UNIVERSITY OF LJUBLJANA

MASTERS THESIS

Load Profiling of Home Appliances Using Load Classification

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in the

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ICT

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Declaration of Authorship

I, Jakob JENKO, declare that this thesis titled, "Load Profiling of Home Appliances Using Load Classification" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

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Chapter 1

Introduction

Climate change calls for a shift to renewable energy and restructuring of the electricity sector. Sources Eurostat, 2022 show as of the time of reading this paper, 44 % of produced electricity in Europe was from combustible sources such as gas, fuel, and coal. Even though that is a significant decrease of 10 % in the last 10 years, it is a significant Co2 emitter. The same source Eurostat, 2022 also states that a third of energy is consumed by the residential sector. It is estimated, that the human population will reach 10 billion inhabitants in the next 10 years, and ever-increasing ownership of electrical appliances such as smartphones, HVACs, and EVs will further increase energy consumption. (elevate this issue) Acknowledging that, reducing consumption in that sector could leave a significant impact on the human footprint.

The EU aims to be climate neutral by 2050, therefore it seeks to improve the efficiency of every part of pollution contributors through The European Green Deal. A large part of these contributors is the Energy sector. A subpart of the energy sector is the residential sector, where many advancements could be made to help to reach the goal.

This could be achieved through various applications and methods that use load profiling and load monitoring as their core technology. Authors in Chuan, Rao, and Ukil, 2014 proposed a method to reduce peak loads by studying consumer appliance usage patterns. Paper Csoknyai et al., 2019 studied consumer usage patterns, and returned feedback that contributed to reducing consumption. Another notable way is the use of distributed energy resources and managing them in such a way as to decrease the net output of energy flow such as the authors describe in Moreno Jaramillo et al., 2021. All described methods would reduce and alleviate the load off the power grid.

Load profiling in building energy consumption is not a novelty and had been in research since the 1980s. While it was thought that aggregated load profiles of households are relatively predictable, recent data obtained using smart meter data showed large deviance from user to user due to different lifestyles, as the author states in Proedrou, 2021. In recent years load profiles have changed due to renewable energy accelerated development of distributed energy resources such as residential photovoltaic power plants, home wind energy, and using EVs and home batteries. Socioeconomic changes such as work-from-home, also drastically reshaped the load profile curve.

Technology advancements in non-intrusive load monitoring and increased adoption of smart energy meters offer a new way of load profiling, that is NILM load profiling.

Chapter 2

Definitions

Author Proedrou, 2021 defines terms as following

- Residential: private residences, with no commercial usage, occupied by one or more persons either full-time or part-time during a calendar year.
- Load: the electricity that all the electricity-powered devices in the household consume in unit time.
- Profile: a graph representing the significant features of the electricity load over time.
- Model: "a formal system that represents the combined processes" Kavousian, Rajagopal, and M. Fischer, 2013 of electricity consumption by all the electricity-powered devices in a private residence/number of residences.

Commonly load profile is a term defined as aggregated power usage of all appliances in a house. Sometimes load profile is used to describe appliance level load profiles.

Besides the above pre-defined terms, I have defined a few of my own to avoid confusion.

- Activation or use frequency profile or (AFP): frequency of use of certain appliance per given unit time
- Appliance level load (ALL) - the electricity that the electricity-powered devices in the household consume in unit time.

The load profile is most commonly presented with a curve, that shows daily power usage.

FIGURE 2.1: "Clustered load profiles. The graph was published by Gerbec et al., 2005"

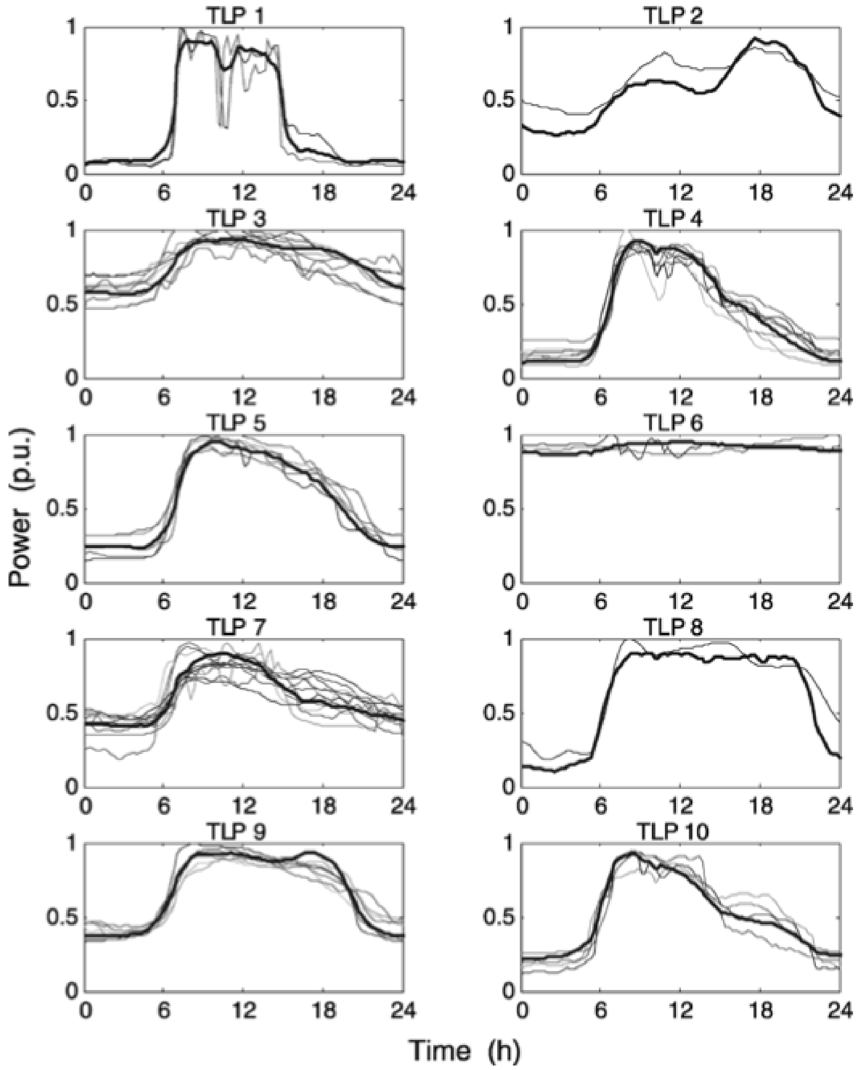


Figure 2.1 depicts 10 clusters of daily load profiles. This is not the only way to present it, for example, author Park and Son, 2019 used an image-based presentation.

Chapter 3

Related work

Work relating to load profiling can be found in two research verticals or topics. The first one is load profiling and load profile models, which in most cases study the load profile curve of the building. Few exceptions study load profiles on appliance-level. The second vertical is anomaly detection in building energy consumption data. While the first topic is closer, there are quite a few connections with the latter. If one wants to do anomaly detection, in some cases, one must first build some kind of "normal consumption profile"

3.1 Load profiling

Load profiling has been researched since 1980. Load-profiling can be performed in two ways: bottom-up and top-down.

A bottom-up approach as Swan and Ugursal, 2009 state "calculates the individual dwelling energy or electricity consumption and extrapolate these results over a target area or region" Whereas with Top-down approach as Swan and Ugursal, 2009 state "uses the total energy or electricity consumption estimates to assign them to the characteristics of the building stock" In other words, Bottom-up sub-meter data, Top-down uses aggregated data. In our case, we take a deeper dive into the bottom-up approach, since it is more relatable.

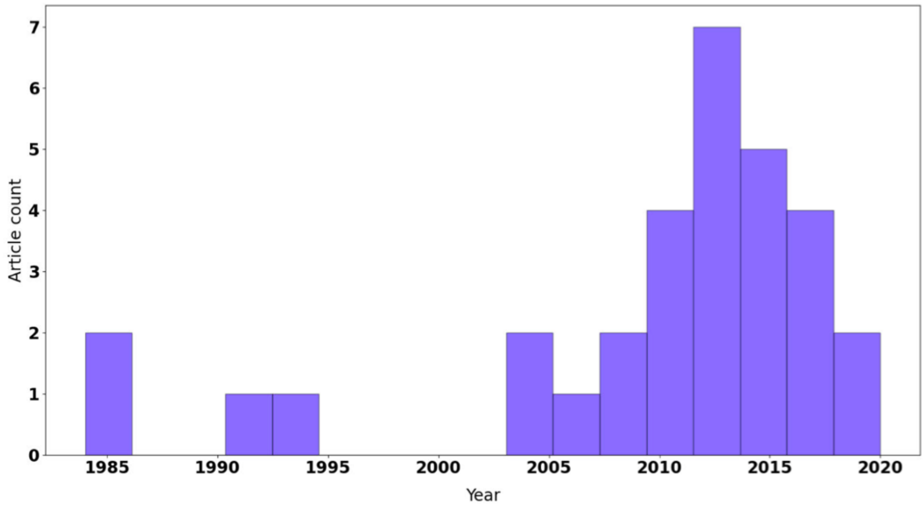
Proedrou, 2021 did a comprehensive review on load profiling. The author defined various load-profile application subgroups such as demand-side management, planning and control design of energy systems, and residential load profiles. The author also grouped modeling techniques as probabilistic models, Markov chains, and Monte Carlo. The author first disclosed the current state of load profiling and issues with past work. They made a review of existing load profiling models and asses the-state-of-the art. The review was structured by different methods. Next, they pointed out future research directions and applications of load profiling models. Finally, the author exposes issues that researchers face and addresses possible solutions with conclusions.

One of the first publications on load profiling was published by Train, Herriges, and Windle, 1985. They used a bottom-up approach using sub-meter data and other socioeconomic and demographic characteristics to create a load profile or statistically adjusted engineering (SAE) as they call it. They can adjust the curve based on weather, dwelling size, and income. In the same year, Walker and Pokoski, 1985 published a paper where they used a bottom-up approach with psychological factors to create probability models of when will an individual use an appliance.

Since then there were two more in 1995. Research picked up the pace in 2005 with 7 publications in 2013 as figure 3.1 shows.

Gerbec et al., 2005 tried to assign typical load profiles to a particular group of consumers based on their activity. To achieve that, they used probabilistic neural

FIGURE 3.1: "Distribution of publications on load profiling from 1985 to 2020. The graph was published by Proedrou, 2021"



networks as a way of classification. Their methodology was tested in real use scenario.

Gao, Liu, and Zhu, 2018 makes use of the bottom-up method to build a forecasting framework for household load profiling, which takes into account the consumption patterns of residents. A model falls into the demand-side management subgroup. They have developed a "single-day extraction model", designed to select the same days by comparing environmental and household factors, which influence energy consumption. By using this approach, they have improved the accuracy of predicting behavioral patterns of dwellers. This method falls into the probabilistic method subgroup. Results show that their method successfully modeled daily usage.

Chuan, Rao, and Ukil, 2014 uses load profiling to optimize energy consumption distribution during the day. This reduces peaks usage and alleviates load off the grid. The author used the bottom-up method, that is, using sum-meter data. Using this data, he made daily usage analyses on a one-hour basis. Using this information he optimized the daily activation of appliances so that peaks usage was not as high. Results show that peak shedding was successful.

Csoknyai et al., 2019 analyzes energy consumption patterns and intervention strategies in residential buildings. Authors achieve this using a "serious game approach" with a combination of direct user feedback using smart meters. The application also provides advice, comparisons, savings, reduction goals, and monitoring. The approach takes into account almost all dimensions of residential energy usage. Their results show that their serious game was not able to induce energy-saving behavior.

Jeong et al., 2021 used extreme points in the appliance usage curve to cluster usage profiles. Usually, the first usage peak is in the morning, and the second one is in the evening. Additionally, they used demographic characteristics that are: region, area, age, salary, etc. to improve the results. Using collected data, they clustered profiles. They had discovered 6 different usage profiles, where every cluster had a physical meaning such as energy-saving, morning heavy, evening heavy, etc.

Another clustering methodology was proposed by Park and Son, 2019, using load image profiles and image processing. They represented time series data as an image. The image is a grid of squares where the y-axis contains monthly data with a resolution of one day, x-axis contains daily data with a resolution of one hour. Grid if color filled with an algorithm that authors developed, where red means more activity and blue less. Using digital image filters they transformed the type-1 image to type-2 and from there used a threshold to obtain type-3. Using that information they clustered data based on images similarly. They used three different clustering methods: k-means, FCM, and EM algorithm. Using the Davies-Bouldin index, they were able to prove that image-based clustering performs better than non-image.

Abreu, Câmara Pereira, and Ferrão, 2012 clustered different load profiles using electricity consumption data and surveys. They profiled residential homes. They used PCA and k-means resulting in 5 clusters. Similar to other load profiling papers.

Whereas most of the above-mentioned papers focused on aggregated consumption of building to build a load profile, authors Issi and Kaplan, 2018 focused on appliance-level load profiling. Their main contribution was to create a realistic per appliance load profile. They developed a wireless measurement system with smart plugs that enabled them to obtain power signatures for each appliance. They evaluated the data and based on observations they determined working cycles for each appliance. Furthermore, they concluded that 15 % of consumed power can be shifted, where they took tariffs into account.

3.2 Anomaly detection in building energy consumption data

A review on Anomaly detection in building energy consumption data was written by Himeur et al., 2021. Here, the authors took a deep dive into detecting anomalies in energy consumption in buildings. The author first makes an overview of existing anomaly detection schemes and applications. Second, they perform a critical analysis and an in-depth discussion of the state-of-the-art. Next, they describe current trends such as NILM anomaly detection. Finally, they assemble a set of future research directions. Both reviews pointed out that NILM anomaly detection or NILM load profiling is a possible future research direction.

Rashid, Stankovic, et al., 2019 authors propose an algorithm that functions on top of existing state-of-the-art NILM algorithms Hidden Markov model, combinatorial optimization, Latent Bayesian Modeling, and Graph-based Signal Processing. They focus on three appliances, a fridge, freezer, and heater. Their metric was the number of operation cycles and energy used within those cycles. They implemented sigma variables to represent standard deviation and used rule-based anomaly detection. So if energy or counts are significantly larger than the mean then the day is considered anomalous. Their rule had only one manual setting and that was a number of standard deviations before the sample was considered anomalous. Their results show that sub-meter anomaly detection works decently whereas NILM based anomaly does not work at all.

Rashid, Singh, et al., 2019 published another paper in the same year, where they took a similar approach, except that they used only compressor-based appliances such as fridges and air conditioners. They also added a rule to their existing rule-based anomaly detection algorithm, but the results still showed that NILM algorithms are not there yet.

Castangia et al., 2021 used disaggregated sub-meter data to detect anomalies in use consumption. They used a private dataset of 20 homes from northern Italy with no synthetic anomalies. Dataset included data from 2018 to 2020 meaning it included covid induced anomalies. The authors first pre-processed the data by aggregating input load in hourly energy consumption, the second derived additional features, which are the time of use and duration of the activation. They use that data to detect single-pint deviations for which they implemented isolation Forest algorithm and anomalous trends for which to detect, they implemented Change Point Detection.

3.3 Table of profiles

While in related work I examined load profiling in general, this chapter focuses on how data in load profiles is presented. It can be portrayed in various shapes and forms, using all kinds of attributes and features to do so. First, main load profiling features will be defined. Second, using these features a general load profile table will be constructed. Third, references from related work and use cases will be mapped to the table. Using this information main features will be selected. Fourth, using a reduced feature set a more detailed table will be formed. Again, the table will be populated using the same references as before. Finally, using this information a research direction will be formed.

3.3.1 Feature set

Using related work and use case references, we can extract the most commonly used features to portray load profiles.

- power
- time
- operating time (how long appliance or appliances is turned on)
- appliances (a set)
- Number of activations (How many times appliance or appliances were turned on)

3.3.2 General table

Using these features we can form a table with all possible combinations. Some combinations do not make logical sense and the others repeat themselves. Combinations marked with X are such examples. Table 3.1 is then populated with references from previous chapters.

TABLE 3.1: General table of load profiles

	frequency	appliances	number of activations	power (avg)	operating time
appliances		X	X	X	X
number of activations	X	[7]	X	X	X
power (avg)	X	[42]		X	X
power (array)	2015	X	X	X	X
power (histogram)			X	X	X
operating time	X	[23]	[39] [38] [3]	[3]	X
time array	X	X	[7]	[11] [13] [4] [24] [49] [17] [16] [22] [1] [26] [39] [38] [21] [3] [8] [27] [11] [6] [34] [25] [16]	[15]

Based on table 3.1 it is possible to see that the most commonly published feature combination is time and power. This combination will be used as a baseline when making a more detailed table. Although the operating time feature was explored in a few publications a bit, and it seems quite promising, we are focusing on activation-based histogram representation. Based on table 3.1 it is possible to see that not much attention was given to it.

3.3.3 Detailed table

This section will focus on exploring possible load profiles using activation-based histogram representation, while using the power feature as a baseload. Features from 3.1 will be explored in higher detail. They will be split and arranged in a way that all 21 publications and power-based presentations will be divided into as many groups as possible. This should expose possible activation-based profiles as well as unpublished power-based profiles.

Sub-features

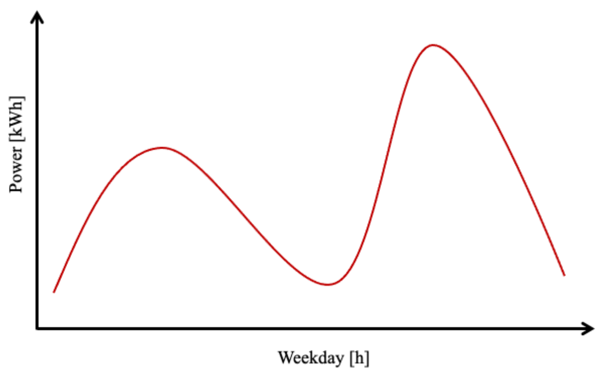
Main features were already described in section 3.3.1. It is possible to further divide them into smaller so-called sub-features. These are reshaped and grouped as follows:

- Way of presenting a profile
  - Per-house load profile
  - Per-appliance load profiles
  - Per-house and per appliance load profile
- By time range of profile
  - Daily
  - Weekly
  - Monthly
  - Yearly
- Way of measuring usage
  - Average power use
  - Activation or frequency of activation
  - Operating time

Sketches of load profiles

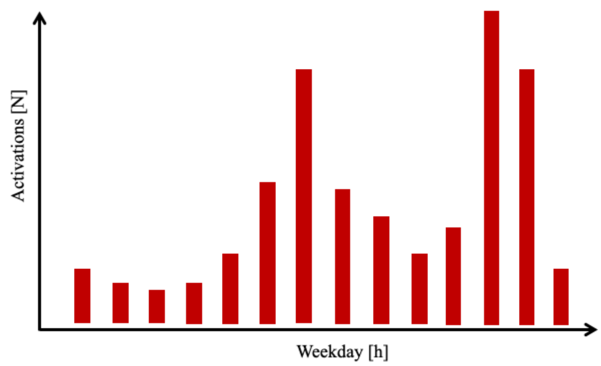
A most common way load profiles are presented is a daily power consumption profile such as shown in figure 3.2. The graph is a sketch, but it represents a standard load profile with morning and evening peaks.

FIGURE 3.2: "Average daily usage profile for an appliance or a building"



Some references include daily usage profiles as a histogram of activation at a point in a day, such as a figure 3.3.

FIGURE 3.3: "Histogram of daily activations profile for an appliance or a building"



All figures can present whole-house usage or per-device usage. Each presentation has its pros and cons. To present more information sub-meter data can be used to represent whole-house usage with per-appliance contributions. Such as on figure 3.4 and 3.5.

FIGURE 3.4: "Histogram of daily activations profile for an appliance A and B"

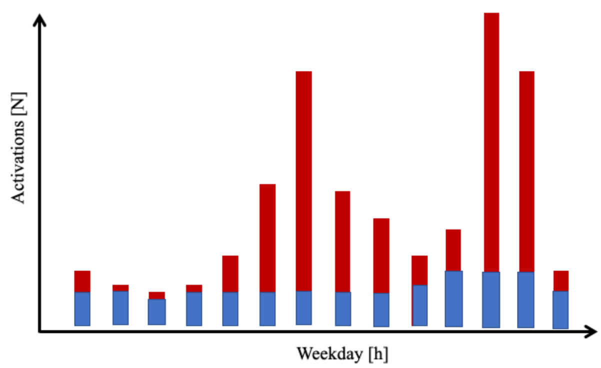
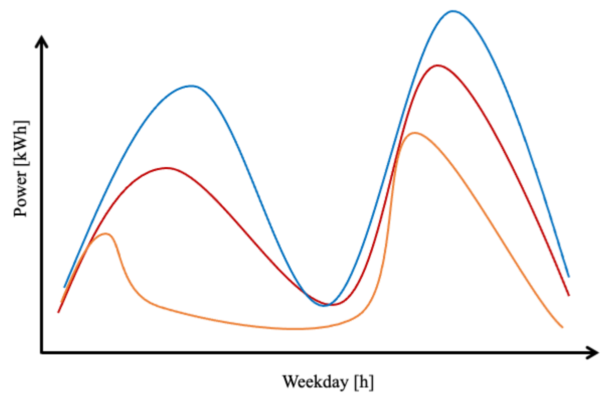


FIGURE 3.5: "Average weekday power consumption for appliances A, B and C"



To present as much information as possible all above-mentioned attributes can be presented in a multidimensional way such as heatmap in a way shown in figure 3.6 and 3.7.

FIGURE 3.6: "Number of daily activations / power consumption of one appliance / house in one month period"

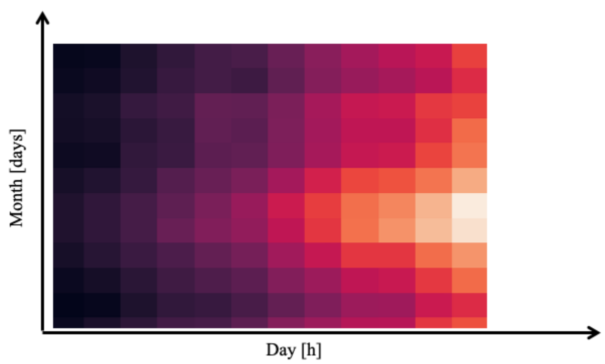
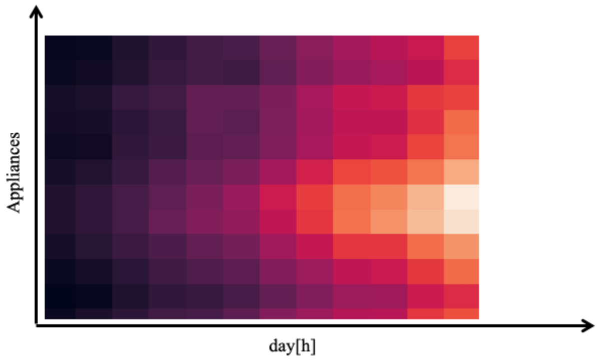


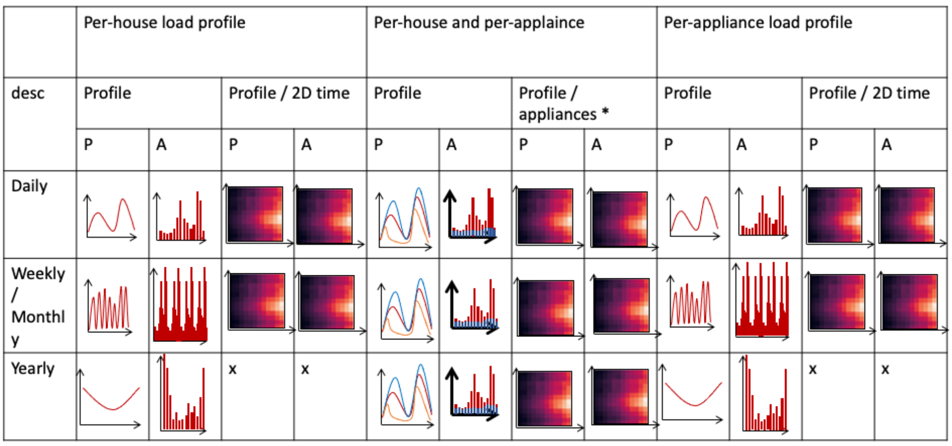
FIGURE 3.7: "Number of activations / power consumption for each appliance in one month period"



3.3.4 Table of combinations or detailed table

The above-shown profiles can be combined, yielding a new way of displaying the data. Bellow, a map with combinations of the above-mentioned profiles is presented. The purpose of table 3.8 to generate and show possible combinations. Some combinations that had similar output were grouped, and some that could not be sketched were discarded.

FIGURE 3.8: "Table of combinations"



	Per-house load profile				Per-house and per-applaince				Per-appliance load profile			
desc	Profile		Profile / 2D time		Profile		Profile / appliances *		Profile		Profile / 2D time	
	P	A	P	A	P	A	P	A	P	A	P	A
Daily												
Weekly / Monthly												
Yearly			x	x							x	x

Figure above 3.8, uses sub-features from previous subsection 3.3.3. In general, the table is formatted in a way that features from columns are used in the x-axis of a plot, and rows are used in the y or z-axis of a plot.

The column of the table presents the time domain. Dailymeans that the load profile presents average usage for one day, weekly means it presents usage for a week. To be clear, for one to construct a decent daily profile, one needs a few weeks of data. The same goes for yearly profiles, in that case, one needs many years' worth of data.

The top row of the table is composed of 3 main groups. The first group focuses on per-house energy consumption. The second group examines the energy consumption of each appliance in a house separately. Third group analyses all appliances in a building.

The next row of the table is further divided into two groups. First is the profile group which presents the given usage unit on the y-axis and time on the x-axis. Next is a profile with a time group. In this case, we present the given usage unit on the z-axis and then time on the x and y-axis. Here, the second-time dimension can be anything from a week to a year. In the case of the per-house subgroup includes appliances instead of time. Example for this is figure 3.7. The last columns present the usage unit, that is power (P) or a number of activations (A).

3.3.5 Mapping references to the table of profiles

To find useful load profiles, references from related work must be mapped.

TABLE 3.2: Table presents previously mentioned load profiles

Description	Per-house				Per-appliance				Per-house per-appliance			
	LP		+ daily time dimension		LP		+ daily time dimension		LP		Appliances side by side	
Range of time axis	P	A	P	A	P	A	P	A	P	A	P	A
Daily	[11] [13] [4] [24] [6] [49] [17] [16] [22] [1] [26]		[43] [34] [26]		[39] [38] [21] [3] [8] [27]	[25]			[11] [6] [16]			
Weekly/ Monthly	[13] [4] [24]								[5]			
Yearly	[13] [4] [24]											

As can be seen from table 3.2, most of the work (14 publications) has been done with standard daily load profiles with per-house power usage such as figure 3.2. Quite a lot of work (6 publications) has been done with per appliance daily power profiles. A few publications were based on weekly and yearly load profiles, a few used two-dimensional time and power presentation. Only one publication found used activation and time-based histogram such as shown in figure 3.3. During the research I focused on publications from minority classes, meaning not all existing publications for standard load profiles are included. The purpose of table 3.2 is to present missing scientific contributions and patterns of publications.

3.3.6 Mapping use-cases to the table of combinations

Table 3.3 includes arranged publications from chapter 5. Similar pattern emerged as in table 3.2.

TABLE 3.3: Table presents references mentioned in use cases chapter

Description	Per-house				Per-appliance				Per-house per-appliance			
	LP		+ daily time dimension		LP		+ daily time dimension		LP		Appliances side by side	
Range of time axis	P	A	P	A	P	A	P	A	P	A	P	A
Daily	[9] [44] [30] [50] [28] [18] [51]				[30] [48] [36] [27]				[11]			
Weekly/ Monthly	[44] [24]											
Yearly	[44]											

3.3.7 Table of use case groups

Table 3.4 presents same publications as 3.3, but only group names are shown. The table indicates how groups are arranged. Where anomaly detection and elderly care are dominating in the per-appliance part of the table, energy-saving and grid management are dominating in a per-house part of the table.

TABLE 3.4: Table presents references mentioned in use cases chapter

ES - energy saving GM - grid management AD - anomaly detection EC - elderly care X - unfeasible	Per-house				Per-appliance				Per-house per-appliance			
	LP		2D time LP		LP		+ daily time dimension		LP		Appliances side by side	
Range of time axis	P	A	P	A	P	A	P	A	P	A	P	A
Daily	ES, GM				AD, EC, ES				GM			
Weekly/ Monthly	ES											
Yearly	ES		X	X			X	X				

The figures listed above clearly depict the void not filled by publications. Although they may not be published, they still have a possible use case. In table 3.5 empty spaces are filled with possible use cases for given load profiles.

TABLE 3.5: "Proposed use cases for profiles"

ES - energy saving GM - grid management AD - anomaly detection EC - elderly care X - unfeasible	Per-house				Per-appliance				Per-house per-appliance			
	LP		2D time LP		LP		+ daily time dimension		LP		Appliances side by side	
Range of time axis	P	A	P	A	P	A	P	A	P	A	P	A
Daily	AD, ES, GM,	AD, ES, GM,	ES, GM	ES, GM	AD, EC, ES, GM	AD, EC, ES, GM	AD, EC, ES, GM	AD, EC, ES, GM	AD, EC, ES, GM	AD, EC, ES, GM	AD, EC, ES, GM	AD, EC, ES, GM
Weekly/ Monthly	AD, ES, GM	AD, ES, GM,	ES, GM	ES, GM	AD, ES, GM	AD, ES, GM	AD, ES, GM	AD, ES, GM	AD, ES, GM	AD, ES, GM	AD, ES, GM	AD, ES, GM
Yearly	ES, GM	ES, GM,	X	X	AD, ES, GM	AD, ES, GM	X	X		AD, ES, GM	AD, ES, GM	AD, ES, GM

3.3.8 Table of load profile potentials

Some combinations are indeed illogical and again others are less useful in a practical sense. The next table will try to rate the scientific potential of the profiles based on two characteristics. First is how well data is presented to the user, meaning that the load profile is clear at what it is presenting. The second is the effectiveness when being used in an algorithm, or in other words, how well data is presented to a machine. These characteristics can not be easily measured, but it is possible to extract them based on the pattern of publications. To do that, we have to make two assumptions. The first one would be, that the larger the number of publications, the larger is the effectiveness of presenting the data to a human. The second would be, that the larger the number of use cases, the better the effectiveness of presenting the data to a machine. Using these two assumptions, we propose the following table. The table has four possible classes.

- 1 - The load profile satisfies both assumptions and has a high utility rate and high research potential.
- 2 - The load profile does not satisfy one of the above-mentioned assumptions and has mid-research potential.
- 3 - The load profile does not suffice any of the above-mentioned assumptions and has low research potential
- X - The load profile is inexplicable.

TABLE 3.6: Proposed classification of profiles

	Per-house				Per-appliance				Per-house per-appliance			
	LP		2D time LP		LP		+ daily time dimension		LP		Appliances side by side	
Range of time axis	P	A	P	A	P	A	P	A	P	A	P	A
Daily	1	2	1	1	1	1	1	1	1	1	1	1
Weekly/ Monthly	1	2	3	3	1	1	3	3	2	2	2	2
Yearly	1	3	X	X	2	2	X	X	3	3	2	2

3.3.9 Table of possible future research directions

Using all the above-mentioned tables we can use superposition to generate a universal table, that will present possible research directions. The load profile has to satisfy the following rules. The first is that the load profile should have no publications or yet discovered use cases. The second one is that the profile should be at least in the second class of potential defined in subsection 3.3.8.

TABLE 3.7: Possible future research contributions

	Per-house				Per-appliance				Per-house per-appliance			
	LP		2D time LP		LP		+ daily time dimension		LP		Appliances side by side	
Range of time axis	P	A	P	A	P	A	P	A	P	A	P	A
Daily		2		1			1	1		1	1	1
Weekly/ Monthly		2			1	1					2	2
Yearly					2	2					2	2

Table 3.7 presents load profiles that we will pursue in this paper. We will focus on profiles from the first class and activation frequency type of usage. When the aforementioned parameters are applied, the end result is table 3.8

TABLE 3.8: Load profiles to be pursued

	Per-house				Per-appliance				Per-house per-appliance			
	LP		2D time LP		LP		+ daily time dimension		LP		Appliances side by side	
Range of time axis	P	A	P	A	P	A	P	A	P	A	P	A
Daily				1				1		1		1
Weekly/ Monthly						1						
Yearly												

Based on the table 3.8 we propose the following profiles for activation frequency: per-house daily-monthly profile, per-house weekly-yearly profile, per-appliance weekly profile, per-appliance daily-monthly, per-appliance weekly-yearly, per-house and per-appliance daily profile (stacked), per-house and per-appliance daily profile (appliance side by side)

Chapter 4

Possible use cases

The load profiling method has a lot of different use cases across different fields. It can be used to save energy by studying users usage patterns and returning feedback. Electrical energy providers could use that same data to optimize the management of their grid, with minimal impact on users daily lives. This method could also be used to help the elderly in case of an accident and help prevent one. It could be used to detect all kinds of early malfunctions in the operation of appliances and help save energy. Occupancy detection, research, and development are all areas where profiling could be used.

4.1 Energy saving

As mentioned before many applications for load profiling could be used to reduce energy use and increase energy efficiency. With the emerging EV-market and ever-increasing installation of heat pumps, more and more energy is being used in form of electricity. This means, most of the current power grids would have to be upgraded to keep up with demand.

On the other side, more and more photovoltaic systems are being installed, which is slowly shifting energy production towards end-users. Slowly energy grid is starting to shift towards so-called distributed energy resources or "DER" Moreno Jaramillo et al., 2021. DERs includes all kinds of micro-energy sources such as PV, wind power, water power, and all kinds of energy accumulators that can store and release energy when needed such as heat pumps with hot water storage, home batteries, and EVs that can be used as a battery.

With smart management, these appliances could be used in a way that would reduce the net flow of energy and alleviate the load off the power grid. A way to achieve this is via load profiling and load modeling. To manage the appliances, a control system would have to be put in place Hledik and Lee, 2021. It would be enough to control a few appliances that consume most of the energy.

Since consumers take part in producing the energy, they are often called "prosumers" Parag and Sovacool, 2016. They will be an essential part of the European Union's plan to reach zero-energy buildings and near-zero-energy buildings Parliament and Council of the European Union, 2021. The directive was accepted in 2010 and was recast in 2021. The plan is set to be realized in the next decade.

An actual use case would be an EV owner with an installed PV system and heat pump, who works from home on occasions. In this case, two profiles would be developed. Normal workday and work from home day. Additional information would be obtained from the users calendar. On a normal workday, the system would use PV energy to heat the water and store it, based on the user profile. On work-from-home days, the system would start charging the car with the morning sun, using only the PV energy. In the evening hours, when consumption rises and production falls, EV could inject the power back into the house. Again using appliance load profiles to mitigate net energy flow as close to zero as possible (zero-energy building). With the ever-increasing power capacity and increasing range of EVs, more and more battery capacity could be used for mitigation. In the case of grid batteries, similar steps could be taken. This process is called vehicle-to-grid, and it is an important step towards zero-energy buildings Robledo et al., 2018 and Mehrjerdi and Hemmati, 2020.

One other way to use user load profiles is to optimally distribute the load by studying users usage patterns as Chuan, Rao, and Ukil, 2014 and C. Li, Srinivasan, and Reindl, 2015 proposed in their papers. This could be further extended to neighborhoods connected into peer 2 peer energy distribution networks. As mentioned earlier, the way to save energy consumption is to distribute it as locally as possible. Knowing usage patterns of all peers, the system could optimally distribute the energy using DERs across all homes without dwellers even noticing.

Another use case could be using a heat pump and heat storage, where besides users usage patterns system would also obtain weather forecasts from the internet. Heat pumps that extract heat from the air are more efficient when temperature differences are smaller. The heat pump could store energy when warm and release the energy when cold. Based on the user usage profile, energy could be optimally distributed.

Many papers have been published, where authors explored ways to reduce the energy consumption of users by studying user consumption patterns, such as Spataru and Gauthier, 2014, Cellura et al., 2013, Verbong, Beemsterboer, and Sengers, 2013 and Spataru and Gauthier, 2014. Energy saving is done through instant feedback, reduction goals, rewards, and by comparing their user profile to the average user as the authors did in Csoknyai et al., 2019. Source Commission et al., 2006 states that as much as 20 % of energy could be saved by managing the consumption.

4.2 Grid management

An increasing percentage of renewable resources is troubling energy distributors, due to the nature of renewable resources. In the prior chapter, it was mentioned how energy-saving measures would benefit users and their peers. One other use case would be cooperation between end-user and energy distribution companies. Joint actions between them would benefit both as authors show in Albadi and El-Saadany, 2008 and Moslehi and Kumar, 2010

The electricity provider could control the main appliances so that load on the power grid is uniform, with as few peaks and valleys as possible. For this to function, users would have to allow the installation of energy meters and controllers on appliances that use the most electricity Shen, Jiang, and B. Li, 2015. One way to achieve this is to control the voltage of loads Zakariazadeh et al., 2014 the other way is to shift the loads in time C. Li, Srinivasan, and Reindl, 2015. This process is called direct load control Hledik and Lee, 2021, and it is part of demand response program Chen, 2018.

"DR program is a voluntary PJM program that compensates end-use (retail) customers for reducing their electricity use (load) when requested by PJM during periods of high power prices, or when the reliability of the grid is threatened." Chen, 2018

The benefit to the user would be lower the cost of charging EVs and heating the building. This is already done through so-called small and high tariffs. More detailed user load profiles would enable the electricity provider to introduce real-time tariffs to the user.

The user would have three options. The first one would be that users can use the appliances as freely as they desire, this would result in a normal tariff. The second option would be to use the appliances as regularly as possible, this would lead to lower tariffs. The third option would be to leave the management of main appliances to the electricity provider. The provider would combine the user appliance load profile and the real-time market price of energy to optimize the cost Graditi et al., 2015. This would lead to free or even negative prices of electricity since distribution companies have to keep the frequency of the grid as stable as possible.

For them to stabilize the frequency, they sometimes have to resort to load shedding. Load shedding is a process where a load is disconnected from the grid to keep the grid in sync Lopes, Moreira, and Madureira, 2006. Commonly whole neighborhoods are being disconnected, affecting their daily lives. Using user load profiles, distribution companies could disconnect the load in a way that would minimally affect the end-user. When they would need to load the grid due to low demand, they could charge EVs free of charge or even pay to do so. This benefits the company as well since they do not need to lower energy production, which can be expensive.

4.3 Elderly care

Demographic changes i.e. aging population is an increasing socioeconomic issue. The elderly are facing many issues when staying at home alone for extended periods. Accidents such as falls or the inability to do choirs due to health-related issues or even dementia-induced issues such as leaving appliances on for long periods could all be detected, using sub-meter data such as authors Visconti et al., 2019 and Patrono, Rametta, and Meis, 2018 explore in their papers.

To detect falls or other issues a normal daily appliance use profile would be developed. It would involve routine behavior of users such as turning on the coffee machine in the morning, the stove and oven at the noon or using the toaster in the evening. All these routines could be measured and tracked. Using this data, a profile would be developed. The probability of an anomaly and a threshold would enable the system to detect an issue.

An example would be: the coffee machine not turning on in the morning or the stove and kitchen vent not being used at the noon. Another issue could be detected if the appliance would be used more frequently or for extended periods of time. This could indicate that the user forgot to turn off the stove, oven, or even a light. The same system could detect that a fridge or a freezer was left open since the duty cycles would be longer and more frequent. As soon as the issue would be detected it would notify the caregiver to check on the patient.

4.4 Anomaly detection

One use case of anomaly detection was already mentioned in the Elderly care chapter. One more thing that could be detected, using load profiling, would be the altered operation of appliances. In the case of a fridge, the system would detect that duty cycles are too long. The increased duty cycle can be caused by cooling liquid leakage, fridge being open or compressor motor malfunction. Heat pumps work on the same basis as fridges, meaning the same anomalies could be detected. The malfunction could also be detected in heating element appliances such as toasters or boilers.

Since mentioned appliances are one of the largest consumers in a household, early enough detection could lead to large energy-saving benefits Rashid, Stankovic, et al., 2019.

4.5 Other

Load profiling could also be used as feedback to the engineers and designers, of how a certain device is being used and if it is being used as designed. This would enable the manufacturers to improve their products according to users needs, without unnecessary features.

Yip et al., 2018 uses anomaly detection algorithms and load profiling to detect energy lost due to non-technical losses. This occurs after the smart-meter is exposed to cyber or mechanical attacks and its measurements are off.

One other use case could be occupancy detection of buildings such as the authors explore in Kleiminger et al., 2013. Information about occupancy could be used as part of elderly care monitoring or in the case of building automation, to run certain tasks when a user enters or leaves the room or a building.

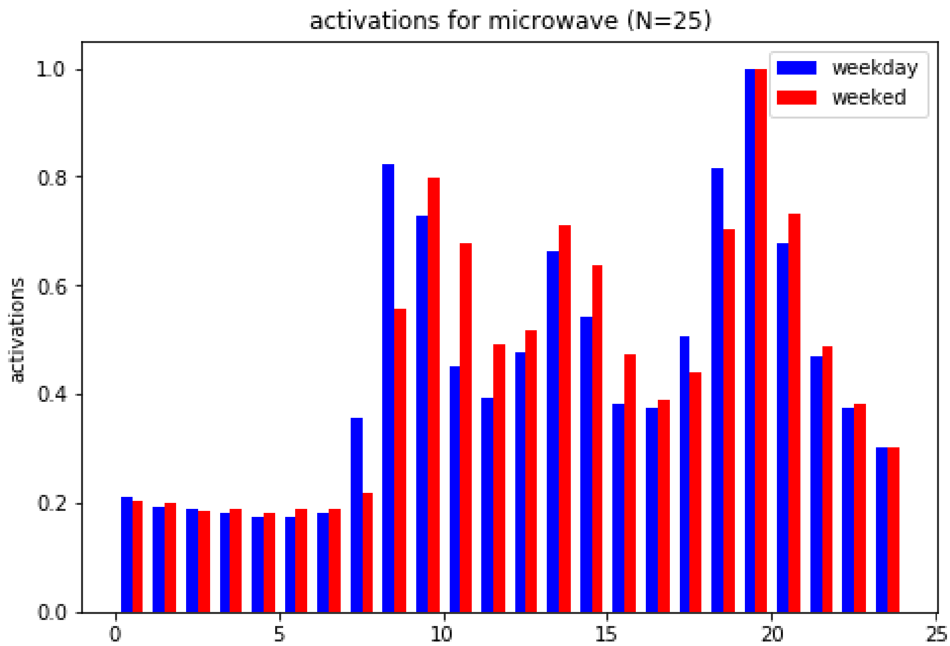
Chapter 5

Contributions

The goal of the master's thesis is to propose suitable consumption profiles for supporting residential building consumption optimization and elderly care management. To achieve this goal, we propose the following steps.

The first step is to obtain a set of datasets. In our case, this will be UK-DALE, REFIT, ECO, REDD, and iAWE. All datasets measured electrical energy consumption for residential buildings. They include main smart meter data, as well as sub-meter data for each appliance in a dwelling. For easier handling datasets will be sliced into 1-hour intervals. Slices will be put through a classical learning classifier to demonstrate the ability to automatically identify and classify the appliances. Data will be then used to generate different daily per appliance usage profiles.

FIGURE 5.1: "Universal normalized daily usage profile for weekend and weekday for a microwave. Superposition of data from 25 homes."



One such example can be seen in figure 5. The histogram shows normalized daily activation for microwaves. It consists of data from 25 homes from 4 different datasets.

During this thesis, more profiles will be presented, using various histogram buckets, dimensions and parameters. Each profile presents data from a different perspective, therefore each profile will have a use case of its own.

A table of existing load profiles will be made. It will enable us to place proposed profiles on a map, and possibly discover new ways to portray load profiles.

Finally, to demonstrate the usage of developed profiles a demo will be presented.

Chapter 6

Presenting proposed profiles

Previously defined profiles will be presented in-depth. In general, each profile has its use case already assigned in table 3.3. Here, we will focus on exposing the main features, issues, and use cases.

Data for profiles in this chapter were used from the REFIT dataset and building 2. Data was collected from 2013-09-18 to 2015-05-28.

6.1 Time ranges

One important thing to mention is to use cases for different time ranges of load profiles. Based on table 3.2 it is possible to see that most publications and 3.3 use daily time range.

Generally, daily profiles are easier to build since they do not need as much data as others do. To build a decent profile one needs enough data. A sufficient amount of data is the amount that covers major events. For a daily profile, a few weeks of data is enough, weekly load profiles need a few months of data, monthly few years, and yearly for around a decade. And this is the main issue, there is rarely enough data to build such profiles. Even then, usage patterns could change over a long period such as a decade. Combining that with a smaller number of use cases for such profiles, reveals why such profiles were not looked into as much.

One more thing about time ranges that need to be mentioned are patterns that they present. Daily profiles present daily usage and enable us to extract contextual events such as waking up, cooking, leisure time, etc. The weekly pattern is also repetitive, and it enables us to see how appliance usage changes over the weekdays and weekends. The monthly profile has none of the above. It is not repetitive since each day of the month can be a different day of the week, and the period is too short to capture seasonal patterns. Alternatively, it could be presented as a week in a month, but there is no significant usage pattern to be revealed. The yearly profile on the other hand presents the seasonal effects on usage such as increased daylight and temperature.

6.2 Per-house

The section will be focused on per-house profiles, meaning whole building usage is presented as a single load profile. This kind of presentation is useful for observing general activation trends in a building. Possible use cases for per-house load profiles are grid management and energy saving.

When it comes to activation load profiles there is one issue compared to power load profiles. To build per-house power load profiles it is possible to use the main power meter, whereas, at activation load profiles, sub-meter data is needed. This can be solved using NILM algorithms, but they are not in a phase of practical use yet.

The daily per-house load profile is also known as the standard load profile. According to table 3.2 this is the most commonly used power profile. Figures 6.1a and 6.1b present usage patterns on different time ranges. The two profiles, therefore present different contextual causes.

(A) "Daily" (B) "Yearly"

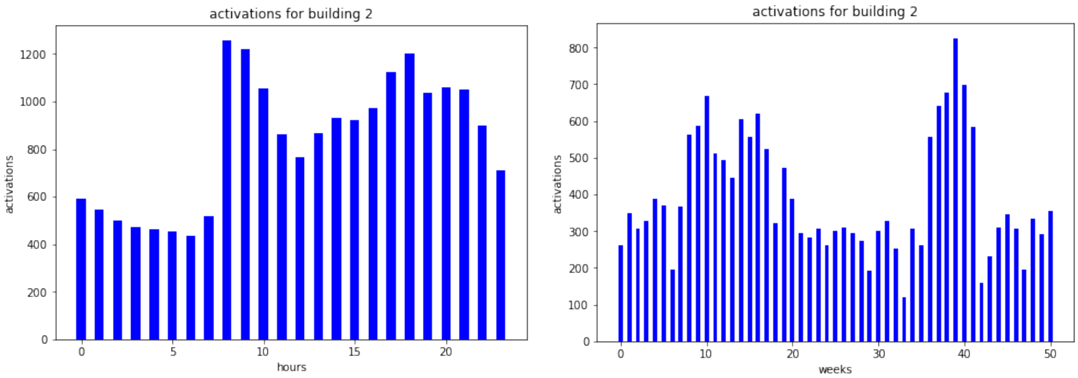
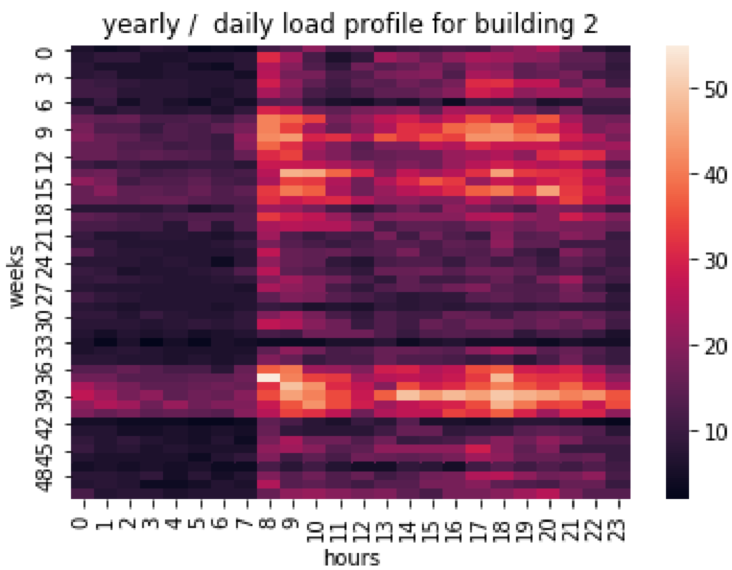


FIGURE 6.1: "per-house load profiles"

6.2.1 Per-house two-dimensional time

Alternatively, it is possible to combine figures 6.1a and 6.1b and present activations as a heat map. The result is a load profile showing more complex activation patterns.

FIGURE 6.2: "Two-dimensional time per-house load profile"

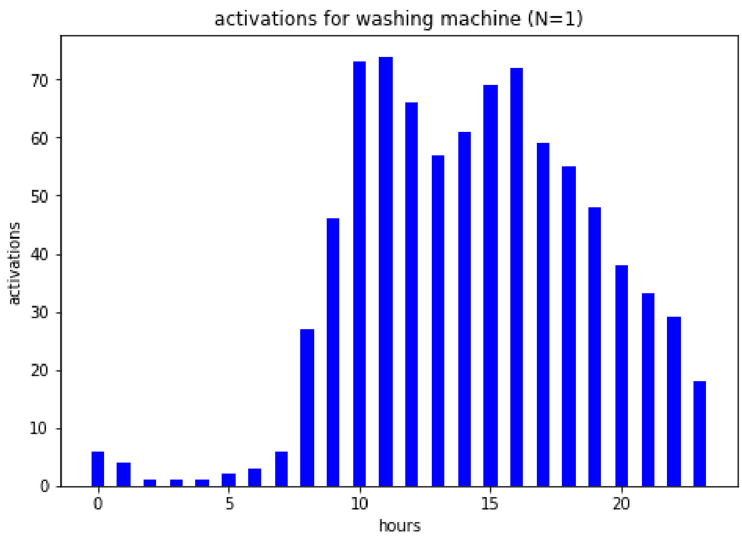


Previously it was mentioned that these kinds of profiles are the most applicable in grid management and energy-saving fields. One such example could be load shedding. Using the Load profile above, electrical energy providers could find buildings with the least activity at that time of day. Combining that with power data, it could disconnect the buildings with the least activity and most power consumption.

6.3 Per-appliance

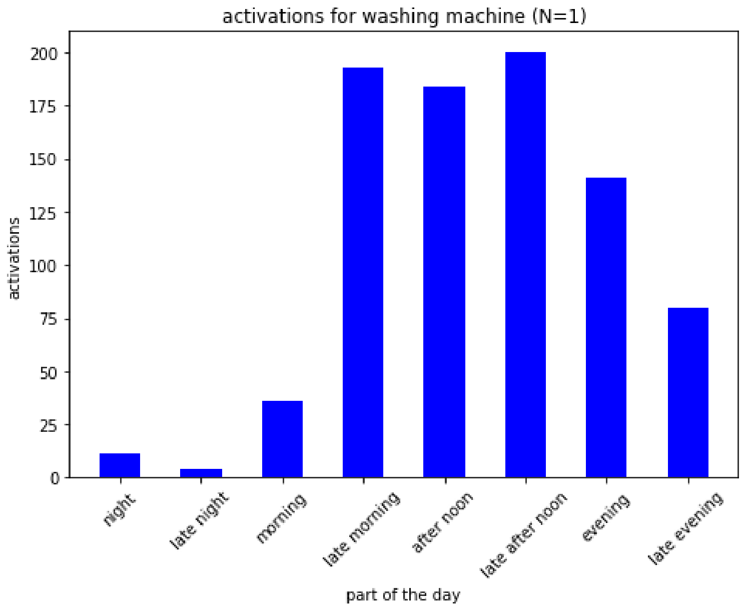
Per appliance load profiles offer a look into the consumption of each appliance. In this case activation load profiles, this is an elemental load profile, since all other profiles are built on top of it. This also means that it is one of the most universal profiles since it can be used in all previously defined use cases. Comparing power and activation profiles in the per-house chapter, it was possible to see that activation-based load profile does not bring significant advantages over power-based load profiles. In the case of per-appliance load profiles, it is possible to analyze the usage of the single appliance in greater detail

FIGURE 6.3: "Daily per-appliance load profile"



Another parameter that was not explicitly mentioned before, is the resolution of load profiles. Histograms can be presented using various resolutions or numbers of buckets. An optimal number of buckets is a number that clearly presents the usage pattern. 3-hour bucket size on figure 6.4 does a good job at presenting the appliance usage at the main parts of the day. This offers a better contextual presentation that is easier to process using algorithms. Parts of the day are:

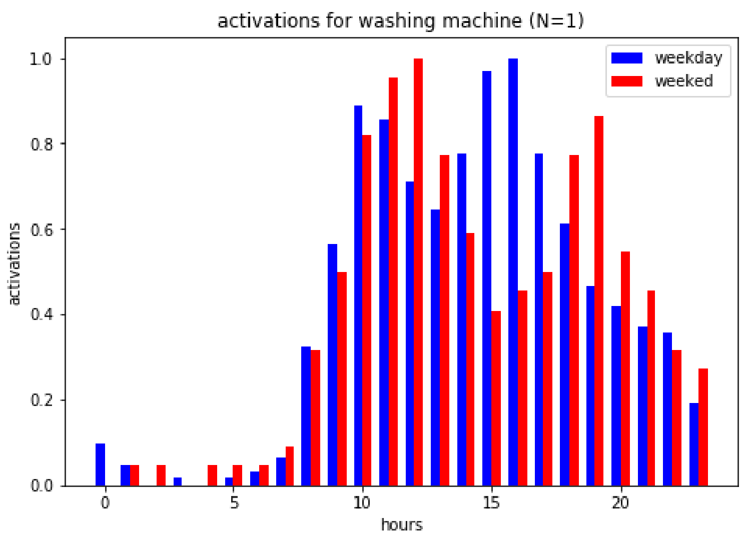
FIGURE 6.4: "Daily per-appliance load profile with larger buckets sizes"



While the low resolution is useful for contextual presentation, high resolution is needed for time-sensitive applications such as elderly care, where we have to detect an accident as soon as possible. The hourly resolution would mean that in case of an accident system would need at least an hour to detect it. While this is sufficient for demonstrating the capabilities, real implementation would need to use lower resolution data.

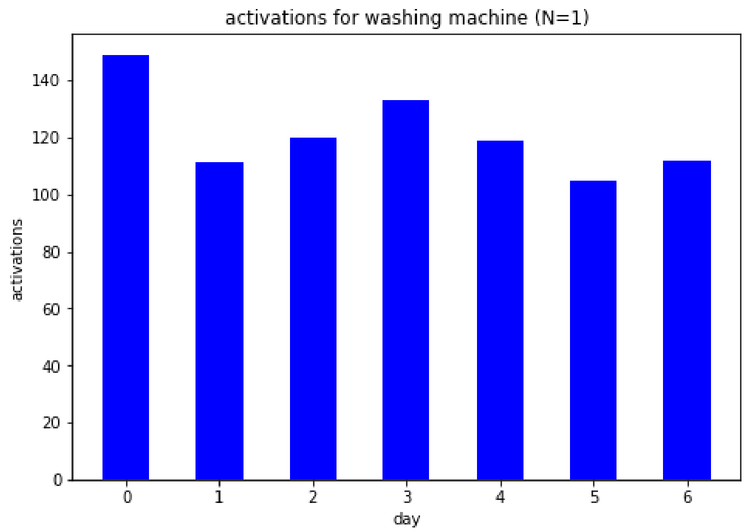
In case, dwellers have different usage patterns during the weekends, two profiles would have to be developed. It is possible to present them both at once such as in figure 6.5. This is essentially a variation of the weekly Load profile that maintains high resolution. Since there are more weekdays than weekend days, activations had to be normalized accordingly.

FIGURE 6.5: "Normalized daily per-appliance with weekday and weekend load profiles"



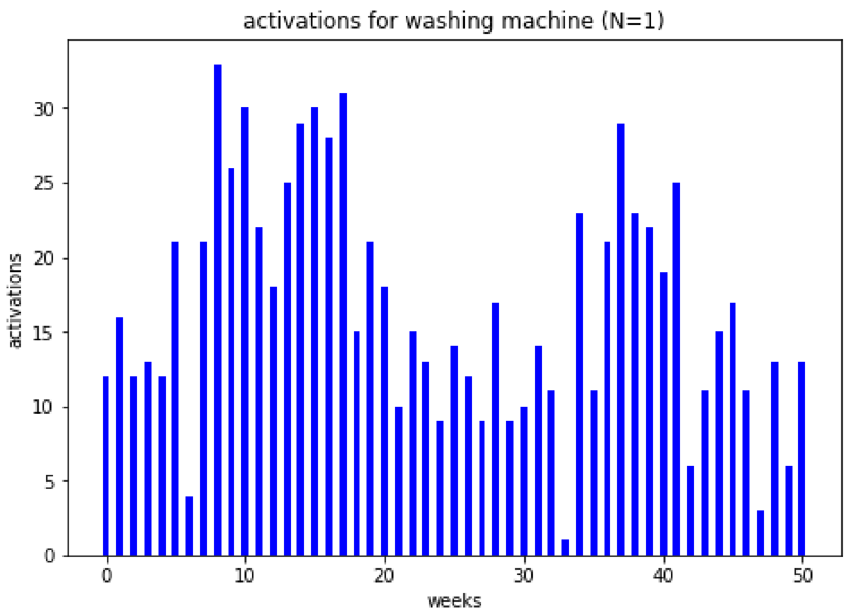
Another way to present weekly data is figure 6.6 This resolution offers a look into how consumption pattern changes over the week. This is useful for applications such as grid management and energy saving. In this particular case, it is possible to see that the user most commonly uses the washing machine on Mondays and Wednesdays. Using a weekly weather report that would indicate high energy production on Wednesday, electricity provider could offer a low cost for energy for that day. This kind of presentation could also be used to detect daily anomalies.

FIGURE 6.6: "Weekly per-appliance load profile"



As mentioned earlier, the monthly presentation does not show any significant usage pattern, where yearly presentation again shows the more broad usage pattern. This is useful for grid management and energy-saving, where one could detect seasonal changes in usage of an appliance.

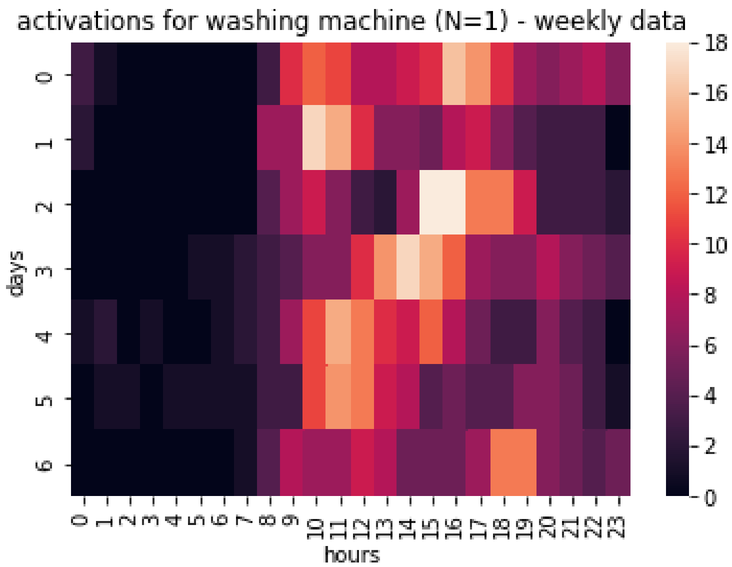
FIGURE 6.7: "Yearly per-appliance load profile"



6.3.1 Two-dimensional time per-appliance load profiles

Using a combination of figures 6.3 and 6.6, it is possible to generate a heatmap 6.8.

FIGURE 6.8: "Two-dimensional time per-appliance load profile"



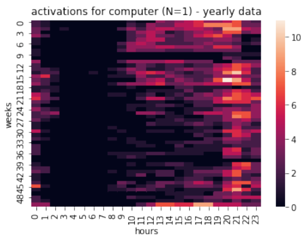
In this case, a similar use case could be fitted as in the first example. The first example used load shedding for when the demand is too high. On the contrary, it can also occur the grid demand is too low. There are two solutions to this issue. The first one is to decrease production, which can be slow and expensive. The second option is to load the grid, which can be done in many ways. One of the ways is to turn on appliances using a control system or notify users to turn on appliances that they have commonly used at that time in the past. Due to the increasing percentage of renewable energy sources, more and more energy peaks will be weather dependent such as wind and cloud coverage. By combining weekly wind forecast, weekly cloud coverage, and users consumption profiles energy providers could notify users to turn on the appliances at peak usage times.

By analyzing figure 6.8 it is possible to see that the user uses a washing machine, on Wednesdays from 15 to 16 o clock quite commonly. Should weather reports indicate high production peaks, the electrical provider should offer low-cost energy for that time of day for all users with similar usage patterns. This could all be automated for appliances such as home grid batteries, water heaters, EVs, or even fridges with a control system. This would mean that operator or electrical distribution company could regulate the demand instantly. By using load profiles it could prioritize appliances that would be used anyway, which would leave minimal impact on users' routines. While renewable energy is cheap to produce, it is expensive to store. Increased adoption of such resources will require a large amount of energy to be stored and released, this process is at best 80 % efficient. If that energy is optimally distributed, less energy would be lost due to conversion.

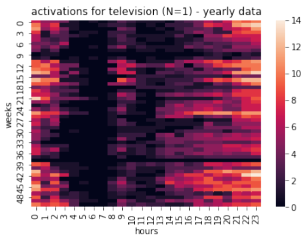
Other two-dimensional presentations

The figures below show how some appliances have a constant usage pattern over a year, whereas again others change it. Examples below are randomly picked appliances from UK-DALE and REFIT.

(A) "Computer"



(B) "TV"



(C) "Washing machine"

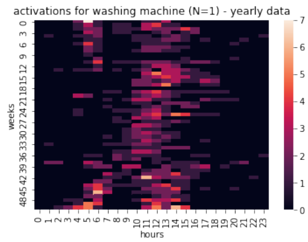
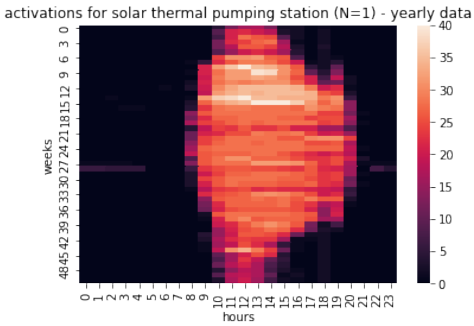


FIGURE 6.9: Various yearly two-dimensional load profile

Another example worth mentioning is one from UK-DALE building 1, where data was collected from 2012-11-09 to 2017-04-26. Roughly 5 years of data mean that it is possible to build a decent profile.

(A) "solar thermal pumping station"



(B) "light"

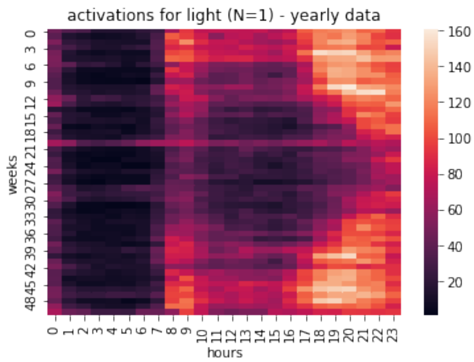


FIGURE 6.10: "Effect of seasonal changes on load profiles"

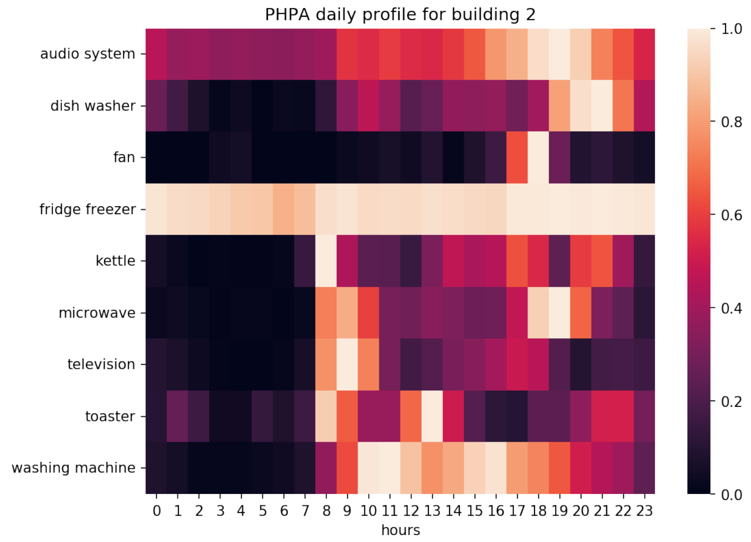
Figures 6.10a and 6.10b show how weather and season affect the usage pattern of appliances.

6.4 Per-house per-appliance

The last group of profiles is a combination of per-house and per-appliance load profiles. Observing the usage pattern of many appliances offers a better look into users' usage patterns. In the case of elderly care, the goal is to observe a group of appliances. Activation of a group of appliances would yield a contextual event. If stove and kettle are commonly used together each morning this use could translate to an event such as breakfast. In order to achieve this, one needs to observe all appliances at once such as shown on figure 6.11.

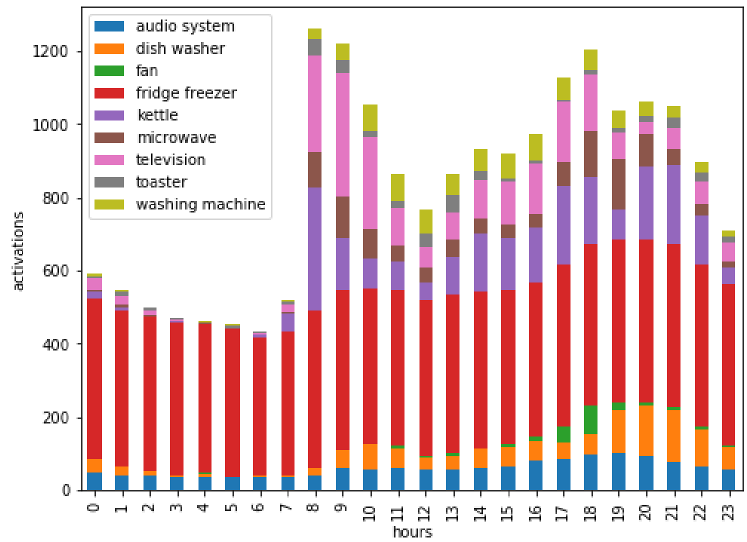
The figure is also a good example of elderly care system, that would detect an anomaly such as fall, or person unable to get up from the bed in the morning. This profile shows that first thing in the morning used are kettle and toaster, and with delay of one hour, microwave and TV. This enables us to construct time thresholds in which appliances should be used. If none of these appliances are activated between set thresholds, morning would be considered anomalous. Although less likely, issues could also occur during the use of appliance. In case elder falls during cooking, toasting bread or opening fridge the duty cycle would increase, which would also be considered an anomaly. In case any of these anomalies are detected, the caregiver would be notified to check on the elder.

FIGURE 6.11: "Daily per-appliance per-house building load profile"



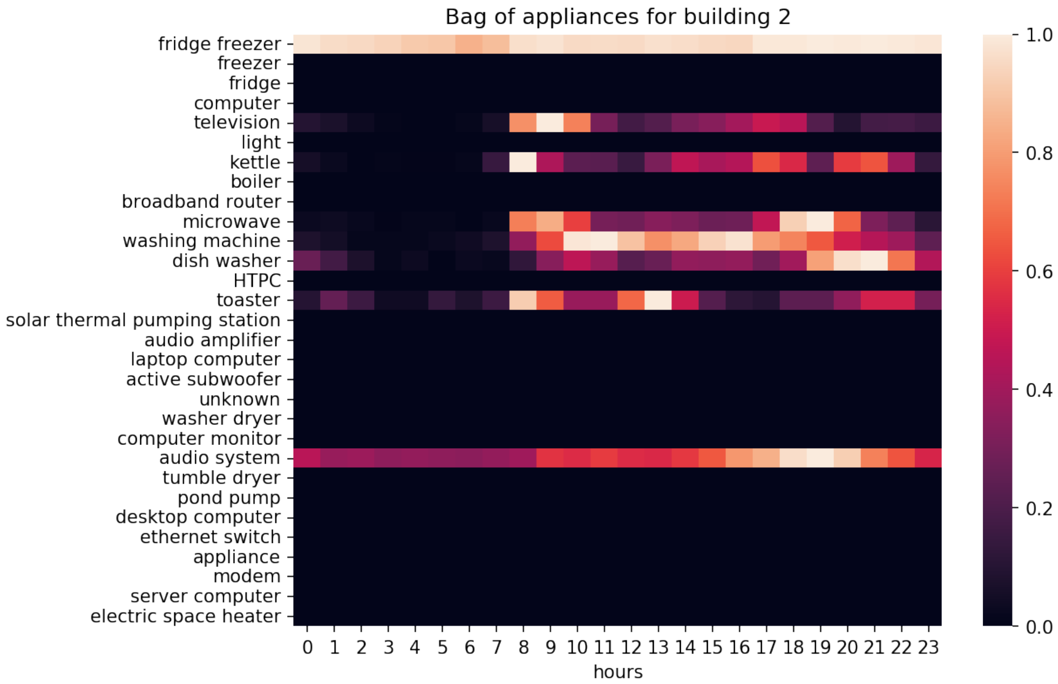
The very same data can be presented in an alternative way, such as shown in figure 6.12. The usage pattern is the same as on 6.1a, except that it is possible to see the contribution of each appliance.

FIGURE 6.12: "Stacked daily per-appliance per-house building load profile"



These load profiles are useful when it comes to analyzing the usage pattern in one building. In order to be able to process the load-profiles a cross many buildings a new profile must be introduced. The idea is derived from the bag-of-words method used in text processing, where a list of most commonly used words is formed, and then used to process the text. Here, It is possible to use the activation data from all five datasets. A list of appliances is sorted by number of activations and then only top 30 appliances are selected. Using this list it is possible to present the usage of each building universally.

FIGURE 6.13: "Universal presentation of per-house per-appliance load profile"



Bibliography

1. Abreu, Joana M., Câmara Pereira, Francisco, and Ferrão, Paulo (2012). "Using pattern recognition to identify habitual behavior in residential electricity consumption". In: *Energy and Buildings* 49, pp. 479–487. ISSN: 0378-7788. DOI: https://doi.org/10.1016/j.enbuild.2012.02.044. URL: https://www.sciencedirect.com/science/article/pii/S0378778812001363.
2. Albadi, M.H. and El-Saadany, E.F. (2008). "A summary of demand response in electricity markets". In: *Electric Power Systems Research* 78.11, pp. 1989–1996. ISSN: 0378-7796. DOI: https://doi.org/10.1016/j.epsr.2008.04.002. URL: https://www.sciencedirect.com/science/article/pii/S0378779608001272.
3. Azizi, Elnaz, Beheshti, Mohammad T. H., and Bolouki, Sadegh (Nov. 2021). "Appliance-Level Anomaly Detection in Nonintrusive Load Monitoring via Power Consumption-Based Feature Analysis". In: *IEEE Transactions on Consumer Electronics* 67.4, pp. 363–371. ISSN: 1558-4127. DOI: 10.1109/TCE.2021.3129356.
4. Bitterer, R. and B. Schieferdecker, Prof. Dr. habil. (1999). *Repräsentative VDEW-Lastprofile Aktionsplan Wettbewerb, M-32 99*. VDEW.
5. Boßmann, Tobias, Schleich, Joachim, and Schurk, Robert (June 2015). "Unravelling load patterns of residential end-uses from smart meter data". In:
6. Capasso, A. et al. (May 1994). "A bottom-up approach to residential load modeling". In: *IEEE Transactions on Power Systems* 9.2, pp. 957–964. ISSN: 1558-0679. DOI: 10.1109/59.317650.
7. Carpino, Cristina et al. (Jan. 2020). "Energy performance gap of a nearly Zero Energy Building in Denmark the influence of occupancy modelling". In: *Building Research Information* 48.
8. Castangia, Marco et al. (2021). "Detection of Anomalies in Household Appliances from Disaggregated Load Consumption". In: *2021 International Conference on Smart Energy Systems and Technologies (SEST)*, pp. 1–6. DOI: 10.1109/SEST50973.2021.9543232.
9. Cellura, Maurizio et al. (2013). "The role of the building sector for reducing energy consumption and greenhouse gases: An Italian case study". In: *Renewable Energy* 60, pp. 586–597. ISSN: 0960-1481. DOI: https://doi.org/10.1016/j.renene.2013.06.019. URL: https://www.sciencedirect.com/science/article/pii/S0960148113003121.
10. Chen, Chen (2018). "4 - Demand response: An enabling technology to achieve energy efficiency in a smart grid". In: *Application of Smart Grid Technologies*. Ed. by Lisa Ann Lamont and Ali Sayigh. Academic Press, pp. 143–171. ISBN: 978-0-12-803128-5. DOI: https://doi.org/10.1016/B978-0-12-803128-5.00004-0. URL: https://www.sciencedirect.com/science/article/pii/B9780128031285000040.
11. Chuan, Luo, Rao, D. M. K. K. Venkateswara, and Ukil, Abhisek (2014). "Load profiling of Singapore buildings for peak shaving". In: *2014 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, pp. 1–6. DOI: 10.1109/APPEEC.2014.7065998.

12. Commission, Communication from the et al. (2006). "Action Plan for energy efficiency: realising the potential". In: *COM (2006)* 545.
13. Csoknyai, Tamás et al. (2019). "Analysis of energy consumption profiles in residential buildings and impact assessment of a serious game on occupants' behavior". In: *Energy and Buildings* 196, pp. 1–20. ISSN: 0378-7788. DOI: https://doi.org/10.1016/j.enbuild.2019.05.009. URL: https://www.sciencedirect.com/science/article/pii/S0378778818334790.
14. Eurostat (2022). "Gross and net production of electricity and derived heat by type of plant and operator". In: 62. URL: https://ec.europa.eu/eurostat/databrowser/view/nrg_ind_peh/default/table?lang=en.
15. Fischer, David, Härtl, Andreas, and Wille-Haussmann, Bernhard (2015). "Model for electric load profiles with high time resolution for German households". In: *Energy and Buildings* 92, pp. 170–179. ISSN: 0378-7788. DOI: https://doi.org/10.1016/j.enbuild.2015.01.058. URL: https://www.sciencedirect.com/science/article/pii/S0378778815000845.
16. Gao, Bingtuan, Liu, Xiaofeng, and Zhu, Zhenyu (2018). "A Bottom-Up Model for Household Load Profile Based on the Consumption Behavior of Residents". In: *Energies* 11.8. ISSN: 1996-1073. DOI: 10.3390/en11082112. URL: https://www.mdpi.com/1996-1073/11/8/2112.
17. Gerbec, D. et al. (May 2005). "Allocation of the load profiles to consumers using probabilistic neural networks". In: *IEEE Transactions on Power Systems* 20.2, pp. 548–555. ISSN: 1558-0679. DOI: 10.1109/TPWRS.2005.846236.
18. Graditi, Giorgio et al. (Feb. 2015). "Heuristic-Based Shiftable Loads Optimal Management in Smart Micro-Grids". In: *IEEE Transactions on Industrial Informatics* 11.1, pp. 271–280. ISSN: 1941-0050. DOI: 10.1109/TII.2014.2331000.
19. Himeur, Yassine et al. (2021). "Artificial intelligence based anomaly detection of energy consumption in buildings: A review, current trends and new perspectives". In: *Applied Energy* 287, p. 116601. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2021.116601. URL: https://www.sciencedirect.com/science/article/pii/S0306261921001409.
20. Hledik, Ryan and Lee, Tony (2021). "Chapter 9 - Load flexibility: Market potential and opportunities in the United States". In: *Variable Generation, Flexible Demand*. Ed. by Fereidoon Sioshansi. Academic Press, pp. 195–210. ISBN: 978-0-12-823810-3. DOI: https://doi.org/10.1016/B978-0-12-823810-3.00001-7. URL: https://www.sciencedirect.com/science/article/pii/B9780128238103000017.
21. Issi, Fatih and Kaplan, Orhan (2018). "The Determination of Load Profiles and Power Consumptions of Home Appliances". In: *Energies* 11.3. ISSN: 1996-1073. DOI: 10.3390/en11030607. URL: https://www.mdpi.com/1996-1073/11/3/607.
22. Jeong, Hyun Cheol et al. (2021). "Clustering of Load Profiles of Residential Customers Using Extreme Points and Demographic Characteristics". In: *Electronics* 10.3. ISSN: 2079-9292. DOI: 10.3390/electronics10030290. URL: https://www.mdpi.com/2079-9292/10/3/290.
23. Kattan, Emily, Halasah, Suleiman, and hamed, Tareq a (May 2018). "Practical Challenges of Photovoltaic Systems in the Rural Bedouin Villages in the Negev". In: *Journal of Fundamentals of Renewable Energy and Applications* 8. DOI: 10.4172/20904541.1000258.
24. Kavousian, Amir, Rajagopal, Ram, and Fischer, Martin (2013). "Determinants of residential electricity consumption: Using smart meter data to examine the effect of climate, building characteristics, appliance stock, and occupants' behavior". In: *Energy* 55, pp. 184–194. ISSN: 0360-5442. DOI: https://doi.org/

10.1016/j.energy.2013.03.086. URL: https://www.sciencedirect.com/science/article/pii/S0360544213002831.

25. Kelly, Jack and Knottenbelt, William (Mar. 2015). "The UK-DALE dataset, domestic appliance-level electricity demand and whole-house demand from five UK homes". In: *Scientific Data* 2.1, p. 150007. ISSN: 2052-4463. DOI: 10.1038/sdata.2015.7. URL: https://doi.org/10.1038/sdata.2015.7.
26. Klaassen, Elke, Frunt, Jasper, and Slootweg, Han (June 2015). "Assessing the impact of distributed energy resources on LV grids using practical measurements". In:
27. Kleiminger, Wilhelm et al. (Nov. 2013). "Occupancy Detection from Electricity Consumption Data". In: pp. 1–8. DOI: 10.1145/2528282.2528295.
28. Li, Congmiao, Srinivasan, Dipti, and Reindl, Thomas (Nov. 2015). "Real-time scheduling of time-shiftable loads in smart grid with dynamic pricing and photovoltaic power generation". In: *2015 IEEE Innovative Smart Grid Technologies - Asia (ISGT ASIA)*, pp. 1–6. DOI: 10.1109/ISGT-Asia.2015.7387165.
29. Lopes, J.A.P., Moreira, C.L., and Madureira, A.G. (May 2006). "Defining control strategies for MicroGrids islanded operation". In: *IEEE Transactions on Power Systems* 21.2, pp. 916–924. ISSN: 1558-0679. DOI: 10.1109/TPWRS.2006.873018.
30. Mehrjerdi, Hasan and Hemmati, Reza (2020). "Coordination of vehicle-to-home and renewable capacity resources for energy management in resilience and self-healing building". In: *Renewable Energy* 146, pp. 568–579. ISSN: 0960-1481. DOI: https://doi.org/10.1016/j.renene.2019.07.004. URL: https://www.sciencedirect.com/science/article/pii/S0960148119310249.
31. Moreno Jaramillo, Andres F. et al. (2021). "Load modelling and non-intrusive load monitoring to integrate distributed energy resources in low and medium voltage networks". In: *Renewable Energy* 179, pp. 445–466. ISSN: 0960-1481. DOI: https://doi.org/10.1016/j.renene.2021.07.056. URL: https://www.sciencedirect.com/science/article/pii/S0960148121010612.
32. Moslehi, Khosrow and Kumar, Ranjit (June 2010). "A Reliability Perspective of the Smart Grid". In: *IEEE Transactions on Smart Grid* 1.1, pp. 57–64. ISSN: 1949-3061. DOI: 10.1109/TSG.2010.2046346.
33. Parag, Yael and Sovacool, Benjamin K. (Mar. 2016). "Electricity market design for the prosumer era". In: *Nature Energy* 1.4, p. 16032. ISSN: 2058-7546. DOI: 10.1038/nenergy.2016.32. URL: https://doi.org/10.1038/nenergy.2016.32.
34. Park, Keon-Jun and Son, Sung-Yong (2019). "A Novel Load Image Profile-Based Electricity Load Clustering Methodology". In: *IEEE Access* 7, pp. 59048–59058. ISSN: 2169-3536. DOI: 10.1109/ACCESS.2019.2914216.
35. Parliament, The European and Council of the European Union, the (2021). "Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the energy performance of buildings (recast)". In:
36. Patrono, Luigi, Rametta, Piercosimo, and Meis, Jochen (June 2018). "Unobtrusive Detection of Home Appliance's Usage for Elderly Monitoring". In: *2018 3rd International Conference on Smart and Sustainable Technologies (SpliTech)*, pp. 1–6.
37. Proedrou, Elisavet (2021). "A Comprehensive Review of Residential Electricity Load Profile Models". In: *IEEE Access* 9, pp. 12114–12133. ISSN: 2169-3536. DOI: 10.1109/ACCESS.2021.3050074.
38. Rashid, Haroon, Singh, Pushpendra, et al. (2019). "Can non-intrusive load monitoring be used for identifying an appliances anomalous behaviour?" In: *Applied Energy* 238, pp. 796–805. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2019.01.061. URL: https://www.sciencedirect.com/science/article/pii/S0306261919300613.

39. Rashid, Haroon, Stankovic, Vladimir, et al. (May 2019). "Evaluation of Non-intrusive Load Monitoring Algorithms for Appliance-level Anomaly Detection". In: *ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 8325–8329. DOI: 10.1109/ICASSP.2019.8683792.
40. Robledo, Carla B. et al. (2018). "Integrating a hydrogen fuel cell electric vehicle with vehicle-to-grid technology, photovoltaic power and a residential building". In: *Applied Energy* 215, pp. 615–629. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2018.02.038. URL: https://www.sciencedirect.com/science/article/pii/S0306261918301636.
41. Shen, Jingshuang, Jiang, Chuanwen, and Li, Bosong (2015). "Controllable Load Management Approaches in Smart Grids". In: *Energies* 8.10, pp. 11187–11202. ISSN: 1996-1073. DOI: 10.3390/en81011187. URL: https://www.mdpi.com/1996-1073/8/10/11187.
42. shuma-iwisi, Mercy (June 2009). "Domestic appliances standby power losses: The case of eleven suburbs in the greater Johannesburg," in:
43. Sidqi, Yousra et al. (Oct. 2020). "Flexibility quantification in households: a swiss case study". In: *Energy Informatics* 3. DOI: 10.1186/s42162-020-00126-4.
44. Spataru, Catalina and Gauthier, Stephanie (2014). "How to monitor people 'smartly' to help reducing energy consumption in buildings?" In: *Architectural Engineering and Design Management* 10.1-2, pp. 60–78. DOI: 10.1080/17452007.2013.837248. eprint: https://doi.org/10.1080/17452007.2013.837248. URL: https://doi.org/10.1080/17452007.2013.837248.
45. Swan, Lukas G. and Ugursal, V. Ismet (2009). "Modeling of end-use energy consumption in the residential sector: A review of modeling techniques". In: *Renewable and Sustainable Energy Reviews* 13.8, pp. 1819–1835. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2008.09.033. URL: https://www.sciencedirect.com/science/article/pii/S1364032108001949.
46. Train, Kenneth, Herriges, Joseph, and Windle, Robert (1985). "Statistically adjusted engineering (SAE) models of end-use load curves". In: *Energy* 10.10, pp. 1103–1111. ISSN: 0360-5442. DOI: https://doi.org/10.1016/0360-5442(85)90025-8. URL: https://www.sciencedirect.com/science/article/pii/0360544285900258.
47. Verbong, Geert P.J., Beemsterboer, Sjouke, and Sengers, Frans (2013). "Smart grids or smart users? Involving users in developing a low carbon electricity economy". In: *Energy Policy* 52. Special Section: Transition Pathways to a Low Carbon Economy, pp. 117–125. ISSN: 0301-4215. DOI: https://doi.org/10.1016/j.enpol.2012.05.003. URL: https://www.sciencedirect.com/science/article/pii/S0301421512004004.
48. Visconti, Paolo et al. (June 2019). "A sensors-based monitoring system of electrical consumptions and home parameters remotely managed by mobile app for elderly habits' control". In: *2019 IEEE 8th International Workshop on Advances in Sensors and Interfaces (IWASI)*, pp. 264–269. DOI: 10.1109/IWASI.2019.8791399.
49. Walker, C.F. and Pokoski, J.L. (1985). "Residential Load Shape Modelling Based on Customer Behavior". In: *IEEE Transactions on Power Apparatus and Systems* PAS-104.7, pp. 1703–1711. DOI: 10.1109/TPAS.1985.319202.
50. Yip, Sook-Chin et al. (2018). "An anomaly detection framework for identifying energy theft and defective meters in smart grids". In: *International Journal of Electrical Power and Energy Systems* 101, pp. 189–203. ISSN: 0142-0615. DOI: https://doi.org/10.1016/j.ijepes.2018.03.025. URL: https://www.sciencedirect.com/science/article/pii/S0142061517318719.

51. Zakariazadeh, Alireza et al. (2014). "A new approach for real time voltage control using demand response in an automated distribution system". In: *Applied Energy* 117, pp. 157–166. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2013.12.004. URL: https://www.sciencedirect.com/science/article/pii/S0306261913009884.