i.e. feed point of the household:
  (i) True root-mean-squared value of the voltage $U_{RMS}$
  (ii) True root-mean-squared value of the current $I_{RMS}$
  (iii) Active power $P$, reactive power $Q$, and apparent power $S$
- At the level of distribution boxes (optional):
  (i) Active power $P$, reactive power $Q$, and apparent power $S$
- At appliance level i.e. for each appliance:
  (i) Active power $P$
  (ii) Ambient features (see Section 2.2.3)

The obtained measurement data is analysed and device features are extracted from it. For this reason, the measured data has to be sufficiently fine-grained. Hence, an adequate *measurement frequency* has to be selected. In the past years multiple energy consumption datasets of contemporary households were published [29], [35], [4]. Many of these datasets provide data sampled with a frequency of 1 Hz. The authors of [16] demonstrated that an unsupervised load disaggregation algorithm is able to detect more than 90% of the household's appliances on data, which was measured with a sampling frequency of 1 Hz. In order to detect short time energy consumption events and changes in the appliance‘s state of operation this specific sampling frequency shall also be utilised as the sampling frequency for electrical quantities in a distributed measurement system.

Another important aspect in the discussion of measurements is the *measurement uncertainty*. On the one hand, available commercial smart meters were shown to have a measurement deviation of 10-20% in [47]. On the other hand, open-hardware platforms such as the OpenEnergyMonitor project also reported a measurement error of 10% and more for appliances with a power consumption of 100 W and below. Data analysis and resulting decisions based on measurement data demand for accurate data. A field study involving appliance-level power measurements with an average error of 5.35% were reported in [34]. For these reasons, we define a maximal limit for measurement uncertainties of 10% for aggregate level measurements and 5% for measurements on appliance level.

### 3.1.2 Expandability

More and more households integrate smart appliances as well as smart measurement devices such as networked thermostats. Such devices themselves measure specific physical quantities and ambient features. Furthermore, these devices provide additional data about the household or the inhabitant. For this reason, a distributed measurement system applied in a contemporary household has to be designed in a way to be *extendable* i.e. an open system. Moreover, the system has to be able to interoperate with devices as well as their services in such a smart household.

Smart devices have to be integrated into the distributed measurement system. Owning to this integration, the devices is able to enhance the system with context-specific data. Examples for such devices are smart tags, networked sensors, smart objects, or additional measurement equipment. In summary, any new smart device in the measurement system enhances the functionality by adding additional input data and features to it. For this reason the system shall be compatible to new devices and provide a general interface to easily integrate other devices as well as support the integration of commercial products.

### 3.1.3 Networking

Smart phones, networked white goods, electric vehicles, entertaining systems, and electronic gadgets of any kind are present in almost any household. These distinct appliances all communicate and exploit a wireless or wired communication technology, but not necessarily all the same standards and protocols. Depending on the application and power consumption the built-in communication technology differs. The challenge for a distributed measurement system under these circumstances is to find a way to communicate with as much household appliances as possible, from simple household devices and smart plugs (smart outlets) to low-power networked sensors across the home. Not all of these devices use the same communication technology for several reasons e.g. to minimise the power consumption by utilisation of a low-power communication standard. For this reason, a distributed measurement system in such a versatile-networked household has to exploit *multiple communication interfaces*. We suggest the utilisation of the following technologies:

- Wi-Fi: Due to the stellar ascent of handheld devices such as smart phones and tablets a wide variety of households are equipped with a Wi-Fi network. From this technology it can be expected that it is also present in future households and due to the defined standards the entire home is covered by this kind of network. Furthermore, even prototyping platforms such as the Raspberry Pi or some Arduino micro controller boards nowadays integrate a Wi-Fi module. Therefore the integration of this technology would allow the measurement system to communicate with a wide variety of appliances and devices.

- ZigBee: A wireless low-power radio communication standard used in home automation. Available smart plugs, smart outlets, as well as low-power appliances integrate this communication technology. Furthermore, networked sensors exploit this standard.

- Bluetooth: Another wireless low-power standard. This kind of technology could also be exploited to read sensor values from low-power devices, networked sensors, or smart phones.

- Industrial standards: The measurement system should also be able to communicate with the devices in the main distribution board. Devices of interest in the distribution board are the smart meter and circuit breakers. A common communication standard for such devices is the EIA-485. This protocol allows the system to read the smart meter and control the circuit breakers.

### 3.1.4 Safety & Security

In the context of energy consumption measurements particularly two different aspects have to be considered: Security related to software and networking on the one hand and safety when dealing with the measurement hardware on the other hand.

The respective communication standard exploited by the application defines security measures such as encryption or key authentication to prevent network sniffing, eavesdropping, and unauthorised access to the network. A simple but effective concept is the utilisation of a master device in the network that generates key pairs and regulates the access to the network. Only if a device is registered at the network, it is allowed to contribute data to the measurement.

In terms of hardware the objective is a different one. Every self-designed system's component has to be galvanically isolated from the mains potential in order to make the device touch-safe and guarantee that failures and peaks of the mains cannot result in distortions in the measurement or even damage the measurement equipment. Especially important regarding safety is that every device the user may contact intended or unintended has to *satisfy safety regulations* such as the Conformitè Europèenne CE.

### 3.1.5 Embedded Linux

Especially the design of distributed measurement systems faces a trade-off between hardware cost and benefits. On the one hand residents are not willing to make large investments into measurement hardware and on the other hand the residents expect the measurement system to support a wide variety of services such as data analysis tools, load disaggregation algorithms, and energy-advice programmes to ensure energy savings. In order to provide such services to the residents, a data processing unit is required. Embedded linux platforms represent such processing units. Moreover, such platforms are a low-cost alternative to desktop computers since their architecture is very similar to traditional computers and the utilised operating system is a light-weight version of conventional linux distributions such as Debian or Fedora. In addition, embedded linux platforms have a price below 50€, hybrids platforms with an integrated micro controller cost less than 100€. Embedded linux platforms support a wide variety of software packages for scientific computing as well as high-level programming languages such as Python or Java, which are required to perform data analysis and data processing. Since the release of the Raspberry Pi[1] and the associated public interest in small and low-cost embedded linux platforms multiple such devices were published, such as: the beagle board[2], the Udoo platform[3], or the Arduino Yun[4]. All these platforms are small enough to be integrated into a DIN rail enclosure, which is also used for conventional earth leakage circuit breakers in the distribution board. This allows the installation of such platforms in the distribution board. Hence, the device is able to read measurement devices e.g. smart meters as well as control earth leakage circuit breakers or similar devices in the distribution board.

For these reasons, we propose to consider *embedded linux platforms* in the design of a distributed measurement system since such platforms provide a low-cost alternative to traditional computers. Furthermore, such platforms provide the required software packages in order to perform data processing and can be installed in the household's distribution board.

[1]https://raspberrypi.org/
[2]https://beagleboard.org/
[3]http://www.udoo.org/
[4]https://arduino.cc/en/Main/ArduinoBoardYun

## 3.2 Elements of a Distributed Measurement System

The introduced design aspects illustrate the need for different kinds of measurement devices to obtain a wide variety of physical quantities. Therefore, the elements of a distributed measurement system comprise a smart meter, smart appliances, smart plugs, as well as networked sensors. These elements contribute different kinds of measurement data to the system. The *smart meter* monitors the entire power consumption at the household's feed point in the distribution board. *Smart appliances* on the one hand consume energy and represent household appliances, but monitor their power consumption and provide the obtained data to the system on the other hand. Traditional household appliances are equipped with *smart plugs*, which measure their power consumption. *Networked sensors* are applied in order to record the impact of appliances on their environment i.e. ambient features.

### 3.2.1 Smart Meter

The smart meter is the successor of the conventional electricity meter, which serves as meter for electricity billing since decades. The main purpose of a smart meter is to monitor the household's electricity consumption and transmit the readings to the electricity supplier. Consequently, the smart meter represents a gauged measurement instrument equipped with communication technology. The majority of installed smart meters integrate an EIA-485 interface. This industrial communication standard allows devices to communicate with the smart meter. Moreover, the energy consumption as well as other measured physical quantities can be read via this interface. As demonstrated in [36], a commercial smart meter can be integrated into a distributed measurement system by the EIA-485 interface. An embedded linux platform was utilised to read the smart meter.

The current form of smart meters, the composition of a power meter and communication technology, merely represents a networked meter. Researchers in [33] presented requirements for a new type of smart meter, the cognitive meter. The key idea is to add cognitive abilities to the meter in order to perform load disaggregation and other data analysis techniques. We reinforce the need for a smart measurement device, which is able to gather measurement data, process the gathered data, and draw conclusions from the obtained results. For this reason, the smart meter represents the measurement system's centrepiece and serves multiple purposes:

First, the smart meter measures the household's energy consumption at the feed point. The feed point represents a crucial point of measurement, since obtained data at this point allows conclusions about every single appliance in the household. Therefore, the smart meter has to measure the energy consumption at this point with the maximum sampling frequency that the smart meter is able to apply in order to provide sufficient data granularity.

Second, the smart meter transmits the energy consumption to the electricity supplier in a certain interval. On the one hand the smart meter has to integrate the required communication technology to serve this purpose and on the other hand the smart meter has to be able to communicate with the other measurement devices as well as smart appliances in the household. Furthermore, the smart meter shall gather the obtained measurement data from the remaining measurement devices in the measurement system.

In order to collect the measurement data, the smart meter has to integrate the respective communication technologies. On the contrary, a service-oriented communication could also be applied, such as introduced in[17].

Third, the smart meter has to be able to interpret the obtained data, draw conclusions from it, and give recommendations to the residents. In order to fulfil this purpose, a processing unit is required. This processing unit has to able to process the gathered data. For this reason, the smart meter shall integrate an embedded processor with accordingly firmware. Software packages that could be integrated in such a firmware are energy advisors, such as presented in [36]. These software tools analyse measurement data and create advises for the residents, which shall result in energy savings.

A final aspect concerns renewable energy systems such as photovoltaic cells. The smart meter shall be aware of such systems in the household and modify the runtime schedule of certain appliances due to the amount of obtained energy from the renewable energy source.

### 3.2.2 Smart Plugs

Contemporary household devices are not aware of their own power consumption. Consequently, the power consumption of these appliances has to determined by the application of measurement devices. A general approach is to attach measurement devices such as smart plugs or networked sensors. The former ones consist of a measurement unit, a network interface, and an element to switch the appliance (relay). In order to measure the power consumption of a certain appliance, a smart plug is attached between the power socket and the appliance. This kind of measurement is called intrusive measurement. Therefore, the smart plug monitors only the power consumption of the attached appliance. As a consequence of this kind of installation, the smart plug is able to switch the respective appliance and therefore control it. The smart plugs serve as measurement devices to monitor the power consumption of specific appliances and transmit the obtained data to the smart meter in a certain interval. This kind of measurement data is of special interest in the training phase of machine learning algorithms since the measurement data of a certain smart plug exclusively describes the power consumption of a certain appliance over time. Moreover, power consumption patterns can be created with the aid of such measurement data. Power consumption patterns are applied in correlation filters in order to detect active appliances.

### 3.2.3 Smart Appliances

Smart appliances represent important elements in the scenario of future smart buildings. A smart appliance can be defined as an appliance augmented with measurement and networking units, which follow certain design guidelines [17]. In contrast to old-fashioned appliances, smart appliances are aware of their state of operation as well as of their power consumption. These kind of appliances are able to provide information about their energy consumption as well as other device-specific information to other devices in the network. Furthermore, smart appliances are able to react to environmental influences such as changing temperature or the presence of the user. Present smart appliances in the household shall report their energy consumption as well as obtained environmental data to the smart meter. The process of reporting can for instance be implemented by the utilisation of web services.

### 3.2.4 Networked Sensors

Not all appliances can be equipped with a smart plug in order to record distinctive features of the respective appliance. For some smart plugs the maximum current of a certain appliance may be too large or the appliance itself may not be accessible such as an instant water heater. To overcome this issue networked sensors are applied, which record environmental data.

In [15], an evaluation for smart sensors in smart homes can be found. Also, [7] suggests to collect data from environmental sensors. The gathered information shall improve the training of supervised learning for non-intrusive load monitoring in their system. A special case of environmental sensors was discussed in [6]. The deployment of electromagnetic field detectors (EMF) was suggested to combine information about energy wastage with the appliance power consumption profile. Exploiting the sound waves (noise) that are emitted by appliances was discussed in [21], suggesting to correlate information about energy consumption with sound recordings of the specific appliance. This method shall help identify the state of operation. These examples show the potential of the application of networked sensors and possible approaches to enhance a measurement system with sensor data. A further concept related to networked sensors is context-aware computing as in [14] or [43] presented. The basic idea is to consider contextual information about the appliances. For instance details about the location, time of day as well as time records about appliance usage. The challenge here is to interpret the information provided by the sensors to estimate the power consumption of the respective appliance. As an alternative to networked sensors entire (wireless) sensor networks could be deployed to gather context-specific information as presented in [9] and [41].

The related work shows the possible advantages of environmental data obtained by networked sensors. These sensors are attached to a certain appliance or are placed in the appliance's environment. Depending on the appliance, the networked sensor records light or noise emission, vibrations, heat dissipation or motions. The networked sensors transmit these recorded ambient features to the smart meter.

(a) YoMo Smart Metering Board (b) devDuino Sensor Node (c) Plugwise Home plug

Figure 3.2: Measurement devices for energy and environmental sensing

## 3.3 A Distributed Measurement System

In the previous sections we discussed the design aspects as well as the elements of a distributed measurement system. The purpose of such a measurement system is to measure the power consumption as well as the ambient features of electrical appliances. Through interaction and the exchange of measurement data applications such as smart metering, cost and load forecasting as well as appliance tracking shall be possible. The measurements system we propose consists of three distinct components:

- The *YaY smart meter* comprises a smart metering board as well as an embedded linux platform. The YaY represents the system's centrepiece since it records the energy consumption at the household's feed point, gathers measurement data from the other measurement devices, and utilises an energy advisor tool to provide feedback. To measure the energy consumption of the household, the YaY utilises the YoMo smart metering board, illustrated in Figure 3.2(a).

- The measurement system integrates a set of *Plugwise Home smart plugs*. Figure 3.2(c) shows such a smart plug. These smart plugs are attached to certain appliances and forward their obtained measurement data to the YaY smart meter.

- Several *devDuino sensor nodes* are applied to monitor the ambient features of electrical appliances. Figure 3.2(b) shows such a sensor node. In order to measure these impacts on the environment, the sensor nodes are equipped with different kinds of sensors such as Piezo sensors, temperature sensors, or sound sensors. The sensor nodes transmit the recorded features to the YaY smart meter.

In the following we will introduce the components of the measurement system, present areas of application, and discuss advantages, disadvantages, as well as limitations of the components.

### 3.3.1 YaY - Smart Meter

The YaY (YoMo and Yun) smart meter represents the main component of the distributed measurement system. The YaY smart meter fits into a conventional DIN rail enclosure, which is also used for residual earth leakage circuit breakers. Therefore, this special kind of measurement device can be installed in the distribution board. By application of an EIA-485 adapter, the YaY smart meter is able to communicate with other devices in the distribution board. Such devices can be circuit breakers or commercial smart meters. As Figure 3.3 shows, the YaY comprises a YoMo smart metering board[5] to measure energy consumption, an Arduino Yun micro-controller board to process measurement data, and a ZigBee module to communicate with the Plugwise Home plugs.

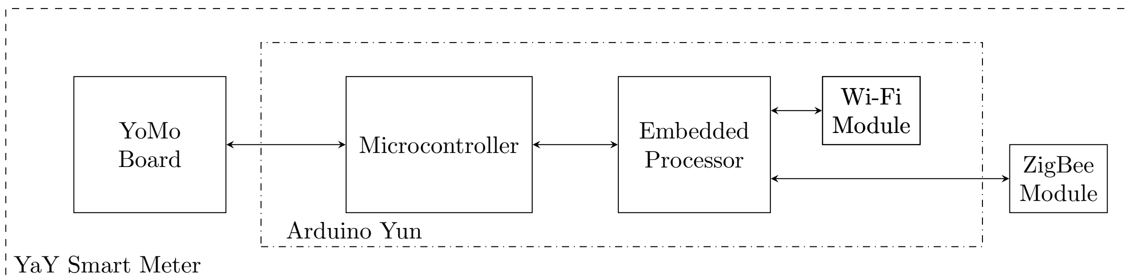



Figure 3.3: Components of the YaY smart meter

The YoMo smart metering board is an extension unit for Arduino micro-controller boards. Figure 3.2(a) shows the metering board. As the figure shows, integrates the YoMo beside components required for measurements also a relay. This relay serves as element to switch the connected appliances. The integrated measurement components provide galvanically-isolated measurements of voltage, current, as well as active, reactive, and reactive power at the mains [26]. The maximum sampling frequency of the YoMo is 5 Hz. Table 3.1 summarises the main specifications including a maximum measurement error of 3.8% for active power measurements. The maximum electrical load that can be monitored to the YoMo is 4.6 kW at 230 V.

The components as well as the interfaces of the YoMo are depicted in Figure 3.4. The key component for measurements represents the energy monitor IC. This integrated circuit computes the level of several physical quantities from the output signals of the voltage sensor and the current sensor. The utilised IC is the ADE7753[6], which implements the serial peripheral interface (SPI). The Arduino Yun reads the measurement results via this interface. Beside the SPI interface, the YoMo integrates several pins for input output operations. Phase in and Phase out indicate the connections for the live conductor. SAG and IRQ represent pins utilised for interrupts. The SAG pin serves as pin for line voltage sag detection. The status of the interrupt request IRQ pin indicates if an interrupt occurred in the ADE7753. The supply voltage is represented by the VDD pin, EN represents the enable pin for the relay.

[5] http://yomo.sourceforge.net/

[6] http://analog.com/media/en/technical-documentation/data-sheets/ADE7753.pdf

| Feature | Abbreviation | Value |
|---|---|---|
| Supply voltage | $V_{dd}$ | 5 V |
| Max. current | $I$ | 20 A |
| Max. input voltage | $V$ | 400 V |
| Max. sampling frequency | $f_s$ | 5 Hz |
| Max. measurement error | $\sigma_P$ | 3.8% |
| Max. measurement error | $\sigma_Q$ | 8.3% |
| Max. measurement error | $\sigma_S$ | 4.04% |
| Internal resistance | $R_i$ | 300 mΩ |
| Power consumption | $P$ | 2 W |

Table 3.1: YoMo Metering board specifications

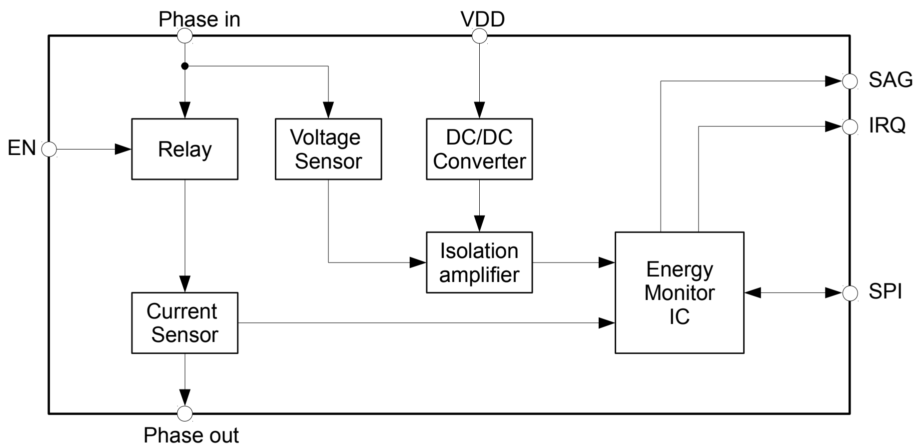



Figure 3.4: Components and interconnection of the YoMo smart metering board

The Arduino Yun is a special kind of embedded hardware that integrates an 8-bit micro controller ATmega32U4 as well as an Atheros AR9331 processor. This unique combination of a micro-controller and an embedded processor makes it possible to execute simple sequential control tasks as well as programs written in high-level programming languages with the same piece of hardware. This corresponds to the way the tasks are divided between the micro-controller and the embedded processor in the context of the application as smart meter. The integrated micro-controller reads the measurement data from the YoMo metering board, reacts to occurring interrupts of the energy monitor IC, controls the relay of the YoMo, and forwards the obtained measurement data to the embedded processor. The embedded Atheros processor is responsible for networking, data processing, as well as data acquisition from the other measurement devices. The most important task is to take over measurement data from the micro-controller as well as the other distributed measurement devices and gather them in a database. The distributed measurement devices form a radio network, which is established and maintained by the Atheros processor. This radio network comprises the networked sensors and the smart plugs, which are attached to certain appliances. The software tools to fulfil this tasks are integrated in the embedded linux distribution Linino[7], which the embedded Atheros processor operates.

The operating system Linino shares a big number of software packages with conventional Linux distributions for desktop computers such as Debian or Ubuntu. These software packages comprise the database management system MySQL, the high-level programming language Python, and the Apache HTTP server. In particular, the database management systems are of great interest for this application, since a big amount of data has to be expected. Therefore, YaY integrates a MySQL database system, which stores the obtained measurement data. The measurement data comprises the aggregated power consumption data provided by the YoMo, the appliance-level power consumption measured by the smart plugs, as well as environmental data received from the networked sensors. This database can be accessed by software tools such as energy advisors in order to draw conclusions from the gathered consumption data.

### 3.3.2 Plugwise Home - Smart Plugs

The application of smart plugs allows the measurement of power consumption at appliance level. From these measurements, precise appliance profiles can be obtained. The introduced measurement system utilises several Plugwise Home plugs[8]. These networked measurement plugs comply with the KEMA Keur safety certificate (number 211754) and fulfil standards such as the IEC 60884-1:2002. This standard regulates the design and conditions for plugs and outlets in households.

The utilised smart plugs communicate via a ZigBee radio network, which is maintained by one of the plugs. The plugs measure the power consumption of the attached appliances simultaneously. For this reason the integrated clocks have to be set initially and are synchronised every hour. The measurement results are forwarded to the YaY smart meter via radio communication every time a new sample is available.

The maximum current for such a Plugwise Home plug equals 16 A. From this follows, that the connected appliance has to be a single-phase appliance and has to have a nominal power consumption less than 3.84 kW.

Table 3.2 summarises the specifications as well as the relevant maximum ratings of the utilised Plugwise Home plugs. One of these specifications is the measurement accuracy $\sigma_P$, which represents the accuracy for measurements with a sampling frequency of 1 Hz. This sampling frequency also represents to the maximum sampling frequency. The measurement accuracy for cumulative measurements over the period of 1 hour equals 1%.

The smart plugs can only be attached to single-phase appliances. Therefore, multi-state appliances have to be monitored by the application of non-intrusive techniques such as load disaggregation.

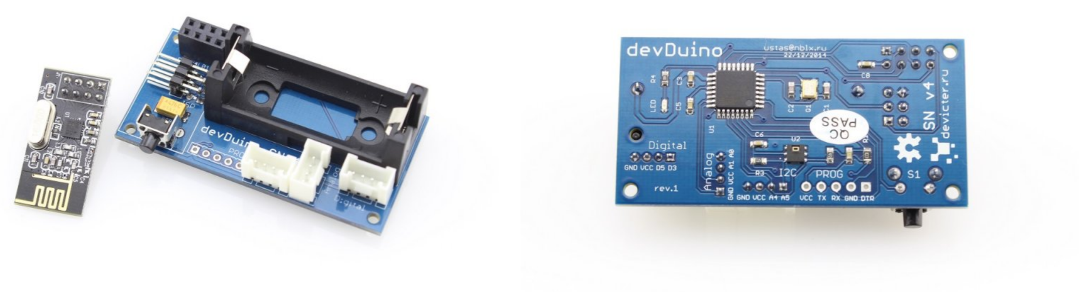
[7]https://linino.org/

[8]https://www.plugwise.com/home-basic

| Feature | Abbreviation | Value |
|---|---|---|
| Supply voltage | $V_{ac}$ | 230 V |
| Max. current | $I$ | 16 A |
| Max. input voltage | $V_{in}$ | 240 V |
| Max. sampling frequency | $f_s$ | 1 Hz |
| Measurement accuracy | $\sigma_P$ | 5% |
| Internal resistance | $R_i$ | 300 mΩ |
| Power consumption | $P$ | 0.55 W |

Table 3.2: Plugwise smart plugs specifications

### 3.3.3 DevDuino - Networked Sensors




(a) Top side of the sensor node

(b) Bottom side of the sensor node

Figure 3.5: The DevDuino sensor node

The integration of environmental networked sensors and wireless sensor networks in the distributed measurement system allows to monitor the impact of appliances on their environment in form of ambient features such as light and sound emission, vibrations, or heat dissipation. Moreover, these ambient features make context-aware computing possible. Context-aware computing can be applied in order to estimate the power consumption of inaccessible appliances and in particular enhance the functionality of the entire system.

Our distributed measurement system integrates several DevDuino sensor nodes[9], which fulfil the purpose of networked sensors. Figure 3.2(b) shows the DevDuino sensor. These sensor nodes can be configured as single networked sensors or form a sensor network. The DevDuino node comprises an ATmega328 micro-controller as well as a low-power radio transceiver nRF24L01+. The node integrates the HTU21D sensor, which serves as temperature as well as humidity sensor. Moreover, up to three environmental sensors can be connected to the sensor node, as Figure shows 3.5(a). These sensors are:

- Piezoelectric sensors: Some appliances emit vibrations at a certain state of operation. These vibrations can be measured by sensors that exploit the piezoelectric effect.

[9] http://wiki.seeedstudio.com/wiki/DevDuino_sensor_node

- Temperature sensors: Household appliances such as electric fires show a high amount of heat dissipation. For this reason, a sensor node equipped with a temperature sensor is able to measure the temperature flow in the surrounding of the respective appliance.

- Sound sensors: Domestic appliances such as blenders, vacuum cleaners, or coffee machines emit a characteristic noise. This noise can serve as ambient feature in order to detect appliances. The utilisation of sound sensors allows to record this special kind of ambient features.

- Luminance sensors: On the one hand allow luminance sensors the detection of light-emitting appliances such as lighting or television sets. On the other hand provide luminance sensors additional information about the environment. For instance the amount of sunlight in the respective room can be determined by application of this sensors. As a consequence of this, the intensity of the lighting can be adjusted to the daylight.

- Gyroscope sensors: A special category of sensors can also be attached to particular appliances. For instance gyroscope sensors can be applied to track motions.

The sensor node defines the sampling frequency, which is applied in the measurement of the ambient feature. The maximum sampling frequency equals 1 Hz. The obtained data is forwarded to the YaY smart meter, which stores the sensor readings.

Beside the support of multiple sensors per device the DevDuino nodes provide another feature of interest, mesh networking. This allows the sensors to form a network, which allows the sensors to be distributed widely in the building. The application of such a sensor network in a household allows to detect and to record influences of certain appliance in a wider sense. This allows the recognition of the purpose, for which the appliance is utilised.

## 3.4 Area of Application

The introduced measurement system collects and stores power consumption as well as environmental sensor data. Consequently, the system can be utilised in order to create energy consumption datasets, which include aggregate-level, appliance-level, as well as ambient data. Such datasets represent ground-truth data for the evaluation of energy management systems as well as appliance detection. Apart from the application as system to create energy consumption datasets we identify two specific applications in the research domain of sustainable smart buildings for our distributed measurement system.

First, the combination of the measurement system and an energy-advisor software tool results in an *energy advisor system*, which is able to deliver device-specific feedback to the resident and provide recommendations in order to achieve energy savings.

Second, the measurement system records appliance-specific characteristics at several levels in the household. These characteristics are recorded at several levels of a household's power distribution network and can be utilised to *generate appliance models.* Appliance models are applied in detection algorithms in order to detect appliances as well as their state of operation. Such detection algorithms can be utilised by load disaggregation algorithms to detect present appliances.

### 3.4.1 Energy Advisor

The distributed measurement system collects and stores appliance data. In order to analyse and interpret the collected data, a specific software tool is required. Energy advisors represent such a software tool. This kind of software tool provides direct feedback as well as recommendations to the residents. Already direct feedback can achieve energy savings up to 10% [3]. To provide such functionality (open-source) energy advisors such as Mjölnir[10] were created [36]. In particular, Mjölnir represents a software framework, which consists of several widgets. These widgets serve to illustrate consumption and production data, give detail about the current energy tariff, show real-time data of the present appliances as well as display current energy consumption events in form of a timeline widget. In general, the widgets display advices and recommendations based on the data, which they read from the measurement database. This database is filled and updated by the distributed measurement system. Therefore, the database contains measured consumption data of the YaY smart meter, the Plugwise Home plugs as well as ambient features recorded by the networked sensors. In general, Mjölnir distinguishes between data from aggregate-level measurements and data from appliance-level measurements. This distinction fits to the measurement philosophy of our system, which monitors the energy consumption at the household's feed point as well as on appliance level. Mjölnir categorises the aggregated power consumption data of the household as *circuit*. This data is obtained by the YaY smart meter. In contrast to such *circuit*, the data obtained from appliance-level measurements are defined as *circles*. Each smart plug in the system is represented by such a circle element. The analysis of the obtained measurement data bases on this distinction between circuit and circle elements. The outcome of the analysis is displayed by the widgets, which provide feedback in different ways to the residents. The compatible Mjölnir widgets for the distributed measurement system introduced in Section 3.3 are:

- Timeline widget: The timeline consists of subsequent as well as parallel consumption events. A consumption event describes the amount of energy that a certain appliance consumed over a given time window. The widget displays the consumed energy $E_{con}$, which is computed from the measured power consumption $P_{measured}$ and the sampling interval $t_{sample}$.

- Device Usage Model widget: Beside power consumption, the distributed measurement system also records the number of times that a certain appliance was switched. The usage model widgets shows the resident how often a certain appliance was utilised.

- Time Series widget: The YaY smart meter measures the overall energy consumption of the household. The time series widget displays this overall energy consumption over time.

- Real-time power usage widget: This widget shows the current amount of power that the household appliances consume.

- Consumption report: The consumption report provides an overview about the energy consumption of the past days.

[10] http://mjoelnir.sourceforge.net/

### 3.4.2 Appliance Detection

The fact of the matter is, that every appliance serves a specific purpose. Whilst it operates to serve this purpose it consumes energy and impacts the environment in a very specific way e.g. sound emission, heat dissipation, or vibrations. These characteristic impacts on the environment can be recorded by environmental sensors. For instance a Piezo sensor is able to record the vibration profile of a certain appliance, a temperature sensor can be applied to measure heat dissipation, a microphone can be utilised to measure the sound emission of certain appliances, or a Gyroscope can be attached to appliances in order to detect motions.

Figure 3.6 shows a sample power consumption of an electric fire and the assumed change of temperature around the appliance over time. The electric fire is an appliance, which operates to warm up air. Consequently, the temperature in its surrounding will rise. The increase of temperature over time can be recorded by temperature sensors and stored as ambient feature. This ambient feature can be utilised to detect the appliance in current readings of a certain temperature sensor since the features describes a specific behaviour of a certain appliance. In the same manner power features can be utilised to detect electrical appliances. Therefore, the current power consumption is monitored over time and examined for known power features. These power features are recorded power consumption patterns of appliances.

In Section 3.3, we introduced a distributed measurement system that records power consumption patterns as well as ambient features of household appliances. Such appliance features can be utilised to detect active appliances by means of their power consumption or of their impact on the environment. Correlation filters serve as components in order to detect appliances. The concept as well as the design of correlation filters is introduced in Chapter 4. The correlation filters examine measurement data for known features. The known features can be a characteristic power consumption behaviour or an ambient feature. These filters apply the Pearson product-moment correlation to analyse the linear relationship between the measurement data and the respective feature, which the filter seeks to detect in the obtained data.

The detection of electric appliances as well as ambient features allows software tools such as energy advisors to generate very specific advices in order to achieve energy savings. Furthermore, power eaters can be identified by application of appliance detection.

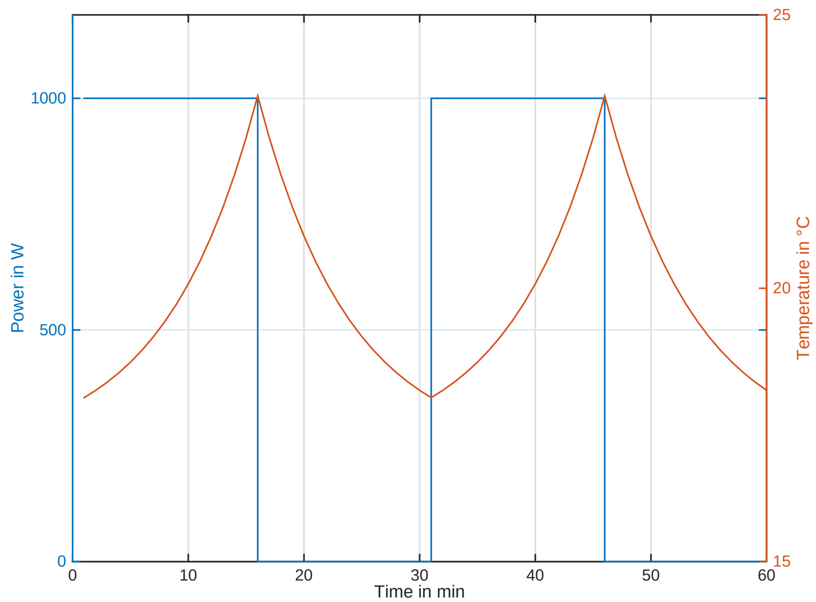



Figure 3.6: Sample power consumption and ambient temperature of an electric fire

## 3.5 Discussion

In a previous section we presented design aspects related to a distributed measurement system. These aspects included functional as well as non-functional requirements. Functional requirements refer to services i.e. functionalities, which the system should provide. The functional requirements in the context of a distributed measurement system comprise measurement requirements, communication interfaces, as well as processing units.

Measurement requirements define which physical quantities are measured by the system, at which level of the household's power distribution network measurements are to be applied, and define the applied sampling frequency as well as the maximum measurement uncertainty of measurement equipment.

In the design aspects we stated that a distributed measurement system is obligated to measure a set of physical quantities at several levels in the household. The levels of interest are the household's feed point as well as the appliance level. The YaY smart meter measures the overall power consumption as well as features related to current and voltage. In particular, the YaY obtains measurement data about the following physical quantities on aggregate level:

- True root-mean-squared value of the voltage $U_{RMS}$
- True root-mean-squared value of the current $I_{RMS}$
- Active power $P$, reactive power $Q$, and apparent power $S$

The aggregate level can be seen as the top level of the distribution network. The terminal points of this network represent the appliances. In the introduced measurement system a set of Plugwise Home measurement plugs is applied to monitor the active power consumption $P$. Furthermore, the distributed measurement system contains networked sensors, which obtain ambient features at appliance level, which record the impact of appliances on their environment such as heat dissipation.

The second aspect related to measurement requirements is the applied sampling frequency. Throughout the elements of the measurement system, a sampling frequency of 1 Hz is applied. This comprises the YaY smart meter, the utilised smart plugs, as well as the networked sensors. This is consistent with the design aspects.

The third requirement regarding measurements is the maximum measurement uncertainty. The introduced design aspects define a maximal limit for measurement uncertainties of 10% for aggregate level measurements and 5% for measurements on appliance level. The YaY smart meter operates on appliance level. As measurement unit, the YaY integrates the YoMo smart metering board. The authors of [26] reported a maximum measurement error of 3.8% for active power measurements, a maximum measurement error of 8.3% for reactive power measurements, and a maximum measurement error of 4.04% for apparent power measurements. Smart plugs are attached to certain appliances to measure power consumption at appliance level. The manufacturer of the utilised Plugwise Home devices reports a measurement accuracy of 5%.

From the suggested list of communication technologies for such a distributed measurement system, Wi-Fi as well as ZigBee are utilised in our system. The DevDuino sensors as well as the smart plugs exploit ZigBee to transmit measurement data to the YaY smart meter. The YaY integrates multiple interfaces, which comprise ZigBee, Ethernet, as well as Wi-Fi. This allows the YaY to communicate with a wide variety of networked devices. Smart plugs, networked sensors, smart appliances, as well as other networked measurement instruments can be read by the YaY. Conversely, this means that a great diversity of devices is able to communicate with the YaY. This provides the residents multiple ways of possible feedback since energy consumption reports as well as energy advices can be displayed in several ways e.g. mobile devices such as smart phones or tablets. Furthermore, the YaY can be equipped with an EIA-485 interface. This industrial interface allows the YaY smart meter to control other devices in the distribution board such as circuit breakers as well as to read other measurement equipment. For instance commercial smart meters, which were installed by the electricity supplier, can be read via this interface.

The central processing unit of the YaY smart meter is the Arduino Yun. The Yun operates the Linux distribution Linino, which was designed for the application in embedded systems as well as for applications in the internet of everything.

Non-functional requirements refer to constraints as well as behavioural properties of a system such as efficiency, portability, reliability, etc. We identified the following non-functional requirements in the context of a distributed measurement system: Safety, security, as well as expandability.

The safety requirements are related to the utilised measurement hardware. Our system integrates two kinds of instruments, which operate in the power distribution network: The YaY smart meter as well as the smart plugs. The YaY smart meter consists of an Arduino Yun board, several communication interfaces, as well as a YoMo smart metering board. This board executes the measurements in the context of the YaY device. As presented in [26], the metering unit of the YoMo is galvanically isolated from the rest of the board. Furthermore, the YaY device is embedded in a DIN rail case and installed in the distribution board of the household. The distributed measurement system integrates several smart plugs, which are attached to appliances. The utilised Plugwise Home plugs meet several safety standards and satisfy the CE regulation.

The application of security measures prevents unauthorised access to measurement data. The discussion of security aspects follows the CIA principle[19]:

- Confidentiality: The recorded energy consumption data as well as information about ambient features is available only to the residents of the household.
- Integrity: The distributed measurement system stores the obtained measurement data in a data base of the YaY smart meter. The YaY only accepts data from devices that were initially registered by the resident. Further on only the YaY device is allowed to edit the dataset as well as adapt configurations of software tools.
- Availability: Data and graphical user interfaces are available as long as the client and the YaY device are part of the same network.

The distributed measurement system was designed to be expandable. This means that the resident is able to add new measurement devices to the system. In particular, networked devices can register themselves at the YaY smart meter in order to contribute measurement data. For this registration an authorisation key is required, which is generated by the resident in the setup phase of the system.

# Chapter 4

# Appliance Detection with Correlation Filters

In the previous chapters we introduced a taxonomy for electrical appliances (see Chapter 2.1) as well as an open-hardware measurement system to monitor electrical appliances (see Chapter 3). In order to generate personalised advices for the user and to be able to draw conclusions how energy savings could be achieved it is advantageous to detect active electrical appliances in the household. Especially, information about the time of day the appliances are operated represents vital information since this information allows conclusions regarding consumer habits. Event detection approaches in load disaggregation algorithms utilise either expert heuristics, probabilistic models, or matched filters [2]. Up to present, several detection techniques based on matched filtering have been proposed. A matched filter correlates an unknown input pattern with a known template pattern. The substantive considerations of a transient event detector for the application in load disaggregation were discussed in [31]. The presented detector applies a preprocessor on the aggregate power signal and performs appliance detection on the disaggregated signals.

A wide variety of related work evaluated possible applications for matched filters in the context of appliance detection. The authors of [39] suggest to detect and distinguish between appliances by means of their turn-on transient patterns. A related idea is presented in [20], in which the authors suggest to detect appliances by matching subpatterns of power signals such as the transients of rising or falling consumption. The classification system in [44] applies Fast Fourier Transform (FFT) on transient current signals by further analysis of the resulting spectrum in order to detect appliances. The presented detector in [30] employs load transient shapes of current signals. The presented work reveals possible strategies and mechanisms to apply correlation filters (i.e., matched filters) as appliance detectors in measurement systems. A system, which performs load identification, was presented in [10] as well as [11]. This system applies genetic programming as well as a neural network to detect appliances based on their turn-on transients. Contrary to related implementations we propose to use full shapes instead of turn-on transients. A full shape (i.e., pattern) describes the behaviour of a certain appliance as well as the physical task that the appliance performs more precisely.

In order to detect appliances on the basis of their power consumption over time we propose a system, which comprises a set of correlation filters (i.e., matched filters) to perform appliance detection, a finite set of template patterns to describe the power consumption behaviour of the appliances over time.

The correlation filters in our system apply template patterns that describe one entire workflow, the power consumption over time, for a specific programme of the respective appliance e.g. a certain washing programme of a domestic washer. Due to this, the derived template patterns represent unique shapes with characteristic transients. We hypothesise that such kind of templates are well-suited to detect and distinguish between appliances based on correlation filters.

The focus of this chapter lies on the design and implementation of the correlation filters for the application as appliance detectors in energy monitoring systems as well as an investigation into the properties and conditions that the template patterns have to fulfil in order to maximise the signal-to-noise ratio (SNR). This chapter is organised as follows:

First, the system requires an element, which serves as appliance detector. Of special interest in appliance detection is the state of operation of the respective appliance i.e. which programme the appliance executes at the moment. Section 4.1 will introduce the design as well as the implementation of the *correlation filters*.

The correlation filters will serve as the appliance detectors in the energy measurement system. In particular, the correlation filters will correlate a certain (unknown) measured pattern with a (known) template pattern. The optimal selection of this template patterns is of great relevance for the performance of the detector. For this reason Section 4.2 will discuss the properties and the optimal selection of power consumption patterns. First, the basic models to resemble the power consumption behaviour by means of power consumption models will be discussed. Adjacently these basic models as well as recorded consumption patterns are evaluated for their noise resilience in order to find the most favourable type of template pattern.

The data provided to the correlation filters is a series of power consumption measurements, i.e., a stream of samples, which is shifted into the correlation filters. This implies the need for a detection mechanism. Section 4.3 will present such a detection mechanism that utilises correlation filters to examine the perfect match of a template pattern within an input stream of measurement samples, the *Matchmaker detector*.

## 4.1 Correlation filter

In communication systems correlation filters are utilised to detect input waveforms and to distinguish between them. We propose to utilise correlation filters to detect appliance consumption patterns in appliance-level measurement data as well as in aggregate-level measurement data.

A correlation filter (matched filter) is a signal processing element, in which the input signal is examined for association to a known pattern, the template. This test for association can be implemented by convolution with the conjugated time-reversed template or by correlation of the input pattern with the template. By means of our application we define a correlation filter as a software tool, which examines two input variables for a linear association by means of the Pearson correlation. The correlation filter contains two registers: The *template register* and the *measurement register*. Both registers are of equal length. The former contains the template pattern, which we seek to detect in the content of the latter register, the measurement register. The data in this register is updated after every measurement and the organisation follows the first in first out (FIFO) method. As input pattern we define the content of the measurement register, which is updated every time a new power measurement sample is available. A threshold value, the correlation threshold denoted by $\gamma$, serves as basis of decision-making for every correlation filter. As we will see in subsequent examinations, this threshold is an influential parameter for appliance detection. As already mentioned, the correlation filter applies the Pearson product-moment correlation, introduced in Section 2.4, to examine the linear association between the input pattern and the template pattern. Listing 4.1 contains the source code of the function *correlate*, which is integrated in the correlation filter. The input of the function is the content of the two registers, template and measurement.

```
def correlate(this, measured, template):
    try:
        Pearson_Coefficient = np.corrcoef(template,measurement)[0][1];
        if (Pearson_Coefficient) > this.gamma:
            return Pearson_Coefficient;
        else:
            return 0;
    except:
        raise CorrException("Correlation not possible!");
```

Listing 4.1: Utilisation of the correlation

To compute the Pearson product-moment correlation, the correlation filter applies the *corrcoef* function, a function embedded in the NumPy package[1]. Depending, if the computed Pearson coefficient exceeds the correlation threshold $\gamma$, the return value of the function *correlate* equals zero or the computed Pearson coefficient. The values of the Pearson coefficient lie in the interval [0,1], where a coefficient of 0 indicates no correlation and 1 full correlation between the two input variables. The distance of the Pearson correlation to full correlation $1 - |r|$ will depend on how precisely the template pattern describes the power consumption over time for a given electrical appliance's workflow. Therefore, it is necessary to investigate which types of template patterns exist in order to describe the power consumption behaviour of electrical appliances. A further question is the impact of noise and measurement uncertainties on the correlation filters.

## 4.2 Power consumption patterns

The purpose of the correlation filter is to detect power consumption patterns. For this reason it will correlate a template pattern $t$ with a measured pattern $w$. If and only if these two patterns are identical, then the result of the Pearson correlation, the Pearson correlation coefficient $r$, equals 1. Any deviation between the two input patterns will result in a correlation coefficient smaller than 1. This deviation may be the consequence of disturbances, measurement uncertainties, or noise. For the sake of simplicity we synthesise all possible sources of deviation in one disturbance variable, the noise vector $\eta$. Therefore, we regard any deviation of the measured pattern from the template pattern as superimposed

[1] http://numpy.org

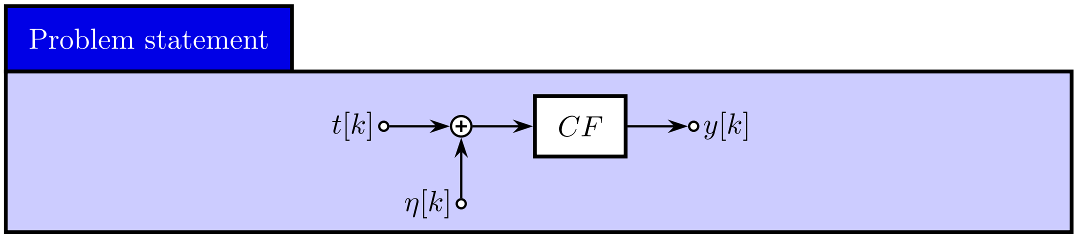



Figure 4.1: Correlation filter as detector for consumption patterns

additive white Gaussian noise (AWGN). Figure 4.1 illustrates the detection problem. At time instant $k$ the correlation filter (CF) computes the correlation coefficient $r = y[k]$ from the stored template pattern $t[k]$ as well as from the measured pattern $w[k]$, which is the superposition of the template pattern and a AWGN vector $\eta[k]$. So the output value, the Pearson correlation coefficient, is evaluated due to relation:

$$r = y[k] = correlate(t[k], w[k]) = correlate(t[k], t[k] + \eta[k]) \tag{4.1}$$

As this relation shows, the AWGN directly influences the correlation coefficient $r$. With increasing noise level the deviation between template pattern $t$ and measured pattern $w$ increases and as a consequence of this the correlation coefficient $r$ decreases. In general, the performance of the appliance detector will depend crucially on the template pattern $t$ we utilise. To obtain this pattern we identify two possible approaches: Either by applying one of the appliance models introduced in Section 2.1 in order *to mimic* the power consumption behaviour or by *extraction* of the power consumption pattern from measurement data. For a certain appliance the former approach generates a generic consumption pattern whereas the latter approach records a specific consumption pattern. Yet it is unclear which of these contrary approaches is better suited for an application. Therefore, we have to investigate the impact of noise on the several types of consumption patterns in order to find the most preferable type for the application in a correlation filter.

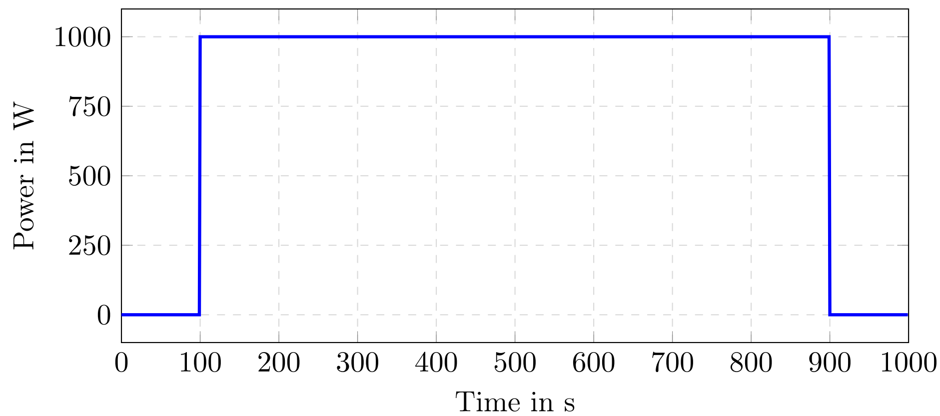
First, we will investigate the influence of noise on the correlation coefficient $r$. The focus will rest on consumption patterns generated out of basic appliance models.

Second, we will compare the robustness against noise between basic consumption patterns and extracted consumption patterns for a telling example.

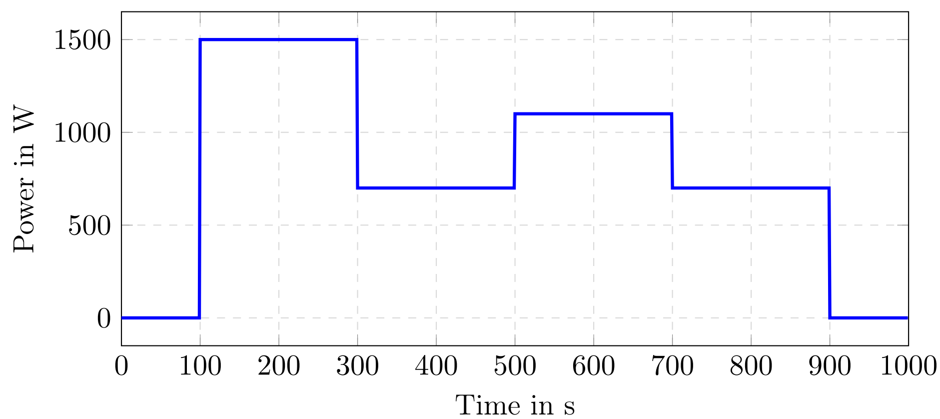
Third, we will evaluate the level of noise robustness of recorded consumption patterns in general.

We hypothesise that recorded consumption patterns are more robust against AWGN than patterns generated from appliance models. In particular, we expect consumption patterns with a high number of distinct power values to be more robust than consumption patterns with a single value or a very few values.

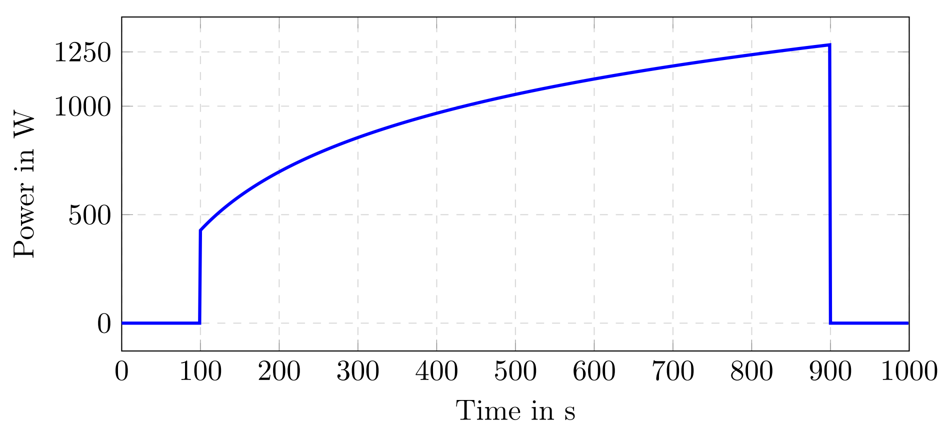
### 4.2.1 Basic Consumption Models




(a) Power consumption pattern for the single-state appliance




(b) Power consumption pattern for the multi-state appliance




(c) Power consumption pattern for the infinite-state appliance

Figure 4.2: Consumption patterns generated from basic appliance models

| Correlation | $\gamma$ | $SNR_{Single}$ | $SNR_{Multi}$ | $SNR_{Inf}$ |
|---|---|---|---|---|
| low | 0.5 | 1.16 | 0.93 | 1.04 |
| medium | 0.6 | 1.5 | 1.2 | 1.34 |
| medium | 0.7 | 1.96 | 1.58 | 1.76 |
| high | 0.8 | 2.66 | 2.14 | 2.4 |
| high | 0.9 | 4.12 | 3.31 | 3.7 |

Table 4.1: Minimal signal-to-noise ratios (SNR) required for a certain correlation threshold $\gamma$

The first approach to generate consumption patterns is to utilise basic appliance models. Such models approximate the actual consumption patterns. As discussed in Section 2.1, we distinguish between three different types of appliance models: Single-state, multi-state and infinite-state models. The first model comprises appliances with one state of operation, the second model includes appliances with multiple states of operation, and the third model describes appliances with an innumerable number of states. In every single state the respective appliance consumes a specific amount of power. This represents a common way to describe the behaviour of the power consumption over time by means of a state-machine approach. Figure 4.2.1 shows the following consumption patterns:

a A single-state power consumption pattern with a power consumption of 1 kW. When the appliance is switched on, it consumes a well-defined amount of power. This value does not change over the time of operation.

b A multi-state power consumption pattern with the power consumption states: 1.5 kW, 0.75 kW, and 1.1 kW. During the time of operation the modelled appliance changes the amount of consumed power multiple times.

c An infinite-state power consumption pattern with power consumption values in [540 W, 1282.62 W]. During the time of operation the amount of consumed power increases over time from the initial value following a pre-defined relation.

The three consumption patterns are of equal length (1000 s) and equal energy (800 kJ). These patterns describe the consumption of specific electrical appliances over time and serve as template patterns for the correlation filter in order to detect them in an input pattern i.e. the measured pattern $w$.

The question arises how much the measured pattern may deviate from the template pattern, so that it can still be detected. We define a pattern as *detected*, if the correlation coefficient $r$ exceeds a certain correlation threshold $\gamma$. The correlation threshold represents a significant parameter of the correlation filter since we define the correlation threshold as the value that the correlation coefficient has to exceed in order to regard the template pattern as detected in the current input pattern. To evaluate this, the input pattern of the correlation filter in the given example was defined as the respective template pattern and additive white Gaussian noise (AWGN). For several correlation thresholds $\gamma$ the maximum added noise was determined, which allowed the patterns still to be detected, i.e., to exceed the respective threshold. Table 4.1 summarises the findings of the evaluation for the given example. In order to compare the results of the evaluations the maximum deviation is expressed as minimum signal-to-noise ratio for the respective appliances. The signal-to-noise ratio puts the desired pattern in relation to the superimposed noise and therefore allows it to compare the results of the different evaluations with each other. To rehearse the significance of the evaluation:

In this regard a low signal-to-noise ratio is desirable since a low ratio states that the respective pattern is able to cope with a high amount of deviation while the correlation coefficient $r$ computed from the template pattern and the superimposed pattern still exceeds a certain correlation threshold $\gamma$. So a low signal-to-noise ratio indicates a certain noise robustness.

For all evaluations stated in Table 4.1 the multi-state appliance shows the lowest SNR. In contrast to that the consumption pattern of the single-state appliance shows the highest SNR for all correlation thresholds. E.g., for a correlation threshold $\gamma$ of 0.8 the minimum SNR that satisfies $r \geq \gamma$ for the single-state appliance equals 2.66, whereas the minimal SNR for the multi-state appliance is 2.14. The multi-state pattern seems to be more robust against deviations than the single-state pattern. Why is that?

Figure 4.2(a) shows the power consumption pattern of the single-state appliance and Figure 4.2(b) shows the power consumption pattern of the multi-state appliance.

The single-state pattern has a rectangular shape with one particular power value. In contrast to that the multi-state pattern can be seen as sequence of several rectangles with distinct height. These clear transitions between the power values originate from the underlying state-machine model.

This sequence of transitions makes the pattern characteristic and shape the pattern in a specific way. This property makes the consumption pattern of the multi-state appliance more resilient towards noise than the single-state one.

A telling example that the height of the transitions between the power values is significant is given by the result of the infinite-state appliance. Figure 4.2(c) shows the power consumption pattern of an infinite-state appliance over time. Starting from an initial power value the amount of consumed power increases continuously. The significant property of the consumption pattern is that the consecutive power values differ in a small amount from each other. So the height of the transition between the power values is a very small one. As values for the minimal SNR of Table 4.1 show, the resilience towards noise may be higher for multi-state appliances than for single-state appliances as a consequence of the vast number of distinct power values but is still above the minimal SNR of the multi-state pattern.

In conclusion, the number of states included in the pattern influence the robustness against noise. However, the consumption pattern may describe a very specific behaviour but a vast number of power values alone does not make the pattern robust. The amount of change between the consecutive power values must be high enough in order to improve detection robustness.

### 4.2.2 Recorded Patterns vs. Consumption Models

In the previous Section, we evaluated the impact of deviations on the correlation coefficient in form of additive white Gaussian noise (AWGN) for three basic power consumption models. These models differ in the number of states (power values) that the model contains. Such power consumption models resemble the actual power consumption pattern of electrical appliances by the application of state machines.

Apart from theoretical models the power consumption patterns can be recorded by measurement instruments. These recorded consumption patterns are discrete in time and we will assume them to be continuous in value, whereas the power consumption models are time and value-discrete. The many distinct power values forming the recorded consumption patterns will make every pattern unique and therefore well-distinguishable from other patterns.

The question arises if recorded consumption patterns are preferable over the consumption models. In other words, are recorded patterns more resilient towards deviations than patterns generated from the basic power consumption models? We will discuss this on the basis of a common household appliance, the refrigerator. The power consumption of a refrigerator can be modelled in two different ways: A single-state model and a multi-state model. The former represents the active period of the device with a rectangular pattern, which has a height equal to the average power consumed in this time window. The latter, the multi-state model, separates the time window into two phases: The transient and the steady phase. The transient phase describes the turn-on behaviour of the appliance. For a refrigerator the consumption patterns begins with an overshoot, which is a result of the integrated compressor, and further slowly approaches a steady power value. The moment, in which the power value converges a steady power value, is the beginning of the steady phase. The steady phase ends when the appliance is turned off.

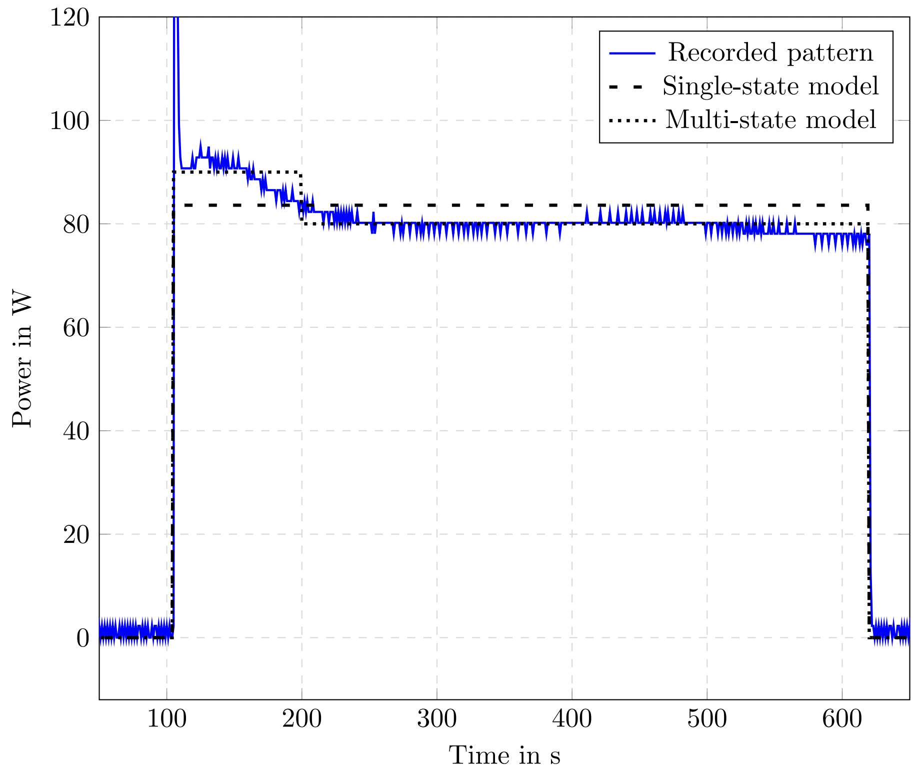
The refrigerator, which we consider, was monitored during the GREEND measurement campaign[2]. Figure 4.3(a) shows three different consumption patterns that describe the power consumption of a refrigerator over time. All these consumption patterns are of equal length, share turn-on as well as turn-off time, and contain an equal amount of energy.

- The **single-state model** resembles the recorded pattern with a rectangular shape. The height of the rectangle is equal to the mean power of 83.6 W.

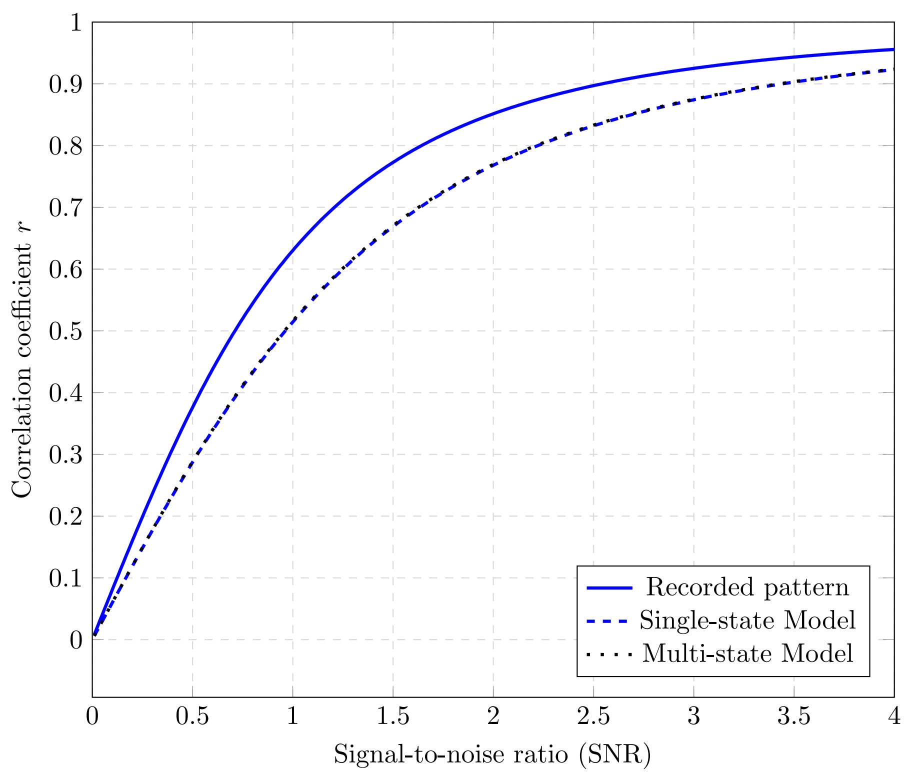
- The **multi-state model** consists of two states to resemble the recorded pattern. Therefore the recorded pattern is divided into two phases: Transient and steady phase. The transient phase begins at 100 s and ends at 200 s. The transient phase represents the turn-on phase of the appliance, in which the power consumption experiences an overshoot and slowly approaches a steady power value. The steady phase represents the time of operation, in which the appliance consumes the steady power value of 90 W.

- The **recorded pattern** is included in the GREEND energy consumption dataset[35]. In this measurement campaign several household appliances in nine different homes were monitored for a time period of one year on appliance level by the utilisation of smart plugs with a measurement frequency of 1 Hz.

[2]GREEND data set, building1, Whirpool ARG 737




(a) Power consumption patterns for a refrigerator




(b) Behaviour of $r$ over increasing signal-to-noise ratio

Figure 4.3: Power consumption patterns as well as their noise resilience for a refrigerator

| Correlation | $r$ | $SNR_{Single}$ | $SNR_{Multi}$ | $SNR_{Rec}$ |
|---|---|---|---|---|
| low | 0.5 | 1.15 | 0.96 | 0.71 |
| medium | 0.6 | 1.5 | 1.24 | 0.92 |
| high | 0.8 | 2.67 | 2.21 | 1.65 |

Table 4.2: Evaluation of consumption models as well as a recorded pattern for noise resilience

The introduced patterns will be evaluated for their noise resilience to investigate which type of pattern, model or recorded, is favourable. Therefore, for each type of pattern the impact of additive white Gaussian noise (AWGN) on the correlation coefficient $r$ will be evaluated for two power consumption models (single and multi-state) and one recorded pattern.

Figure 4.3(b) shows the computed correlation coefficients over the signal-to-noise ratio (SNR) for the three consumption patterns. For a signal-to-noise ratio in $(0, 4]$, the correlation coefficient $r$ is calculated from the respective pattern and the pattern superimposed with AWGN. Table 4.2 summarises the key results of the evaluation. For any signal-to-noise ratio in $(0, 4]$, the correlation coefficient $r$ computed from the recorded pattern is larger than both coefficients computed from the consumption models. From this follows that the recorded pattern is able to withstand a higher amount of superimposed noise. For instance, to achieve a correlation coefficient of 0.6, a signal-to-noise ratio of approximately 1 suffices in the case of the recorded pattern, whereas the SNR has to equal at least 1.24 for the multi-state model. As the evaluation demonstrated, there is a difference in performance between the recorded pattern and the consumption models. This difference originates from the shapes of the patterns. As Figure 4.3(a) shows, the transient phase of the recorded pattern consists of many distinct power values. These values create a characteristic shape. This characteristic shape increases the noise resilience of the recorded pattern. In contrast to the recorded pattern the single-state and multi-state model are of rectangular shape and consist of a minor number of distinct power values. As a consequence of that, the superimposed noise alters the shape of the state models significantly.

The power consumption models, which comprise single-state, multi-state, as well as infinite-state models, resemble power consumption patterns and hence represent approximations of continuous power signals. As a consequence of this approximation, the quantisation of the power values, the number of power values is significantly reduced compared to the recorded pattern. From that follows, as Table 4.2 shows, a lower resilience towards deviations and uncertainties. For this reason we regard the utilisation of power consumption models such as single-state and multi-state as less favourable. In order to detect electrical appliances, we propose to use recorded characteristic power consumption patterns in correlation filters, which apply Pearson correlation.

## 4.3 The Matchmaker detector

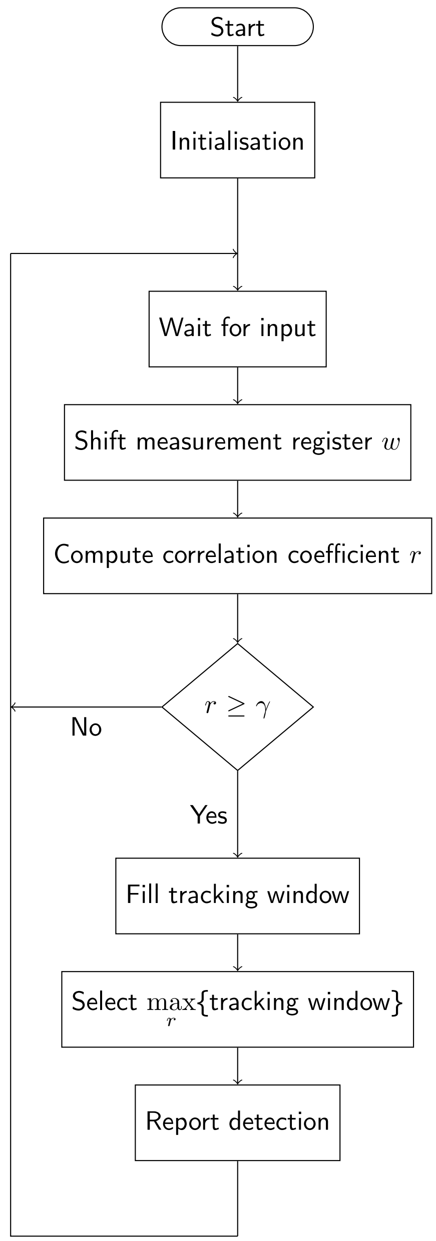



Figure 4.4: The Matchmaker detection algorithm

Networked measurement instruments, such as discussed in Chapter 3, provide power readings in form of a time series of power values i.e. power consumption data. This series includes consumption patterns, which can be utilised to detect active electrical appliances. In Section 4.1, we introduced an element to detect such consumption patterns within measurement data, the correlation filter (CF). The correlation filter applies the Pearson correlation to evaluate the linear relationship between the two input registers, the *template register* and the *measurement register*. The significant parameter to decide if the linear relationship is high enough to classify the pattern as detected is the correlation threshold $\gamma$.

We propose an algorithm to detect power consumption patterns within an input stream of power values, the *Matchmaker detector*. The Matchmaker detector utilises a correlation filter for every power consumption pattern. The detector we propose determines the optimal fit in terms of correlation of the pattern in the input stream and a template pattern.

We denote the input stream of measurement values as $I[k]$.

The Matchmaker detector follows a specific programme flow, illustrated in Figure 4.4. This programme flow comprises the following steps:

1. **Initialisation**: In this setup phase the registers as well as the parameters are initialised. The algorithm loads the template pattern of length $N$ into the template register $t$. At the same time the algorithm shifts the first $N$ elements of the input stream $I[k]$ into measurement register $w$. Further the algorithm sets the length of the tracking window $T$ (default length equals $\frac{N}{2}$) and defines a correlation threshold $\gamma$.

2. **Wait for input**: The algorithm stands idle till the input stream contains new data.

3. **Shift measurement register** $w$: If new data is available on the input, then the algorithm shifts the measurement register $w$ by one position appends the new power value to the register. The substitution of the old value by the new power value follows the first in first out (FIFO) method.

4. **Pearson correlation coefficient** $r$: At this stage, the algorithm computes the Pearson correlation coefficient $r$ out of the template register $t$ and the shifted measurement register $w$. Subsequently, if $r$ is greater or equal to the correlation threshold $\gamma$, the Matchmaker detector begins to fill the tracking window. Otherwise the algorithm cancels further execution and waits for the next sample of the input stream.

5. **Fill tracking window**: If the output of the Pearson correlation $r$ exceeds the minimum correlation threshold, then the algorithm starts to fill the tracking window, denoted by $T$. By this the algorithm examines, if there is a better match, i.e. higher correlation of the measured pattern and the template pattern. Until the tracking window of length $M$ is filled the algorithm repeats the following subroutine $M$ times:

   - Shift the register by one position,
   - compute the correlation coefficient $r$,
   - and store the result in the tracking window.

6. **Select** $\max_r\{tracking\,window\}$**:**

   find perfect match of the template register and the consumption pattern which is the content of the measurement register

The maximum correlation coefficient $r$ corresponds to the perfect match in time. Therefore, the Matchmaker detector evaluates the largest correlation coefficient of the tracking window as well as the point in time, in which the coefficient was computed.

7. **Record detection**: The detector increments the number of detected patterns and marks the time instant of detection.

### 4.3.1 The Tracking Window Mechanism

After initialisation the Matchmaker detector computes the Pearson correlation coefficient $r$ from the patterns stored in the template and the measurement register for every new sample. The magnitude of $r$ can be interpreted as an estimation about how well the two patterns resemble each other. To decide if a pattern was detected, we test if $r$ is equal or greater than a certain correlation threshold $\gamma$. If $r$ exceeds or equals the threshold, then the algorithm starts to track the progress of the correlation coefficient over time i.e., the algorithm computes the correlation coefficients for the next $M$ incoming samples immediately and stores them in the tracking window. At the moment where the tracking window contains $M$ elements, the algorithm selects the biggest element since it represents the perfect match of the template pattern in the input stream. By means of this mechanism the perfect fit of the input and the template pattern can be examined.

One the one hand it is possible to use correlation threshold $\gamma$ as basis of decision-making. This represents an intuitive approach since we record a detection, if the correlation between the patterns is high enough i.e. the correlation coefficient exceeds a certain $\gamma$.

On the other hand, the underlying reason why this is not practicable becomes apparent if we consider an input stream $I[k]$ with length $N$ at time $k$. If the computed correlation coefficient $r$ at time instant $k$ exceeds the correlation threshold, then the detector would record a detection at $k$. However, this doesn't take correlations with the subsequent signal measurements into account. For instance the computed coefficient at time $k + 1$ may be even higher, which means that a recorded detection at $k$ would not give the optimal detection point. We will discuss this problem by means of an example:

Let there be a correlation filter, which consists of two registers A and B both of equal length M. If the content of the registers, i.e., the power consumption patterns, are identical, then the computed correlation coefficient $r$ equals 1. Figuratively, the patterns overlap entirely. If we shift one register by one position and append a null to it, then the overlapping area of the two pattern would decrease. As a consequence of this, $r$ also decreases. The higher the number of shifts, the lower the correlation coefficient $r$ i.e. the smaller the overlapping area, since we shift the patterns apart from each other. Figure 4.5 shows the decrease of the correlation coefficient $r$ for three basic consumption patterns over an increasing number of shifts. The number of shifts can also be seen as a measure to describe in how far the two patterns are shifted apart from each other. In this example the relationship between the coefficient $r$ is not only proportional but also linear. There may not exist a linear relationship between $r$ and number of shifts but for sure the relationship will be a proportional one.

The closer we shift the pattern towards each other, the higher the correlation will be. To be more specific, the correlation will increase until the patterns overlap completely and a local maximum correlation is reached. From this point on any further shift would result in a decreasing correlation. It is of importance to find this local maximum since it represents the *perfect local fit* of the two patterns.

The profound lesson learned from this observation is that a correlation threshold alone is not sufficient to decide if a perfect match of the two patterns appeared. In the context of this problem the exceeding of a threshold can only serve as an initial impulse for an investigation into subsequent correlation in order to detect the perfect local fit. For this reason the Matchmaker detector applies the tracking window mechanism to find the perfect match of the template pattern in the input stream, i.e., the power consumption over time. With this method the Matchmaker provides the number of detected patterns as well as the instants in time when they were detected.

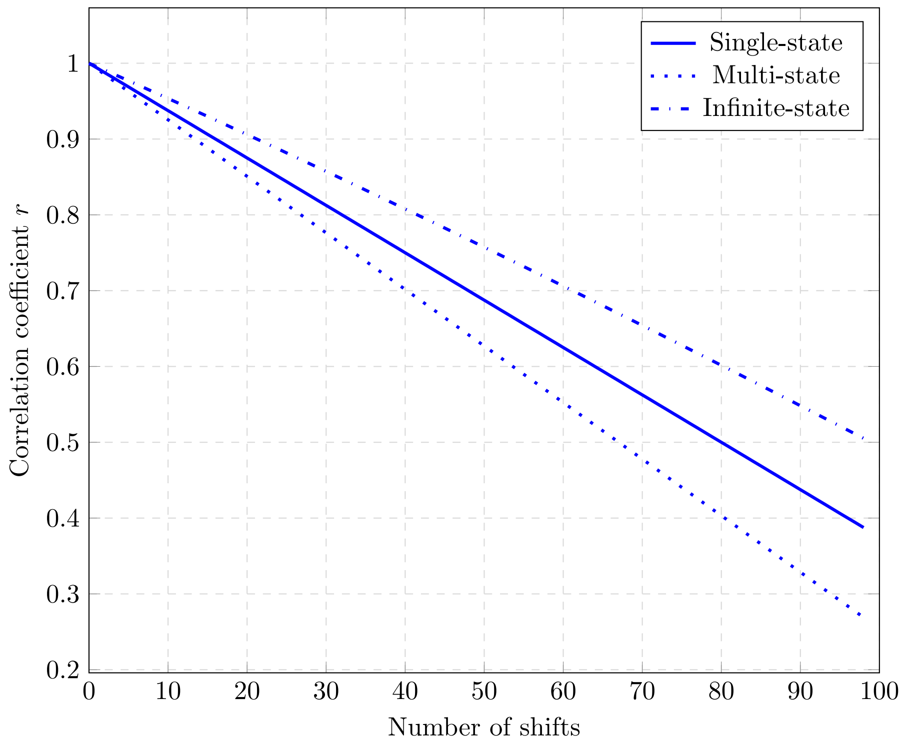



Figure 4.5: Change of $r$ for decreasing overlapping area

# Chapter 5

# Evaluation

The previous chapters presented a distributed measurement system to monitor the power consumption in a household, introduced correlation filters to perform appliance detection as well as a detection algorithm, which bases on the Pearson correlation. The purpose of this chapter is to further investigate in the properties of template patterns as well as the performance assessment of the Matchmaker detector by means of application on an energy consumption dataset.

First, selected *recorded patterns* of household appliances are introduced and their properties are analysed. These patterns serve as templates for the Matchmaker detector in the following investigations.

Second, the Matchmaker detector for homogenous input data is evaluated. The influence of the pattern type on the detection rate is evaluated as well as the optimal selection of the correlation threshold in the presence of a certain noise level.

Third, the performance of the *Matchmaker detector* on real-world consumption data is assessed and the detection rate is determined. This assessment involves the application of the Matchmaker on measurement data from aggregate level as well as measurement data from appliance level.

## 5.1 Recorded Consumption Patterns

For the purpose of assessment of energy management algorithms i.e. load disaggregation solutions, several energy consumption data sets were recorded. Widely applied data sets in the domain of smart homes are the REDD [29], the ECO [4], the AMPds[32], or the GREEND [35]. A comprehensive overview of available data sets can be obtained from the NILM Wiki[1].

In this chapter as well as in the subsequent evaluations we will utilise the GREEND data set. This data set includes appliance-level data recorded by smart plugs with a sampling frequency of 1 Hz in nine households for a period of over one year. In particular, we will extract one characteristic consumption pattern per appliance from household 1. The chosen household cover a wide range of household appliances, which can be classified due to the taxonomy introduced in 2.1. The selected household appliances comprise:

1. **Refrigerator (Whirlpool ARG 737):** A refrigerator is a predictable infinite-state appliance. An embedded thermostat senses the temperature inside the appliance and triggers the integrated compressor. Several times a day the refrigerator cools its content. Since the appliance performs the same task several times a day, the power consumption pattern can be predicted. Figure 5.2(a) shows the extracted power consumption pattern. According to the manufacturer, the annual energy consumption of the ARG 737 refrigerator amounts to 230 kWh. This equals 0.63 kWh per day. As Figure 5.2(b) shows, several subsequent consumption patterns are almost identical.

2. **Dishwasher (Whirlpool ADG 555 IX):** A dishwasher has a number of different washing programmes, of which each one has a well-defined time duration. Furthermore, the power consumption changes over time, since the washing programmes executes several tasks e.g. pump water into the machine, spin-dry the laundry, etc. For this reason we categorise a dishwasher as predictable multi-state appliance. Figure 5.3(a) shows the extracted power consumption pattern for a specific washing programme. According to the manufacturer, the ADG 555 IX dishwasher consumes about 222 kWh per year, which equals 4.26 kWh per week.

3. **Microwave oven (Whirlpool AMW 494/IX):** This built-in device has a nominal input power of 1.3 kW. In general, a microwave oven belongs to the category of multi-state appliances with unpredictable power consumption behaviour. Figure 5.4(a) shows a recorded consumption pattern. Indeed the user is able to adjust the intensity of the radiation, which has a finite number of options, but the lapse of time where oven operates is variable. As a consequence of this, the power consumption pattern belongs to the class of non-predictable patterns. Figure 5.4(b) shows two power consumption patterns of the Whirlpool device, which differ clearly from each other. The first pattern describes two successive operations. In contrast to that, the latter represents one operation. From this follows, that the patterns belong to the same device, but describe different consumption events.

4. **Water kettle (Philips HD 4619):** The household integrates a water kettle with a nominal input power of 0.9 kW. Figure 5.5(a) shows the power consumption over time

[1] http://wiki.nilm.eu/index.php?title=NILM_datasets

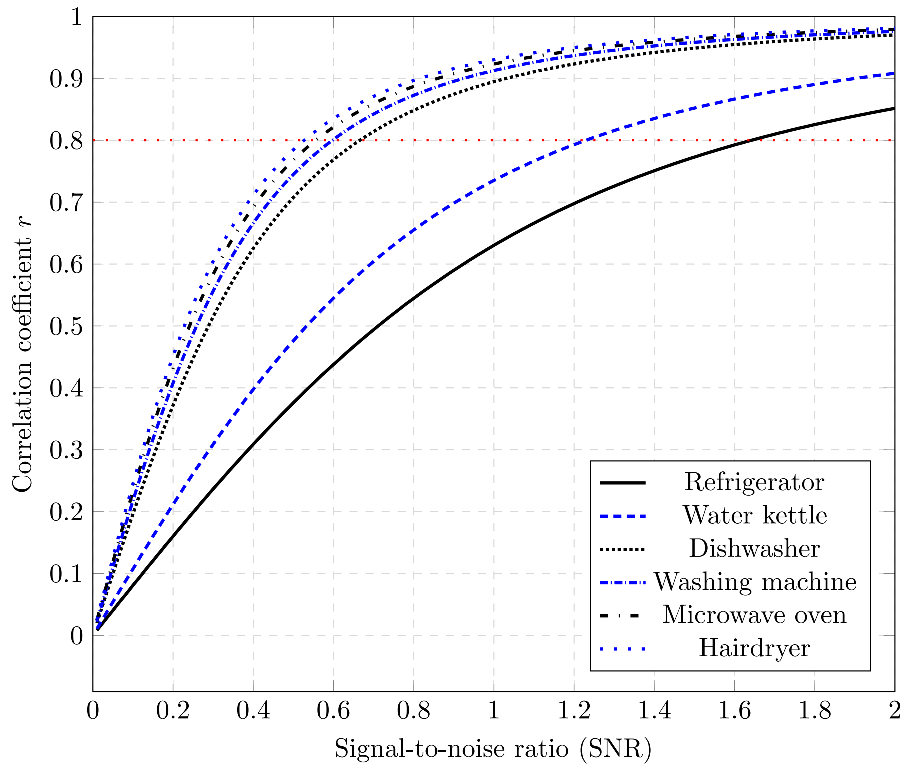



Figure 5.1: Impact of AWGN on the correlation coefficient $r$

for one operation. Depending on the filling degree as well as the initial temperature of the water, the appliance will consume a different amount of energy and therefore the duration till the water boils will differ. Thus the power consumption pattern will vary likewise, as illustrated in Figure 5.5(b). Hence the water kettle belongs to the category of non-predictable single-state appliance.

5. **Washing machine (Zanussi F1215):** A washing machine has a finite number of well-defined washing programmes it can operate, which have a fixed duration and energy consumption. Since the power consumption patterns are predictable the washing machine is classified as a predictable multi-state appliance. The Zanussi F1215 has a nominal power consumption of 2.2 kW.

6. **Hair dryer (Braun 3522):** The household contains a hair dryer with a nominal power consumption of 1.8 kW. This hair dryer is a multi-state appliance, since temperature as well as the strength of the air flow can be adjusted. Due to the fact that the appliance is user-controlled and the operating duration strongly depends on the respective user the appliance is classified as non-predictable multi-state appliances.

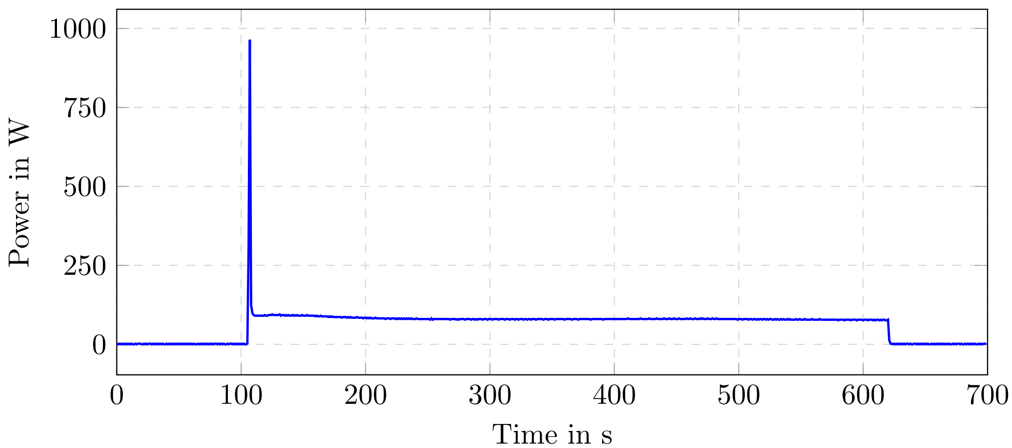
First of all, we will investigate in the noise resilience of the extracted consumption patterns. Therefore, for every consumption pattern the Pearson correlation coefficient $r$ is computed for a signal-to-noise ratio (SNR) in the interval [0.1, 2]. This means that for every SNR in the interval, $r$ is computed for the respective consumption pattern (template) and the same pattern with additive white Gaussian noise (AWGN). The superimposed noise results in deviations between the consumption pattern and the superimposed pattern. By this we aim to evaluate the maximum amount the superimposed pattern may deviate from the template pattern in order to achieve a certain correlation coefficient $r$. This maximum amount will be expressed as signal-to-noise ratio. We hypothesise that this ratio will be significantly lower for the patterns of multi-state appliances than for the other types.

Figure 5.1 shows the impact of AWGN i.e. superimposed deviations on the correlation coefficient for the extracted appliance patterns from the GREEND data set. The trajectories of the multi-state appliances (dishwasher, washing machine, microwave oven, and hair dryer) show a similar trend, whereas there exists a gap between the multi and single-state appliances. For instance, if we demand a correlation coefficient of 0.8 to be the result of the correlation operation, then the SNR for multi-state appliances may be significantly lower than 1 for every multi-state appliance. In contrast to that, for $r = 0.8$ the SNR has to be significantly higher than 1 for the single-state appliances. From this follows that the consumption patterns of multi-state appliances are more resilient against deviations than the ones of single-state appliances. This is a consequence of the difference in characteristics, which the patterns include. The patterns of the multi-state appliances include a high number of distinct power values with characteristic transitions between them while the patterns of single-state appliances integrate a lower amount of such characteristic transitions since the pattern comprises only one state. The important findings that emerge from this observation are:

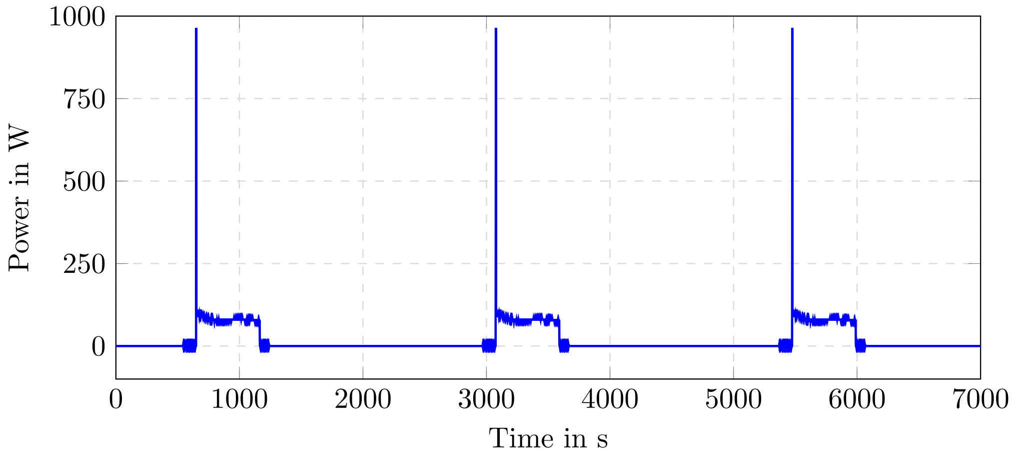
First, the noise resilience, the ability of the pattern to be recognised despite of additive white Gaussian noise (AWGN), depends strongly on the appliance type of the respective pattern. For multi-state appliances the noise resilience will be higher than for single-state appliances.

Second, if the amount of deviation exceeds a certain threshold, then the correlation coefficient $r$ falls below a certain correlation threshold $\gamma$. As a result of this, the correlation filter will not be able to detect the particular appliance.

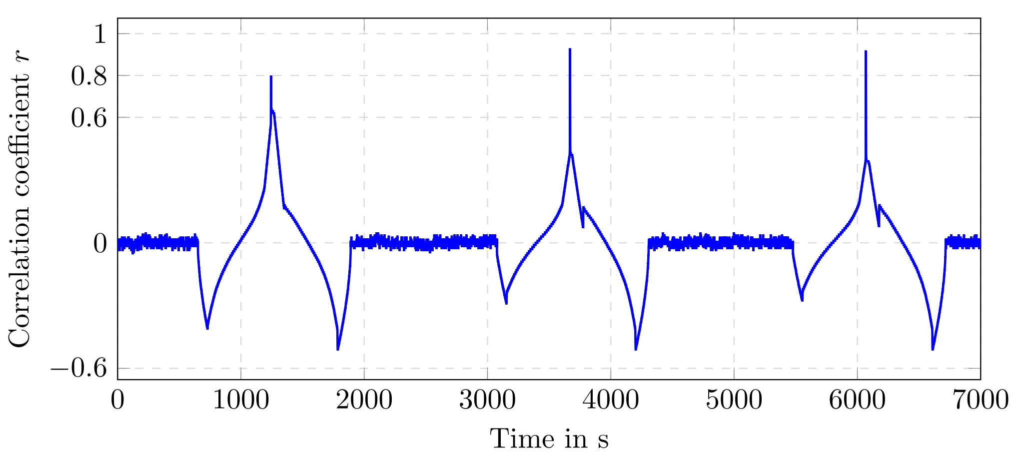
The findings indicate that for excessive noise at the input of the correlation filter the single-state appliances are more likely to not be detected than multi-state appliances as a consequence of the unlike noise resilience. The noise resilience is a property of the respective power consumption pattern and is expressed by the maximum deviation the pattern is able to withstand for a certain correlation threshold $\gamma$. This maximum deviation is expressed by the minimum signal-to-noise ratio $SNR_{min}$. For a correlation threshold $\gamma$ of 0.6 i.e. medium correlation, Table 5.1 summarises $SNR_{min}$ for the respective appliance. Table 5.2 contains the minimum SNR for a correlation threshold of 0.8, which corresponds to high correlation.




(a) Consumption pattern of a refrigerator

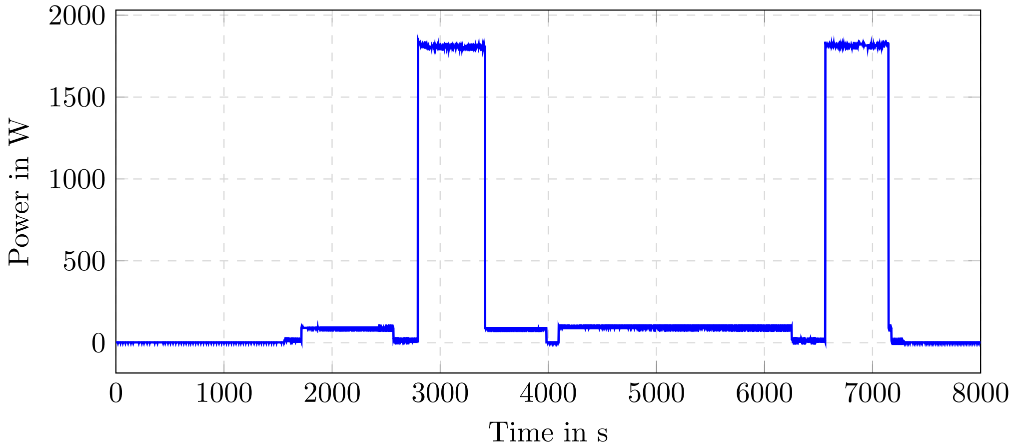



(b) Input signal at the correlation filter

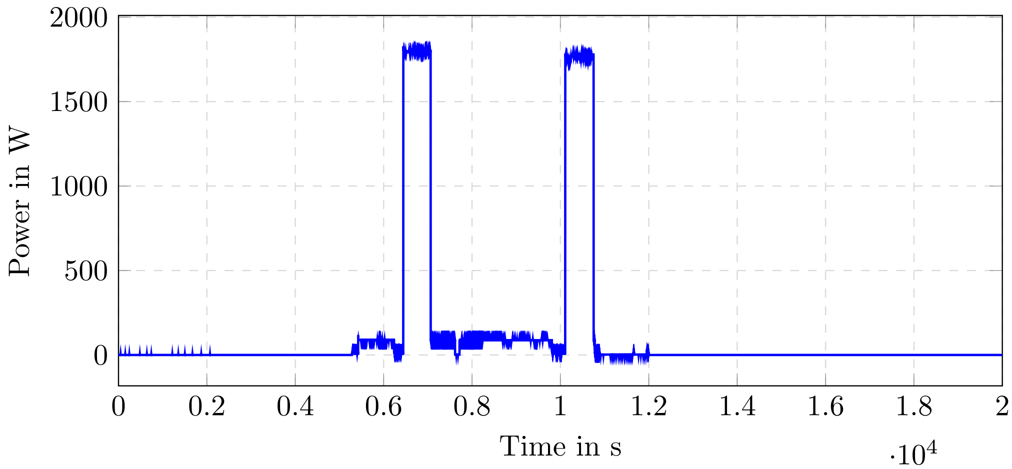



(c) Correlation coefficient $r$ over time

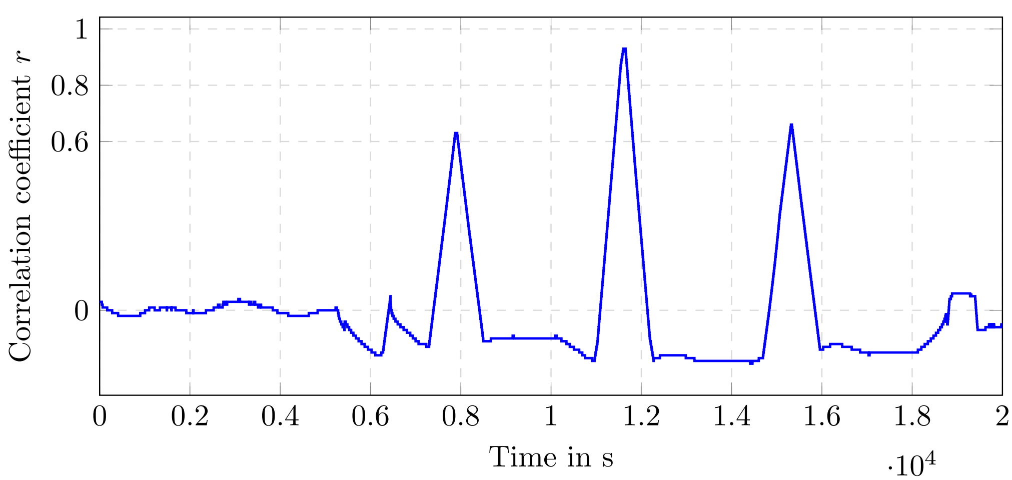
Figure 5.2: Example detections of a refrigerator




(a) Consumption pattern of a dishwasher

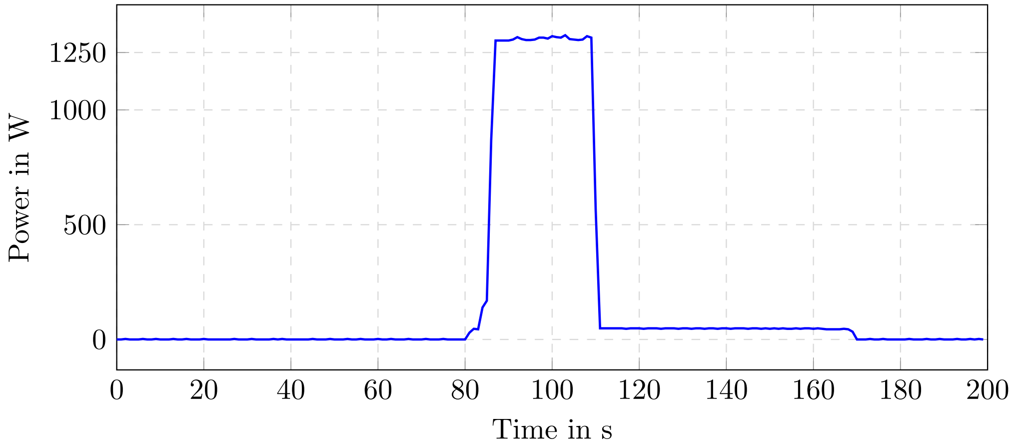



(b) Input signal at the correlation filter

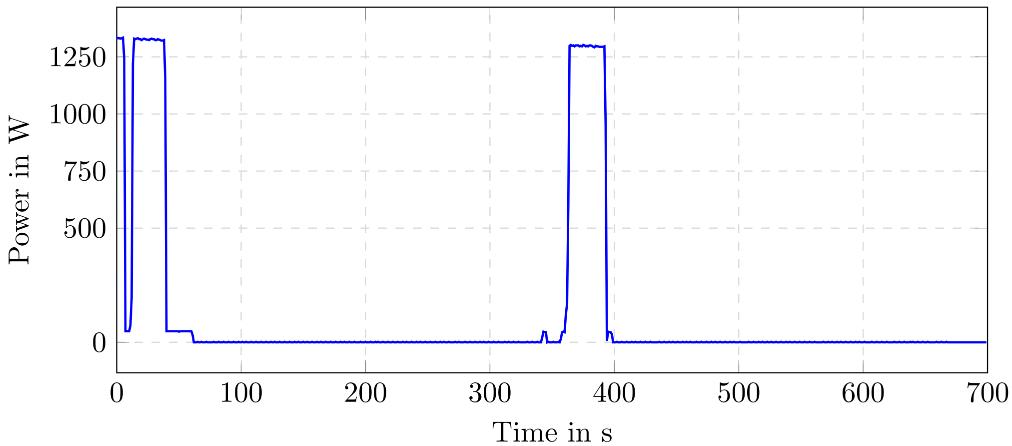



(c) Correlation coefficient $r$ over time

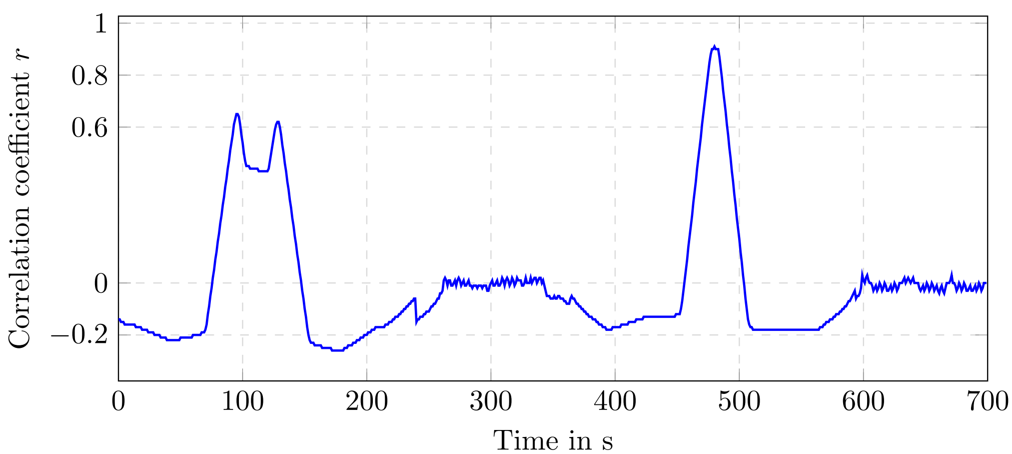
Figure 5.3: Example detections of a dishwasher




(a) Consumption pattern of a washing machine

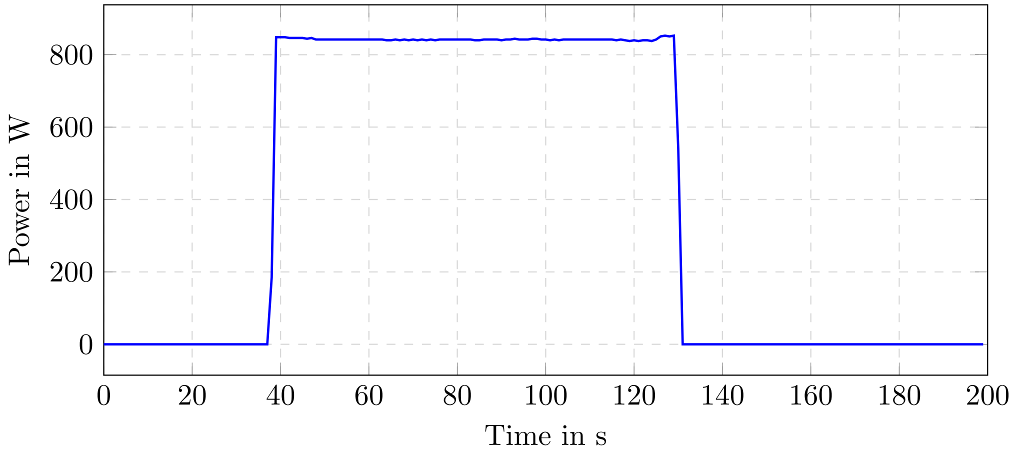



(b) Power signal at the input

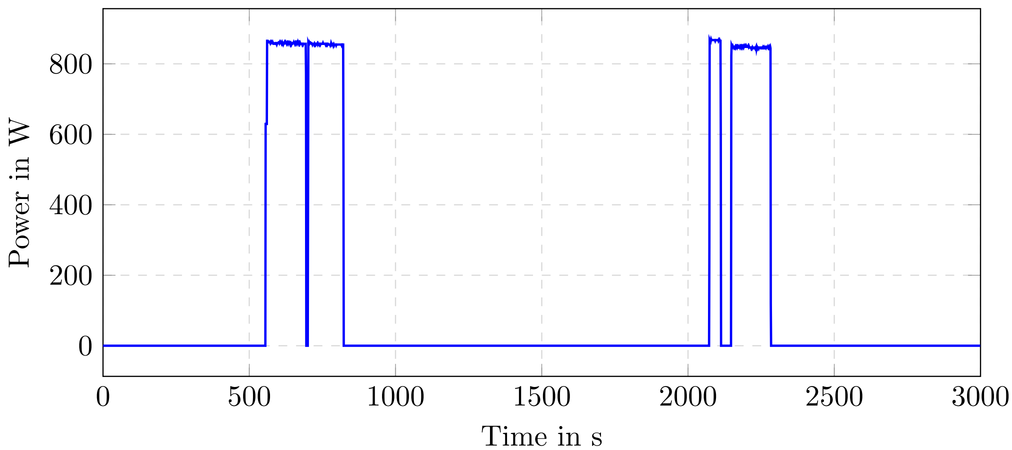



(c) Correlation coefficient $r$ over time

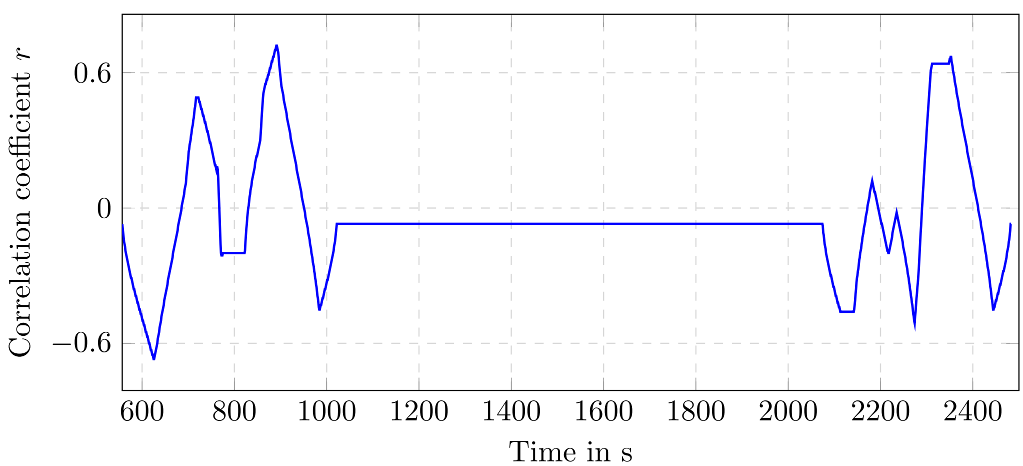
Figure 5.4: Example detections of a microwave oven




(a) Consumption pattern of a washing machine




(b) Power signal at the input




(c) Correlation coefficient $r$ over time

Figure 5.5: Example detections of a water kettle

## 5.2 Impact of Noise on the Detection Rate

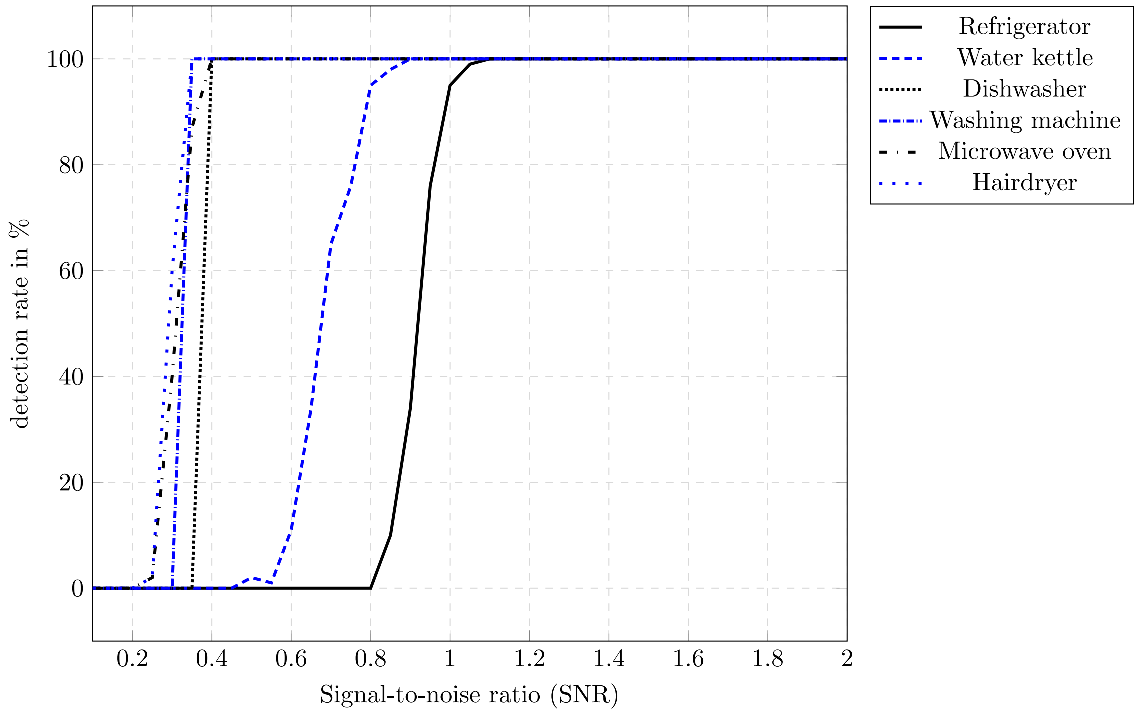
The Matchmaker detector aims to recognise power consumption patterns in an input sequence of measurement samples. By means of correlation between a time frame of this input sequence and a template pattern, the Matchmaker identifies the pattern in the input sequence for a sufficiently high correlation. Whether the Matchmaker recognises the template pattern or not depends on the template pattern and the measured pattern. As discussed beforehand, different types of template patterns exist. In order to compare the amount of deviation that they are able to withstand for a certain correlation threshold, a measure of deviation is required. The signal-to-noise ratio between the template pattern and the superimposed noise represents such a measure of deviation.

The minimal signal-to-noise ratio for a certain threshold reveals, whether this threshold will result in a sufficiently high detection rate or not. The level of this measure depends on the type of the respective template pattern. On the basis of an empirical analysis we will determine the level of this measure for a set of power consumption patterns. This power consumption patterns also serve as template patterns for the correlation filter and were introduced in Section 5.1. These patterns serve as templates to detect the respective appliance. In the process of detection, a certain template pattern is correlated with the input pattern, which usually would be measured by a measurement device. For the sake of investigation in the minimal SNR, this input pattern is defined as the superposition of the respective template pattern and noise. Furthermore, the input pattern consists of $10^4$ subsequent template patterns of the same kind. For each template pattern the minimal signal-to-noise ratio $SNR_{min}$ is evaluated, which is required between the template pattern and the input pattern in order to detect all patterns in the input pattern i.e. to achieve a detection rate of 100%.

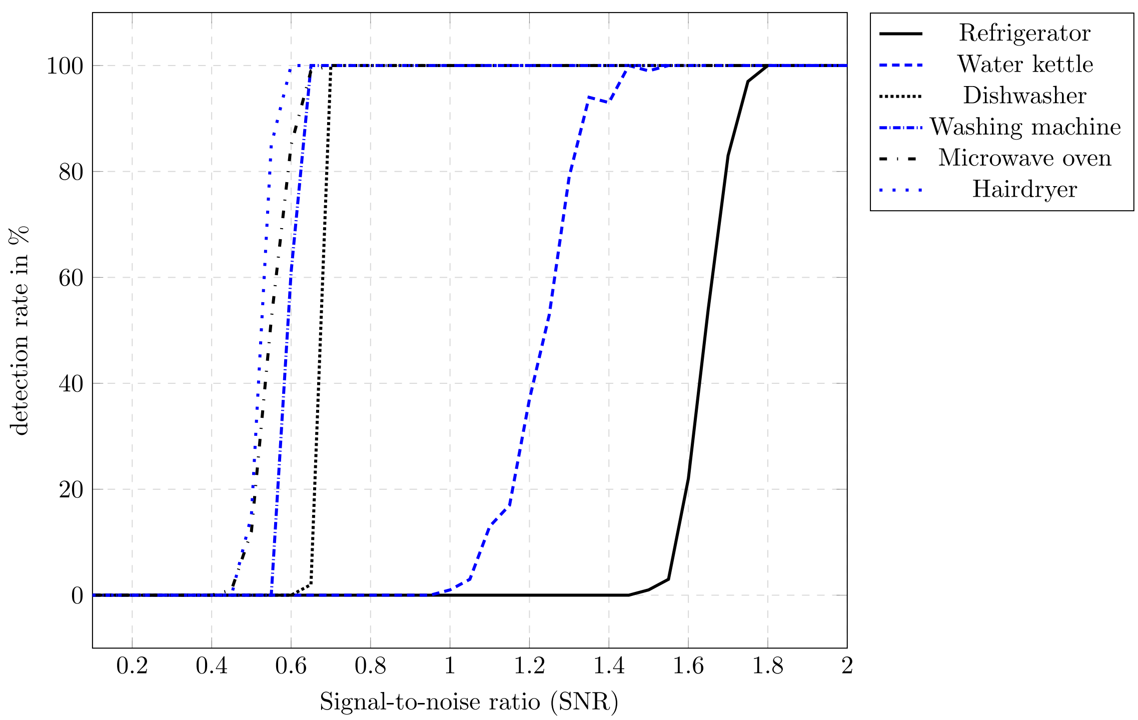
The Matchmaker detector is applied to this input pattern first for a correlation threshold in the region of medium correlation i.e. $\gamma = 0.6$ and then for a correlation threshold in the region of high correlation i.e. $\gamma = 0.8$. The correlation threshold states the minimal level of correlation between input and template pattern that is required in order to declare a detection. Therefore, the minimal SNR will be lower for a correlation threshold in the range of medium correlation than for a threshold in the region of high correlation.

The results of the evaluation, the minimal signal-to-noise ratios for the respective appliances, are summarised in Table 5.1 for a correlation threshold of 0.6. Table 5.2 contains the minimal ratios for a correlation threshold of 0.8. The results approve that a lower correlation threshold results in a lower minimal SNR for every pattern. For instance the minimal SNR for the pattern of the refrigerator equals 1.1 for a threshold in the range of medium correlation i.e. $\gamma = 0.6$ and 1.8 for a threshold in the region of high correlation i.e. $\gamma = 0.8$ The same applies to the remaining five appliances.

On account of this, we propose that the amount of expected noise has to be considered in the selection of the utilised correlation threshold. In the case of a low amount of superimposed noise the utilisation of both a medium and a high correlation threshold is reasonable. However, in the case of a high amount of superimposed noise the optimal selection of an appropriate threshold is more complicated. On the one hand, a correlation threshold in the range of medium correlation i.e. $0.6 \leq \gamma < 0.8$ results in a higher detection rate than a correlation threshold in the range of high correlation. Therefore, a medium correlation threshold maximises the detection rate. On the other hand, a correlation




(a) Influence of the signal-to-noise ratio on the detection rate for a correlation threshold $\gamma$ of 0.6




(b) Influence of the signal-to-noise ratio on the detection rate for a correlation threshold $\gamma$ of 0.8

Figure 5.6: Impact of noise on the detection rate

threshold in the range of high correlation i.e. $0.8 \leq \gamma < 1$ decreases the number of false detections i.e. false alarms. Therefore, a high correlation threshold minimises the false alarm rate.

| Appliance | Type | $SNR_{min}$ |
|---|---|---|
| Refrigerator | single-state | 1.1 |
| Water kettle | single-state | 0.9 |
| Dishwasher | multi-state | 0.4 |
| Washing machine | multi-state | 0.4 |
| Microwave oven | multi-state | 0.35 |
| Hairdryer | multi-state | 0.35 |

Table 5.1: Minimal signal-to-noise ratios for $\gamma = 0.6$

| Appliance | Type | $SNR_{min}$ |
|---|---|---|
| Refrigerator | single-state | 1.8 |
| Water kettle | single-state | 1.55 |
| Dishwasher | multi-state | 0.7 |
| Washing machine | multi-state | 0.65 |
| Microwave oven | multi-state | 0.65 |
| Hairdryer | multi-state | 0.6 |

Table 5.2: Minimal signal-to-noise ratios $\gamma = 0.8$

In the previous section we observed that the amount of deviations a template pattern is able to withstand depends on the pattern type e.g. single-state or multi-state. The template patterns with several distinct power consumption values and therefore a characteristic shape show a better performance than patterns with a small number of distinct values i.e. a less characteristic shape. The comparison of the detection rates approves this observations in two different ways.

First, the obtained minimal signal-to-noise ratios, summarised in Table 5.1 and in Table 5.2, show different levels for single-state and multi-state appliances. In particular, a clear gap between single-state appliances and multi-state appliances can be observed. One of these single-state appliances is the refrigerator. For a correlation threshold of 0.6, the refrigerator's minimal SNR equals 1.1. Meanwhile, the minimal SNR for the hairdryer, one of the multi-state appliances, is significantly lower with a level of 0.35.

Second, the observed gap between the detection rates increases with the correlation threshold. Figure 5.6(a) shows the detection rates of the six appliances for a correlation threshold of 0.6. The trajectories of the multi-state appliances cluster together, whereas a clear gap to the single-state appliances exists. This gap increases further for higher correlation thresholds, as Figure 5.6(b) confirms. The figure shows the detection rates for a correlation threshold of 0.8 i.e. high correlation. As the figure shows, the trajectories for multi-state appliances also for high correlation thresholds cluster together. In contrast to that, the distance between the trajectories of single-state appliances also increases.

The level of the detection rate and in particular the minimal SNR of the respective template pattern strongly depends on the type of the utilised template pattern. This matter of fact has to be considered in the selection of the correlation threshold for the respective detector. In general, we propose a high correlation threshold for appliances with multi-state patterns and a medium correlation threshold for appliances with single-state pattern.

## 5.3 Matchmaker Detector on an Energy Consumption Dataset

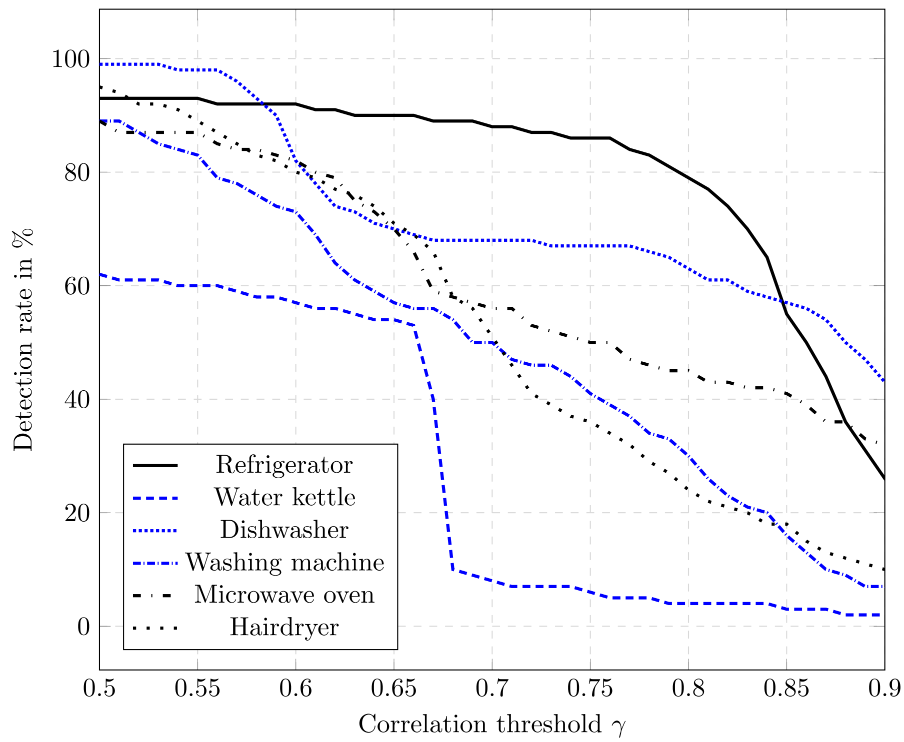
This section addresses the performance assessment of the Matchmaker detector. Therefore, the Matchmaker detector is applied to one entire year of energy consumption data. This energy consumption data is extracted from the GREEND data set and serves as ground-truth in our assessment. In this assessment, the *detection rate* serves as measure of performance. This rate is defined as the ratio between the number of detected patterns in the input data and the number of patterns integrated in the ground-truth data.

In order to detect a certain pattern, the Matchmaker requires a template pattern, which describes the power consumption of a certain appliance over time. In this assessment, the Matchmaker utilises the template patterns presented in Section 5.1. These patterns represent recorded power consumption patterns and characterise several household appliances such as a refrigerator, a dishwasher, a microwave oven, a water kettle, a washing machine, and a hair dryer.

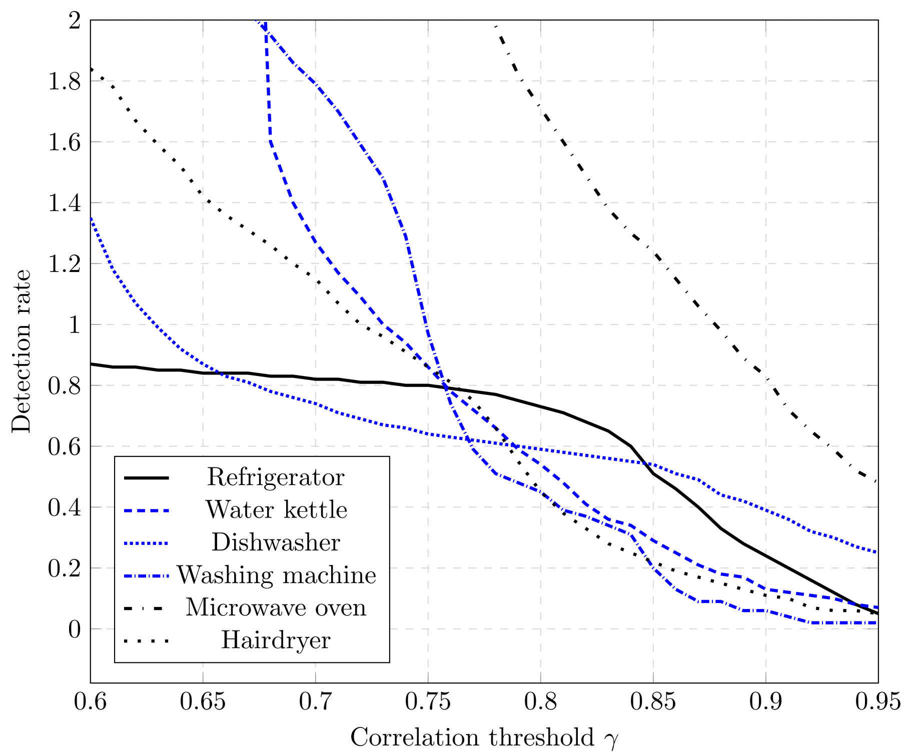
The correlation threshold $\gamma$ describes the minimum correlation, which has to be exceeded in order for the Matchmaker detector to recognise the template pattern in the input data. The performance of the Matchmaker detector is assessed for thresholds in the interval $[0.5, 0.95]$. For selected correlation thresholds of this set the Matchmaker detector scans the ground-truth data for the familiar template patterns. On the basis of the number of detected patterns, the respective detection rate is computed for $\gamma$ in the set $[0.5, 0.95]$ with a step size of 0.01. In this way the performance for low, medium, as well as high correlation on the data record is measured with high granularity.

First, *appliance-level* consumption data serves as input data for the Matchmaker detector. Appliance-level consumption data is acquired by instruments that are attached to a certain appliance e.g. smart plugs. Therefore, the obtained data contain exclusively consumption data of one particular appliance.

Second, *aggregate-level* consumption data serves as input data for the Matchmaker detector. Aggregate-level data is obtained by measurement devices, which meter the power consumption at a central position of the distribution network e.g. the feed point of a certain household. Measurement devices such as smart meters serve as instruments on aggregate level. The recorded consumption data describes the aggregate power consumption of the respective building. Consequently, the Matchmaker detector scans an aggregate input pattern.




(a) Impact of the correlation threshold $\gamma$ on the detection rate in appliance-level data




(b) Impact of the correlation threshold $\gamma$ on the detection rate in aggregate-level data

Figure 5.7: Detection Rate of the Matchmaker detector

### 5.3.1 Detection on Appliance Level

Data acquired on appliance-level exclusively contains information about the energy consumption of one particular appliance. Devices such as smart plugs are attached to a certain appliance to exclusively monitor its energy consumption. The recorded energy consumption is expressed as a time series of power consumption measurements. A (moving) time window of this time series represents the input pattern (measured pattern) of the Matchmaker detector.

In order to detect a certain appliance, the Matchmaker correlates the input pattern with the corresponding template pattern. The template pattern describes the power consumption of the respective appliance over time. The strength of the correlation gives information about the deviation between these two patterns throughout the input data. On the one hand, this deviation influences the number of detected appliances and consequently the detection rate. On the other hand, the Matchmaker detector integrates a parameter, which can be adjusted in order to influence the detection rate, the correlation threshold $\gamma$. This parameter originates from the embedded correlation filter. The purpose of this parameter is to serve as threshold in order to decide if the computed correlation coefficient $r$ is high enough to declare a detection. From another perspective, the correlation threshold defines a minimum amount of resemblance that the correlation has to indicate in order to declare a detection. For this reason, the impact of the correlation threshold on the detection rate has to be determined.

If the threshold $\gamma$ is defined in the range of high correlation e.g. $\gamma = 0.8$, then this will result in a lower detection rate than for $\gamma$ in the range of medium correlation e.g. $\gamma = 0.6$. In order to prove this hypothesis, the Matchmaker detector is applied to appliance-level data for a set of correlation thresholds. The utilised appliance-level data covers one year of energy consumption data. The consumption patterns of the six appliances presented in Section 5.1 are to be detected by the Matchmaker. Figure 5.7(a) shows the detection rates over a set of correlation thresholds $\gamma$ for the selected household appliances. Equal to Section 2.4, we distinguish between low, medium, and high correlation in the case of the correlation threshold $\gamma$. As the trajectories show, the detection rates decrease significantly for an increasing correlation threshold.

According to the appliance taxonomy in Section 2.1, the power consumption behaviour of appliances can be divided into *predictable* and *non-predictable* behaviour. From the selected household appliances in this evaluation the refrigerator, the dishwasher, as well as the washing machine belong to the category of appliances with predictable power consumption behaviour. Predictable power consumption in our context means that the shape of the power consumption over time can be predicted for a certain programme.

The Matchmaker detector provides the best performance for an appliance with predictable power consumption pattern. This appliance is the refrigerator, although Figure 5.1 indicated the highest sensitivity towards deviations (compared to the other appliances). The refrigerator achieves the highest detection rate for medium as well as high correlation, as Figure 5.7(a) shows. For a correlation threshold $\gamma$ in the range of low and medium correlation, the Matchmaker is able to detect more than 80% of the patterns in the input data. The reason for this comparably high detection rate is the optimal selection of the template pattern. The utilised template pattern describes a specific physical task that the refrigerator periodically performs. This task is to cool the content of the refrigerator. Due to the repetition of this physical task, the deviation between the template pattern and the measured power consumption is small enough to detect most of the patterns.

The dishwasher as well as the washing machine likewise belong to the category of appliances with predictable power consumption pattern. In contrast to the refrigerator, the detection rate for medium and high correlation is substantially lower than for the refrigerator. For a correlation threshold $\gamma$ of 0.8, the Matchmaker detects 62% of the patterns of the dishwasher and 30% of the patterns in the case of the washing machine. This performance gap is a result of the detection approach. The more distinct programmes an electrical appliance comprises, the lower the detection rate for the Matchmaker detector will be.

In this evaluation, the Matchmaker detector applies one power consumption pattern of a certain appliance in order to detect the respective appliance for all possible programmes, which the appliance may execute. For appliances such as a refrigerator, which comprises only one possible programme, the Matchmaker detector shows a high performance. In contrast to that, the performance is significantly lower for appliances with a set of possible programmes, which the appliance may execute such as dishwashers or washing machines. By means of one template pattern the Matchmaker detector aims to detect a set of possible programmes, which the appliance possibly executed. If the ratio between the respective template pattern and the pattern of the executed programme exceeds the threshold $SNR_{min}$, then the Matchmaker will not be able to detect the appliance. The threshold $SNR_{min}$ defines the minimum amount of resemblance, which the template pattern and the measured pattern have to fulfil in order for the Matchmaker to declare a detection.

Because of these findings, we propose to pursue a specific detection strategy: On appliance level, the Matchmaker detector shows a high performance for appliances with predictable power consumption patterns, as Figure 5.7(a) endorses. In particular, the best performance is achieved if the Matchmaker aims to detect a specific programme of a certain appliance. Therefore the emphasis of the detection has to be on the recognition of specific programmes an appliance may execute. Since an appliance may comprise a set of such specific programmes, the Matchmaker has to relate the respective patterns of these specific programmes with a certain appliance. As a consequence of this, a set of power consumption patterns per appliance is required to detect the multiple programmes and their characteristic power consumption pattern.

The power consumption patterns of electrical appliances can be divided into *predictable* and *non-predictable* patterns. Predictable patterns describe specific programmes, which the appliance is able to execute. These programmes have a fixed duration and therefore a predictable energy consumption. From this follows that the execution of two identical subsequent programmes will produce similar power consumption patterns.

In contrast to predictable patterns, the duration as well as the energy consumption of non-predictable patterns can't be predicted. Appliances, which produce non-predictable consumption patterns, don't have programmes with a fixed duration. For this reason the shape of the power consumption pattern is not predictable. Examples for appliances with non-predictable consumption patterns are water kettles, microwave ovens, and hairdryers.

Figure 5.7(a) shows the detection rate of the Matchmaker over the correlation threshold $\gamma$. For a correlation threshold of $\gamma = 0.6$, which corresponds to the range of medium correlation, 80% of the patterns for the hairdryer and the microwave oven were detected, whereas less than 60% of the patterns for the water kettle.

In the case of a correlation threshold in the range of high correlation e.g. $\gamma = 0.8$, the detection rate declines under 50% for all appliances with non-predictable power consumption pattern in this evaluation. With a rising correlation threshold, the minimum amount of resemblance decreases. This minimum amount of resemblance is defined by the ratio of the template pattern and the measured pattern, $SNR_{min}$. In the case of the non-predictable appliances in this evaluation, the ratio between template and measured pattern is below the demanded threshold for more than every second measured pattern. This is a consequence of the strongly varying shape of the power consumption pattern. To overcome this issue, we propose an empirical approach to select the optimal template pattern for a certain non-predictable appliance. To maximise the detection rate for a certain electrical appliance with non-predictable power consumption, we propose to follow a specific procedure:

1. In an observation period, every power consumption pattern of the respective appliance is recorded and appended to the set of patterns for the appliance.

2. In an evaluation period, the power consumption pattern with the *median* energy consumption is examined. This pattern will serve as template pattern for the respective appliance.

### 5.3.2 Detection on Aggregate Level

The power consumption of electrical appliances can either be determined on appliance or on aggregate level. Appliance-level measurements record the power consumption of a single appliance, whereas aggregate-level measurements record the power consumption at a central point of the power distribution network e.g. the feed point of a building. Instruments such as smart meters measure the aggregate power consumption. Consequently, this aggregate power consumption represents the superposition of multiple power consumption patterns. The Matchmaker detector can be applied to aggregate-level data in order to detect electrical appliances. The detection is performed by means of correlation between measured patterns and template patterns, which were extracted from appliance-level measurements.

In order to investigate if the Matchmaker detector is applicable to data provided by smart meters, the detector is applied to aggregate-level measurement data. This data is obtained by the superposition of the appliance-level data applied in Section 5.3.1. This data contains the power consumption of several household appliances over the period of one year. The Matchmaker detector scans this household consumption data for a set of template patterns. These template patterns, introduced in Section 5.1, describe specific programmes of household appliances.

In the previous evaluation, the detector was applied to data obtained by appliance-level measurements. Consequently, the detector was unable to perform a false detection (false alarm) since the input data exclusively contained information about the power consumption of the respective appliance. In contrast to this, on aggregate-level measurement data it is possible that the detector performs an incorrect recognition i.e. false alarm. This is because the aggregate-level measurement data is a superposition of multiple power consumption patterns. As a consequence of this superposition, a significantly higher amount of deviations between expected and measured pattern has to be expected, which will influence the detection rate of any detector applied to the aggregate-level data. Figure 5.7(b) illustrates the detection rates over the correlation threshold $\gamma$ for the electrical appliances introduced in Section 5.1. The detection rate is defined as the ratio between the number of detected patterns and the number of patterns contained in the measurement data. As Figure 5.7(b) confirms, decrease the detection rates for the six household appliances for an increasing correlation threshold. In contrast to the evaluation on appliance-level, in this evaluation the detection rates exceed the 1 mark. A detection rate greater than 1 states that more patterns were detected than the ground-truth data contains in fact. This is a consequence of incorrect detections performed by the Matchmaker detector, as a result of false alarms. The lower the correlation threshold $\gamma$ is set, the higher the number of false alarms and therefore, the higher the detection rate. The correlation threshold defines a minimal amount of resemblance expressed as correlation between the stored template pattern and the measured pattern. If this threshold is defined in the range of high correlation e.g. $\gamma = 0.8$, then on the one hand the detection rate will be lower than for medium correlation, but on the other hand likewise the number of false alarms will be significantly lower. For this reason a trade-off between number of false alarms and the detection rate exists.

Figure 5.7(b) shows the detection rates for six household appliances over the correlation threshold $\gamma$. These detection rates were obtained by application of the Matchmaker detector to the aggregated energy consumption data over the period of one year. For correlation thresholds in the range of medium correlation $0.6 \leq \gamma < 0.8$, the detection rates show a high amount of false alarms. One exception represents the detection rate of the refrigerator, which remains under the 1 mark for all applied correlation thresholds. The highly incorrect detection rates of the other appliances in the range of medium correlation are a consequence of false alarm detections. Such detections are declared by the Matchmaker, when the correlation threshold $\gamma$ is exceeded by the correlation between input pattern and template pattern.

In the context of aggregate-level measurement data, the input pattern is a superposition of several power consumption patterns. If the template patterns of two appliances closely resemble each other, then the Matchmaker will very likely perform a false alarm detection. This false alarm detection represents an incorrect detection. In order to minimise the number of false alarm detections for a certain appliance, the correlation threshold $\gamma$ has to be defined in the range of high correlation i.e. $\gamma \geq 0.8$. As the results of the evaluation in Figure 5.7(b) confirm, the detection rates decrease under the 1 mark for all electrical appliances with predictable power consumption. In this evaluation, such appliances are the refrigerator, the dishwasher, and the washing machine. In particular, the detection rate of the refrigerator shows a conformable trend to the evaluation on appliance level, which is displayed in Figure 5.7(a). As the Figure confirms, a clear gap in performance between the refrigerator's pattern and the remaining patterns exists. This gap originates from several characteristics of the refrigerator.

First, the refrigerator periodically performs an identical operation. For this reason the stored template pattern and the (predictable) input pattern resemble each other closely. On account of this close resemblance, the deviations between the template pattern and the measured patterns are small enough to demand a high correlation threshold. Such a high correlation threshold e.g. $\gamma \geq 0.8$ decreases the chance of performing a false detection.

Second, the pattern of the refrigerator contains a characteristic turn-on transient, as Figure 5.2(a) shows. In particular, the overshoot during the transient phase shapes the power consumption in a specific manner. Such characteristics make template patterns unique and well-distinguishable from other patterns.

In summary, the application of the Matchmaker detector on aggregate-level data faces a trade-off between number of false alarms and detection rate. To minimise the number of false alarms we propose the application of a correlation threshold in the region of high correlation i.e. $\gamma \geq 0.8$. In general, a high correlation threshold decreases the number of false alarms and consequently also the detection rate. On the contrary, we aim to maximise the detection rate in order to provide an optimal performance of the Matchmaker detector. The performance of the Matchmaker inherently depends on the applied template patterns, which are correlated with the measured patterns. As demonstrated in Figure 5.7(b), the Matchmaker provides the best performance for appliances with predictable power consumption patterns. Peculiarly, predictable patterns with characteristic transients represent optimal template patterns such as the template pattern of a refrigerator.

On the basis of the evaluation's results on aggregate-level data and the discussed characteristics of the template patterns, we propose:

- the utilisation of a correlation threshold in the region of high correlation $\gamma \geq 0.8$,
- the detection of appliances with predictable power consumption patterns,
- to compose template patterns of appliance-specific transients,

for applications, in which the Matchmaker is employed on aggregated energy consumption data.

# Chapter 6

# Conclusion

## 6.1 Contribution

This thesis provided contributions in the research domain of smart metering and low-cost energy management systems for households. In particular, we identify contributions in the area of appliance modelling, appliance monitoring, and appliance detection.

In the area of appliance monitoring, this thesis introduced a novel taxonomy for electrical appliances. It extends related work by introducing a notion of predictability for each appliance. In other words, our taxonomy distinguishes if the shape of a certain electrical or ambient appliance feature is predictable or not.

The contribution of this thesis in the area of appliance monitoring comprises the introduction of design aspects and the implementation of a distributed measurement. The analysis of design aspects lead to the selection of required measurement devices, which fulfil distinct purposes. These measurement devices form a distributed measurement system. The purpose of this distributed measurement system is to record and monitor steady-state features, transient-state features, and ambient features of electrical appliances. Therefore, the introduced system integrates a smart meter, a set of smart plugs, and several networked sensors. The smart meter integrates the YoMo smart metering board. This open-hardware board measures the power consumption as well as V-I features at the household's feed point. The smart plugs are attached to household appliances in order to measure their power consumption. The networked sensors record the impact of electrical appliance on the environment i.e. ambient features. These ambient features comprise heat dissipation, sound emission, or vibrations. The distributed measurement system is utilised to record and store appliance features.

Certain detectors utilise appliance features as template patterns. This thesis presented such an appliance detector, the correlation filter. Correlation filters can be applied by conventional computer systems as well as by embedded computer systems. In particular, the correlation filter operates the Matchmaker algorithm to detect appliances by means of certain electrical or ambient appliance features. The respective feature is recorded and a consumption pattern is generated. The findings in this thesis indicated that a consumption pattern with a high number of distinct values results in an optimal detection rate. A particularly high difference in performance was observed between recorded consumption patterns and patterns that were generated from state-machine models.

The performance of the Matchmaker detector was assessed on the energy consumption data set GREEND. The assessment was performed on consumption data of single appliances and on aggregate consumption data such as readings provided by smart meters. For appliances with predictable features, the results approved a high performance for consumption data from single appliances as well as aggregate consumption data. In contrast to that, the performance of the Matchmaker detector is significantly worse, which indicates that the Matchmaker detector is not an appropriate detector for appliances with non-predictable features. However, we propose a detection policy for non-predictable features in order to maximise the detection rate for non-predictable features.

## 6.2 Economical aspects

The Matchmaker detector demands low hardware requirements. For this reason, the detector can be applied on conventional desktop computers as well as on embedded computer systems such as a Raspberry Pi. Therefore, the detector can be utilised in low-cost home energy measurement systems. Such systems present a low-cost alternative to expensive commercial home monitoring systems. Thus, asset costs can be reduced by the installation of such a low-cost home energy measurement system HEMS.

The deployment of a low-cost HEMS would allow the resident to detect abnormal appliance behaviour. Because of ageing, some electrical appliances consume more energy than a new appliance of the same kind. Such phenomenons were reported in [5], where a common household device consumed due to ageing effects three times more energy than at the time of purchase. A distributed measurement system, which utilises detection algorithms such as the Matchmaker detector, would be able to detect ageing effects and would suggest the user to replace the respective device. By means of suggestions like this, such a system assists the owner in saving costs and in detecting power eaters. Furthermore, the system would be able to detect the point in time, where an appliance will require maintenance. The observation of steady-state, transient-state, and ambient appliance features makes this detection possible.

## 6.3 Outlook

The Matchmaker detector represents a universal detection tool since it utilises correlation filters in order to detect appliances by means of their appliance features. These features may reflect the power consumption of a certain programme or the impact of an appliance on the environment i.e. ambient features.

Future work should determine how the distributed measurement system and the correlation filters can be combined with artificial intelligence (AI). In particular, the correlation filters represent simple tools that serve to detect specific behavioural patterns. This detection can either be used to identify an appliance or to indicate abnormal behaviour. The distributed measurement system gathers appliance features of the appliances in the household. By means of machine learning an AI is possibly able to precisely study the present appliances in the household as well as their characteristics. Moreover, an AI may serve as cognitive unit that recognises specific events in the household such as the arrival of a resident or certain habits. The application of such a cognitive unit may allow to achieve significant energy savings by the identification of power eaters and the recognition of ageing effects of electrical appliances.

A second research perspective lies in the field of load disaggregation. Load disaggregation algorithms aim to identify electrical appliances in aggregate power readings. The application of correlation filters and the Matchmaker detector could improve the identification of electrical appliances by means of particular features. Moreover, a big number of load disaggregation algorithms suffers from difficulties in distinguishing between appliances with similar power consumption profiles. The appliance profiles generated by our system consist of power features as well as ambient features. In particular, the ambient features may allow to distinguish between appliances with similar power consumption profiles.

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