MONERGY: ICT solutions for energy saving in Smart Homes

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Technical Report

Validation and analysis of results

Bewertung und Analyse der Ergebnisse

Validazione e analisi dei risultati

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Abstract

The main goals of the MONERGY project are:

- To increase the inter-regional knowledge of technologies and solutions in the field of Smart Grids.
- To promote the research and the innovation in ICT by targeting solutions that have an impact on the reduction of energy consumption within houses by considering the peculiarities of the Friuli Venezia-Giulia (FVG) and Carinthia (CAR) regions.

Within MONERGY, the objectives of WP5 (entitled *Validation of Usage Models and Energy Saving Analysis*) are:

- To test the functionalities of the hardware validation platform resulting from the research results in WP4
- To experimentally validate the use of the monitoring system in real-life scenarios, by means of a measurement campaign in households in CAR and FVG
- To analyze measurements in order observe commonalities and differences between the regions
- To formulate policies that considers such peculiarities to improve energy efficiency

This deliverable presents the outcome of the work carried out within WP5. In particular, it reports the outcome of the measurement campaign carried out in the regions to monitor real-life scenarios. The GREEND dataset resulting from such research effort is presented and analyzed to gain further insights into energy usage behavior. Specific policies aiming at improving energy efficiency in households are consequently formulated and implemented in an automatic system.

Executive summary

This deliverable includes the results of the research carried out within WP5. In particular, the following topics are addressed.

- **Monitoring campaign and GREEND dataset** - The MONERGY home energy management system (HEMS) has been installed in 8 households in Friuli Venezia Giulia and in Carinthia. Within each household, the power consumption of 9 electrical appliances is monitored with intervals of one second. The monitoring campaign and the dataset that has been obtained are presented.

- **Validation and analysis of results** - The GREEND dataset is analyzed to gain further insights into energy consumption behavior in the regions. In particular, the dataset has been used in WP5 to derive usage models of energy consumption and analyze analogies and differences between energy consumption patterns in Italy and Austria.

- **Policies for energy efficiency** - As main outcome of the data analysis policies improving energy efficiency are formulated. The analysis is then implemented in an open-source energy management system to extend the benefits to other householders.

Contents

List of Acronyms

ADSL asymmetric digital subscriber line

ANN artificial neural network

CAR Carinthia

CDF cumulative distribution function

DVD digital video player

DSO distribution system operators

EGH episode-generating hidden Markov model

EM expectation maximization

FVG Friuli Venezia Giulia

GPS global positioning system

GUI graphical user interface

HEMS home energy management system

HVAC heat, ventilation and air conditioning

JT junction tree

LCD liquid cristal display

LED light emitting diode

NILM non-intrusive load monitoring

NIOM non-intrusive occupancy monitoring

PLC power line communication

RAM random access memory

SHG smart home gateway

SP smart plug

WDs weekdays

WEs weekend days

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Section 1

Introduction

The deployment of renewable energy generators, such as photovoltaic and wind turbines, as well as the diffusion of electric vehicles, yields instability in the offer and demand of energy in the grid. In order to control the amount of energy required by their customers, utilities are getting progressively involved in demand-side management programs. Accordingly, consumers can shift consumption of particularly energy-demanding appliances (e.g., electric vehicles) to off-peak periods. These programs include the promotion of efficiency and energy conservation, by raising the awareness of customers towards the footprint of their daily activities. From a technical point of view, to effectively implement these programs, it is necessary to collect consumption information and process them in a way that most of the benefits can be made.

Some information on the energy consumption is available in the literature as the result of past measurement campaigns. An overview of such prior works is presented in [MEE$^+$14]. Basically, [MEE$^+$14] reveals that the available information present some strong limitations. Prior measurement campaigns target a low number of houses/devices, provide measurements with a low sampling rate, or they perform monitoring for a limited period of time. Within the MONERGY project we performed a massive monitoring campaign aimed to collect the information on the energy consumption of the Carinthia (CAR) and Friuli Venezia Giulia (FVG) regions. The large number of monitored houses, 8, the fine monitoring accuracy, one measure per second, the large number of monitored devices per site, 9, and the long duration of the monitoring period, 1 year, put the MONERGY database among the most complete and accurate results presented so far.

The MONERGY campaign is a part of the last WP of the project, and it follows from the research activity carried out within the WPs 2, 3 and 4. In the former two WPs, we have reviewed the existent monitoring solutions pointing out the limits, especially in connectivity/coverage terms, and we have studied the impact of the user interface in presenting the monitoring results. Furthermore, we have proposed, designed and validated a) practical solutions that overcome the existent connectivity limitations and that are based on hybrid communication schemes where both power line communication and wireless technologies are deployed, and b) a graphical interface that implements the suggestions from users collected by the MONERGY survey. In WP4, we have developed custom monitoring platforms and we have setup the solution that we have developed for monitoring purposes. The practical consequence was the deployment of the developed HEMS into selected households in CAR and FVG, in which we monitored individual devices. The resulting dataset is GREEND. GREEND has been publicly released and it has been used in WP5 to gain deeper insights into energy usage behavior in the regions.

This deliverable includes the results of the research carried out within WP5 (entitled *Validation and Analysis of Results*), which concerns the analysis of energy consumption data gathered in the regions, in order to derive usage models and formulate policies towards an increased efficiency. In particular, the analysis revealead that savings up to 34% are possible without significant impact on the user lifestyle. To extend the benefits of the data analysis and the formulated policies, we introduce a web-based energy management system and we release it for open use.

The deliverable is organized as follows. Section 2 overviews the measurement campaign and its outcome, the GREEND dataset. An extensive analysis is then provided and discussed in Section 3. Main outcome was the formulation of energy efficiency policies, which are reported and implemented in Section 4. Finally, the deliverable is concluded in Section 5.

Section 2

The measurement campaign

One of the main activities of the MONERGY project is the conduction of a measurement campaign to observe actual energy use in the regions. This section reports criticalities encountered during the campaign and provides an overview of the collected dataset.

2.1 Criticalities

When undertaking the effort of providing a measurement campaign spanning over 1 year we faced several issues:

- **inhabitants' acceptance** while householders self-selected for the campaign, we experienced in one case a misuse in the measurement platform which persisted after a full hardware replacement. The platform worked correctly for several days sending the data to the server but eventually went down again. While the householder periodically restarted the gateway, the situation kept repeating until the householder deliberately dropped out the campaign. Consequently, we decided to exclude the household from the final dataset. A similar situation manifested in building 6 due to a relocation, as well as in building 0 because the householders decided to stop the campaign at the end of 2014 (1 year).

- **network coverage** as analyzed in [DTME14], coverage issues can arise from the use of a Zigbee sensor network for energy management. We mitigate this issue with a best-effort polling mechanism, in which we poll all nodes within a 1 second time period and retrials are performed only when enough time is left. While normally this works fine, error situations due to network coverage can create consecutive invalid measurement values, which we mark as "NULL" in the final dataset.

- **node disconnection** when polling sensor values, the specific library used can introduce timeouts in presence of node disconnections and error conditions. As previously explained in [MEE+14], a mechanism was introduced to blacklist unplugged nodes. This has the undesired effect of introducing consecutive “NULL” values in the final dataset.

- **server quota** in two cases issues arised from the use of an external server to store the dataset. The company server, being used for other purposes, was out of reach for two days in conjunction with a regional event (i.e., Lange Nacht der Forschung). In the second case, we exceeded the given storage quota with the consequent fail of uploading from the monitored households.

2.2 Dataset overview

The main outcome of the measurement campaign was the GREEND dataset, the first 1 year long power consumption dataset for Austria and Italy. The first version of the dataset released[1] on October 31st 2014 contains roughly 10 GB of data stored as comma separated value (CSV) files. The selection of consumption scenarios follows the analysis we presented in [MEDT13, KME+14] and the project deliverable [LW13], and in particular:

- *House #0* a detached house with 2 floors in Spittal an der Drau (AT). The residents are a retired couple, spending most of time at home.

- *House #1* an apartment with 1 floor in Klagenfurt (AT). The residents are a young couple, spending most of daylight time at work during weekdays, mostly being at home in evenings and weekend.

- *House #2* a detached house with 2 floors in Spittal an der Drau (AT). The residents are a mature couple (1 housewife and 1 employed) and an employed adult son (28 years).

- *House #3* a detached house with 2 floors in Klagenfurt (AT). The residents are a mature couple (1 working part-time and 1 full time), living with two young kids.

- *House #4* an apartment with 2 floors in Udine (IT). The residents are a young couple, spending most of daylight time at work during weekdays, although being at home in evenings and weekend.

[1] http://sourceforge.net/projects/greend/files/

- *House #5* a detached house with 2 floors in Colloredo di Prato (IT). The residents are a mature couple (1 housewife and 1 employed) and an employed adult son (30 years).
- *House #6* a terraced house with 3 floors in Udine, (IT). The residents are a mature couple (1 working part-time and 1 full time), living with two young children.
- *House #7* a detached house with 2 floors in Basiliano (IT). The residents are a mature couple, with one being retired and therefore spending most of time at home.

In the following, the sites will be referred to with the notation S#, with # being the number of the site. The device configurations for the selected households are shown in Table 2.1.

At the time of writing 30 people downloaded the dataset and filled the form available on the MONERGY project page. Fig.2.1 shows the proportion of users for the way the got to know about the dataset.

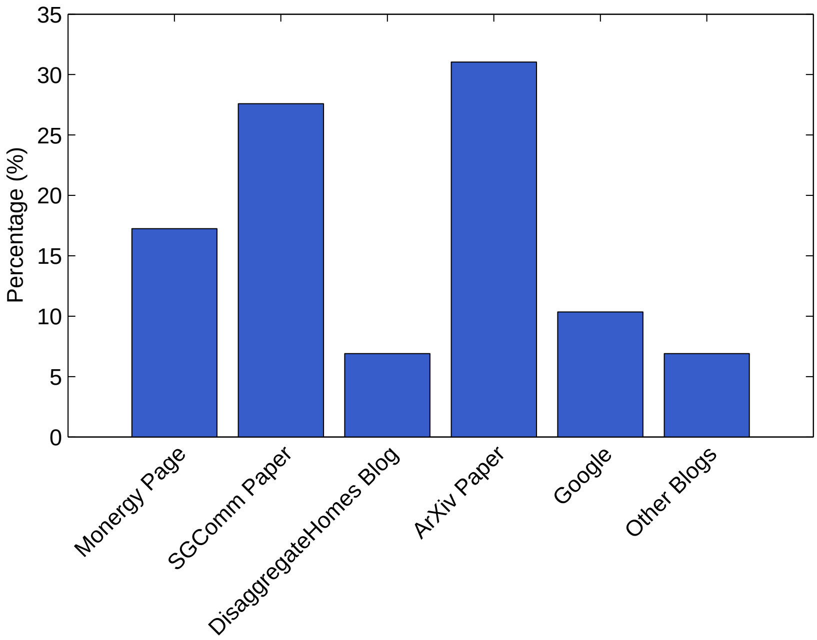


Figure 2.1: Proportion of users for the way they got to know about the dataset.

Table 2.1: Device configurations in the monitored households

House	Devices
0	Coffee machine, washing machine, radio, water kettle, fridge w/ freezer, dishwasher, kitchen lamp, TV, vacuum cleaner
1	Fridge, dishwasher, microwave, water kettle, washing machine, radio w/ amplifier, dryier, kitchenware (mixer and fruit juicer), bedside light
2	TV, NAS, washing machine, drier, dishwasher, notebook, kitchenware, coffee machine, bread machine
3	Entrance outlet, Dishwasher, water kettle, fridge w/o freezer, washing machine, hairdrier, computer, coffee machine, TV
4	Total outlets, total lights, kitchen TV, living room TV, fridge w/ freezer, electric oven, computer w/ scanner and printer, washing machine, hood
5	Plasma TV, lamp, toaster, stove, iron, computer w/ scanner and printer, LCD TV, washing machine, fridge w/ freezer
6	Total ground and first floor (including lights and outlets, with whitegoods, air conditioner and TV), total garden and shelter, total third floor.
7	TV w/ decoder, electric oven, dishwasher, hood, fridge w/ freezer, kitchen TV, ADSL modem, freezer, laptop w/ scanner and printer

Section 3

Data Analysis

Energy monitoring campaigns return a large amount of data that needs to be processed in order to extract the useful information, in general, in statistical terms. Clearly, the higher the accuracy and the number of sites being monitored, the larger the amount of collected data. It follows the complexity of managing and processing the database, and, further, of presenting statistical results that are of some interest.

Load monitoring is a research theme of great interest and several monitoring campaigns were presented in the literature. A complete review of the main results is provided in [MEE$^+$14]. Monergy aims at analyzing and improving user's energy awareness as result of an extensive measurement campaign carried out in CAR and FVG during 2014. As compared to prior works, the MONERGY campaign is characterized by a) a larger number of houses, b) a longer monitoring period and c) a rather high sampling resolution. In detail, the number of houses is 8, the monitoring period is expected to exceed one year, and the resolution is 1 power measure per second. Furthermore, the campaign is intended to understand the habits of people living in two regions, in order to possibly highlight similarities and differences.

This section presents the results of the statistical analysis performed on the database of power measurements collected during the MONERGY campaign. The study addresses the connectivity issues experienced during the campaign, and the statistics of the power consumption of the monitored loads. Furthermore, the analysis points out the contribution of the monitored loads to the total energy consumption, infers the consumption of the non-monitored loads, and discusses the user's awareness and the utility of the the time-slotted energy tariffs. The latter studies are limited to the Italian database, for which the information about the power consumption of the sites is provided by the monthly bills.

The remainder of this section is divided as follows. Section 3.1 introduces the statistical analysis. Section 3.2 and 3.3 show the results for CAR and FVG, respectively. Finally, Section 3.5 is dedicated to the analysis of bills of Italian sites, and to the study of the time slotted energy tariffs, an Italian peculiarity enabled by the digital electric energy meter, that allows for a variable energy pricing during different day times.

3.1 Introduction to the Data Analysis

The database of measurements is expected to exceed 2 billion acquisitions in time, i.e., a huge amount of data that needs to be processed. We aim to extract some useful information by means of statistical analysis and, in this section, we detail the processing we performed to obtain the results that we provide in Sections 3.2-3.3. In particular, we perform:

- the connectivity failure analysis;
- the power consumption analysis.

In the following sections, we describe the processing we adopted to obtain the results from the raw measurement database.

3.1.1 Connectivity Failure Analysis

Connectivity limits are among the main impairments of commercial energy monitoring systems. A detailed review of main limitations is provided in [LW14a, DTME14]. Basically, [LW14a, DTME14] highlights that current wireless and wireline technologies adopted by HEMS are not adequate to fulfill the coverage requirements of Italian/Austrian residential buildings. Now, beside the theoretical limits pointed out in [LW14a], it is interesting to see how connectivity limits impact practically on the collected data.

In this respect, we focus on the percentage of daytime a monitored device is not accessible and we refer to the quantity as connectivity failure percentage, $Q^{(s,d)}$, where $s = 0, \ldots, 7$ and $d = 1, \ldots, 9$ denote the site and the device, respectively. A device, and more specifically the smart plug that monitors the device, could be not accessible for two reasons: because it is physically disconnected from the power network, thus not fed, or due to a connectivity failure. In both the cases, the MONERGY gateway cannot assess the power consumption of the device and this event represents an unsuccessful reading. The gateway associates a NULL power consumption value to an unsuccessful reading. Thus, from the analysis of NULLs of the collected dataset, we can infer the statistics of unsuccessful readings. Subsequent NULL values form a NULL period. The duration of a NULL period is given by the difference between the timestamp of the last and the first NULL measure. We aim to distinguish between the connectivity failures and device disconnections. NULL periods associated to disconnections can last from minutes to hours or even days because it is reasonable to assume that when a device is disconnected by the user, it remains disconnected for quite a long time. In the same way, it is reasonable to assume that connectivity failures may last no longer than few minutes. Herein, we assume that connectivity failures yield to NULL periods no longer than 5 minutes.

Table 3.1: Data extracted from the power measure in S4

timestamp	device								
01/02/14	#1	#2	#3	#4	#5	#6	#7	#8	#9
22:49:31	36.52	0.0	0.0	0.0	N	N	2.17	0.0	0.0
22:49:32	38.67	0.0	0.0	N	N	N	0.0	0.0	0.0
22:49:33	38.67	N	0.0	N	N	0.0	2.17	0.0	0.0
22:49:34	36.53	N	0.0	N	N	0.0	0.0	0.0	N
22:49:35	38.67	N	0.0	N	N	0.0	2.17	0.0	N
22:49:36	38.67	N	0.0	N	N	0.0	0.0	0.0	N
22:49:37	36.53	N	0.0	N	N	0.0	2.17	0.0	N
22:49:39	38.67	N	N	N	0.0	0.0	0.0	0.0	N
22:49:40	36.53	N	N	0.0	0.0	0.0	2.17	0.0	N

Let us consider an example. Table 3.1 reports some measures extracted from the dataset collected in S4. The Table reports the power consumption of the 9 monitored devices in an interval of 10 seconds. NULLs are denoted with N. As it can be seen, the gateway experiences difficulties assessing devices 2, 3, 4, 5, 6, and 9. In particular, device 4 shows a NULL period of about 7 seconds. Therefore, according to the definition we proposed, device 4 experiences a connectivity failure of about 7 seconds.

In the following, we compute $Q^{(s,d)}$ as the ratio between the sum of NULL periods observed for device d of site s during the monitoring interval T and the duration of T. We focus on the daily connectivity failure percentage. Thus, T lasts approximately 1 day. Furthermore, results are presented in percentage terms.

3.1.2 Power Consumption Analysis

In principle, the measurement campaign is supposed to get a power acquisition every second for an overall monitoring period of about one year. This would yield to approximately 31.5 million measures per device. Non-idealities reduce the actual number of acquisitions, but the latter keeps still high. In this respect, we synthesize the information by studying the power consumption per hour, day and month basis.

Firstly, we need to manage NULL values. NULL readings are representative of a disconnection of the device or a connectivity fault, as detailed in Section 3.1.1. In the former case, it is reasonable to substitute NULLs with the zero value, as if the device is disconnected there is no power consumption. In the latter case, we substitute NULLs due to connectivity faults with the last valid power measure before the NULL interval. In fact, it is reasonable to assume that the device is still consuming power regardless connectivity problems. We distinguish NULL periods due to connectivity faults or disconnections as described in Section 3.1.1. Fig. 3.1 shows the actual measure, where NULLs are represented as -1, and the same measure where NULLs are processed. In the figure, connectivity faults are less visible as they yield to NULL periods of extremely short duration. The monitoring system collects power

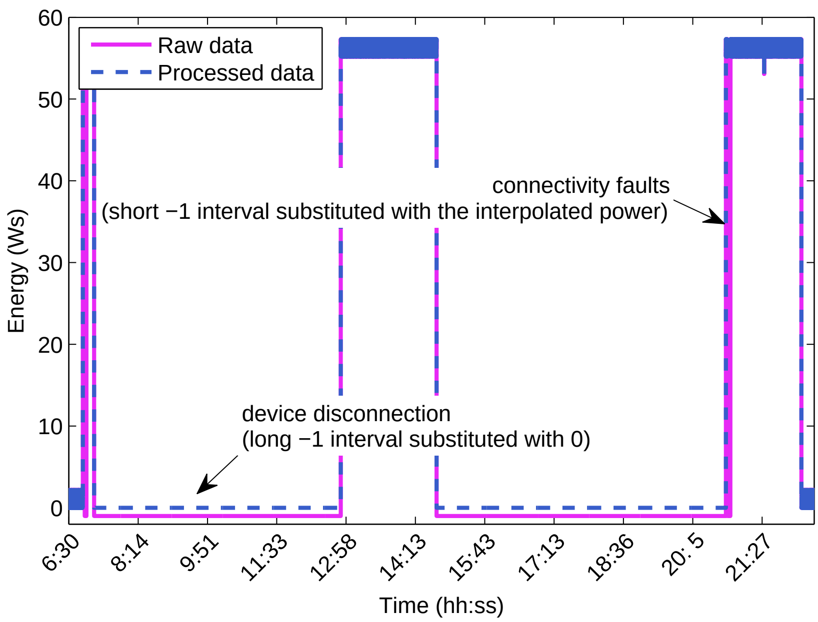


Figure 3.1: Measured power before and after processing NULLs.

measures. From the power measure, we obtain the instantaneous energy. Let us denote with t_1, t_2, and P_1 the time stamp of two subsequent measures and the power measure at the time instant t_1, respectively. The instantaneous energy E_i of the time interval $[t_1, t_2]$ associated to the power measure P_1 is given by $E_i = P_1(t_2 - t_1)$. We measure the energy in kWh and we always state the measurement interval, typically, one minute.

We further condense the results and, for each site, we provide the pie chart of the relative power consumption of the monitored devices during a month period, and the histogram of the power consumption of the monitored devices per month.

3.2 Data Analysis in CAR

We begin with the Austrian households, for which we firstly make an analysis of connection failures and we later report the share over the overall monitored consumption.

3.2.1 Null Analysis in CAR

Figs. 3.2-3.3 show the daily percentage of connectivity failures experienced in sites S0, S1, S2, and S3. In site S0 the position of the gateway is good enough to reach all nodes in a few hops. As visible in Fig. 3.2, a higher connection failure percentage is noticed for the washing machine (basement), the vacuum cleaner (hall), as well as the kitchen lamp and the water kettle (kitchen). The situation is more confused in site S1, in which the gateway was placed in the lounge, in proximity of the audio amplifier which nevertheless shows rather high connection failure rate. The lounge is annexed to the small kitchen, in which the measuring nodes are placed in less than 2 m distance each other. A third case is represented by the bathroom devices (i.e., washing machine and charger) and the bedside lamp (bedroom), which are separated by 2 walls from the main gateway. Site S2 provides a clearer scenario, with the gateway being placed in the lounge, in proximity of the UPS and the computer. The coffee machine and the dishwasher have a pretty low connection failure rate, along with the washing machine (utility). The small cooking appliance placed in the hall presents the highest connection failure, together with the spin dryer (utility) and the food processor (kitchen). In site S3 the hub was placed in the lounge, in proximity of the computer and the television, which can benefit from a close distance. This applies also for the outlets connected to the kitchen devices, namely the fridge, coffee machine, water kettle and dishwasher, which are mainly sepa-

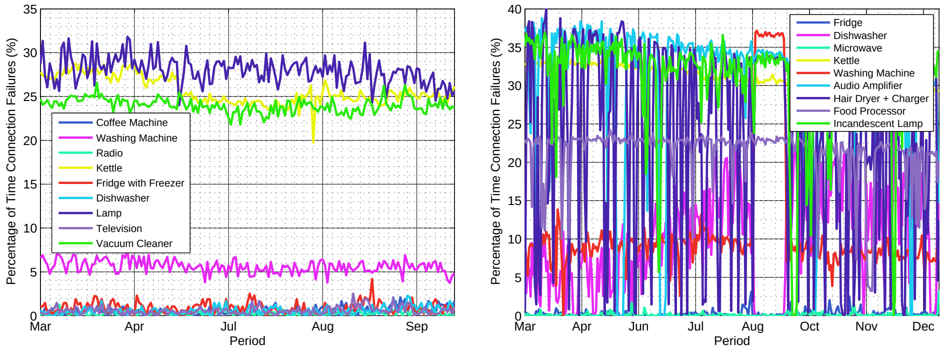


Figure 3.2: Connectivity failure analysis of site S0 (on the left) and site S1 (on the right).

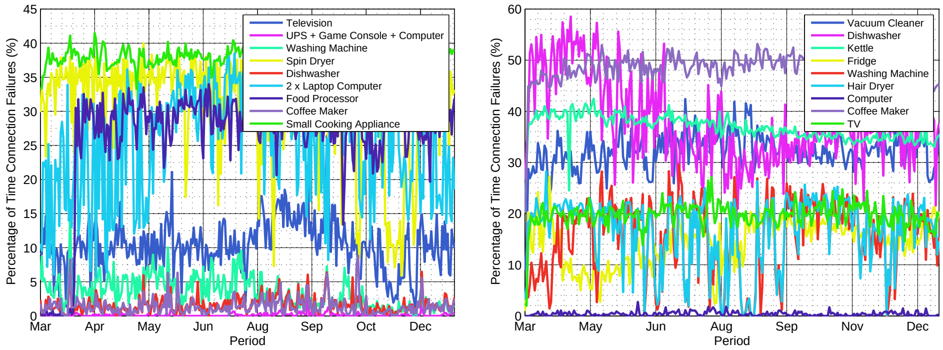


Figure 3.3: Connectivity failure analysis of site S2 (on the left) and site S3 (on the right).

rated from a wall. On the contrary, the outlets monitoring the washing machine and the hair dryier are placed upstairs, which often determines connection failures. To mitigate such situation, a monitoring outlet was placed in the hallway, middle way between the bathroom and the rest of the network.

3.2.2 Power Consumption Analysis in CAR

This section provides an analysis of energy consumption in sites S0, S1, S2, S3. In particular, Figs. 3.4 to 3.7 report a pie chart and an histogram for each site. The fridge is the most consuming device in all cases, determining between the 40 and 47%. Moreover, consumption peaks are observable for the fridge in the summer period. A remarkable share is also given by the dryer, the dishwasher and the washing machine. The scenario is similar in site S1, in which we also remark the presence of

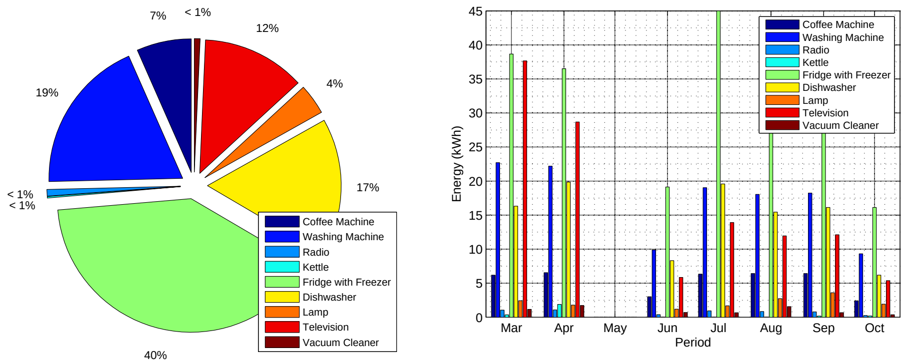


Figure 3.4: Power consumption plots of site S0.

multiple incandescent lightbulbs. The monitored bedside lamp alone determines the 2% of the monitored consumption, which translates into more than a kWh every month.

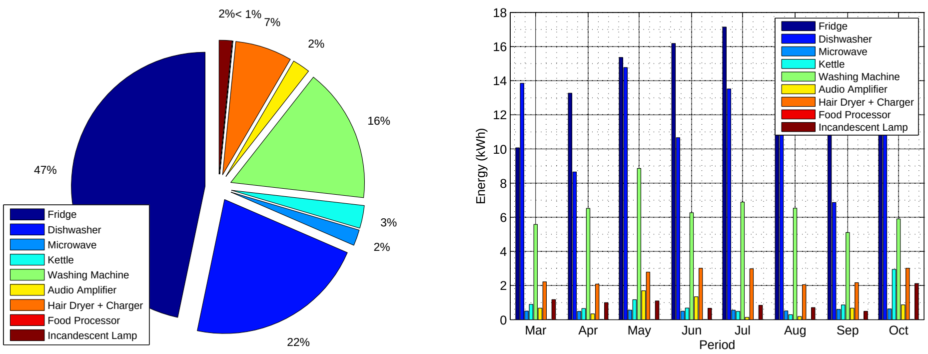


Figure 3.5: Power consumption plots of site S1.

In site S2, a relevant share is accounted by the plasma TV, which determines most of consumption in the household. In addition, a remarkable contribution is given by the stand-by consumption resulting from consumer electronics (i.e., uninterruptible power supply with network attached storage, game console and personal computers). Site S3 (see 3.7) reports a similar situation, with the desktop computer accounting for the 22% of the monitored consumption. As visible, this accounts for more than 12 kWh every month.

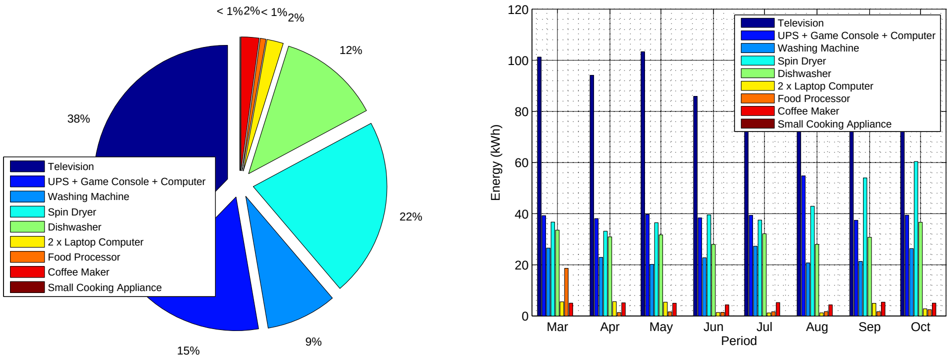


Figure 3.6: Power consumption plots of site S2.

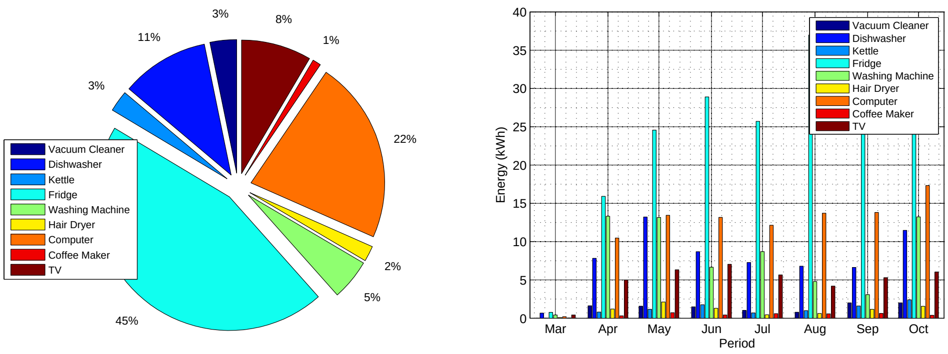


Figure 3.7: Power consumption plots of site S3.

3.3 Data Analysis in FVG

We now focus on the Italian database and we provide the statistical results obtained from the collected data. The structure of the Section reflects that of Section 3.2 in order to facilitate a clear and direct comparison of the results.

3.3.1 Null Analysis in FVG

We herein discuss the connectivity failures experienced during the measurement campaign. Figs. 3.8-3.9 show the daily percentage of connectivity failures experienced in sites S4, S5, S6, and S7.

In site S4, the position of the gateway is fine, as it represents a good compromise in terms of distance between all devices. In fact, the percentage of connection failures is balanced among all devices. Only devices in the kitchen exhibit a larger percentage of connection failures. Namely, they are the LCD TV, the extractor hood and the fridge.

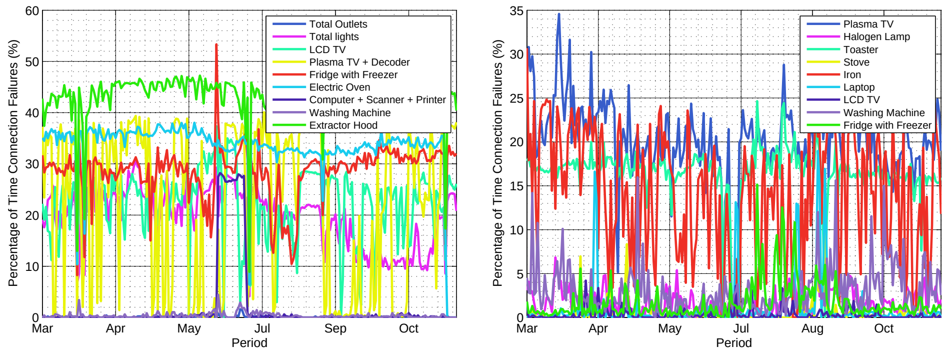


Figure 3.8: Connectivity failure analysis of site S4 (on the left) and site S5 (on the right).

In site S5, results point out difficulties in collecting data from the plasma TV, the iron and the toaster. Such difficulties are expected since these devices are placed far from the gateway. However, the position of the gateway is constrained by the need of cabled Internet connection. Fig. 3.10 shows the planimetry of site S5. The available outlets are represented with blue squares. The site is square-shaped with a side dimension of 10 meters. The gateway, the plasma TV and the toaster are connected in the bedroom, in the living room and in the kitchen, respectively. The iron is connected in the correspondence of plasma TV, but on the lower floor. As it can be seen, the system is not able to ensure reliable communications with the smart plugs when several walls

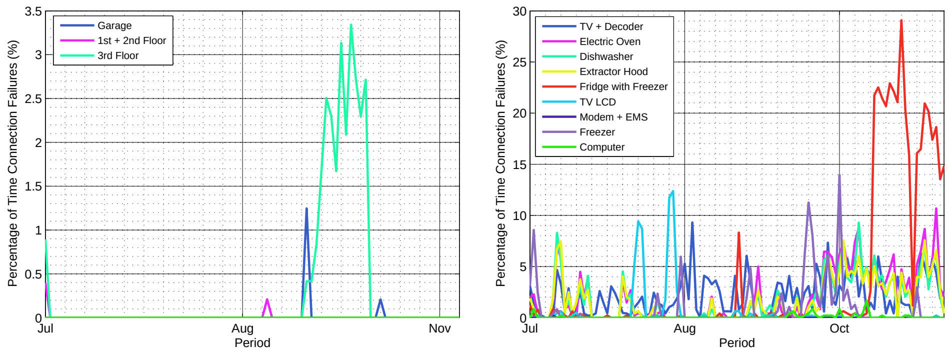


Figure 3.9: Connectivity failure analysis of site S6 (on the left) and site S7 (on the right).

are inbetween. Differently to site S4, the remaining devices are well connected as they exhibit low percentages of time connection failures. Hence, in site S5, the position of the gateway does not ensure a balanced percentage of connectivity failure time between devices. In sites S6 and

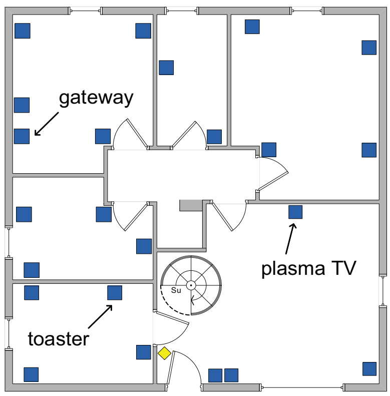


Figure 3.10: Topology of Site S5.

S7, the percentage of connectivity failures drops significantly. This result is expected. In fact, in site S6, the smart plugs are all installed in the main panel and they are all close to the gateway. In this site, the monitoring campaign aims to collect the overall energy consumption rather than the consumption of each single device. In site S7, we monitored 9 devices that are all closely arranged to the gateway, i.e., they are less than 5 meters far away from the gateway, in most of cases with no walls in between.

3.3.2 Power Consumption Analysis in FVG

This section provides a statistical analysis of the energy consumption of the monitored devices in sites S4, S5 and S7. Site S6 is excluded because, therein, the monitoring campaign targets only the total consumption. Figs. 3.11 - 3.13 report a pie chart and an histogram plot for each site. In site S4, the total outlet power consumption is excluded from the analysis. The pie chart provides the relative energy consumption of the monitored devices in September 2014 and it assumes 100% to be the total monitored energy during the same month. The histogram reports the monthly power consumption of the monitored devices. Thus, the pie enables inferring the role that each device plays in the total energy consumption. The histogram highlights fluctuations in the energy consumption / the use of the devices. Note that the pie reflects the bars of the histogram in September.

In all cases, the fridge is the device responsible for the largest consumption, namely, between 24% and 46% of the total monitored energy consumption. Televisions have a large impact on the consumption as well. Namely, they are responsible for 20%, 25%, and 39% of the total monitored energy consumption of site S4, S5 and S7, respectively. The values gather contributions from both the LCD and plasma TVs. However, we note that the largest contribution is, generally, from the plasma TV. The reason is twofold. The energy consumption of the plasma TV is approximately double that of LCD and, further, plasma TVs are installed in the living room, thus they are switched for a longer time rather than LCDs. This suggests to exchange the LCD TV with the plasma TV in order to reduce the power consumption. The tip will be further addressed in Section 4.4.

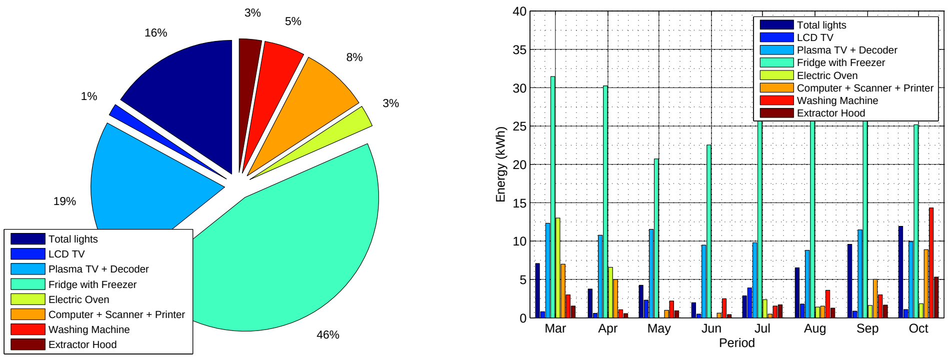


Figure 3.11: Power consumption plots of site S4.

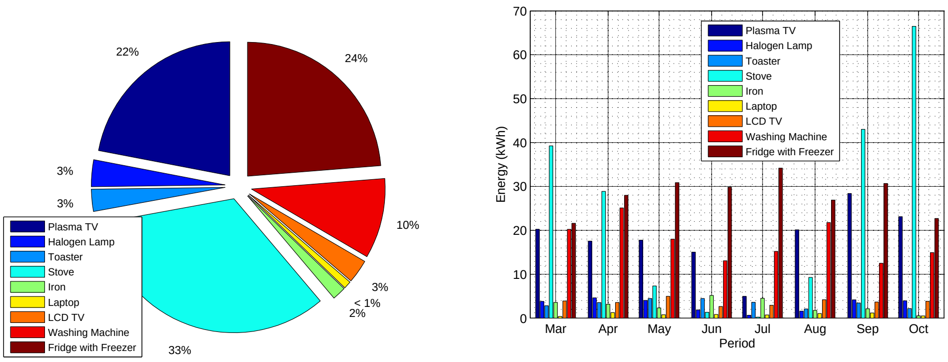


Figure 3.12: Power consumption plots of site S5.

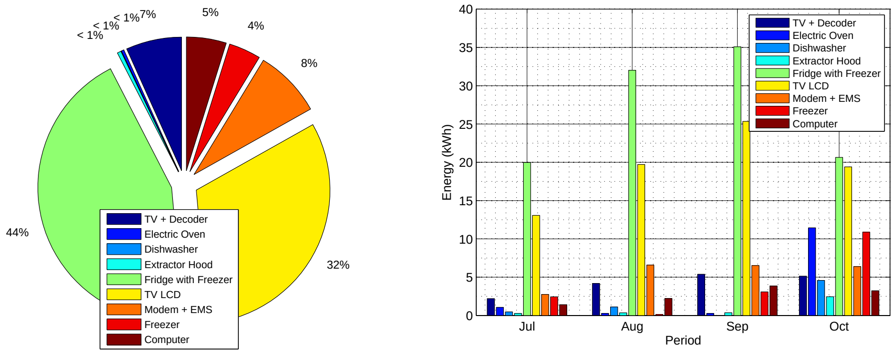


Figure 3.13: Power consumption plots of site S7.

To understand further the role of TVs, it is interesting to note that in site S4 and S5 the TVs consume more than the washing machine, namely, a device that is commonly recognized as energy-hungry. In fact, the washing machine is responsible for only 5% and 10% of the monitored energy consumption of September. Furthermore, in site S5, the aggregate consumption given by the washing machine and the iron is even lower than the energy consumption due to TVs.

Now, let us focus on monthly fluctuations. In site S4, the fridge and the plasma TV show a regular behavior. We note a strong variation of the power consumption of the electric oven, the PC, the LCD TV and the washing machine, with a minimum during the warmest months, from May to July. In site S5, the largest variation is due to the stove that, as expected, is mostly used during the coldest months. The halogen lamp reflects the variations of the daytime during different months and it is limited in June and July. Finally, in site S7, energy consumption variations can be observed, e.g., for the fridge or the electric oven, but they cannot be related to some seasonal change as in other sites.

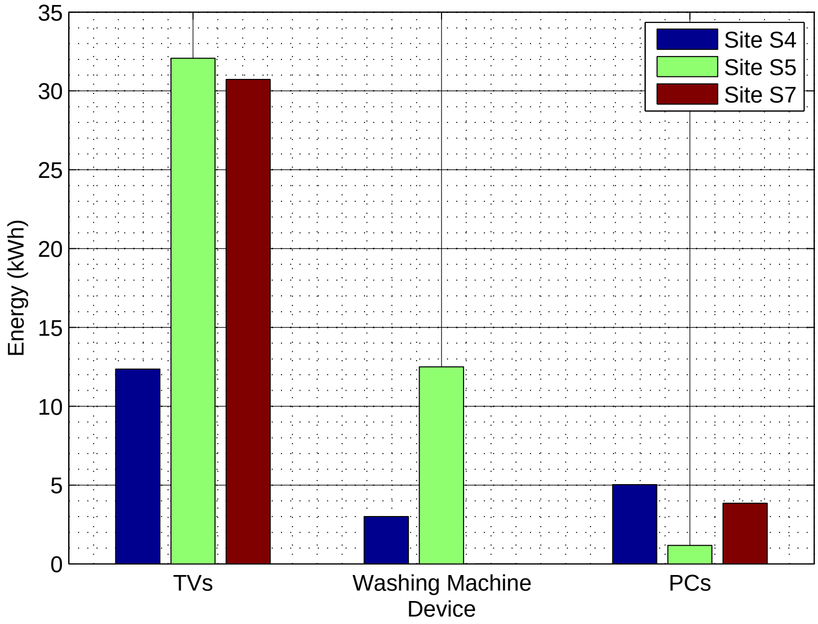


Figure 3.14: Comparison between similar devices from different sites.

To enable a deeper comparison between sites, Fig. 3.14 gathers the energy consumption of similar devices from different sites. Results refer to the month of September. We target the washing machine, the TVs and the computer. The energy consumption due to TVs is similar for sites S5 and S7, and it is interesting to note that in both sites there are elderly users. In fact, Fig. 3.14 reveals a large spread of the washing machine consumption, i.e., it is more than double in site S7 respect to S6. Finally, we note the large consumption due to the PC in site S4. This is due to the fact that, herein, the users spend part of the time working from home and that the users are young and more familiar with the technology.

3.4 Role of the Monitored Devices in FVG

The monitored loads are responsible for a minor part of the overall power consumption, namely, about 40%, 25% and 16% of the total energy consumption in site S4, S5 and S7, respectively, assuming 100% to be the total power consumption reported on the bill during the monitoring period. This result is interesting and it can be related to a) the connectivity limits of the monitoring platform and b) the low user awareness about the energy consumption.

Connectivity limits reduce the set of devices that can be monitored. For instance, in site S7, users aimed to monitor the washing machine, but the coverage limitations of the monitoring platform make it unfeasible. Similarly, in site S5, two fridges were not reachable. In this case, a dedicated platform was setup afterwards to get the consumption of only these two devices. Results are reported in Section 4.4.3.

The user awareness impacts on the choice of the monitored loads. Namely, we monitored the loads that the users believe to be the main responsible for their energy consumption, i.e., we followed the user suggestions in the choice of the loads. However, sometimes the monitored loads were not as significant as expected. For instance, in Site S5, the main concern was about the halogen lamp. In fact, results demonstrate that the halogen lamp impacts for less than 1% of the total power consumption.

As a final remark, we note that in Austria the information about the monthly energy consumption is still not available. In this respect, we speculate that, in Austria, the monitored energy consumption is even a lower percentage of the total energy consumption because, differently to Italy, the water heating system relies on electricity instead of gas [MEDT13].

3.4.1 Inferring the Non-Monitored Loads

The analysis of the electricity bills reveals that the non-monitored consumption is a substantial part of the total energy consumption. In this respect, we aim to infer the loads responsible for the non-monitored part of the total energy consumption. Firstly, let us focus on site S4. Beside the monitored devices, an interview with the users revealed the presence of the devices reported in Table 3.2. Furthermore, Table 3.2 reports the power consumption and the usage (in hours/month) of each device. Note that these values are obtained from the information provided by users and not from actual measurements.

Table 3.2: Inferring the non-monitored loads of site S4.

Description	Usage (hours/month)	Power Consumption (kW)	Monthly Consumption (kWh/month)
Iron	6	1	6
Hair drier	4	1	4
Vacuum cleaner	10	1	10
Microwave oven	4	1	4
ADSL modem	-	0,033	23
Monergy platform	-	0,011	8

We can derive the pie chart of the consumption considering the non-monitored loads and assuming 100% to be the energy consumption reported on the bill. We focus on a monitoring period of 1 month, i.e., May 2014. Fig. 3.15 shows the result. During the reference period, the consumption of the non-monitored devices is about 67 kWh over a total energy consumption of 110 kWh. Among the non-monitored devices, we note the large impact of the ADSL modem and even the MONERGY gateway. A further 11% of consumption is due to devices that cannot be clearly identified, as mobile phone chargers, etc.

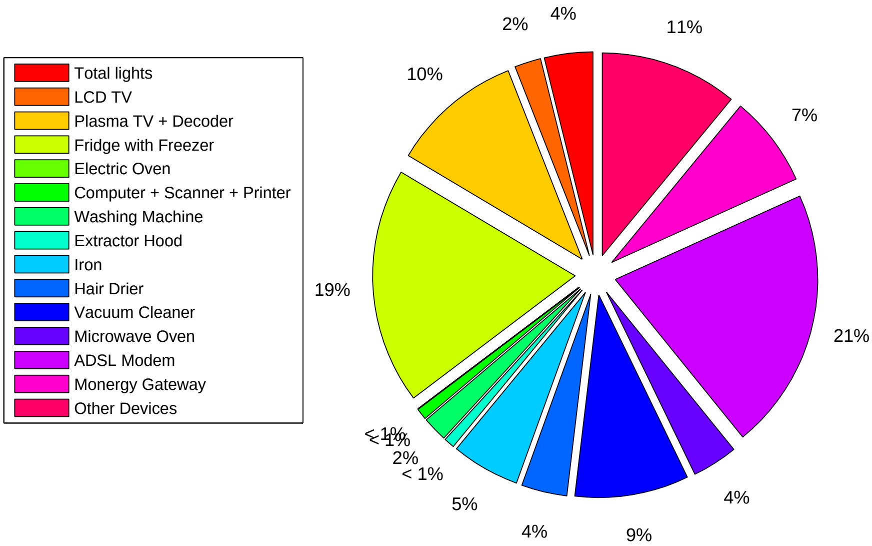


Figure 3.15: Pie chart of the energy consumption of site S4 considering the non-monitored loads. The reference period is May 2014.

As another example, let us focus on site S5. Table 3.3 reports the non-monitored devices that users identified. The former two, i.e., the fridge and the freezer were monitored with a dedicated platform to get their actual power consumption. The remainder values were speculated from the information provided by the users. Again, we derive the pie chart of the energy consumption for the reference period of May 2014. Fig. 3.16 shows the result.

Table 3.3: Inferring the non-monitored loads of site S5.

Description	Usage (hours/month)	Power Consumption (kW)	Monthly Consumption (kWh/month)
Fridge	-	0,029	21
Freezer	-	0,048	34
Modem	-	0,033	23
Monergy gateway	-	0,011	8
Hair drier	2	1	2
Vacuum cleaner	4	1	4
Tapis roulant	16	1	16

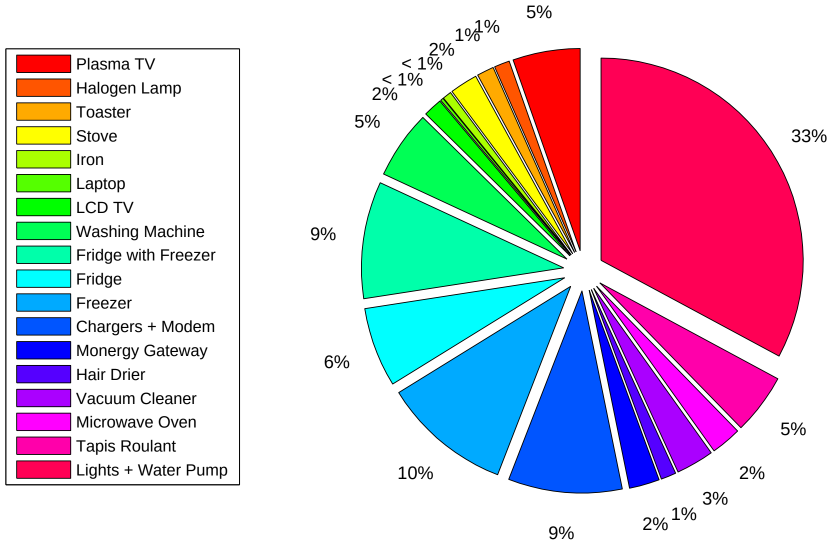


Figure 3.16: Pie chart of the energy consumption of site 5 considering the non-monitored loads. The reference period is May 2014.

During the reference period, the total power consumption is about 330 kWh, and the contribution due to the non-monitored devices is 239 kWh. The plot highlights the large contribution of the fridge and the freezer. The two devices are not monitored due to the connectivity limitations. Furthermore, a large amount of energy consumption is due to the lights and a water pump that is used to empty a catch basin. In this respect, site S7 is characterized by a large deployment of inefficient incadescent lamps. Also for site S7 it is interesting to note the large amount of energy consumption due to the ADSL modem and the monergy gateway. The aggregate contribution is about 11% of the total, i.e., more than the consumption due to the Plasma TV and the LCD TV, or due to the washing machine. In this respect, switching off the modem and the gateway during night hours may provide some benefit, as discussed in Section 4.4.4.

3.5 Billing and Time Slotted Energy Tariffs

In this section we discuss current pricing mechanisms in CAR and FVG, to analyze regional differences in terms of billing and investigate potential room for savings. While in Carinthia there exists various initiatives towards the rollout of digital meters, a large scale installation is still missing. This means that billing still takes place with electromechanical meters, normally being checked once per year. As reported in [MEDT13], a common solution to mitigate energy costs is to install a night meter to supply water boilers. Let us select EKG Klagenfurt and Kelag as examples. For simplicity we report final prices that already include taxes. The EKG Klagenfurt[1] charges respectively 16,55 cent/kWh for day time (i.e., Strom Basis) and 12,677 cent/kWh for night time (i.e., Strom Nacht). This already includes delivery costs, while the basis energy cost (i.e., Arbeitspreis) would be respectively 8,748 cent/kWh and 6,984 cent/kWh. Kelag (Kärntner Elektrizitäts AG)[2] provides various alternatives for household provisioning. In the Kelag-PUR[3] plan the basis energy cost is 8,484 cent/kWh under a 10.000 kWh/year consumption, and 0,12 for each exceeding kWh. It is also remarkable that the providers declare their power originating for 90.04 % from hydroelectric and 5.11 % from wind (STW), and 100 % from hydroelectric (Kelag).

On the contrary, in Italy the energy price depends on the energy tariff, the quantity of energy that is consumed in one year and on the time of the day. The time-slotted energy pricing is made possible by the advanced smart grid functionalities provided by the digital meter. In Italy, more than 32 million digital meters were installed by ENEL, the main Italian distribution system operators (DSO). The digital meter allows for the automatic meter reading, an accurate power measure, and it enables a flexible energy pricing. Specifically, ENEL divides the day/hours in two slots, namely:

- T1, from Monday to Friday between 8 AM and 7 PM,
- T2, during the remaining hours/days and during public holidays.

Within each time slot (T1, T2), the price of energy varies according to four categories of consumption, i.e., C1, C2, C3 and C4. The price policy is aimed to stimulate people consuming less. The higher the consumption, the higher the price. Table 3.4 reports the energy consumption

[1] http://www.stw.at
[2] http://www.kelag.at/index.jsp
[3] http://haushalte.kelag.at/content/page_kelag_pur.jsp

intervals associated to the four categories. Table 3.5 shows the cost of the energy for each category/tariff and the single entries that contribute to the total cost. Tables refer to the offer by ENEL for residential users (contracts below 3kW)[4], it provides only the components associated to the power consumption, i.e., not the fixed costs related to the contract, and it is updated to February 2015. As we can see, the energy price is the only part of the total cost that depends on the time slot, i.e., T1 or T2. The difference between the energy price of the two time slots is equal to 0,637 euro cent per kWh, that corresponds to a price reduction that ranges between 2% (for C4) and 5% (for C1).

Table 3.4: Energy consumption categories.

Category	Lower Bound (kWh/year)	Upper Bound (kWh/year)
C1	-	1800
C2	1801	2640
C3	2641	4440
C4	4441	-

Table 3.5: Cost of energy in Italy.

		Energy Price (Eur/kWh)	Price of Delivering Fixed + Variable (Eur/kWh)	Grid Services (Eur/kWh)	TOT (Eur/kWh)
T1	C1	0,06731	0,01381	0,046392	0,127512
	C2	0,06731	0,01711	0,101512	0,185932
	C3	0,06731	0,02066	0,165762	0,253732
	C4	0,06731	0,02446	0,208432	0,300202
T2	C1	0,06094	0,01381	0,046392	0,121142
	C2	0,06094	0,01711	0,101512	0,179562
	C3	0,06094	0,02066	0,165762	0,247362
	C4	0,06094	0,02446	0,208432	0,293832

3.5.1 Energy Consumption within the Monitored Houses

The monitored sites in Italy are an almost complete set of representative cases. From site S4 to site S7, they span categories C1, C3, and C4, i.e., from the lowest to the maximum. The annual energy consumption,

[4] http://www.enel.it/it-IT/clienti/enel_servizio_elettrico/tariffe_per_la_casa/tariffe_biorarie_per_la_casa/

and the category of sites S4 to S7 are reported in Table 3.6. Site S7 consumes 3.74 times the energy of site S6. The power consumption of the two sites corresponds to approximately 545 and 146 W/hour, respectively. Thus, the database of the Monergy measures is representative of quite different, though realistic, scenarios.

Table 3.6: Per-year consumption and price category of Italian sites.

	Category	Energy Consumption (kWh/year)
Site 4	C1	1277
Site 5	C4	4778
Site 6	C3	3349
Site 7	C3	4099

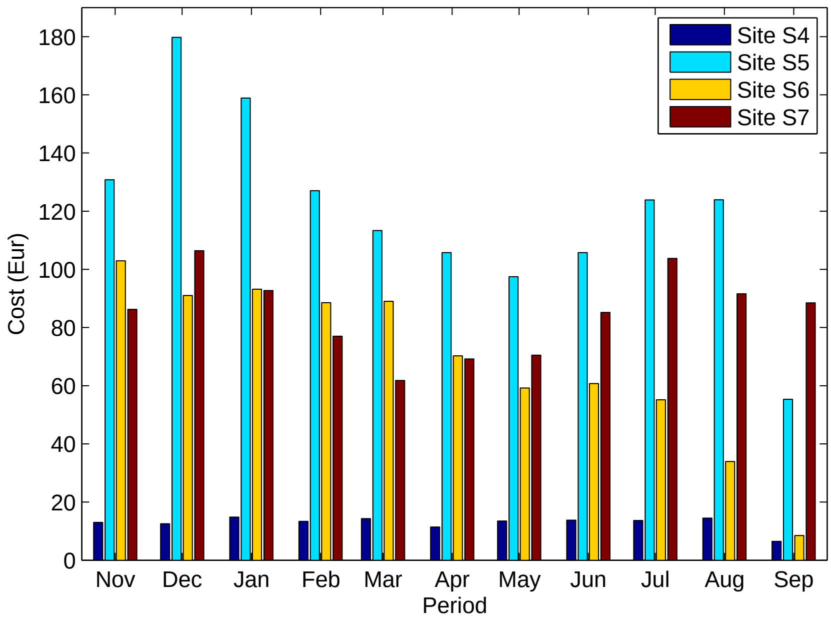


Figure 3.17: Total energy consumption of Italian sites per month.

Fig. 3.17 compares the monthly consumption of the Italian sites. Results are reported in Euros, and numbers have been obtained multiplying the monthly energy consumption reported in the bill by the energy cost as detailed in Table 3.5. Thus, taxes and other costs not related to the energy consumption are not accounted. The figure focuses on the period from November 2013 to September 2014 that includes the monitoring period considered in the analysis in Section 3.3. We note the following. First, the difference in terms of electricity expense between site S4 and S5 is impressive. It settles always above 100 Eur/month. Second, the monthly energy consumption, and thus electricity expense, of sites S5-S7 exhibits a large fluctuation if compared to that of site S4. Two remarkable peaks can be observed, approximately in December and in between July and August. The former peak can be associated to the Christmas holidays, during which users are supposed to stay more at home. The latter peak can be related to the use of the air conditioning systems and due to the summer holidays period as well. In site S5, the difference between the largest peak and the lowest notch can be quantified in about 120 Euro. Second, the energy consumption of site S4 is rather regular because one of the users worked partly from home (teleworking) and guests were present and spent part of their time at home during the reference period. Therefore, there is no significant difference for this site between holidays and working periods. Finally, the expense of site S6 decreases significantly during August and September because the users were not at home for quite long periods during these months. This result suggests the interesting correlation between the energy consumption and the occupancy. The topic is further addressed in Section 4.2.

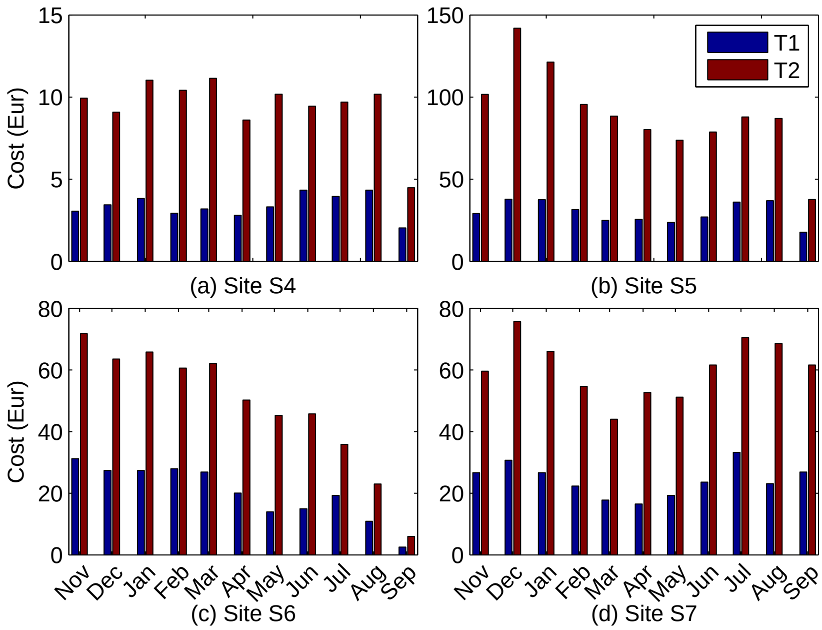


Figure 3.18: Time-slotted energy consumption of Italian sites per month.

Let us investigate the energy consumption distribution over the time slots. Fig. 3.18 shows the T1 and T2 electricity expense of each of the four Italian sites. We note the following. First, the expense consumption during T2 is higher. This result reveals that the most of the power consumption is during the time slot T2, that corresponds to the evening and night hours, holidays and week ends, i.e., when people are mostly at home. Second, the variation of the electricity expense, and thus of the power consumption, highlighted by Fig. 3.17 is mainly associated with the energy consumption during T2. This result is expected as well. In fact, Christmas holidays fall in T2 and justify the peak of December, while air conditioning systems are mostly used during evening and night hours, thus motivating the peak in between July and August.

Now, let us focus on the monitored devices. We focus on sites S4, S5 and S7. Figs. 3.19-3.21 report the consumption of the monitored devices during the two time slots T1 and T2. Results are provided in percentage terms, such that, for each device the sum of the energy consumed during the time slots equals 100% and the plots are obtained considering the period from March 2014 to October 2014.

In general, users are aware about the convenience provided by the time-slotted energy tariff because the monitored devices operate mostly during T2. The users of site S5 exploit better than others the time slot T2. This conclusion is supported by the large spread between the energy consumption percentage during T1 and T2. In particular, it can be seen that the use of the washing machine (device $\#8$) and the iron (device $\#5$) during T1 is limited to less than 20% of their total power consumption. Clearly, some other devices cannot be scheduled during a specific time slot. For instance, the toaster (device $\#3$) is used during lunch time as well. It follows the balanced consumption in T1 and T2.

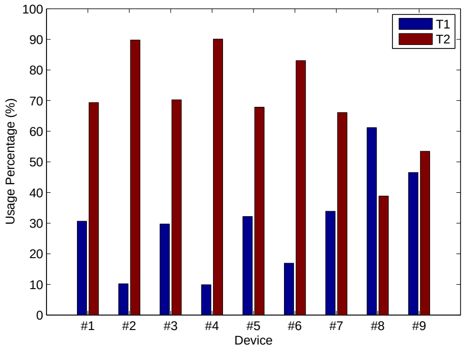


Figure 3.19: Usage percentage per device and time slots of site S4.

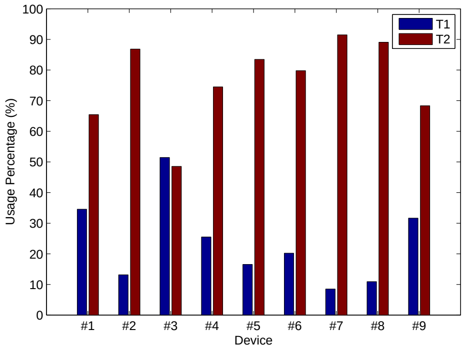


Figure 3.20: Usage percentage per device and time slots of site S5.

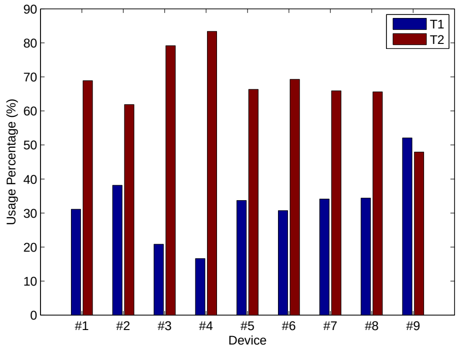


Figure 3.21: Usage percentage per device and time slots of site S7.

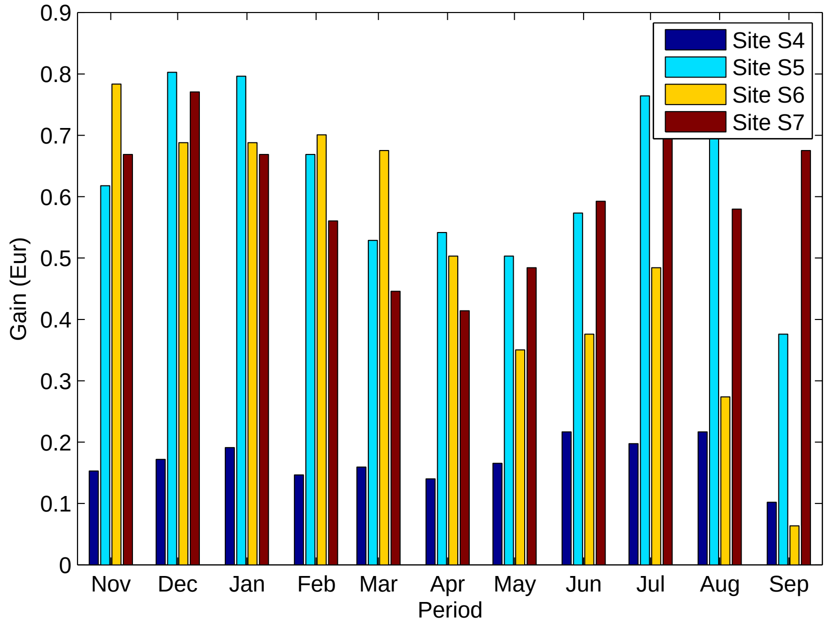


Figure 3.22: Expense gain provided by shifting all the consumption to T2 per month and site.

3.5.1.1 Can Time-Slotted Tariffs Shape Consumption?

As discussed in Section 3.5, current energy tariffs offer none (i.e., for Austria) or very little (i.e., for Italy) incentive to promote load shedding towards cheaper time slots. Although the user's awareness of time-slotted energy tariffs is quite high in Italy, the actual gain provided by the use of the devices during the time slot T2 is minimal. For instance, let us focus on site S4. Herein, the washing machine is mostly used during time slot T1, as it can be noted from Fig. 3.19. During the monitored period the energy consumption due to the washing machine of site S4 in T1 and T2 is 19 kWh and 12 kWh, respectively. The total energy cost caused by the washing machine is 3.9 Eur and shifting completely the use of the appliance in T2 would yield savings for about 12 cents, i.e., not enough to convince the users changing their habits. Now, extending the approach to the entire site consumption, we simulate the expense gain provided by shifting the entire energy consumption to T2. Fig. 3.22 shows the result per site and month. As it can be noted, with the current pricing policy the gain is minimal and does not encourage users to exploit the time-slotted energy tariff.

As deducible from the above presented analysis, the current tariff plans offer either none or very little incentive to postpone energy usage towards off-peak periods (e.g., night). In Austria the lower energy price is motivated by the large availability of renewable energy sources, especially hydroelectric, as well as the higher demand from electric devices. As shown in [MEDT13], in Austria electric energy is being largely exploited for cooking purposes as well as for water and space heating. On the contrary, in Italy those functionalities are deployed using mostly gas-powered devices. However, the need for new coordination mechanisms, such as more dynamic pricing mechanisms, will become clearer with the growing diffusion of electric vehicles.

3.5.2 Energy Consumption of the Monergy Platform

The Monergy HEMS consists of a gateway and 9 smart plugs [LW14b]. Table 3.7 reports the energy consumption of the whole HEMS. As we can see, although the energy consumption in one hour is relatively small (11.17 Wh), the total energy consumption per year reaches about 100 kWh. We can now compute the cost of the energy required by the Monergy HEMS. In particular, assuming that in one year there are about 3374 hours in T1 and 5386 in T2, we obtain the results reported in Table 3.8. As we can see, the cost ranges between 12 and 29 Eur depending on the category of energy. Hence, for instance, the users of site S5 pay approximately 29 Eur to keep the monitoring platform running.

Table 3.7: Power consumption of the Monergy HEMS.

	Energy consumption single device (Wh)	Number of devices	Total energy consumption per month (kWh/month)	Total energy consumption per year (kWh/year)
Gateway	2,17	1	1,562	19,009
Plug	1	9	6,480	78,84
Total			8,042	97,849

Table 3.8: Cost of energy consumed by the Monergy HEMS.

Category	Cost (Eur)
C1	12,09
C2	17,81
C3	24,44
C4	28,99

Section 4

Exploitability of the results

The data analysis presented in the previous section is an excellent starting point for a wide range of applications. This section presents some. The aim is to deliver useful information of the user's lifestyle, and formulate tips that can influence positively the user habits.

Among the most interesting applications based on the energy consumption analysis, herein we present the user energy profile, the user occupancy, and we formulate some tips to save energy. The user energy profile is the pattern of the energy consumed within a monitored site, the user occupancy infers the presence of people from the analysis of the aggregate power consumption. The suggestions consist of actions that can be taken by users to limit the power consumption and thus to save money. They are based on the analysis of the actual power consumption of the sites monitored during the Monergy campaign.

Automated tools are necessary to actually extend the benefits gained through the energy usage analysis. To this end, a system is proposed to elaborate energy usage data and provide users with tailored feedback and energy advice.

This chapter is divided as follows. Sections 4.1 and 4.2 deal with the user's energy profile and occupancy. Section 4.5 formulates policies for an improved energy efficiency. Finally, Section 4.6 introduces Mjölnir, an open solution for energy advice that implements the automated analysis of the measured data.

4.1 User Energy Profile

Data gathered during the monitoring campaign can be used to derive the whole energy profile, namely, the pattern of the energy consumed by each of the monitored houses during the day. The derivation of the energy profiles requires the knowledge of the total energy consumption at regular interval. Therefore, in our case, it can be computed for sites S4 and S6. In site S4, the total consumption is obtained aggregating the consumption due to outlets and lights. In site S6, the total consumption is obtained aggregating the consumption from the meters of the three parts of the house. Energy profiles can be used for different ends, that is:

- to detect unexpected energy waste;
- to predict the energy demand;
- to make social studies on the habits of inhabitants.

Fig. 4.1 shows the cumulative distribution function (CDF) of the total energy consumption of site S4. In particular, sub-figure (a) is related to

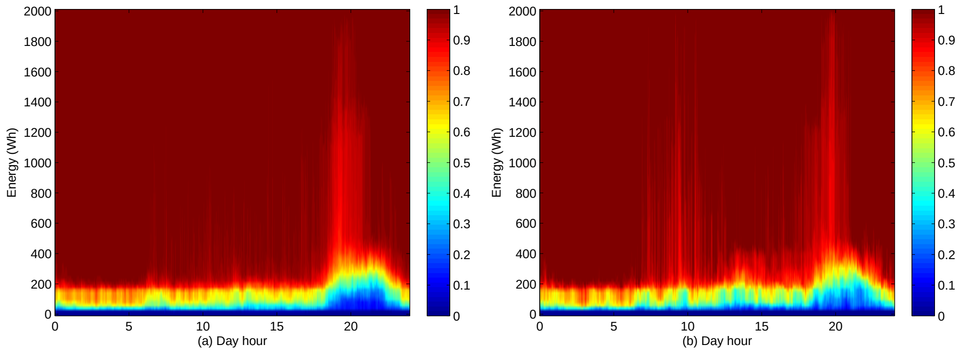


Figure 4.1: CDF of the energy consumption of site S4 during week days (on the left) and weekend days (on the right).

the weekdays (WDs), and the sub-figure (b) to the weekend days (WEs). Weekdays and weekend days have been treated separately since the energy demand may be different within these two periods due to different habits of the users, e.g., for working reasons. CDFs are derived using the data measured from March to October 2014.

Fig. 4.4 shows the 95th percentiles of the total energy consumption for site S6 during WDs and WEs. The energy demand is lower or equal to the shown values with probability equal to 0.95. As expected, the energy demand is different during WDs and WEs. In particular, since the users of site S4 work during the week, we see that the corresponding energy demand is lower during the week days. Nevertheless, the peaks of energy consumption during the weekdays between 8.00 AM (when the couple leave home) and 6.00 PM (when they come back from work) are due to the presence of hosts during the months of June, July and

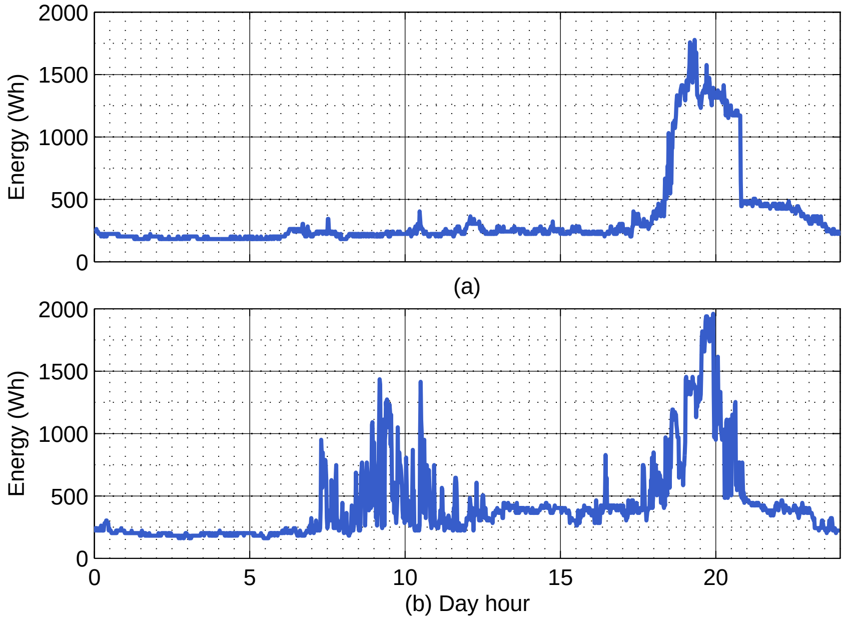


Figure 4.2: 95% percentile of the total consumption of site S4 during week days (on top) and weekend days (on bottom).

October. Another interesting observation is that after 6.00 PM the energy demand is very similar during weekends and weekdays. Figs. 4.3 and 4.4 respectively show the CDF and the 95th percentiles of the total energy consumption for site S6. Looking at Fig. 4.4, we notice that either during the WDs or the WEs consumption are high, this suggests that people are at home also during the WDs. Although, it is out of the scope of the present analysis, we want to notice that by looking at the 95th percentiles, it is possible to derive some habits of the users. In particular, we can guess the time they wake up and go to sleep. In site S4 (see Fig. 4.2) the young couple seems to wake-up at around 6.30 AM and go to sleep after 11.00 PM, furthermore, some small peaks are present during the nights of the WEs, these are due to the lights that are switched on when people come back home from outside. In site S6, people seem to wake up at 5.30 AM during WDs and around 6.00 AM during WEs, whereas they go to sleep at around 10.00 PM.

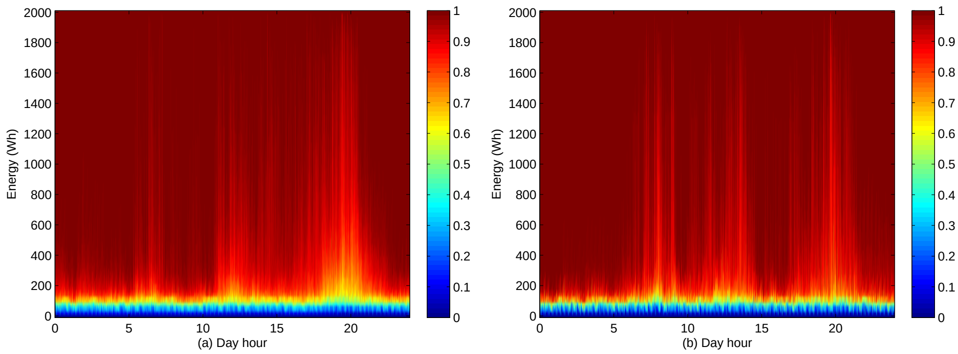


Figure 4.3: CDF of the energy consumption of site S6 during week days (on the left) and weekend days (on the right).

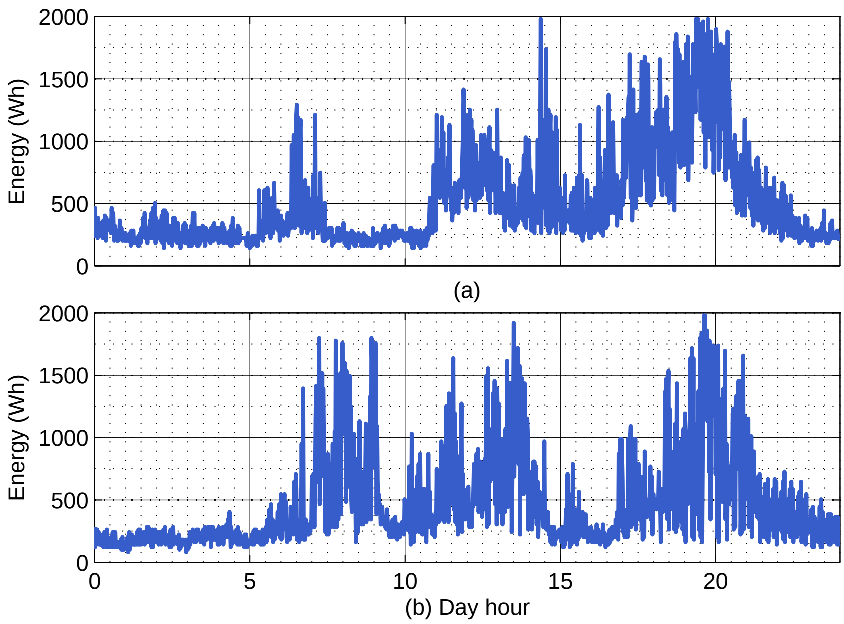


Figure 4.4: 95% percentile of the total consumption of site S6 during week days (on top) and weekend days (on bottom).

4.2 Inferring Occupancy

Occupancy detection is the problem of inferring presence of people in environments. Many different approaches have been considered in the literature: motion detection, doors opening, use of acoustic sensors and/or cameras, use of global positioning system (GPS) and localization systems through smart phones. Nevertheless, only a few works propose to use energy consumption data to develop occupancy detection techniques [CBS+13]. To this end, the assessment of occupancy detection requires a suitable dataset, offering either an aggregated or a disaggregated power draw, along with a description of consumption scenarios. In particular, the activity of user-driven devices is relevant to infer the presence in the environment. In this respect, note that the operations of such devices can be postponed biasing the presence detection.

A simple approach based on the use of energy consumption data to detect occupancy was presented in [CBS+13]. Therein, the authors developed an algorithm called non-intrusive occupancy monitoring (NIOM). In particular, NIOM guesses the presence of people at home by comparing the average, the variance and the maximum value of the current energy consumption with threshold values. The threshold values are computed during inactivity periods, namely when the activity of residents does not add energy consumption to the baseline consumption, e.g., the consumption of devices such as fridge, heat, ventilation and air conditioning (HVAC) systems etc. Accordingly, the thresholds are computed every night when people are supposed to sleep. As both power values and threshold values are computed over time slots of fixed duration, the duration of the slot is an important parameter affecting the estimation. Although occupancy detection through energy consumption observation is a cheap and non-intrusive solution, it is shown being rather inaccurate in determining the occupancy during periods of inactivity. In order to give an example, we focus on site S4 and the S6. We chose these scenarios because we have measured the total energy consumption, which allows for better estimating the baseline during inactivity periods. For site S4, we consider eight months of measurements (March - October 2014), while for site S6, we consider four months (July - October 2014), we then apply the NIOM algorithm as described in [CBS+13]. The time slot duration is chosen equal to 15 minutes. As done in the previous section, we consider two cases, the WDs and the WEs. The baseline, within which the baseline threshold values are computed, was chosen at night between midnight and 5.00 AM. Fig. 4.5, on the left, reports the occupancy obtained for site S4 applying the NIOM algorithm to the measurements of the weekday 27 March and the weekend day 12

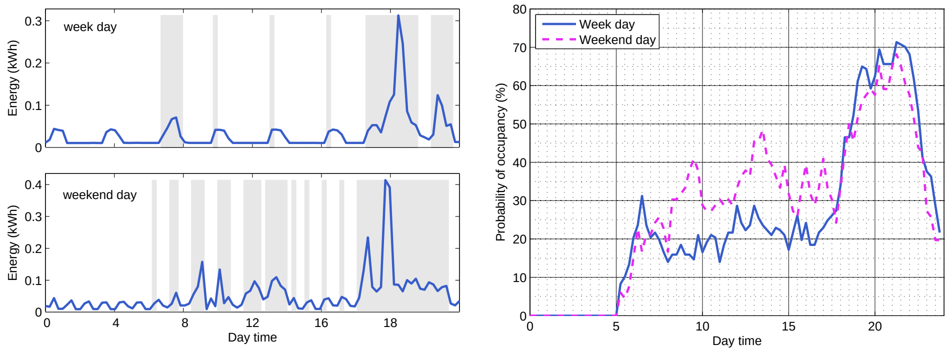


Figure 4.5: Daily occupation (on the left) and CDF of the occupation probability (on the right) for site S4. The Daily occupation refers to 27 March (weekday) and 12 July 2014 (weekend day).

July. The right plot of Fig. 4.5 shows the probability of occupancy obtained for WDs and WEs. Firstly, we note that, as expected, the results obtained between midnight and 5.00 AM do not indicate any activity. Secondly, we note a good agreement between the derived probability of occupancy and the habits of residents. Residents stated that, during WDs, they usually wake up at 6.45 AM, they leave around 8.00 AM to go to work and they are back home around 6.00 PM. During WEs residents tend to spend more time at home during the day. Fig. 4.6 shows the results for site S6 where similar considerations can be done.

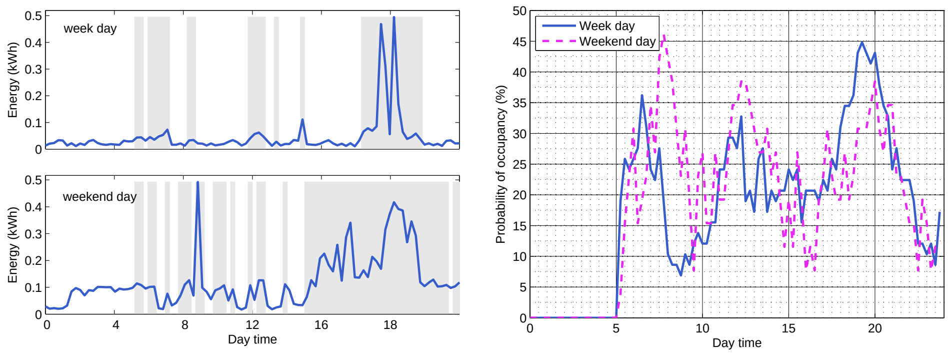


Figure 4.6: Daily occupation (on the left) and CDF of the occupation probability (on the right) for site S6. The Daily occupation refers to 25 August (weekday) and 20 July 2014 (weekend day).

4.3 Modeling individual appliance usage

Appliance usage modeling is the problem of describing the usage of individual devices, given a log stream of status changes. This can be achieved through different approaches, such as association rule mining [KKK12], ANN [AUF02], episode-generating hidden Markov model (EGH) [TTTCR13] and Bayesian networks [HPJ10, CVD$^+$10]. The intuition is that starting of user-driven devices tends to regular patterns which can be modeled. The main reason to model device start is the possibility to predict users' necessities, activities and occupancy. This is necessary for better scheduling resources beforehand as well as suggesting best times to run certain devices. As we previously shown in [MEE$^+$14], this can be done using statistical and machine learning models. In this section we analyze the appliance starting probability of user-driven devices, as extracted from the GREEND dataset on hourly intervals.

4.3.1 Appliance usage in site S2 and S3

We focus here on site S2 in the period between February 15th and October 28th 2014. Fig. 4.7 shows the power readings on Febrary 22nd 2014. The main reason for selecting S2 as case study is the overall amount of usage events, which is higher for the setting of the retired couple. Based on the device operation, we specify device-specific thresholds (Table 4.1) and extract starting events[1]. The processed starting events can now be

Table 4.1: Selected thresholds for site S2

Device	Threshold [W]
Plasma	300
NAS, Console, PC	50
Washing machine	1000
spin dryer	1600
dishwasher	1000
notebooks	40
food processor	40
coffee machine	800
small cooking appliance	120

grouped by hour and day type (i.e., weekdays, saturdays and sundays),

[1] `http://sourceforge.net/projects/monergy/files/Gateway/processor_v2.py/download`

and used to compute a starting probability. In detail, we count the number of starting events for each hour interval and we normalize it to the total for the dataset.

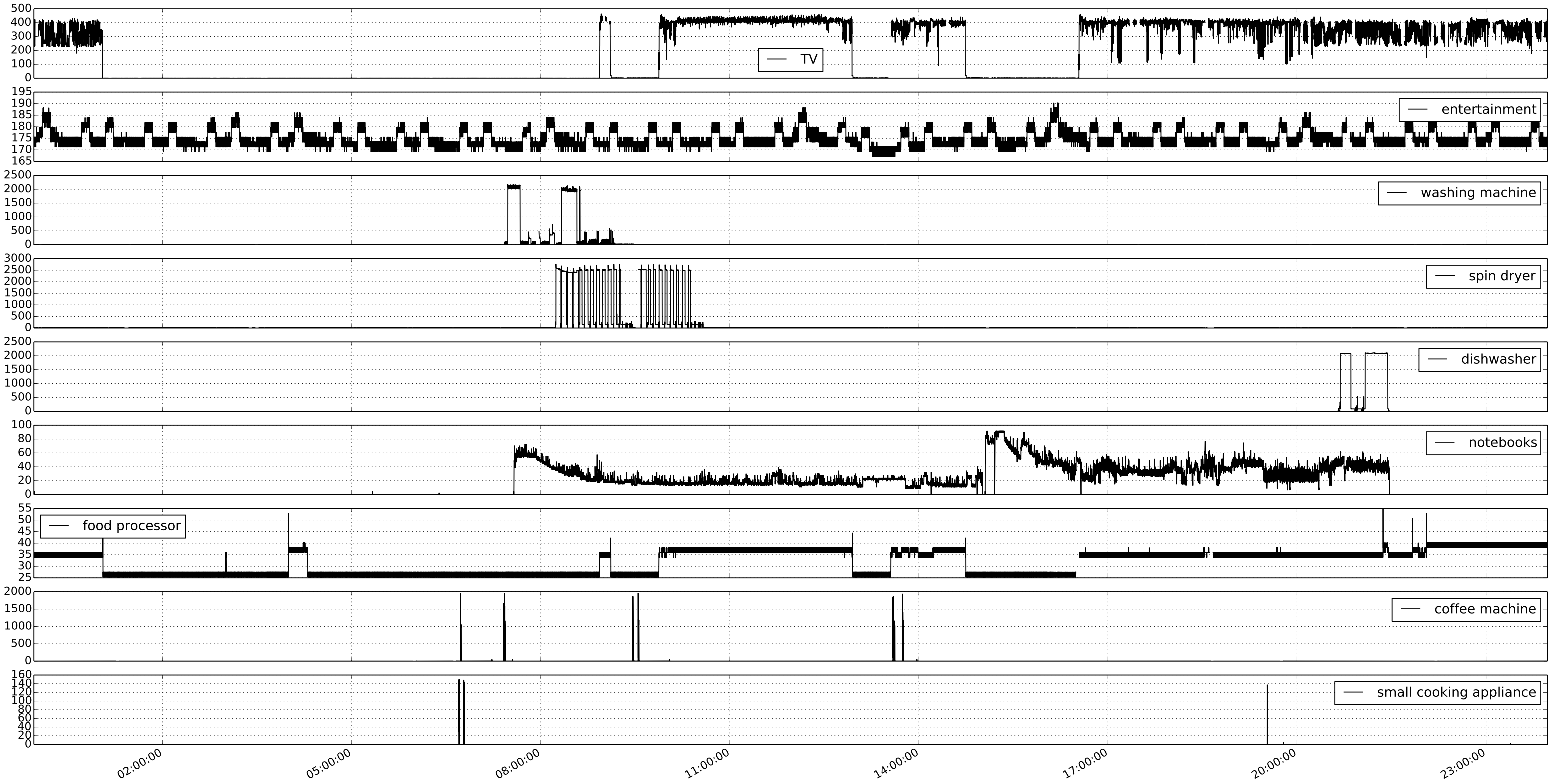


Figure 4.7: Raw power readings (in Watts) collected on February 22nd 2014 in site S2

Fig. 4.8 shows the starting probability for the last 4 monitored devices in site S2: notebooks, the food processor, the coffee machine and the small cooking machine (i.e., bread machine). As for site S3 concerning the family with young kids, Table 4.2 reports the thresholds used for event detection. As visible in Fig. 4.9, the vacuum cleaner, the washing

Table 4.2: Selected thresholds for site S3

Device	Threshold [W]
Vacuum cleaner	1000
Dishwasher	1000
Water kettle	1600
Fridge	400
Washing machine	1000
Hair dryer	900
PC	50
coffee machine	800
TV	40

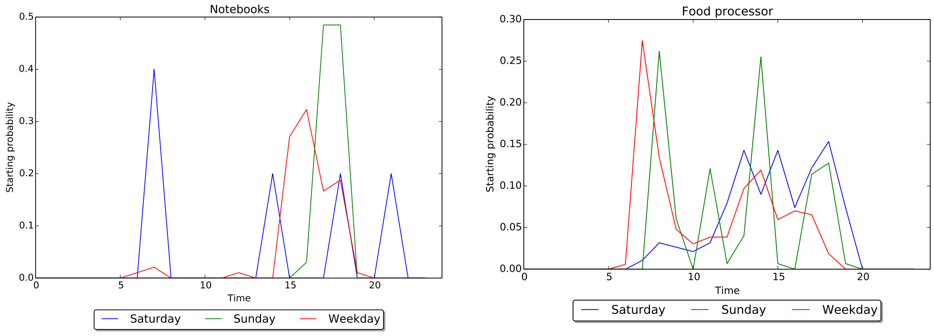
machine and the water kettle show rather regular usage patterns. On the contrary, the fridge is being used every hour, thus determining the distribution in Fig. 4.9d.

4.3.2 Modeling appliance usage

As seen in the previous Sect. 4.3.1, device starting events can be processed to build an expectation of usage based on event frequency. While this intuition provides a useful reference showing the distribution of starting events, we did not consider the dependency between usage events, such as operating multiple times the device in different periods of the day. Techniques for the automatic learning of usage models are thus necessary. In this section we build and assess various appliance usage models. For the purpose, we implemented and publicly released the appliance usage model manager[2], a graphical tool that can handle various models: i) artificial neural networks, ii) bayesian networks and iii) support vector machines [ME14]. The tool can extract and visualize the models, as well as interact with simulation tools via a TCP socket.

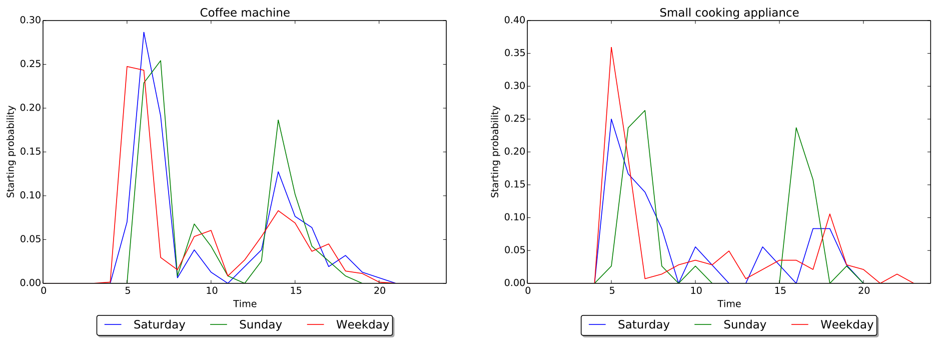
As previously shown, the coffee machine of both S2 and S3 represents a valid candidate to give an example. We start by modeling the problem as an ANN, using an input for each hour of the day and type of day (i.e., weekday, saturday and sunday). The network was trained us-

[2] https://sourceforge.net/projects/umma/



(a) Notebooks

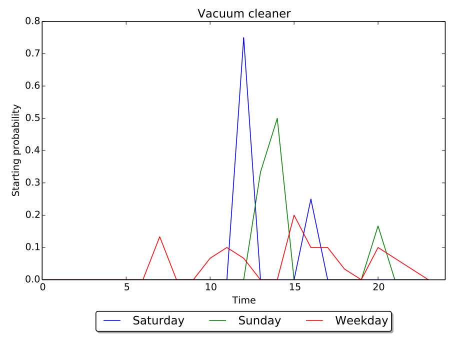
(b) Food processor



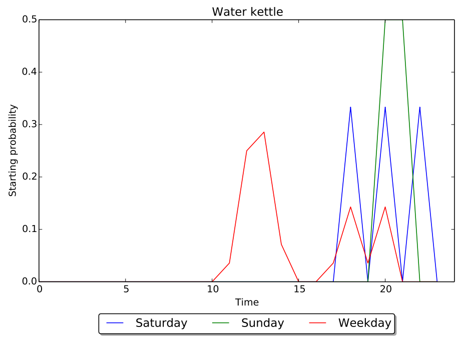
(c) Coffee machine

(d) Small cooking appliance

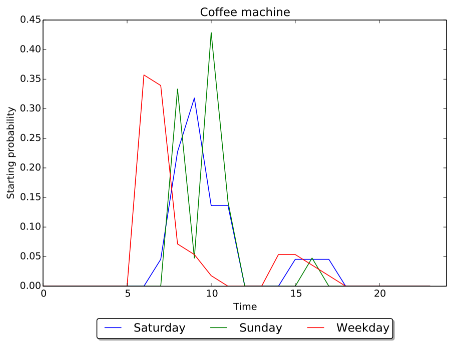
Figure 4.8: Starting probability of selected devices for site S2



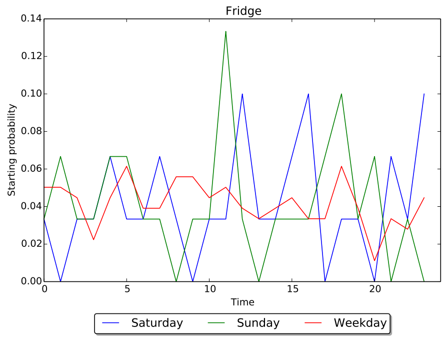
(a) Vacuum cleaner



(b) Water kettle



(c) Coffee machine



(d) Fridge

Figure 4.9: Starting probability of selected devices for site S3

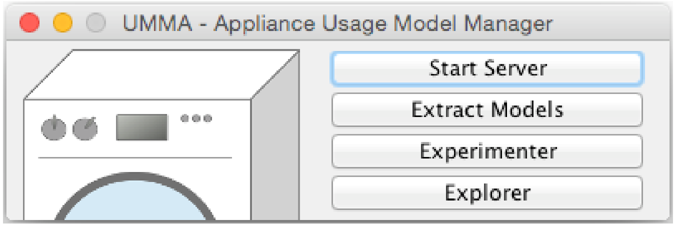


Figure 4.10: The main GUI of the appliance usage model manager tool

ing backpropagation limited to 1000 iterations for performance reasons. Fig. 4.11 and 4.11 report the output of the model respectively for S2 and S3, given different day type and hour. As visible, the number of operations in S3 is lower than in S2 (i.e., 99 against 986 events), which also complicates the learning of a usage model, being the number of inactivity much higher than usages. For site S3 the learning of neural network can easily minimize the input/output error and terminate quicklier.

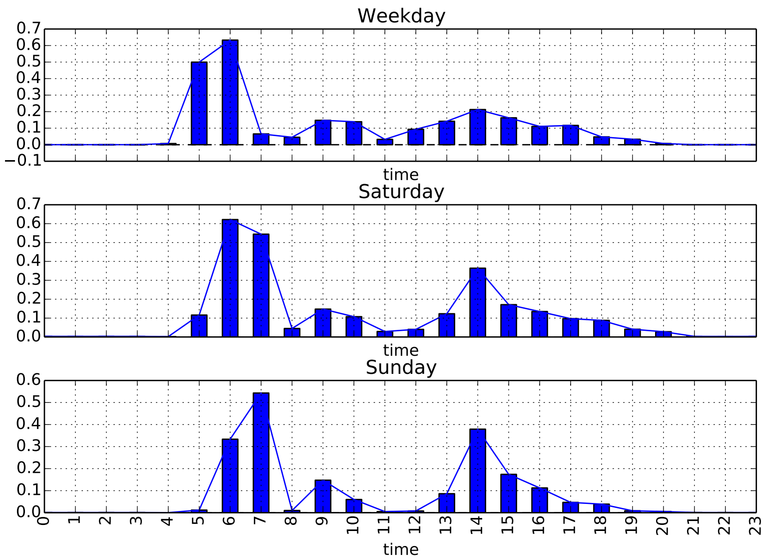


Figure 4.11: The usage model of the coffee machine in S2 using an ANN

We further model the problem as a Bayesian Network, as in Fig. 4.13. The model allows for predicting device starting while also considering previously concluded operations which started in the interval. For simplicity we omit in this example the month information. The network is then trained using expectation maximization (EM), and exact inference is performed using the junction tree (JT) algorithm. The histograms shown in Fig.4.14 agree with the ones previously shown in Sect. 4.3.1.

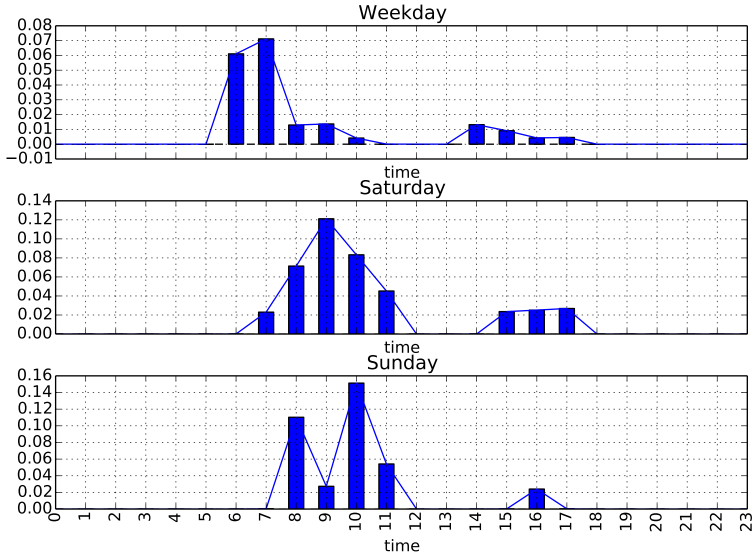


Figure 4.12: The usage model of the coffee machine in S3 using an ANN

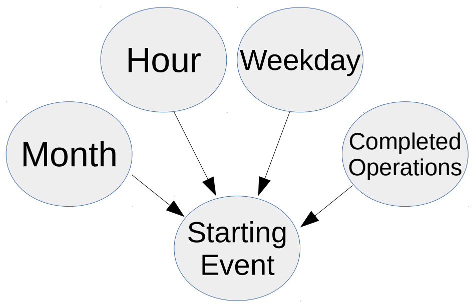
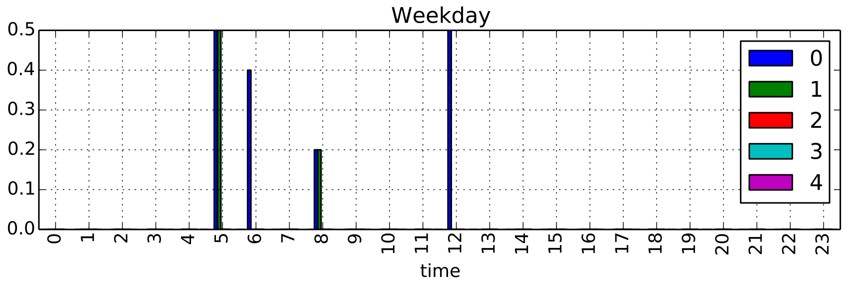
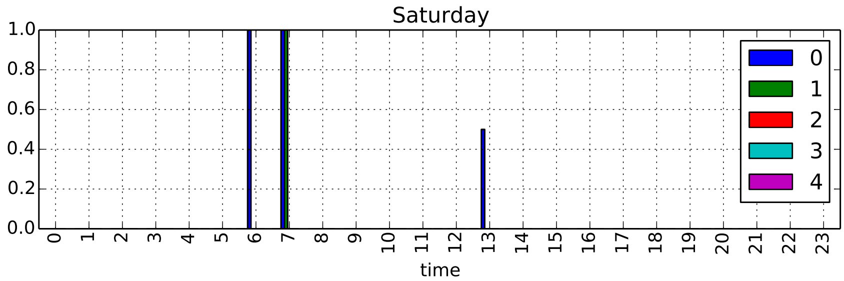


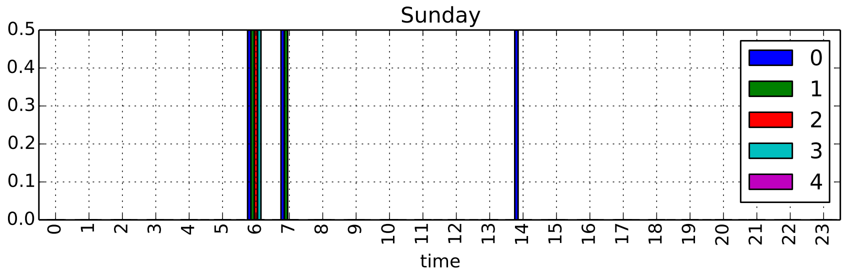
Figure 4.13: The Bayesian network



(a) Starting probability in weekdays



(b) Starting probability in saturdays



(c) Starting probability in sundays

Figure 4.14: Starting probability of selected devices for site S2

4.4 Tips to Save Energy

The main outcome the users expect from the monitoring campaign is a set of suggestions they can implement to reduce the energy consumption and, ultimately, to save money. This section presents some tips derived from the analysis of the collected data and quantifies the amount of savings provided by the adoption of each specific action in the sites being monitored. The analysis reveals that savings up to 34% are possible without significant impact on the user lifestyle.

4.4.1 Tip #1: Flip the Plasma TV with an LCD TV

When present, the plasma TV is the most deployed by users. It is normally placed in the living room, while LCD TVs are confined to other rooms, as the kitchen or bedrooms. However, plasma consumes much more than LCD. Fig. 4.15 show the energy consumption profile of the plasma (42”) and the LCD TV (37”) of respectively site S4 and S5 during an acquisition of one day. As it can be noted, the plasma TV consumes

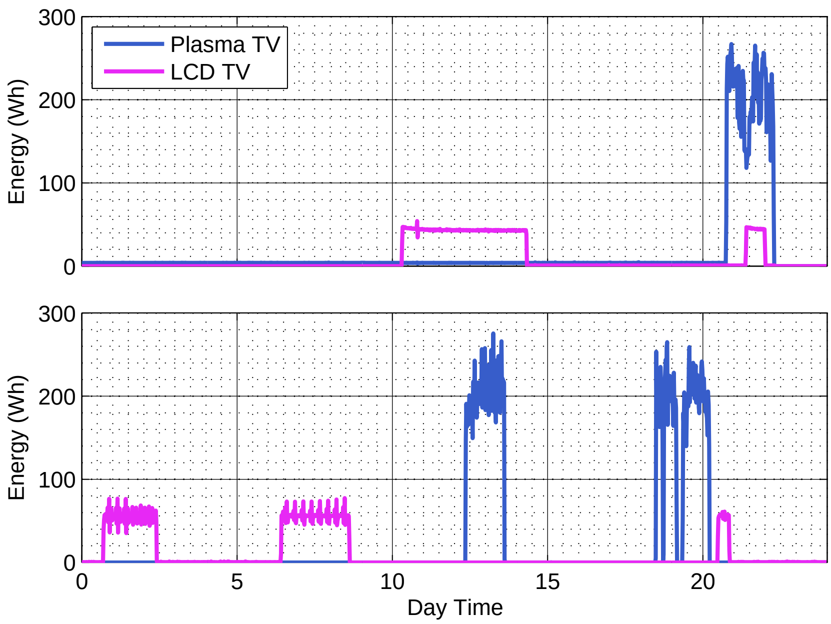


Figure 4.15: Energy consumption comparison of the plasma and the LCD TVs of site S4 (on top) and site S5 (on bottom).

between two and three times the energy of the LCD TV. While the devices have different size, the relationship will also hold for TV of the same size. Therefore, it is reasonable to exchange the LCD with the plasma TV in order to get significant energy savings. However, other technological differences, such as different resolution and distance from the device might affect this choice. Let us try to quantify savings. According to the values in Fig. 4.15, we approximate the hourly energy consumption, i.e., in one hour of activity, of the plasma and LCD TV be 200 Wh/hour and 80 Wh/hour, respectively. Hence, we can obtain the hours of activity of such devices as the ratio between the total consumed energy and the hourly energy consumption. In site S4, we estimate 421 and 148 working hours for the plasma TV and the LCD TV, respectively. In site S5, we estimate 771 and 404 working hours. Now, let us flip the working hours of the plasma and the LCD TVs, i.e., we simulate a position exchange of the devices. We compute the new overall energy consumption and results reveal that the new energy consumption is 34% and 23% lower than the actual one of site S4 and S5, respectively. We remark that this has been made possible simply by flipping the position of the devices, without the need of substituting them with new models.

4.4.2 Tip #2: Switch off the stand-by devices

Standby mode is responsible for a large waste of energy. In standby, the device is not completely switched off and absorbs power. However, it is not performing its main functionality. Several reasons motivate the standby mode. Among these, to let the device be remotely controllable or to let it be ready for a prompt switch on under user request. For instance, the digital video player (DVD) player, the radio, the TVs, or the air conditioning system need to be fed to receive the switch on command from the remote controller. Similarly, the computers need to keep refreshed the random access memory (RAM) for a prompt reboot after a suspension. Also mobile phone chargers absorb power even if they are not used, but connected to the outlet because their internal AC/DC circuitry is fed. The power absorbed by devices in standby mode may be as low as some mW, but it can even exceed tens of W[3]. In this respect, it is important to understand that even a power consumption of 1 W can lead to a considerable waste of energy if observed over a long period of time. To quantify further the waste due to standby, let us consider an example extracted from one of the measurement sites.

The analysis reveals that, in site S7, the television and the decoder are always switched on and in stand-by mode. Fig. 4.16 shows the measured energy consumption during subsequent days. The power consumption is approximately 6.57 W that yields to an annual energy con-

[3] Lawrence Berkeley National Laboratory, “Standby Power Summary Table”, online: http://standby.lbl.gov/summary-table.html

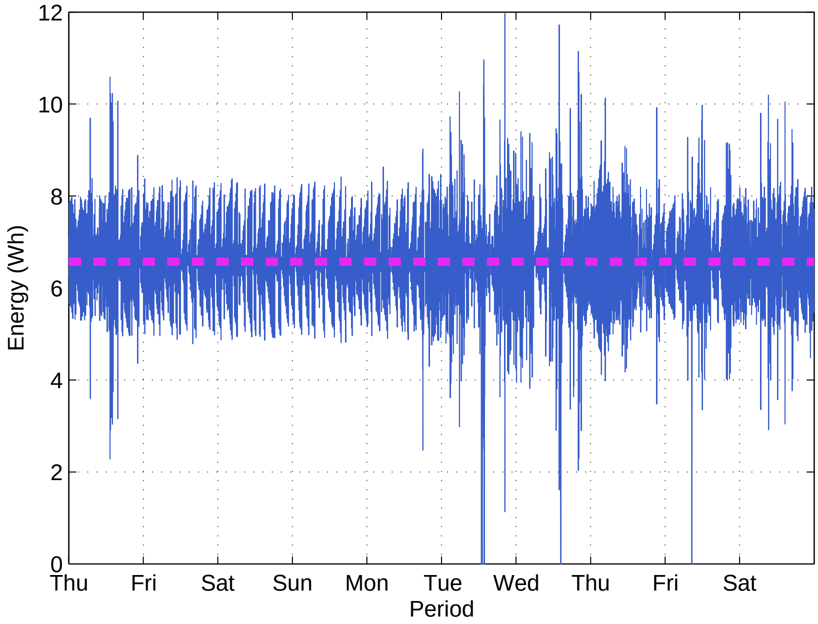


Figure 4.16: Measured energy absorbed by the TV + decoder of site S7. The mean value is also shown.

sumption of 57.57 kWh, or, equivalently 1.4% of the total energy consumption of site S7 (4099 kWh). Now, we can assume that 10 is a reasonable number of devices per site that are in standby mode all over the year. Among these, the washing machine, the air conditioning system, the TVs. Therefore, we conclude that about 14% of the total energy consumption is wasted due to standby.

4.4.3 Tip #3: Substitute the old devices

Old appliances are inefficient as they implement rarely strategies for the reduction of the energy wastes. In addition, degradation due to utilization yields to further wastes that worsen the problem. Therefore, substituting the appliances with new ones becomes an interesting option since energy savings would motivate the investment.

In this respect, an application example is provided by two old fridges installed in site S5. The devices do not belong to the set of monitored appliances due to the coverage limitations of the monitoring platform. They were not reachable. Thus, we measured their consumption with a dedicated monitoring platform installed for a week on site, according to the desire of the users. Results revealed an energy consumption of about 47.7 Wh and 28.6 Wh, for a total amount of 56 kWh per month and 668 kWh per year. This number could be reduced to below 258 kWh per year by replacing the two freezers with two freezers belonging to A+++ energy class[4]. The resulting energy saving would be equal to 34 kWh per month that corresponds to the 11% of the total energy consumption of site S5 as reported in Table 3.6. Furthermore, we note that, substituting the fridges helps moving the category of site S5 from C4 (the most expansive) to C3, with a significant reduction of the energy cost.

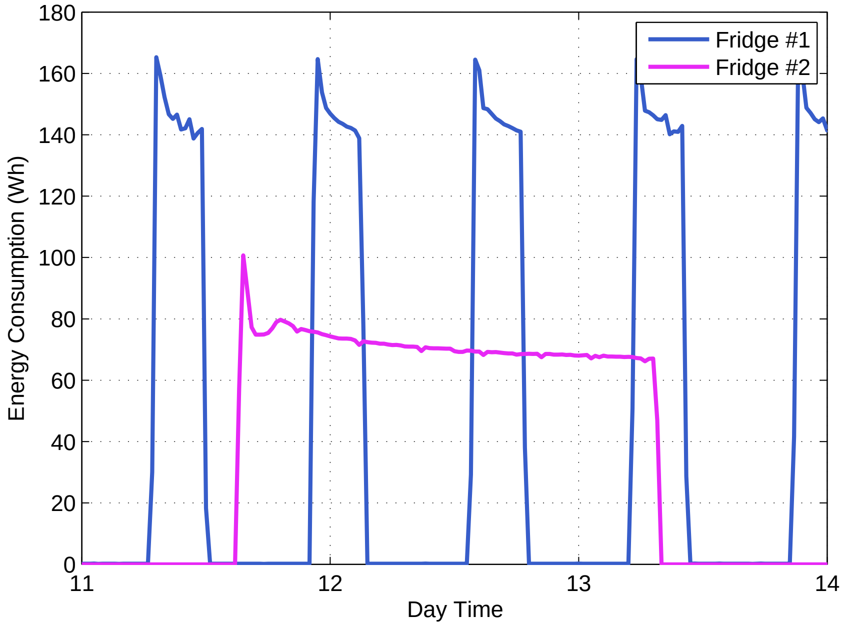


Figure 4.17: Power consumption of an old fridge and an old freezer in site S5 during a time interval of three hours.

4.4.4 Tip #4: Switch off the ADSL modem when unused

The asymmetric digital subscriber line (ADSL) modem is switched on all the day, but users surf the Internet for a few hours a day. Now, the power consumption of an ADSL modem with WiFi and Ethernet functionalities is about 30 W [5] that means approximately 263 kWh per year. Let us assume to switch on the modem for about 3 hours per day and during the entire weekend. In this case, the total power consumption would be

[4]The computation of energy consumption given by A+++ freezer has been made by assuming that the energy efficiency index (EEI) is equal to 22, the volume of the freezer is equal to 302 liters, and the appliance category is the 7.

[5]http://www.downloads.netgear.com/files/GDC/DGND3700V2/DGND3700v2_UM_05June2014.pdf

98 kWh per year, i.e., about 37% of the energy consumed if the device is always switched on. Clearly, this tip applies to all cases where the Internet connection is not required for other applications/needs, such as VoIP.

4.5 Recommendations to increase efficiency

The analysis carried out in the previous section provided several potential ways of improving energy efficiency, including:

1. **Lighting** replacing incandescent bulbs with energy saving ones;
2. **Device diagnostics** replacing old appliances with more energy efficient ones, expecially regarding white goods but also involving consumer electronics (e.g., LCD/light emitting diode (LED) TV in place of a plasma TV);
3. **Shedding of standby losses** switching off consumer-electronic devices when people are not likely to be at home, such as ADSL modems and TVs;
4. **Device shifting** shifting of particularly energy demanding devices to off-peak periods, in order to operate loads in cheaper time periods. This includes both deferral and preference of efficient devices to energy demanding ones, as shown in tip #1.

While these policies have a general validity, the benefits of the data analysis is limited to the users involved in the campaign.

4.6 Automating the analysis

To extend the energy efficiency policies to the region of CAR and FVG, we implemented an open-source energy advisor framework. The system is able to collect energy usage information, autonomously analyze it and provide users with tailored feedback to improve their efficiency.

4.6.1 The Mjölnir framework

Mjölnir is a web-based energy management system capable of visualizing energy consumption and production information.

Available data sources are: i) aggregated building production and consumption information, ii) power readings from selected circuits and devices and iii) energy usage events. The current version 0.2 Mjölnir provides:

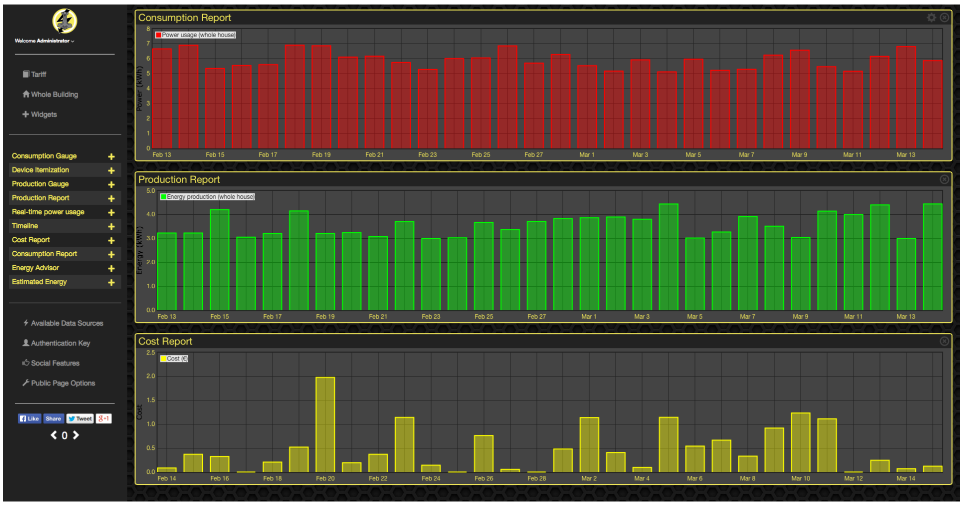


Figure 4.18: The Mjölnir interface 0.2

- **Credit-based device management** Each monitored device is associated to a credit, which is decreased upon device usage [ME13]. This provides a fine-grained consumption resolution, providing an understanding of the cost of operating each device.

- **Device metadata** To determine the applicability of certain analyses, each device is described through the following attributes: type (e.g., fridge), mobility and room, curtailability, autonomy (i.e., user control) and stand-by mode. In particular, the room and device metadata are based on the large vocabulary introduced in [KK14]. This makes the integration with analysis frameworks sharing this data model (e.g., non-intrusive load monitoring (NILM) toolkit [BKP$^+$14]) possible.

- **Tariff-based energy data analysis** The analysis tool is based on a price model, which is expressed as energy tariffs.

- **Modular interface** The interface exploits Bootstrap[6] and can be seamlessy visualised on both mobile terminals (e.g., smartphones and tablets) and computers. Moreover, the framework is organized on pages and cells and based on the concept of widget, which provides both modularity and flexibility to the interface structure. A widget can provide various features, such as displaying charts or forecasting energy consumption, and can be placed in those cells. This also allows users to progressively adapt the feedback system

[6]http://getbootstrap.com

in order to display energy information in a language that is meaningful to them: by placing things next to each other and only concentrate on interesting matters.

- **Social features and public profile page** Social features allow users for sharing their performance with their peers, including social networks and blogs. To this end, we distinguish public and private pages of users. A public page is meant to be the public user's profile. Also, actual and estimated energy consumption and production for the current day is provided as a summary that can be embedded in external web pages (e.g., blogs).

Among available widgets are:

- **Production/Consumption report** showing daily energy information over the last month;
- **Cost report** showing daily energy cost over the last month;
- **Production/Consumption gauge** showing energy use for the current day;
- **Energy estimation** showing an estimation of energy production and consumption for the current day, as based on the previous days;
- **Device itemization** showing the consumption and cost per device, over the current day, week and year;
- **Timeline** showing energy usage events per device, and described by their consumption and cost;
- **Energy advisor** returning messages based on usage behavior in order to increase efficiency;
- **Appliance usage** showing the usage models of user-driven devices, as in Fig. 4.8 and 4.9.

The framework is open-source and available as SourceForge project[7]. We refer to the project documentation for further information on functionalities and setup.

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

4.6.2 Energy efficiency policies for the regions

The recommendations formulated in Sect. 4.5 were implemented in the *Energy Advisor* widget as follows:

- **Device diagnostics** advices replacement of appliances and it is thus useful to improve non-user-driven devices (e.g., fridge)
    1. Select non-user-driven devices
    2. Compute average consumption for each device type for all users[8]
    3. Retrieve devices whose average consumption is higher than the one for the device type of a certain threshold τ_1 (e.g., 30%) and suggest replacement
- **Device shifting**
    1. Select user-driven devices
    2. Rank devices by their average consumption (according to consumption events)
    3. Rank tariffs by cost in order to select the best and worst tariffs available
    4. Suggest to use the device in the cheapest tariff and report the potential savings computed as $s = (l \cdot t) - (l \cdot c)$, respectively with l average consumption for the device, c and t cheapest and most espensive energy tariffs.
- **Shedding of standby losses** suggests to switch-off devices in standby mode (such as displays, decoders, DVD players, battery chargers without load, air-conditioning systems) in periods of not use (e.g., night). This tip can be always returned for devices with a standby mode, although higher effectiveness can be achieved by exploiting an occupancy model.
- **Device curtailment and moderate usage**
    1. Select user-driven devices;
    2. Rank devices by their positive deviation from the average number of usage for the device type and cost;
    3. Suggest to reduce the amount of times the device is being used and compute the yearly savings as extrapolated from the running cost spent for the current month;

[8] Can be done periodically and cached in a separate location

Section 5

Conclusions

This deliverable has presented the work carried out within the WP5 of the Monergy project.

The GREEND dataset resulting from a year-long measurement campaign offers detailed power usage information that can be used to assess energy management systems before their deployment. On one hand, we have reported a description of issues arising from such a long term measurement campaign, along with potential ways to tackle those problems. The dataset has been then used within WP5 to derive energy usage profile of inhabitants of Carinthia and Friuli Venezia Giulia. The main outcome has been the analysis of commonalities and differences and the formulation of practical recommendations to save energy. In particular, the analysis has revealed that savings up to 34% are possible without significant impact on the user lifestyle.

Furthermore, our analysis is beneficial to designers of home energy management systems, as it provides an understanding of energy usage practices that can be exploited for the design of the next-generation of HEMS. In particular, to solve the connectivity issues and to size the system in order to be able to monitor all the relevant loads.

Finally, to extend the benefits of the data analysis and the formulated policies, we have introduced a web-based energy management system and we have released it for open use. The Mjölnir open-source framework provides a working system able to automatically analyze energy usage data and accordingly return tailored feedback. We have engaged with the initialization of such a project and we expect this tool to play an important role for researchers working with energy management systems.

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