UNIVERSITY OF LJUBLJANA

MASTER'S THESIS

Development and Analysis of new Activation Based Load Profiles

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A thesis submitted in fulfillment of the requirements for the degree of Masters of Electrical Engineering

June 5, 2023

"In science, great oaks grow from little acorns."

D. Everett

Zahvala

Rad bi se zahvalil naslednjim osebam, brez katerih ta magistrska naloga ne bi bila mogoča. Doc. znan. sod. Carolini Fortuni in izr. prof. dr. Marku Meži za vso podporo in usmeritve, ki sta mi jih nudila pri izvedbi raziskave. Znanstveni in odprtokodni skupnosti, ki je zagotovila podatke in orodja, ki so bila uporabljena v delu. Hkrati bi se rad zahvalil prijateljem in sodelavcem, ki so z razpravami pomagali spodbuditi ideje, ki so bile predstavljene v magistrskem delu. Zahvaljujem se moji družini, ki me je navdihovala, podpirala in spodbujala, da sem se odločil za študij. Nazadnje bi se zahvalil svoji partnerki Niki, ki me je skozi vsa leta študija podpirala v vseh možnih pogledih.

Povzetek

V tej magistrski nalogi raziščemo možnost uporabe profilov porabe električne energije za naslavljanje ovir samostojnega bivanja starejšega prebivalstva. Osrednja tema magistrske naloge je učinkovita predstavitev podatkov s pomočjo profilov porabe. Optimizacija porabe energije lahko bistveno zmanjša ogljični odtis človeka, saj se v Evropski uniji tretjina električne energije porabi v gospodinjskem sektorju.

Podnebne spremembe zahtevajo prehod na obnovljive vire energije in prestrukturiranje energetske industrije. V Evropski uniji se tretjina energije porabi v gospodinjstvih, zato je zmanjšanje porabe v tem sektorju ključnega pomena za zmanjšanje človekovega ogljičnega odtisa. Evropska unija si prizadeva biti do leta 2050 podnebno nevtralna, zato išče načine za izboljšanje učinkovitosti vseh onesnaževalcev skozi Evropski zeleni dogovor. Velik del k onesnaževanju prispeva energetski sektor, kjer bi z analizo porabe energije lahko naredili veliko izboljšav, ki bi pomagale doseči zastavljeni cilj.

Druga težava, s katero se srečujemo, je staranje prebivalstva. Podaljševanje samostojnega življenja starejših posameznikov bi lahko izboljšal dobrobit starejših občanov ter zmanjšal pritisk na zdravstvene in socialne storitve. Z analizo profilov porabe električne energije lahko zaznamo razne nenavadnosti v vzorcih porabe, ki so lahko posledica padcev, kapi ali spremenjenega vedenja zaradi demence. Ob takšnih zaznavi spremenjenih vzorcev vedenja lahko pravočasno okrepimo in poskrbimo za starejše posameznike, ki živijo sami.

Definicija profila porabe je grafični prikaz porabe energije v določenem časovnem obdobju, ki nam omogoča analizo in vpogled v navade potrošnje. Takšni profili se navadno uporabljajo za analizo porabe električne energije, vendar bi jih lahko uporabljali tudi za analizo drugih virov energije, kot so plin, nafta ali celo voda. Za prikaz magnitude porabe se navadno uporablja moč (P) ali energijo (E) v nekem časovnem obdobju, najpogosteje čez dan. V tem delu smo se osredotočili na aktivacijske profile porabe. Aktivacijski profili predstavljajo časovne odseke, v katerih poraba presega določeno mejno moč. Za pridobitev teh profilov uporabljamo različne metode obdelave podatkov. Najpreprostejši pristop je določitev mejne moči aktivacije, pri čemer se šteje, da je aktivacija prisotna v vsakem časovnem odseku, ko poraba preseže to mejo. V samem delu smo uporabili bolj kompleksno metodo, katero smo tudi opisali v Poglavju 3.

Različne vrste profilov porabe se lahko uporabijo za različne namene. Nekateri profili so osnovani na dnevnih, tedenskih, mesečnih ali letnih časovnih intervalih in zavzemajo porabo celotnega gospodinjstva, spet drugi pa se osredotočajo na specifične gospodinjske naprave. Poleg dvodimenzionalnega prikaza s pomočjo grafov lahko iste podatke predstavimo v tridimenzionalnem prostoru s pomočjo toplotnih kart, kjer toplota predstavlja magnitudo aktivacij oziroma porabe v nekem časovnem obdobju.

Poleg analize porabe, lahko profile uporabimo za analizo proizvodnje energije, na primer fotovoltaičnih sistemov ali vetrnih elektrarn. V primeru domačih sončnih elektrarn bi nam takšna predstavitev omogočala optimalno uskladitev porabe s potrošnjo, tako bi lahko zmanjšali obremenitve na omrežja. Takšne aplikacije profilov so številne in segajo od gospodinjstva in industrije do upravljanja z omrežjem in odkrivanja anomalij v porabi. Takšne aplikacije profilov porabe in spremljanje naših navad bi pripomogle k bolj učinkoviti potrošnji, kjer bi majhno zmanjšanje porabe na veliki ravni lahko pripomoglo k opaznemu zmanjšanju ogljičnega odtisa.

V sklopu poglavja 2 smo naredili pregled obstoječih raziskav in primerov uporabe profilov porabe. Za lažji pregled trenutnega dela smo raziskave predstavili v preglednici profilov, ki nam je razkrilila profile, ki še niso bili raziskani ali uporabljeni. Vrzeli so nam omogočile razvoj novih, prej ne uporabljenih aktivacijskih profilov.

Za razvoj in izdelavo profilov so potrebni podatki v obliki časovnih vrst, ki vsebujejo informacije o porabi energije. Uporabili smo pet podatkovnih zbirk (UK-DALE, REFIT, ECO, REDD in iAWE), ki so merili porabo električne energije v gospodinjstvih. Skupaj smo imeli podatke 30 gospodinjstev, vsa so se nahajala na geografskem prostoru Evrope, razen enega, ki se je nahajal v Aziji, bolj natančno v Indiji. Poleg podatkov glavnega števca so podatki vsebovali informacijo o porabi vseh naprav znotraj gospodinjstva, kar nam je omogočalo razvoj profilov porabe za specifične naprave. Zbirke podatkov so bile ponovno vzorčene in razdeljene na enourne intervale za lažje ravnanje in analizo.

V poglavju 4 smo se osredotočili na predstavitev in analizo obstoječih profilov s poudarkom na primerih uporabe. Poglobljeno znanje nam je omogočalo predstavitev in umestitev novih aktivacijskih profilov.

V poglavju 5 smo uporabili enega izmed novih trodimenzionalnih profilov skupaj z metodo t-SNE (t-distributed stochastic neighbor embedding). To je nelinearna metoda zmanjševanja dimenzij visoko dimenzijskih podatkov. Rezultat te metode je nizko dimenzionalen zemljevid, po navadi dvodimenzionalen, kjer so skupaj vzorci, ki so si podobni v visoko dimenzionalnem prostoru. V primeru linearnih metod za zmanjševanje dimenzij, kot je PCA, lahko nizkim dimenzijiam pripisujemo določene lastnosti, med tem ko pri nelinearnih metodah nizke dimenzije nimajo posebnega pomena. Pomembna je le razdalja med točkami, saj ta predstavlja podobnost vzorcev. Podobni vzorci po navadi formirajo gruče, le te pa lahko uporabimo za analizo navad porabe. S pomočjo metode t-SNE smo zgradili zemljevid naprav, le ta pa omogoča boljše razumevanje značilnosti in vzorcev porabe med različnimi napravami. Med drugim smo prepoznali, da je v profilih porabe znotraj gospodinjstev prisotna rutina. Razdalja med vzorci na zemljevidu predstavlja jakost rutine. bolj kot so vzorci skupaj, bolj močna je rutina določenega gospodinjstva.

Prisotnost rutine znotraj gospodinjstev pomeni, da lahko odkrivamo razna odstopanja v porabi. Bolj kot je bila rutina močna v preteklosti, bolj smo lahko prepričani, da gre za nenavaden dogodek v primeru nenavadnega vzorca. Primerna ciljna publika za tako metodo so starejši posamezniki, ki živijo sami. Za podaljšanje njihove samostojnosti, obenem pa ohranjanje njihove varnosti lahko analiziramo njihove vzorce porabe in v primeru anomalije obvestimo negovalca o potencialni težavi, kot je recimo padec. Starejši imajo po navadi bolj ustaljene vzorce porabe, kar je za tak sistem zelo primerno. Pasivni sistem morda ni tako hiter pri odzivanju, kot pametne zapestnice, ki bi padce zaznale takoj. Pasivni sistem ima ključno prednost v tem, da deluje neprekinjeno in ne invazivno. V primerih, kjer bi uporabili samo en števec, je tak sistem tudi veliko cenejši, saj bi lahko uporabili že obstoječo infrastrukturo. Za razvoj sistema smo uporabili enega izmed prej še ne raziskanih aktivacijskih profilov porabe, ki smo ga identificirali z uporabo preglednice. Sama metoda je bolj natančno opisana v Poglavju 6. Le-ta temelji na principu zaznavanju aktivnosti, kot so priprava zajtrka, kosila ali gledanje televizije.

Čeprav nismo imeli podatkov z dejanskimi anomalijami, smo ugotovili, da je rutina povprečnega gospodinjstva dovolj visoka za uporabo zgoraj omenjenega sistema. Rezultati kažejo, da je rutina povprečnega gospodinjstva znotraj določenih časovnih obdobij več kot 80 %. To pomeni, da bi bil vsak peti vzorec označen kot lažno pozitiven. Sistem smo prilagodili za rabo v dejanskih okoliščinah, z izgradnjo iterativnega učenja, kjer sistem lahko zaživi že po enem mesecu uporabe in se z časom izboljšuje. Pomembna ugotovitev je, da ima povprečno gospodinjstvo dovolj močno rutino za detekcijo anomalij. Ob predpostavki, da je rutina starejših še višja, bi se s tem dodatno izboljšala zanesljivost. Nazadnje smo izračunali korelacijo med rutino in evklidsko razdaljo med vzorci na t-SNE zemljevidu. Čeprav so se uporabile druge metode in drugi profili, je bila korelacija skoraj 80 %. Rezultat nakazuje, da razdalja vsebuje informacijo o rutini, kar pomeni, da bi lahko uporabili metodo t-SNE za podobne aplikacije.

Prihodnje raziskave na tem področju ponujajo veliko odprtih možnosti za izboljšavo trenutnega pristopa. Za bolj točne rezultate bi se lahko poslužili metode, kjer bi modelirali različne sintetične anomalije in jih vstavili v obstoječe podatke. Dodatno bi sistem lahko postavili okolje, kjer živijo starejši posamezniki. Realne anomalije, bi nam omogočile dokončno evaluacijo sistema. Obstajajo podobne metode, zato bi bilo bistvenega pomena primerjati točnost naše metode z ostalimi publikacijami. Dodatno bi lahko primerjali točnost metod, kjer se za detekcijo padcev uporabljajo senzorji, kot so pametene zapestnice.

Ugotovili smo, da lahko z metodo t-SNE zaznamo prisotnost rutine, kar bi nam posledično omogočalo zaznavo anomalij, podobno kot pri našem sistemu razvitem v poglavju 6, kjer smo uporabili podatke števcev vsake posamezne naprave. Prednost te metode je, da smo uporabili podatke glavnega števca, kar bistveno poveča uporabnost tega pristopa. Enostavnost namestitve sistema je bistvenega pomena za uspešno uvajanje novih tehnologij. V tej luči bi bila evalvacija in razvoj takšnega sistema visokega pomena in ena izmed možnih smeri prihodnjih raziskav. Poleg t-SNE bi bilo zanimivo preveriti ostale metode zmanjševanja dimenzij, kot so PCA ali bolj napredna UMAP metoda. Uporaba tako razvitih, kot tudi novih profilov s temi metodami bi lahko izboljšala trenutni pristop merjenja jakosti rutine ali celo razkrila nova področja uporabe.

Menimo, da je naše delo prispevalo nova orodja za razumevanje in odkrivanje anomalij v porabi električne enegije, kjer sta energetska učinkovitost in podaljševanje samostojnosti starejših sta le dva primera uporabe, ki smo jih naslovili. Še vedno se je treba veliko naučiti o tem, kako in katere LP lahko uporabimo za izboljšavo kakovosti našega življenja. Medtem, ko smo v preglednici profilov zapolnili nekaj vrzeli, prepuščamo znanstveni skupnosti, da zapolni preostale.

Ključne besede: profiliranje porabe, energetski podatki, učinkovita poraba, zmanjšanje dimenzionalnosti, oskrba starejših, zaznavanje anomalij

Abstract

This work explores the potential of electrical energy data and how load profiles can be used to address issues such as the optimization of electrical energy consumption patterns and the aging population. The efficient presentation of energy data through load profiles is a constant narrative throughout the thesis. Optimizing consumption has the potential to significantly reduce the human footprint since a third of electrical energy in the EU is consumed in the residential sector. Furthermore, we utilize load profiles to address issues such as the aging population. We developed an elderly care assisted living system to detect anomalies in the usage patterns of the elderly. The system identifies accidents such as falls, strokes, or dementia-induced altered behavior.

We performed a comprehensive review of existing publications and use-cases. These publications were mapped into a table, which revealed gaps in the load profiles that were not yet researched or used. Next, we analyzed the load profiles and using t-SNE presented how profiles are related in high dimensional space.

With the successful implementation of the elderly care system, we confirmed that unused load profiles are applicable. The findings of this thesis showcase the untapped potential of energy data where the table of profiles provides a foundation for further research in this area.

Keywords: load profiling, energy data, energy saving, dimensionality reduction, elderly care, anomaly detection

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List of Abbreviations

LP	**L**oad **P**rofile
TP	**T**able of load **P**rofiles
P	**P**ower (profile)
A	**A**ctivation (profile)
ZEB	**Z**ero **E**nergy **B**uilding
DR	**D**emand **R**esponse
AD	**A**nomaly **D**etection
EC	**E**lderly **C**are
DER	**D**istributed **E**nergy **R**esources
HVAC	**H**eating, **V**entilation and **A**ir **C**onditioning
EV	**E**lectric **V**ehiecle
PV	**P**hoto **V**oltaics
EU	**E**uropean **U**nion
NILM	**N**on **I**ntrusive **L**oad **M**onitoring
t-SNE	**t**-distributed **s**tochastic **n**eighbor **e**mbedding
PCA	**P**rincipal **C**omponent **A**nalysis
EDA	**E**xploratory **D**ata **A**nalysis

Chapter 1

Introduction

Climate change calls for a shift to renewable energy and restructuring of the electric power industry. Source [25] shows that 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 carbon dioxide emitter. The same source [25] 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 elevate this issue. Acknowledging this, reducing consumption in the residential 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 as their core technology. Authors in paper [20] proposed a method to reduce peak loads by studying consumer appliance usage patterns. Paper [23] 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 [49]. 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 LPs 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 paper [56]. In recent years LPs have changed due to renewable energy accelerated development of distributed energy resources such as residential photovoltaic power plants, home wind energy, and using EVs with home batteries. Socioeconomic changes such as work-from-home, also drastically reshaped the LP curve.

The thesis aims to propose and develop new, previously unused LPs, that will contribute to mitigation of the raised issues. Presenting consumption with the right LPs will help dwellers be more aware of their consumption and in turn, increase their energy efficiency. Energy efficiency is the basis of our research, throughout the thesis we will explore LPs that were not yet utilized. We will perform an exploratory data analysis (EDA) to make sense of what they are, and what information they contain. This obtained knowledge will be used in a practical use-case to showcase that these profiles can be effectively utilized. We will design an elderly care assisted living monitoring system to detect anomalies in consumption patterns to detect strokes and falls.

Before we fully disclose our contributions, let us first have an overview of what LPs are and in which other use cases they can be utilized, besides the ones just mentioned.

1.1 Definition and Types of LPs

Author Proedrou [56] defines terms as follows:

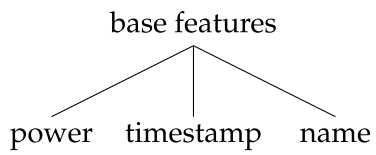
- Load: the electricity that all electricity-powered devices in the household consume in unit time.
- Profile: a graph representing the significant features of the electricity load over time.

In other words, LPs are a graphical presentation of the consumption features of a building over time. Here, features could be anything that presents consumption. In most cases that is electrical power, measured in kilowatts. The time range used to present the consumption could be anything from daily, weekly, monthly to yearly.

One thing to mention here is, that although the buildings were mostly consuming energy in the past, nowadays, they also produce it. While this may slightly alter the definition of LPs, it has also made them more useful, as they can now be used to depict both energy consumption and production. Throughout this thesis, we primarily focus on the use of load profiles to represent electricity consumption, but it's important to consider their potential for presenting energy production as well.

1.1.1 Feature Set

To identify the base features of energy consumption in buildings, we need to examine the way that consumption is typically measured. Three main features allow us to determine the amount of energy being used by a user:



If we translate these features to the time domain and observe them over a specified amount of time, new features emerge. One such example is the observation of electrical power over one hour. This results in the amount of energy consumed often referred to as energy E, which is one of the most common ways used to bill a customer for his power consumption.

We can also extract features such as the number of activations or time of operation for each activation. This can be done using sensors to detect activity or even extract this from power consumption data. In cases where we are observing individual appliances, this can be done using simple signal processing techniques. In cases where we are observing buildings, this could be achieved using more complex disaggregation algorithms also known as NILM (non-intrusive load monitoring) algorithms. NILM algorithms enable us to detect consumption patterns of multiple appliances from a single power meter.

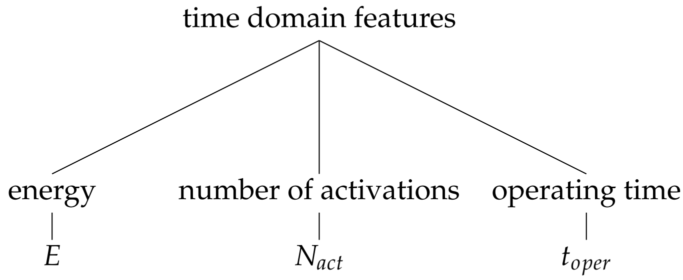
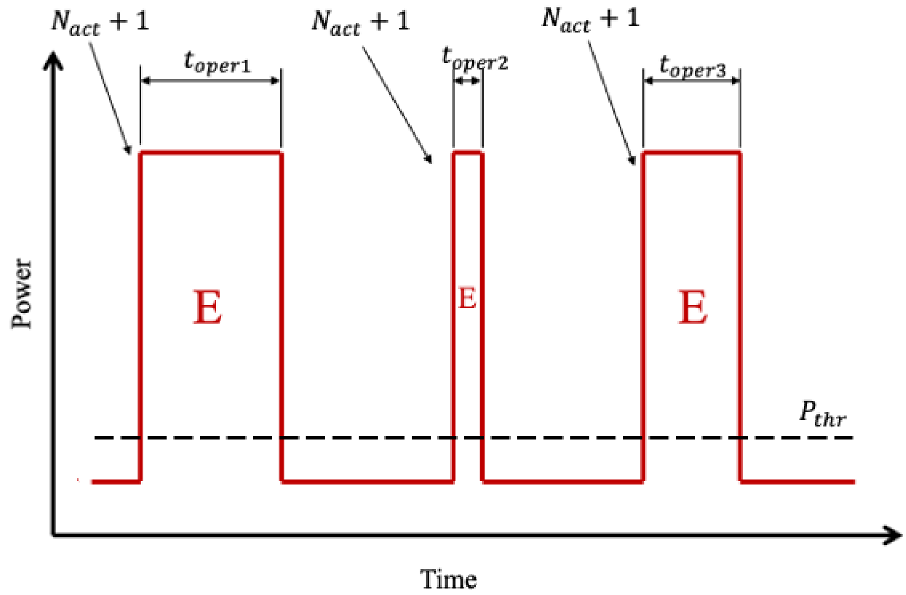


FIGURE 1.1: Simple signal processing of power consumption for a single appliance



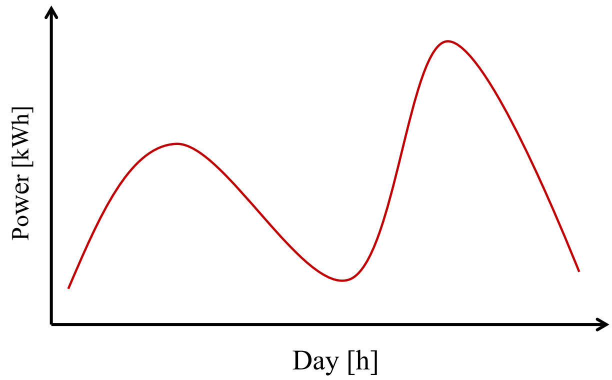
As we can see in Figure 1.1 all three time-domain features can be extracted from the graphical presentation. The amount of energy consumed, denoted as E, is equal to the area under the graphical presentation or in other words integral of power over time. The number of activations, denoted as N_{act}, can be measured based on the number of times the power value exceeded some pre-defined threshold P_{thr}. The time between on and off events is denoted as t_{oper}, where we use the same threshold as with N_{act}. While there are other features, such as time between activations, or total operational time that could be extracted, these are not commonly used in related work.

1.1.2 Types of LPs

Power LP

Combinations of the features result in many possible types of LPs that enable us to present the data. The most commonly used type of LP is average power consumption over some time. One such example can be seen in Figure 1.2. Here, we used daily timescale, since it is so commonly used, it is also known as the standard daily LP. It can be used to portray per-building as well as per-appliance data. It is one of the most versatile LPs, and it is used in fields such as demand response, anomaly detection and zero-energy buildings. While the LP in Figure 1.2 is a sketch, it still presents consumption trends in morning and evening peaks.

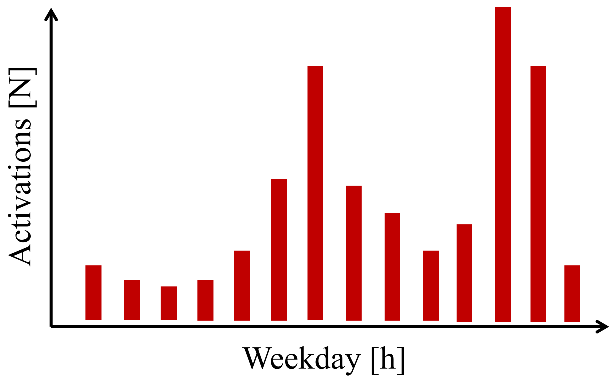
FIGURE 1.2: Average daily usage profile for an appliance or a building



Activation LP

Alternatively, we can use a histogram-based presentation to present a number of activations feature such as can be seen in Figure 1.3. Here, we split the given timescale into discrete intervals also known as buckets. These buckets are then filled with activations that had taken place in a given interval. In the case of Figure, 1.3 timescale is a day, and it was split into 12 intervals. While this is not real-world data, we can still observe consumption patterns throughout the day with morning and evening peaks. Activation LP is usually used to portray per-appliance data. In order to portray per-building data, we would need to install a power meter for every appliance in the building. This LP has the very same use-cases as the power type and can be used in the same fields, but as mentioned, it is less practical for per-building LPs. While Figure 1.3 presents the same data as Figure 1.2, due to data processing, it could potentially reveal more relevant consumption patterns. The downside is that we have to invest additional time to process power data into activations.

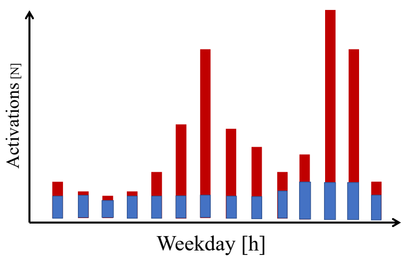
FIGURE 1.3: Histogram of daily activations profile for an appliance or a building



Per-Building Per-Appliance LP

The next two types of LP, known as per-building per-appliance LPs, can be used to present both whole-building usage and per-appliance consumption. Figure 1.4a and 1.4b provide two such examples. In the case of activation LP, we concatenate activations of each appliance and label them accordingly. This approach enables us to see the contribution of each appliance to the total number of activations in each bucket. The per-building per-appliance LPs hold the potential to be used in the same fields as the first two types, but practically they are primarily used in demand response. This additional information enables us to better understand the data and potentially discover patterns that we otherwise would not be able to.

(A) Daily per-building per-appliance activations LP for appliances A and B



(B) Daily per-building per-appliance power LP for appliances A, B and C

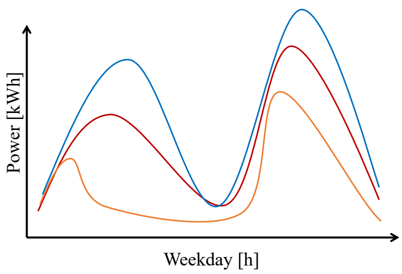
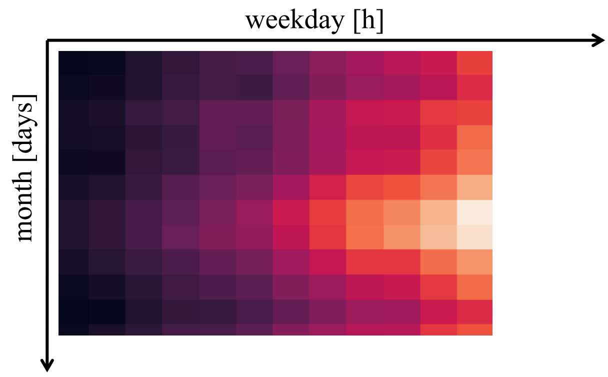


FIGURE 1.4: Per-building Per-appliance LP

Heatmap LPs

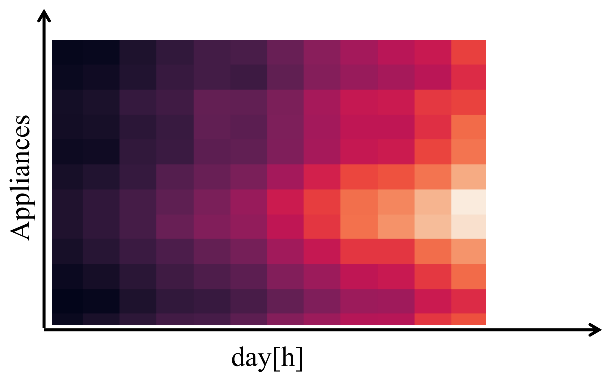
The last type is a heatmap LP, they can be further divided into two subtypes. The first type is LPs which consist of two-time dimensions and use color to display consumption. Such LP can be used to depict both activation and power consumption features and can present per-building consumption as well as per-appliance data. All this makes them very versatile. Figure 1.5 provides an example of this subtype. This format allows us to see the consumption pattern throughout each day in a month. The brightness represents the activity of the household or a particular appliance. The brighter the plot, the more activity for that hour of that day of the month. One thing to keep in mind when reading such a profile is that the origin is placed in the upper left corner.

FIGURE 1.5: Number of daily activations/power consumption of one appliance/house in one-month period



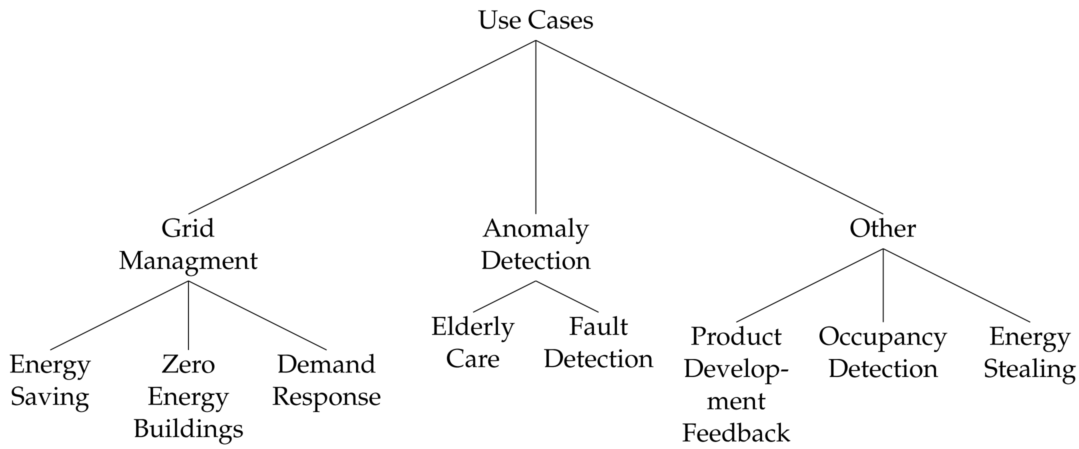
The second subtype is essentially Per-building Per-appliance LP, just portrayed differently. Instead of plotting consumption data as the sum of contributions from each appliance, we present their consumption side by side. These LPs share the same uses as Per-building Per-appliance LPs, given their fundamental similarities. Figure 1.6 provides a sketched example of this subtype.

FIGURE 1.6: Consumption for each appliance in a day



While there are many features and many more types of LPs out there, we have selected the ones that are most commonly used. There are also many versions of the LPs above with different timescales, where each has a different use case. A more comprehensive presentation of these use cases will follow in Chapter 4, with a detailed classification provided in Section 2.3.

1.2 LP Use-cases



The load profiling method has a lot of different use cases across different fields. In our study, we will categorize these use cases into three classes.

The first class relates to grid management. For instance, it can be used to save energy by studying users' usage patterns and returning feedback, with suggestions on how to optimize consumption. In scenarios where buildings have grid batteries and PV installed, the same feedback could be used to minimize the amount of energy being drawn from the grid. These are so-called zero-energy buildings (ZEB). Electrical energy providers could leverage demand response programs in combination with the LPs to optimize the management of the grid, with minimal impact on users' daily routines.

The second class involves anomaly detection. The LPs could be used to help the elderly in case of an accident or even help prevent one. They could be used to detect all kinds of early malfunctions in the operation of appliances, which would reduce service costs and save energy.

The final class, labeled 'other', encompasses occupancy detection, development feedback, and energy theft detection as potential use cases where LPs could be applied.

A more detailed description of each use-case with publications will be addressed in the following chapter, specifically in Section 2.2.

1.3 Data

To construct the LP, we need time-series data that contains information about energy consumption. While LPs are generally used to analyze the usage of electrical energy they could be applied in many areas. For example, LPs could be used to analyze any other utilities such as gas, oil or even tap water. Furthermore, while this thesis focuses on analyzing the consumption of electrical energy, LPs can be applied to analyze production. Finally, while we focused on optimizing residential energy consumption patterns, the same approach can be applied extended to industrial or office settings.

In the thesis, we used the following five datasets: UK-DALE [39], REFIT [57], ECO [8], REDD [43], and iAWE [6]. All datasets measured electrical energy consumption in residential buildings. They include main smart meter data, as well as sub-meter data for each appliance in a dwelling. While some datasets offered versions with high frequency with sampling rates up to 40 kHz, we focused on the low-frequency variations with sampling rates at around 1 Hz.

The utilized datasets had frequencies ranging from 1 Hz for the ECO dataset, down to 1/8 Hz for the REFIT dataset. To ensure compatibility, we resampled all datasets to 1/6 Hz. The missing samples were forward-filled with a limit of 5, meaning that if up to 30 s of data was missing, its value was set to the last known value; otherwise, it was left missing. For easier management, datasets will be divided into 1-hour intervals. The exact methodology will be presented in Chapter 3 of the methodology section.

1.4 Contributions

The primary objective of the master's thesis is to propose suitable LPs for supporting residential building consumption optimization and elderly care management. To achieve this goal, we propose the following steps, where each step is a contribution to the scientific community.

1. Surveying the state-of-the-art LPs (Chapter 2)

The first contribution involves a review of existing research and use cases. Drawing from various publications, we construct a comprehensive table of LPs. We are the first to analyze LPs from this perspective, which provides an overview of related work by mapping it onto a table. This table reveals LPs that have not yet been utilized. We then examine use cases to determine the potential application fields for each LP.

2. Development of multidimensional activation LPs (Chapter 4)

Empty gaps in research motivated us to pursue our next contribution: the development of multidimensional activation LPs. Here we offer an in-depth look into both existing and newly proposed LPs, showcasing how they represent consumption patterns. We also apply these LPs and discuss potential scenarios and use cases for their application. Each LP reveals a different pattern and, therefore, serves a different use case.

3. Visual analysis of activation LP's (Chapter 5)

The third contribution involves exploratory data analysis (EDA) through visualizations. Here, we leverage the LPs that we have proposed and analyzed, using the t-SNE dimensionality reduction algorithm to understand the relationships within the data.

4. Propose a new anomaly detection method for elderly care (Chapter 6)

This newly obtained knowledge should help us provide the final contribution, where we utilize LPs that have not been previously considered. We design and construct an assisted living system for elderly care by utilizing one of the proposed LPs. The system can detect anomalies in the daily routine of an elderly individual. Should an anomaly is detected, the caregiver is notified to check on the individual. This system is simple, efficient, and ready for real-world application.

Chapter 2

Related Work and Table of Profiles

In the first part of the chapter, we will review the existing work done and show possible use-cases for the load profiles. In the second part, we will present the most commonly used LP features. Utilizing these, a table of profiles will be constructed. The table will be populated using the publications from the first part of the chapter. This will provide us with an overview of existing work and expose possible gaps in scientific research.

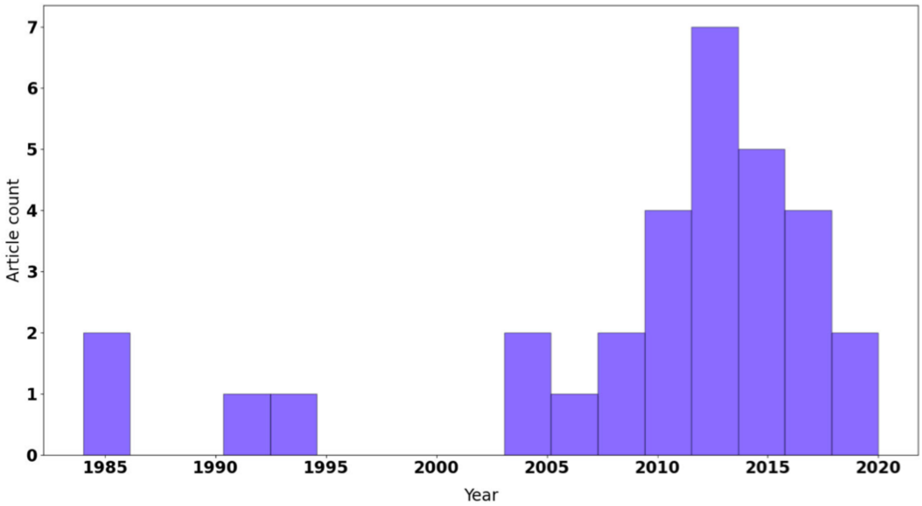
2.1 Related Work

Research related to load profiling can be divided into two verticals. The first involves load profiling and LP models, which in most cases study the LP curve of a building or appliance. The second vertical focuses on anomaly detection in energy consumption data There are quite a few connections between the two. For example, in order to detect anomalies, one must first build some form of "normal consumption profile", or in other words, an LP.

2.1.1 Load Profiling

One of the earliest publications on load profiling was published by Train et al.[67]. They used a bottom-up approach using sub-meter data and other socioeconomic and demographic characteristics to create an LP or statistically adjusted engineering (SAE) as they call it. They adjusted the curve based on weather, dwelling size, and income. In the same year, Walker et al.[72] 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 related publications in 1995. Research picked up the pace in 2005 with 7 publications in 2013 as shown in Figure 2.1.

FIGURE 2.1: Distribution of publications on load profiling from 1985 to 2020. The graph was published by [56].



Load profiling can be performed in two ways: bottom-up and top-down. A bottom-up approach as authors in [66] describe "calculates the individual dwelling energy or electricity consumption and extrapolates these results over a target area or region" Whereas with top-down approach as authors in [66] describe "uses the total energy or electricity consumption estimates to assign them to the characteristics of the building stock" In other words, bottom-up uses sub-meter data, Top-down uses aggregated data. In this study, we delve further into the bottom-up approach.

The author in [56] conducted 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 LPs. They also grouped modeling techniques as probabilistic models, Markov chains, and Monte Carlo. The author first disclosed the current state of load profiling and identified issues with past work. They made a review of existing load profiling models and asses the-state-of-the art. Next, they pointed out future research directions and applications of load profiling models. Finally, the author exposed issues that researchers face and addresses possible solutions with conclusions.

Gerbec et al.[28] tried to assign typical LPs to a particular group of consumers based on their activity. To achieve that, they used probabilistic neural networks as a classification method. Their methodology was tested in real-use scenarios.

Gao et al.[27] employed a bottom-up method to build a forecasting framework for household load profiling, which takes into account the consumption patterns of residents. This model falls into the demand response use cas. 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 the behavioral patterns of dwellers. Their results demonstrated that their method successfully modeled daily usage.

Chuan et al.[20] used load profiling to optimize energy consumption distribution during the day. This reduces peak usage and alleviates load off the grid. The author employed the bottom-up method, using sub-meter data. By analyzing this data on an hourly basis, they optimized the daily activation of appliances to lower peak usage. Their results showed successful peak shedding.

Csoknyai et al.[23] analyzed 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.[36] 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 and 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 et al.[52], 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 is 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 et al.[1] clustered different LPs using electricity consumption data and surveys using data from residential homes. They used PCA and k-means resulting in 5 clusters, a result similar to other load profiling papers.

Whereas most of the above-mentioned papers focused on aggregated consumption of a building to construct an LP, authors [35] focused on appliance-level load profiling. Their main contribution was to create a realistic per-appliance LP. They developed a wireless measurement system with smart plugs that enabled them to obtain power signatures for each appliance. After evaluating the data and observing appliance usage, they determined the working cycles for each appliance. Furthermore, they concluded that 15 % of the consumed power could be shifted, taking tariffs into account.

2.1.2 Anomaly Detection in Building Energy Consumption Data

A review on anomaly detection in building energy consumption data was written by authors [31]. 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 et al.[59] 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.

The same author published another paper [58] 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.[17] 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. The 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-point deviations for which they implemented the isolation Forest algorithm and anomalous trends for which to detect, they implemented Change Point Detection.

2.2 Use-cases

The general classification of use-cases was done in Section 1.2. In this section, we will focus on presenting these use-cases in great detail. This will be achieved by analyzing the use-case publications and in some instances proposing additional solutions.

2.2.1 Grid Management

Zero Energy Buildings and Energy Saving

As mentioned before many applications for load profiling can be used to reduce energy use and increase energy efficiency. With the emerging EV-market and the ever-increasing installation of heat pumps, more and more energy is being consumed in the form of electricity. This means, that 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" [49]. DERs include 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 through load profiling and load modeling. To manage the appliances, a control system would have to be put in place [33]. 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" [51]. They will be an essential part of the European Union's plan to reach zero-energy buildings and near-zero-energy buildings [53]. 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 occasionally. In this case, two profiles would be developed. Normal workday and work-from-home day. Additional information would be obtained from the user's 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, EVs could inject the power back into the house. The aim would be to use appliance LPs 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 as authors mention in [60] and [48].

One other way to use user LPs is to optimally distribute the load by studying the user's usage patterns as authors in [20] and [44] 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 the usage patterns of all peers, the system could optimally distribute the energy using DERs across all homes without residents even noticing.

Another use-case could be using a heat pump and heat storage, where in addition to the user's usage patterns, the 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's usage profile, energy could be optimally distributed.

Many papers have been published, where authors [64] [18] [69] [64] explored ways to reduce the energy consumption of users by studying user consumption patterns. 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 the paper [23]. Source [22] states that as much as 20 % of energy could be saved by managing consumption.

Demand Response

An increasing percentage of renewable resources is posing challenges for energy distributors, due to the nature of renewable resources. In the previous Chapter 1, it was mentioned how energy-saving measures would benefit users and their peers. Another use-case would be cooperation between end-user and energy distribution companies. Joint actions between them would benefit both, as the authors show in their papers [2] and [50].

The electricity provider could control the main appliances so that the 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 et al. state in [61]. One way to achieve this is to control the voltage of loads [75] and the other way is to shift the loads in time [44]. This process is called direct load control as Hledik and Lee state in their book [33], and it is part of demand response program [19].

"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." [19]

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

The user would have three options. The first one would be that users can use the appliances as freely as they desire, resulting in a normal tariff. The second option would be to use the appliances as regularly as possible, leading to lower tariffs. The third option would be to leave the management of main appliances to the electricity provider via direct load control. The provider would combine the user appliance LP and the real-time market price of energy to optimize the cost [29]. This would lead to free or even negative prices of electricity since distribution companies need 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 [45]. Commonly whole neighborhoods are disconnected, affecting their daily lives. Using user LPs, 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 distribution company as well since they do not need to lower energy production, which can be expensive.

2.2.2 Anomaly Detection

One use-case of anomaly detection was already mentioned in the Elderly care Chapter 6. Another aspect 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, the fridge being open, or compressor motor malfunction. Heat pumps work on the same basis as fridges, meaning the same anomalies could be detected. Malfunctions could also be detected in heating element appliances such as toasters or boilers. Since the aforementioned appliances are one of the largest consumers in a household, early enough detection could lead to substantial energy-saving benefits [59].

Elderly Care

The 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 perform chores 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 explore in their papers [71] and [54].

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 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 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.

2.2.3 Other

Load profiling could also be used as feedback for the engineers and designers, indicating how a 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.[74] use 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.

Another use-case could be occupancy detection of buildings, as explored by Kleiminger et al. [41]. 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.

2.3 Table of Profiles

In the first part of this Chapter, we focused on the general concept of load profiling and reviewed the existing literature on the topic. In this second part, we will delve into the various ways in which load profiling data can be presented using LPs. We will begin by constructing a general LP table from previously defined features in Section 1.1.2 Subsequently, we will map the references and use cases from the related work reviewed in previous chapters to this table and select the main features to use. Utilizing this reduced set of features, we will create a more detailed LP table and populate it with information from the same references. Finally, we will use this information to identify potential areas for future research in this field.

2.3.1 General Table

Utilizing features defined in Section 1.1.2 we can form a Table with all possible combinations. Table 2.1 is then populated with references from previous chapters. To understand the table more comprehensively, let's imagine that each feature is used as an axis label when plotting.

TABLE 2.1: General table of LPs

	power	number of activations
time	[20] [23] [12] [38] [72] [28] [27] [36] [1] [40] [59] [58] [35] [4] [17] [41] [20] [15] [52] [39] [27]	[16] [39]
operation time	[4]	[59] [58] [4]

Table 2.1 shows a combination of base features of power and time with 21 publications. For example, one such profile can be seen in Figure 1.1 or 1.2 and is also known as standard LP (SLP).

As we have seen in the previous section, the two other features, operation time and the number of activations are a derivation of the base features. Three other papers have used a combination of these two features. This LP shows how many times the appliance was activated for a certain amount of time. It is commonly used for anomaly detection.

Derived features can be used in combination with the base features. The combination between power and operation time LP shows how long an appliance operated for a certain amount of time. Only one publication used this set of features. Combining the time and number of activations LP could, for example, indicate the time of day when the appliance is most frequently used. We found only two publications that used this set of features.

Based on Table 2.1 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, we are focusing on activation-based histogram representation. Based on Table 2.1 it is possible to see that not much attention was given to it.

There are many more ways to present the data. An extended Table can be found in Appendix B.

2.3.2 Detailed Table

This section will focus on investigating possible activation-based LPs, while using the power LPs as a baseline. Features from 2.1 will be explored in greater detail. They will be partitioned and arranged in a way that all 21 publications using 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

General features were already described in Section 1.1.2. 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-building
  - Per-appliance
  - Per-building and per-appliance
- By time range of profile
  - Daily
  - Weekly
  - Monthly
  - Yearly
- Way of measuring usage
  - Average power use
  - Number of activations

2.3.3 Table of Combinations or Detailed Table

The above-shown profiles can be combined, yielding a new way of displaying the data. Bellow, Table 2.2 with combinations of the above-mentioned profiles is presented. The purpose of Table 2.2 is to illustrate possible LP combinations. Some combinations that had similar outputs were grouped, and some that could not be visualized were discarded.

The LPs and figure graphics used in Table 2.2 were sourced from Section 1.1.

Table 2.2, uses features from the previous Section 2.3.2. In general, Table 2.2 is formatted in a way that employs features from the columns (time range) as the x-axis of a plot, while the rows (consumption data) are used as the y or z-axis of a plot.

The column of Table 2.2 represents the time domain. "Daily" indicates that the LP presents average usage for one day and "Weekly" indicates that 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 applies to yearly profiles, in that case, multiple years' worth of data are necessary.

The top row of Table 2.2 consists of three main groups. The first group focuses on per-building energy consumption. The second group examines the energy consumption of each appliance in a house separately. The third group analyses all appliances in a building.

The next row of Table 2.2 is further divided into two groups. First is the LP group, which presents the given usage unit on the y-axis and time on the x-axis. Next is an LP with an additional time axis. 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-building, the subgroup includes appliances instead of time. An example of this is Figure 1.6.

The last row presents the usage unit, that is power (P) or the number of activations (A).

In cases where the feature combination does not make sense, it is marked with an X.

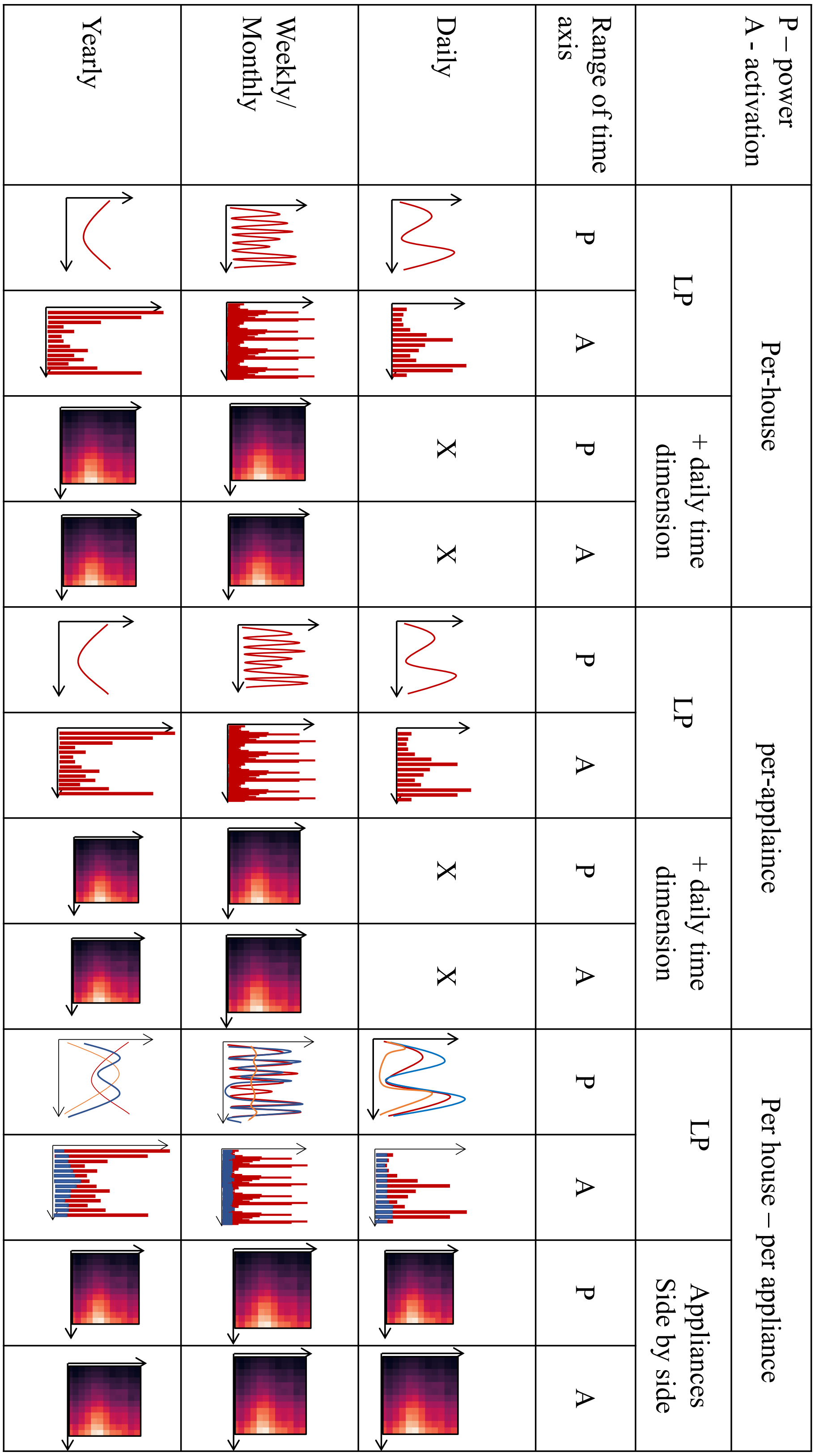


FIGURE 2.2: Table of combinations

2.3.4 Mapping References to the Table of Profiles

To find useful LPs, references from the related work Section 2.1 must be mapped to the Table 2.2.

TABLE 2.2: Table presents previously mentioned LPs

P - power A - activation	**Per-building**				**Per-appliance**				**Per-building per-appliance**			
	LP		**+ daily dim.**		**LP**		**+ daily dim.**		**LP**		**Appl. by side**	
Interval	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**
Daily	[39] [20] [23] [12] [38] [15] [72] [28] [27] [36] [1] [40]		X	X	[59] [58] [35] [4] [17] [41]	[39]	X	X	[20] [15] [27]	[39]		
Weekly/ Monthly/	[23] [12] [38]		[63] [52] [40]			[16]			[14]	[16]		
Yearly	[23] [12] [38]											

As can be seen from Table 2.2, most of the work (14 publications) has been done with standard daily LPs that include per-building power usage such as Figure 1.2. 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 LPs and a few used two-dimensional time and power presentations. Only one publication used an activation and time-based histogram such as shown in Figure 1.3.

An important thing to note here is that during the research we focused on publications from minority classes, meaning not all existing publications for standard LPs are included. The purpose of Table 2.2 is to present missing scientific contributions and patterns of publications.

2.3.5 Mapping Use-Cases to the Table of Profiles

Table 2.3 includes arranged publications from the use-cases Section 2.2. A similar pattern has emerged as in Table 2.2.

TABLE 2.3: Table presents references mentioned in use-cases Chapter

P - power A - activation	Per-building				Per-appliance				Per-building per-appliance			
	LP		+ daily dim		LP		+ daily dim		LP		Appl by side	
Interval	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**
Daily	[18] [64] [48] [74] [44] [29] [75]		X	X	[48] [71] [54] [41]		X	X	[20]			
Weekly/ Monthly/	[64] [38]											
Yearly	[64]											

2.3.6 Table of Use-Case Groups

Table 2.4 presents the same publications as Table 2.3, but only group names are shown. The groups represent the main use cases from Sections 1.2 and 2.2.

- ZEB - zero energy buildings
- DR - demand response
- AD - anomaly detection
- EC - elderly care
- X - unfeasible

The Table 2.4 indicates how groups are arranged. In the per-appliance part of the table, anomaly detection and elderly care are dominant, while zero-energy buildings and demand response are dominant in the per-building part of the table.

TABLE 2.4: Table presents references mentioned in use-cases Section 2.2

P - power A - activation	Per-building				Per-appliance				Per-building per-appliance			
	LP		+ daily dim		LP		+ daily dim		LP		Appl by side	
Interval	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**
Daily	ZEB, EC		X	X	AD, EC, ZEB		X	X	DR			
Weekly/ Monthly/	ZEB											
Yearly	ZEB											

The Figures listed above clearly depict the void that is not filled by publications. Although they may not be published, they still have a possible use case. In Table 2.5 empty spaces are filled with possible use-cases for the given LPs.

TABLE 2.5: Proposed use-cases for profiles

P - power A - activation	**Per-building**				**Per-appliance**				**Per-building per-appliance**			
	LP		**+ daily dim**		**LP**		**+ daily dim**		**LP**		**Appl by side**	
Interval	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**
Daily	AD, ZEB, DR,	AD, ZEB, DR,	X	X	AD, EC, ZEB, DR	AD, EC, ZEB, DR	X	X	AD, EC, ZEB, DR	AD, EC, ZEB, DR	AD, EC, ZEB, DR	AD, EC, ZEB, DR
Weekly/ Monthly/	AD, ZEB, DR	AD, ZEB, DR,	ZEB, DR	ZEB, DR	AD, ZEB, DR	AD, ZEB, DR	AD, ZEB, DR	AD, ZEB, DR	AD, ZEB, DR	AD, ZEB, DR	AD, ZEB, DR	AD, ZEB, DR
Yearly	ZEB, DR	ZEB, DR	ZEB, DR	ZEB, DR	AD, ZEB, DR	AD, ZEB, DR	ZEB, DR	ZEB, DR	ZEB, DR	AD, ZEB, DR	AD, ZEB, DR	AD, ZEB, DR

2.3.7 Table of LP Potentials

Some combinations are indeed illogical, and others are less useful in a practical sense. The next Table 2.6 will try to rate the utilization potential of the profiles based on two characteristics. The first characteristic is how well data is presented to the user, meaning that the LP is clear about 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 cannot 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 assumption would be, that the larger the number of publications, the larger the effect of presenting the data to a human. The second assumption 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 2.6, which has four possible classes.

- 1 - The LP satisfies both assumptions and has a high utility rate and was already researched (very useful, but with low research potential).
- 2 - The LP satisfies only one of the above-mentioned assumptions (has mid-research potential).
- 3 - The LP does not suffice any of the above-mentioned assumptions and was not yet researched or practically used (high research potential, could be hard to utilize).
- X - The LP is inexplicable (does not make any sense).

TABLE 2.6: Proposed classification of profiles

P - power A - activation	Per-building				Per-appliance				Per-building per-appliance			
	LP		+ daily dim		LP		+ daily dim		LP		Appl by side	
Interval	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**
Daily	1	3	X	X	1	2	X	X	1	2	3	3
Weekly/ Monthly/	1	3	2	3	3	2	3	3	2	2	3	3
Yearly	1	3	3	3	3	3	3	3	3	3	3	3

2.3.8 Table of Possible Future Research Directions

To find future research directions we must look into profiles that were least researched, such profiles are marked with the number 3 on Table 2.6. Some profiles were not researched because they may not present data as well, and some were simply overlooked. This is why we have built the following Table 2.7. The Table was populated as follows:

- (1) - The LP has high potential.
- (2) - The LP has mid-potential.
- Empty - The LP has low potential or was already researched.
- X - LP is inexplicable

The process of evaluation was a bit complicated, but it can be summed up to the following rules.

If the LP was used as a power profile, can it also be used as an activation profile? Here, we must use common sense. For example. If we follow this rule for per-building power LPs, it turns out that activation LPs are not as useful since they are based on per-appliance LPs. In other words, to build per-building activation LPs we need per-appliance (sub-meter) data anyway. That is why we have assigned them to the second class.

The second rule was applied to 3D profiles. In the case where one dimension was commonly used, it is probably worth investigating it with a combination of additional dimensions.

Following these rules, Table 2.7 was constructed.

TABLE 2.7: Possible future research contributions

P - power A - activation	Per-building				Per-appliance				Per-building per-appliance			
	LP		+ daily dim		LP		+ daily dim		LP		Appl by side	
Interval	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**	**P**	**A**
Daily		(2)	X	X			X	X			(1)	(1)
Weekly/ Monthly/		(2)		(1)	(1)		(1)	(1)			(2)	(2)
Yearly					(2)	(2)					(2)	(2)

Table 2.7 presents the possible future research directions. While some LPs have mid-research potential according to our rules, they are still worth investigating. In science, it often happens that use-cases change over time and research that seemed inapplicable suddenly finds its place.

We will focus on profiles with high research potential and use the number of activations as a unit of measure. When the aforementioned parameters are applied, the result is Table 2.8.

TABLE 2.8: LPs to be pursued

<table>
<tr><td rowspan="2">P - power
A - activation</td><th colspan="4">Per-building</th><th colspan="4">Per-appliance</th><th colspan="4">Per-building per-appliance</th></tr>
<tr><th colspan="2">LP</th><th colspan="2">+ daily dim</th><th colspan="2">LP</th><th colspan="2">+ daily dim</th><th colspan="2">LP</th><th colspan="2">Appl by side</th></tr>
<tr><th>Interval</th><th>P</th><th>A</th><th>P</th><th>A</th><th>P</th><th>A</th><th>P</th><th>A</th><th>P</th><th>A</th><th>P</th><th>A</th></tr>
<tr><th>Daily</th><td></td><td></td><td>X</td><td>X</td><td></td><td></td><td>X</td><td>X</td><td></td><td></td><td></td><td>(1)</td></tr>
<tr><th>Weekly/
Monthly/</th><td></td><td></td><td></td><td>(1)</td><td></td><td></td><td></td><td>(1)</td><td></td><td></td><td></td><td></td></tr>
<tr><th>Yearly</th><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

The profiles shown in Table 2.8 are our direction of research. In the next part of the thesis, we will try to utilize and present these LPs. This will be done as follows. In Chapter 5 we will use

- Per-building daily-weekly LP
- Per-appliance daily-weekly LP

with a t-SNE neighboring algorithm to find how they are related in high dimensional space. In Chapter 6 we will use

- Per-building Per-appliance daily LPs with appliances side by side

To build assisted living system for the elderly.

Chapter 3

Methodology

The following chapter includes the methodological procedures that are common for all chapters. More detailed methodological procedures will be described in each chapter separately.

3.1 Data

We already briefly presented the datasets in the first chapter in Section 1.3. Here, we will provide an in-depth presentation of the datasets, describing we processed and cleaned the data.

3.1.1 Non-Intrusive Load Monitoring (NILM)

While the NILM method was described in Chapter 2, we will reintroduce it as part of the methodology. NILM is a method that enables us to disaggregate consumption patterns of the whole building from a single meter. The conventional method would be to install a meter for each consumer. An alternative would be NILM. With this method, one meter can be used to find out which appliances consume the most energy.

The data used here was collected for the purpose we did on Non-Intrusive load Monitoring (NILM) in publication [10]. We utilized this data to perform a classification of appliances using deep learning. By transforming time series data into images using Gramian Angular Fields (GAF), we created a stack of multiple images forming a video. Using deep learning architecture, specifically LSTM that used a stack of images as input, we were able to classify appliances with an F1 score of 80 %. Such techniques can be applied to identify appliances in unlabeled datasets or to detect potential mislabeling in existing datasets.

3.1.2 Dataset Selection

The Table 3.1 was published on the NILMTK [7] wiki page. NILMTK is a tool developed by authors in paper [7], aiming to make the development of NILM algorithms easier by standardizing a format in which building energy consumption datasets are stored. They also developed converters to convert existing datasets into a universal format.

This enables engineers to simply load and process multiple datasets. NILMTK includes a dataset converter from most of the datasets from Table 3.1.

TABLE 3.1: List of NILM datasets.

Dataset	Sampling rate	Duration	Buildings	Subject	Country	Availability
Dataport	1 Hz to 1 minute	4+ years	1200	multiple	US	Licensed
BLOND-50	50 kHz/6.4kHz	213 days	1	office	Germany	Public
FIRED	12 kHz to 1 Hz	101 days	1	residential	Germany	Public
REDD	16500 Hz / 1 Hz	100 days	5	Residential	US	Request access
BLUED	12000 Hz	7 days	1	Residential	US	Request access
UK-DALE	16000 Hz / 1 Hz	2 years	6	Residential	UK	Public
PLAID	30000 Hz	5 seconds	55	Appliances	US	Public
WHITED	44000 Hz	5 seconds	9	Appliances	Multiple	Public
Tracebase	1 Hz	1 day	158	Appliances	Germany	Request access
DRED	1 Hz / 1 min	150 days	1	Residential	Netherlands	Public
AMPds	1 minute	2 years	1	Residential	Canada	Public
RAE	1 Hz	72 days	1	Residential	Canada	Public
iAWE	1 Hz	73 days	1	Residential	India	Public
HES	2 minutes	1 year	251	Residential	UK	Request access
REFIT	8 seconds	2 years	20	Residential	UK	Public
ECO	1 second	200 days	6	Residential	Switzerland	Public
COMBED	30 seconds	30 days		Office	India	
IHEPCDS	1 minute	4 years	1		France	
SMART	1 Hz	60 days	3		USA	
LIT-Dataset	15 kHz	30 seconds	26	Residential	Brazil	Public

Pruned version of the Table published by authors on NILMTK[7] wiki page. Full table available here `https://web.archive.org/web/20190607094329/http://wiki.nilm.eu/datasets.html`.

The reason why more datasets were not selected from the Table 3.1, was because we followed the criteria:

1. Sampling rate between 1 Hz and 1/10 Hz
2. Duration more than 30 days
3. Subject had to be a residential area building
4. Include main meter as well as sub-meter measurements
5. Has to be accessible

After applying these criteria we were left with the following datasets:

- UK-DALE [39]
- REFIT [57]
- ECO [8]
- REDD [43]
- iAWE [6].

While the Dataport dataset seems to be the best fit and of the best quality, it did sadly not meet our criteria as it is a closed dataset available only via license.

3.1.3 Processing

After datasets were obtained and converted they were ready to be processed. We decided to slice the data into hourly slices so that it will be easier to find missing data and build LPs.

Firstly we resampled the time series data to 1/6 Hz. This had to be done because datasets were sampled at different frequencies. A frequency of 1/6 Hz is commonly used since it has a good ratio between resource usage and NILM algorithm performance. Resampling was done using the Pandas resample function. We used a forward fill parameter with a limit of 5. This means that in case of missing data, we will fill in no more than 5 samples with the last known value.

Secondly, we sliced the time series data into hourly slices. One sample every 6 seconds means, there were approximately 60 samples in every slice.

Thirdly, we removed slices with missing data. This was done for all slices where there was more than 20 % of data missing. In cases where less than 20 % of data was missing, we forward-filled it with the last known value. In the worst case, we forward filled 12 samples.

Finally, resampled and cleaned data was stored in the .hdf file.

3.1.4 Splitting and Evaluation

In some cases, datasets had to be split to allow for the empirical evaluation of the algorithm developed in Chapter 6. The data was split into train and test sets, where 80 % of the data was used for training and 20 % percent of the data for testing. The data was split based on the number of samples, so in some cases where there is a lot of missing data, the time window of test data might be longer, although it contains only 20 % of the samples.

3.1.5 Dataset analysis

Table 3.2 presents the five datasets we utilized. The second column displays the number of samples for each dataset after resampling. We also divided the number of samples by 10^6, to make the column comprehensible.

TABLE 3.2: Summary of datasets and their characteristics

Dataset	Samples (M)	Buildings
REFIT	192.46	20
UK-DALE	55	5
ECO	21.7	6
iAWE	6.43	1
REDD	5.89	6

Note: Samples are abbreviated as M for millions.

The figures below show where time splits between train and test data were done. At the same time, we can also observe the health of each dataset. By healthy dataset, we consider a dataset that has a long uninterrupted timeline with many buildings.

REFIT

The REFIT [57] dataset included data for more than 15 buildings, as can be seen in Figure 3.1 below. The dataset in general is of the highest quality since it is the longest with the least missing data. This means this dataset should give the most relevant results.

FIGURE 3.1: Timeline for REFIT

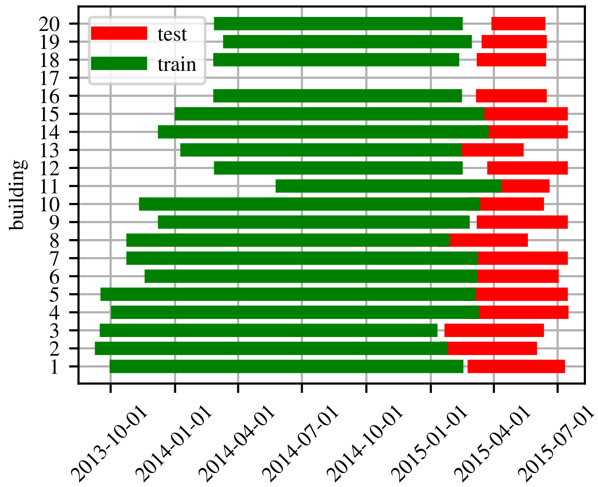


Figure 3.3 presents appliances sorted by a number of samples, where the top 10 were selected. Together, REFIT contains data for 23 different appliances from 20 homes.

TABLE 3.3: Appliances sorted by number of samples for REFIT

Appliances	Instances	Samples (M)
fridge freezer	15	47.19
television	20	40.14
freezer	13	37.91
computer	12	18.04
fridge	7	12.18
dishwasher	15	5.70
washing machine	20	5.59
microwave	17	5.49
pond pump	1	4.38
broadband router	2	2.85

Note: Samples are abbreviated in millions as M.

UK-DALE

Although the UK-DALE [39] dataset is of similar size, most of the data is from building 1. In general, it includes 5 years of data, but only for some appliances, many of them are rarely used. Considering these factors, there were numerous issues with building 1, leading to its exclusion.

Another issue that can be seen in Figure 3.2 is that there is not enough data for building 3. The test includes only a week of data, which is not enough for representative results, therefore it was excluded. The rest of the buildings seem healthy.

FIGURE 3.2: Timeline for UK-DALE

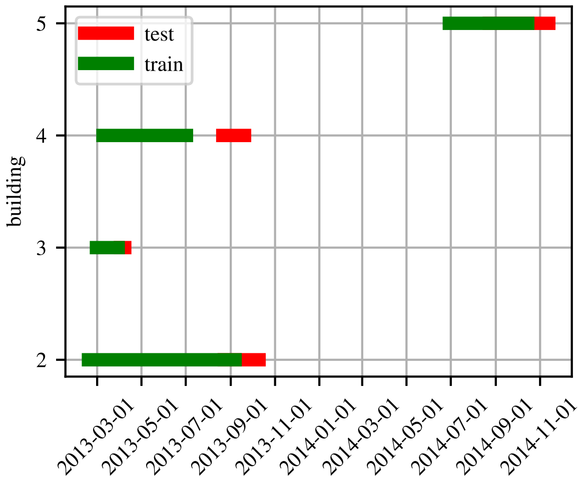


Figure 3.4 presents appliances sorted by a number of samples, where top 10 were selected. Together, UKDALE contains data for 53 different appliances.

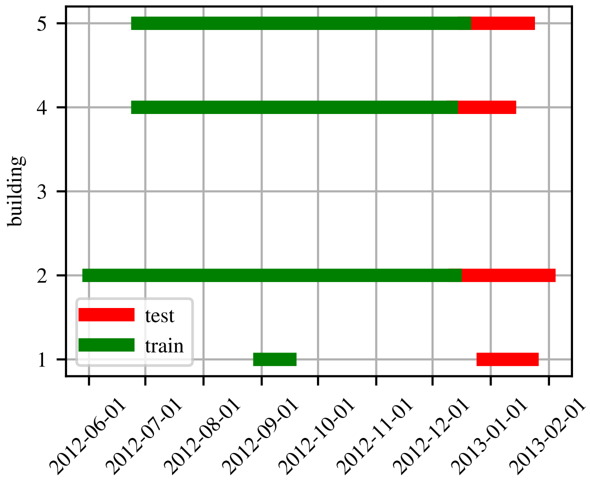
TABLE 3.4: Summary of datasets and their characteristics

Appliances	Instances	Samples (M)
light	15	9.86
fridge freezer	2	8.83
HTPC	1	4.87
solar thermal pumping station	1	4.25
audio amplifier	2	4
boiler	2	3.75
computer monitor	4	3.2
television	3	2.59
desktop computer	3	2.55
laptop computer	4	2.1
microwave	3	1.8

ECO

ECO [8] dataset has a length of data similar to UK-DALE. The only issue is building 1, where there is a lot of missing data. This is a good example of how data is split, it is split based on several samples, meaning that there is 80 % in the train bar, due to missing data the second bar is longer.

FIGURE 3.3: Timeline for ECO



ECO was down-sampled by a factor of 6, which drastically reduced the number of samples, as can be seen in Table 3.5 While the dataset is short, due to resampling, there is significantly less missing data, and in turn, it is of higher quality."

Appliances	**Instances**	**Samples (M)**
freezer	4	5.58
fridge	6	4.26
computer	3	2.69
HTPC	5	2.61
audio system	1	0.98
laptop computer	5	0.85
television	1	0.70
lamp	3	0.56
broadband router	1	0.16
washing machine	1	0.12

TABLE 3.5: Summary of appliances in the ECO dataset

3.2 Activation Detection

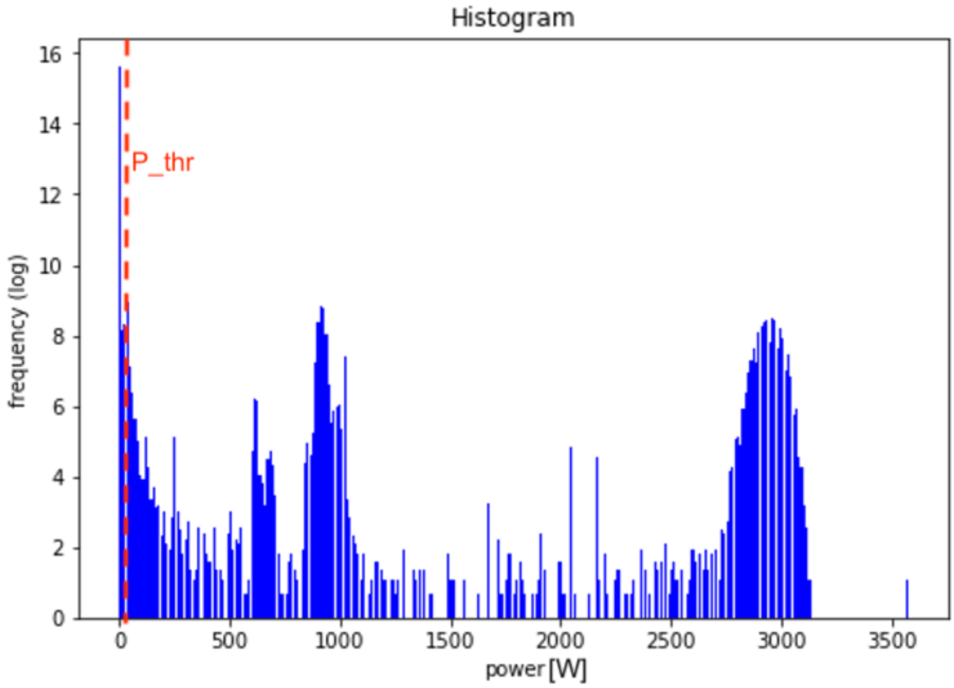
How appliance activations are extracted was already mentioned in Section 1.1.2. There we stated, the activation occurs when consumption exceeds P_{thr}. This is portrayed in Figure 1.1 in the same Section.

This threshold was selected as the standard value of 10 W. This value is used as a standard threshold in NILMTK [7].

However, this hard-set value is an issue for appliances that consume small amounts of energy, yet still exhibit interesting usage patterns. One such example would be a mobile phone charger or broadband router. Moreover, issues could occur even with some loads such as smart TVs, which may consume more than 10W even when they are not operating.

To verify that this was not an issue we came up with a test. We created a histogram of power values, with a resolution of 10 W, where one such example can be seen in Figure 3.4. For appliances that are mostly off, the first bucket should be the most populated. This was true for the majority of appliances and with that, they passed the test. For the ones that this was not true, we manually checked them and were either discarded or given a new threshold. The new threshold was manually set between the first and the second frequency peak.

FIGURE 3.4: Histogram of power values for Toaster



When we are observing Figure 3.4, we have to keep in mind that the frequency scale is logarithmic. Another thing to note is, that Figure 3.4 is also an LP, that we mention expanded table of LPs in Appendix B. This LP is useful for the detection operation modes. In this case, we can see that the toaster has three operating modes, where each peak is a unique mode. One peak is at 3 kW, the second at 1 kW, and the third at 0.7 kW. By setting thresholds around these peaks, we could create three different LPs, each presenting a distinct usage pattern.

3.3 Infrastructure and Software Used

To process the data and to obtain the results, we utilized the environment and virtual machines provided by Google Colab [11]. They offer access to Google GPU-accelerated compute machines with 12 GB of RAM. Furthermore, Colab provides access to Drive cloud storage, where the dataset and results were stored. While running the experiments, we made use of Drives pooled cloud storage, which is available to students of the University of Ljubljana.

For development and version control, GitHub was used.

Within the Colab which employs a Jupyter [42] environment at its core, we made use of various Python libraries. To store and read the datasets in hdf5 format we used h5py [21] and Pickle [68]. The pandas [47] library was employed to load datasets into RAM and handle them. For handling the large matrices and calculating we used NumPy [30]. To visualize the results we used Matplotlib [34] and Seaborn [73].

For easier implementation, such as of the t-SNE, a Scikit [55] and SciPy [70] libraries were used.

Chapter 4

Presenting Proposed LPs

This Chapter will provide an analysis and in-depth presentation of LPs from Section 2.3.3. In general, each profile has its use-case already assigned in Table 2.3. Here, we will focus on exposing the main features, issues, and use cases of the aforementioned LPs.

Using the same pattern as in Table 2.2, we will first present per-building LPs with different time ranges. We will begin with simple LPs and then progress to more advanced LPs with two-time dimensions. Secondly, following the same pattern, we will present per-appliance profiles. Finally, we will present per-building per-appliance LPs. The data for profiles in this chapter was used from building 2 from the REFIT dataset discussed in Section 3.1.

4.1 Time Ranges

Time ranges are an important part of the LP since each reveals a distinct usage pattern. Throughout the thesis, we used four different time ranges: daily, weekly, monthly and yearly.

The daily profiles are the most commonly used LPs, as can be seen in Table 2.2 In general, they are the easiest to build since they do not need as much data as the 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 LPs need a few months of data, monthly profiles need a few months, and yearly profiles need a few years. 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 in Table 2.2.

One more thing about time ranges that needs to be mentioned is the 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. On the other hand, 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.

4.2 Per-Building LPs

The section will focus on per-building profiles. Per-building profiles refer to representations where the whole building usage is presented as a single LP. This kind of presentation is useful for observing general activation trends in a building. Possible use cases for per-building LPs are grid management and energy saving.

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

The daily per-building LP is also known as the standard LP. According to Table 2.2 this is the most commonly used power profile. Figures 4.1a and 4.1b present usage patterns on different time ranges. These two profiles, therefore present different contextual cases.

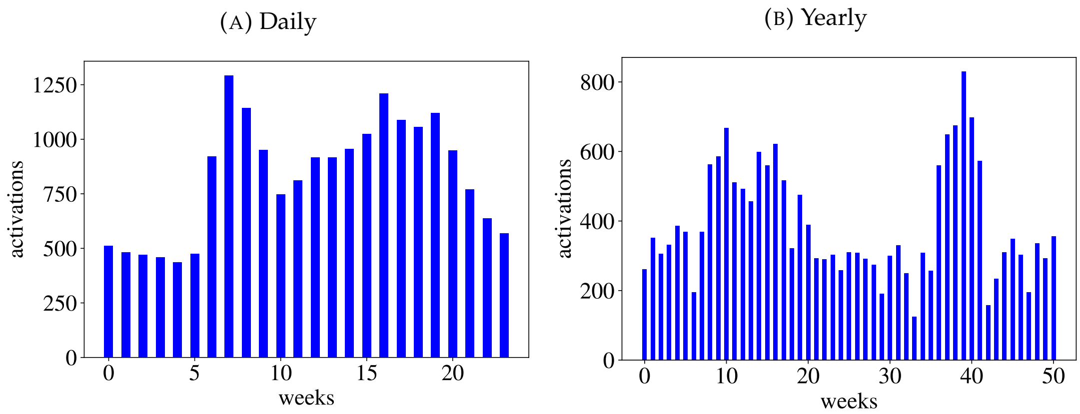


FIGURE 4.1: Per-building LPs

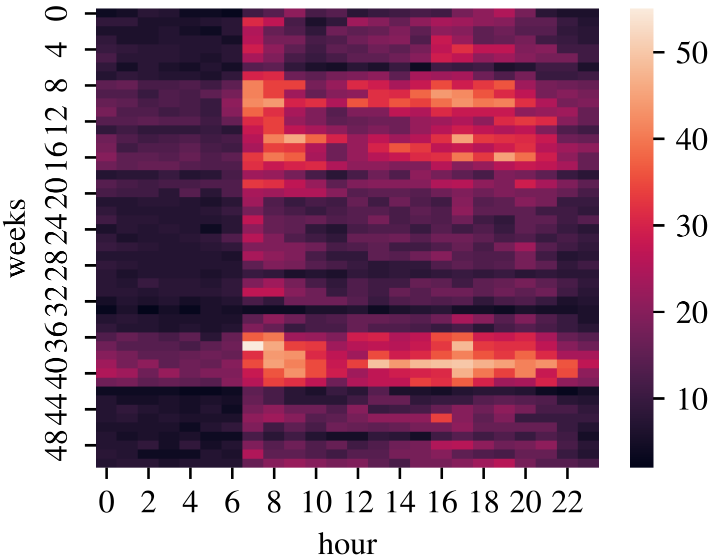
The first Figure 4.1a shows how activations change throughout the day. It is possible to see that there is some activity even during the night and early morning. These activations can mostly be related to fridges or other appliances that are not directly activated by users. Around 8 in the morning, it is possible to detect the first peak. This can be related to morning chores. Then, around noon, a dip occurs. The reason behind this is likely that the dwellers are not home. In the afternoon, the rate of activations slowly increases until it peaks around 19 o'clock. This slow rise could be a contribution of each dweller arriving home at different times of the day.

The second Figure 4.1b shows how activations change over the year. Again, it is possible to observe two peaks. One in the spring and the other in autumn. It is hard to correlate the activity with the seasonal effect since it seems like the activity is about the same in mid-winter as in mid-summer. The exact reason behind this pattern remains unknown.

4.2.1 Per-Building Two-Dimensional Time LPs

Alternatively, it is possible to combine Figures 4.1a and 4.1b and present activations as a heat map. The result is a Figure 4.2 showing more complex activation patterns.

FIGURE 4.2: Two-time-dimensional per-building LP



By combining the figures and presenting them with a heat map, additional features are revealed. For example, the black lines are those that likely present the vacation or other events where dwellers are away from home.

When analyzing Figure 4.1b it seems like dips in activity are for a similar reason, but Figure 4.2 shows these two dips from a different perspective. The peak activity in Figure 4.2 shows a routine or a pattern similar to what was seen in 4.1a, one peak in the morning and one in the evening. The same pattern can be observed in the winter dip, even though the pattern is less clear it is present. The same cannot be said for the summer dip in the middle of the plot. Here, while the morning peak is visible, the evening one can barely be detected.

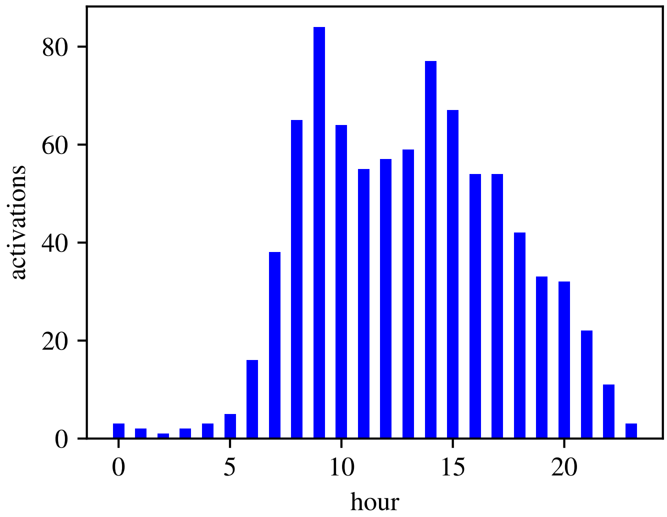
Another point to note is that the increased activity at the start of the fall indicates increased activity throughout the night and day. This could suggest that a new appliance was installed, which increased the number of activations.

Previously, in Section 2.2.1, it was mentioned that these kinds of profiles are the most applicable in grid management. One such example could be load shedding. Using the LP above, electrical energy providers could find buildings with the least activity at a particular time of day. By combining this with power data, they could disconnect the buildings with the least activity and most power consumption.

4.3 Per-appliance

Per-appliance LPs offer a look into the consumption of each appliance. In the case of activation LP, this is an elemental LP, as all other activation LPs are built on top of it. This also means that it is one of the most universal profiles since it can be used in the use-cases defined in Section 2.2

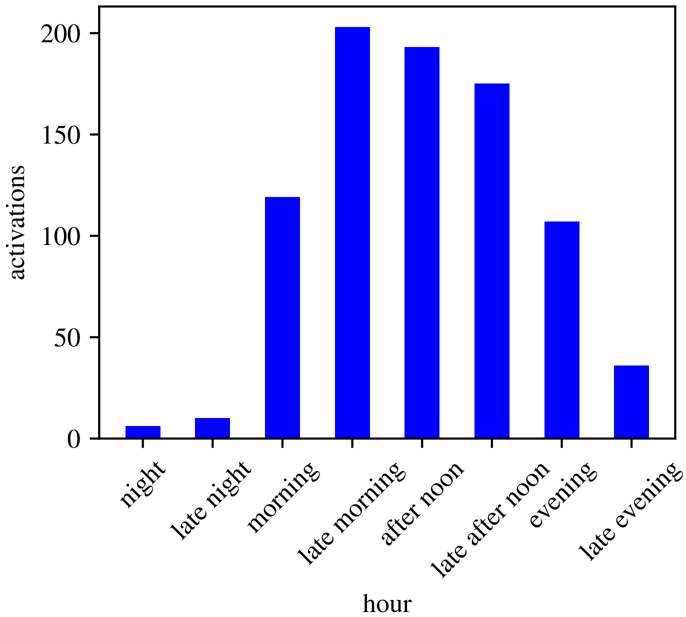
FIGURE 4.3: Daily per-appliance LP



Looking at Figure 4.3, we can detect a similar pattern as in per-building Figure 4.1a. While the peaks are closer together, the pattern remains. One thing to notice here is, that the washing machine is used only during the day. This means that this household does not use the cheaper nighttime tariffs.

Another parameter that was not explicitly mentioned before is the resolution of LPs. Histograms can be presented using various resolutions or numbers of buckets. An optimal number of buckets is one that presents the usage pattern clearly. The 3-hour bucket size in Figure 4.4 does a good job of presenting the appliance usage at the main parts of the day. This offers a better contextual presentation that is easier to process using algorithms. As we can see in Figure 4.4, by increasing the extent of buckets, the two peaks join together into one larger peak. This coincides with the point of the presentation, where we want to present a more general pattern in key parts of the day.

FIGURE 4.4: Daily per-appliance LP with larger buckets sizes

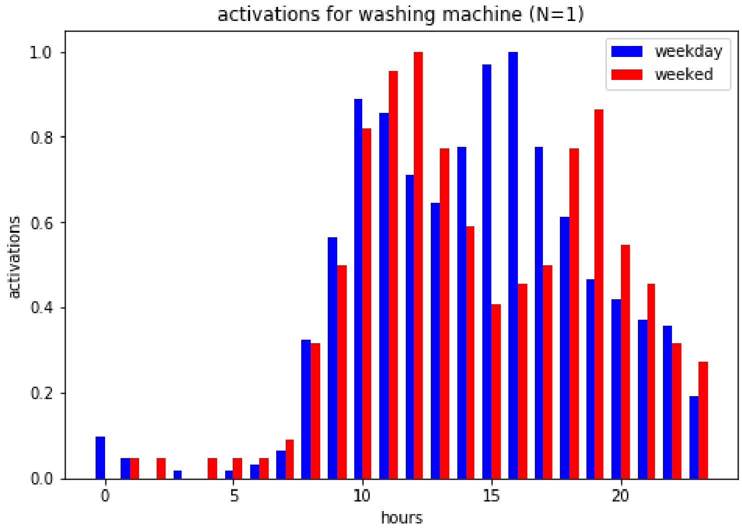


While the low resolution is useful for contextual presentation, high resolution is needed for time-sensitive applications such as elderly care, where we have to detect an accident as soon as possible. The hourly resolution would mean that in case of an accident, the system would need at least an hour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

In the case where 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 shown in Figure 4.5. This is essentially a variation of the weekly LP that maintains high resolution. Since there are more weekdays than weekend days, activations had to be normalized accordingly.

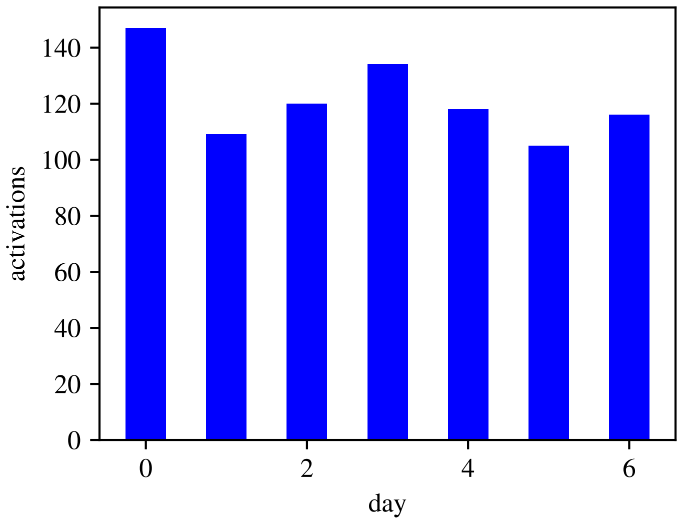
Figure 4.5 again shows the same pattern as seen in Figure 4.3. What we can observe here is how these two patterns are the same but are shifted in time. On weekdays the first peak occurs at around 10 AM and the second at around 3 PM. On weekends the first peak does not occur until 12 AM and the second at around 6 PM. This shift in the pattern shows that while there is a change in behavior between weekends and weekdays it is not a drastic one, at least in this case.

FIGURE 4.5: Normalized daily per-appliance with weekday and weekend LPs.



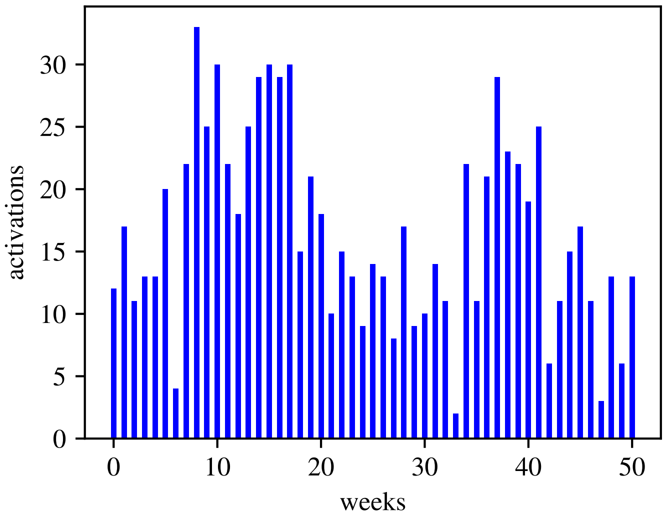
Another way to present weekly data is shown in Figure 4.6. In this case, weekdays are numbered, where 0 stands for Monday and 6 for Sunday. This resolution offers a look into how the consumption pattern changes over the week. This is useful for applications such as grid management or energy saving. In 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, the electricity provider could offer a low cost for energy on that day. This kind of presentation could also be used to detect daily anomalies.

FIGURE 4.6: Weekly per-appliance LP



In Section 4.1 we mentioned that the monthly presentation does not show any significant usage pattern, so it was not shown here. The yearly presentation again shows the more broad usage pattern, which can be seen in Figure 4.7. This is useful for grid management and energy saving, where one could detect seasonal changes in the usage of an appliance.

FIGURE 4.7: Yearly per-appliance LP

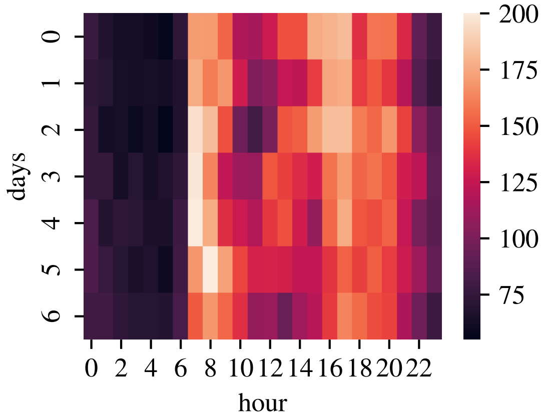


When comparing the pattern from Figure 4.7 to the pattern from Figure 4.1b it is possible to see the very same pattern. When making a quick comparison, they seem like the same image, But only when taking a closer look it is possible to see that differences do exist. We can make a similar conclusion here, as we did for Figure 4.1b. It is hard to do any deeper analysis without the metadata.

4.3.1 Two-Dimensional Time Per-Appliance LPs

Using a combination of Figures 4.3 and 4.6, it is possible to generate Figure 4.8.

FIGURE 4.8: Two-dimensional time per-appliance LP



In this case, a similar use-case could be fitted as in the first example in Section 4.2.1. The first example used load shedding when the demand was too high. However, it can also occur if 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 direct load control system or notify users to turn on appliances that they have previously used at that time. Due to the increasing percentage of renewable energy sources, more and more energy peaks will be weather dependent. By combining weekly wind forecasts, weekly cloud coverage, and user consumption profiles energy providers could notify users to turn on their appliances at peak usage times.

By analyzing Figure 4.8 it is possible to see that the user commonly uses a washing machine on Wednesdays from 15 to 16 o'clock. Should weather reports indicate high production peaks, the electrical provider could 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 the grid operator could regulate the demand instantly. By using LPs 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. The 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

Figures 4.9 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.

The Figure 4.9a shows how the computer usage changes over the year. In the first quarter, the computer was used from 10:00 a.m. to 8:00 p.m. In week 18 it is possible to observe that the computer is being less and less used throughout the day. Starting from week 40 it is again possible to see that the computer is getting more and more use in the morning hours. This is a good example of how can a usage pattern slowly change through the year. Since the pattern seems to bounce back, it could be seasonally correlated.

The second example is Figure 4.9b. It shows how TV usage changes over the year. Compared to the computer, it is possible to see that the pattern looks a lot more persistent with slight changes. Interestingly enough, when a close-up observation is made, it is possible to see that at the time when the computer was at its peak, the TV was at its low. And when the usage of the computers decreased, the usage of the TV increased. Due to the lack of metadata, it is difficult to know the exact reason behind it.

The advantage of this change is, that it takes a few weeks before it changes. This will be important later in Chapter 6 when we will be designing an elderly care system, that will be based on periodical user behavior. This slow change gives the system time to adapt.

One observation of quick behavior change can be made in weeks 8-11 and weeks 38-37, where we can see a black row on all three sub-Figures in Figure 4.9. The instant decrease in activity is probably a vacation.

The last Figure is 4.9c where the LP portrays the yearly use of the washing machine. In this case, the seasonal pattern is much clearer. It seems like the appliance was used in the early morning hours of the winter and early spring. This practice suddenly stops at week 13, and it reappears back in week 36.

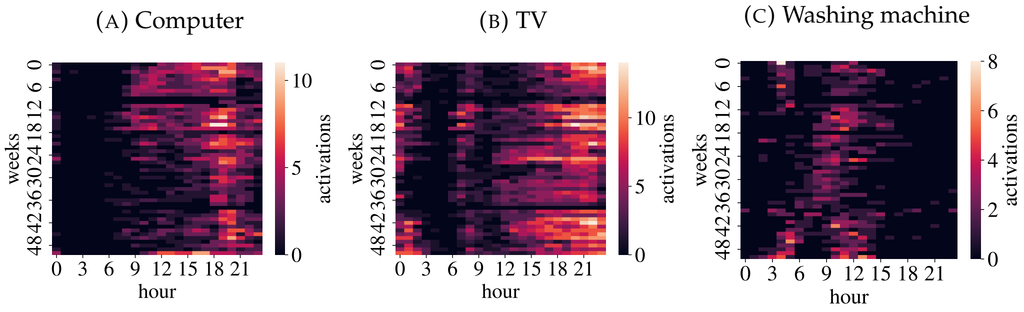


FIGURE 4.9: Various yearly two-dimensional LPs for building 4 from REFIT.

Another example worth mentioning is Figure 4.10 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.

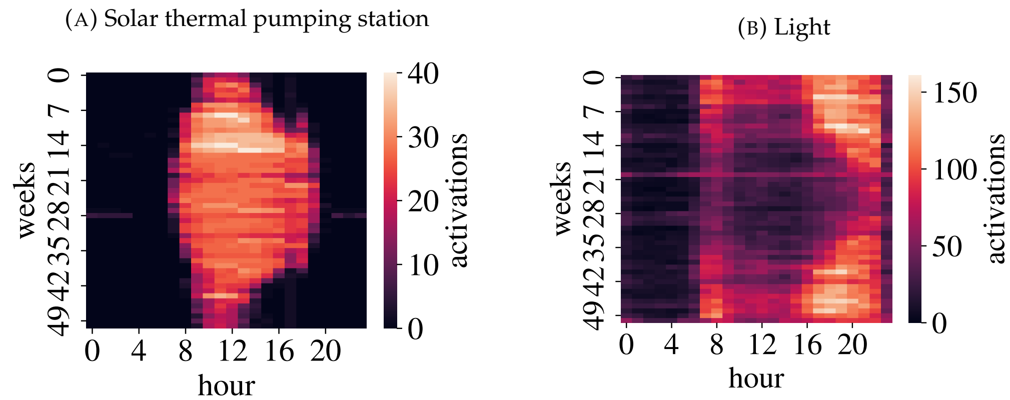


FIGURE 4.10: Effect of seasonal changes on LPs

Appliance on Figure 4.10a activates when water in solar collectors heats up to a certain threshold. Since water heats up based on the strength of solar radiation, we can observe the change in solar radiation throughout the year for the UK.

Appliance on Figure 4.10b on the other hand works quite the opposite. We usually turn on the light when the solar radiation falls below a certain threshold, and turn it off when we sleep. This Figure 4.10b is one of the best examples, where we can observe the combined effect of user behavior, in this case, sleep, and the seasonal effect of changing solar radiation on users' behavior.

Combining Figures 4.10a and 4.10b enables us to differentiate between the two.

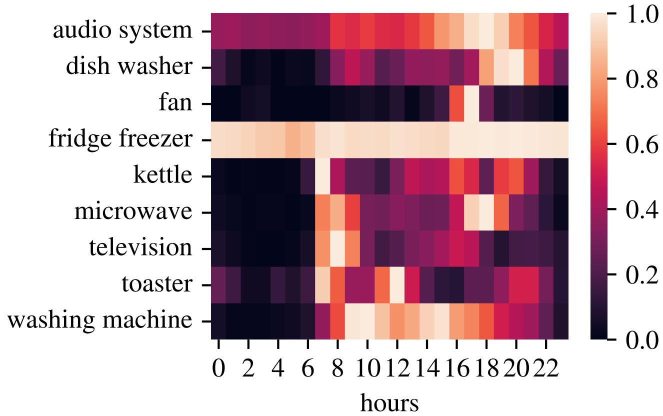
4.4 Per-Building Per-Appliance

The last group of profiles is a combination of per-building and per-appliance LPs. 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 a stove and kettle are commonly used together each morning this use could translate to an event such as breakfast. To achieve this, one needs to observe all appliances at once such as shown in Figure 4.11.

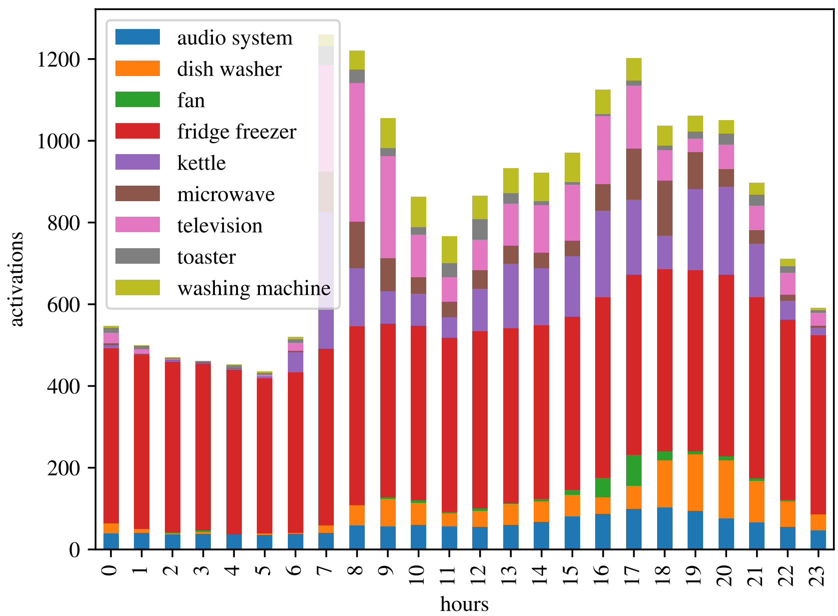
Figure 4.11 is also a good example of the elderly care system that would detect an anomaly such as a fall, or a person unable to get up from the bed in the morning. This profile shows that the first things used in the morning are a kettle and toaster, and with a delay of one hour, microwave and TV. This enables us to construct time thresholds in which appliances should be used. If none of these appliances are activated between set thresholds, the morning would be considered anomalous. Although less likely, issues could also occur during the use of appliances. In the case that an elder falls during cooking, toasting bread, or opening the 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 4.11: Daily per-appliance per-building building LP



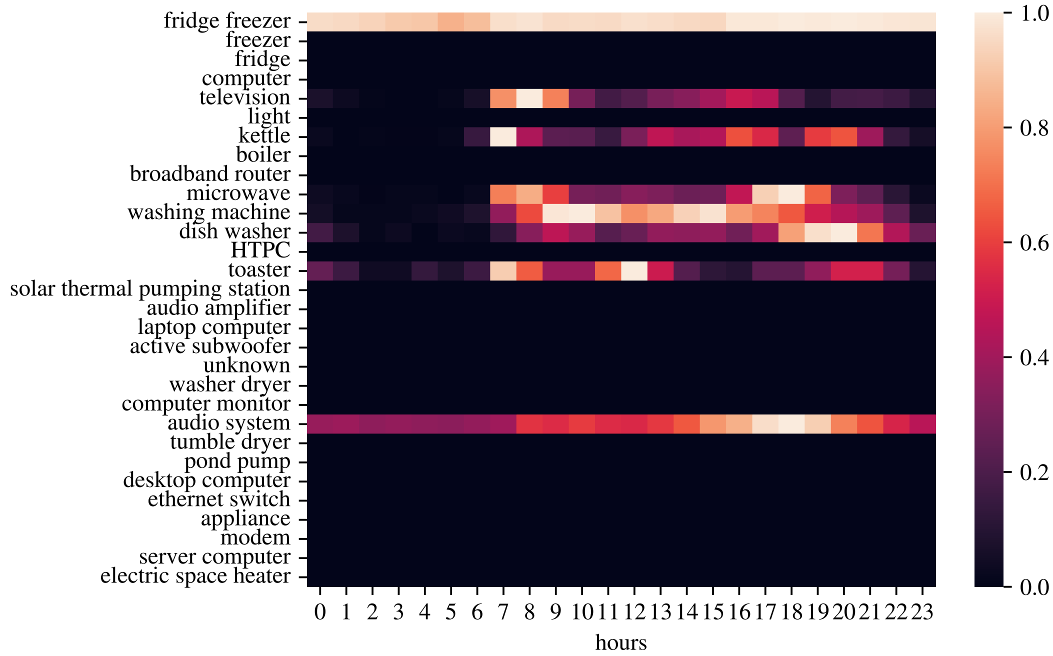
The very same data can be presented in an alternative way, as shown in Figure 4.12. The usage pattern is the same as that on 4.1a, except that it is possible to see the contribution of each appliance.

FIGURE 4.12: Stacked daily per-appliance per-building building LP



These LPs are useful when it comes to analyzing the usage pattern in one building. To be able to process the LPs across many buildings, a new profile, seen in Figure 4.13, must be introduced. The idea is derived from the bag-of-words method used in text processing, where a list of the 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 the number of activations, and then only the top 30 appliances are selected. Using this list, it is possible to present the usage of each building universally. This solves the issue of different appliances in different buildings.

FIGURE 4.13: Universal presentation of per-building per-appliance LP



While analyzing Figure 4.13, we can see that the fridge freezer is most commonly activated. Since there is no pattern and it is activated randomly, the pattern is presented as a white line. To balance the graph, we have normalized the activations. If we had not done this, we would observe only the fridge freezer due to its activation dominance.

Other, more dynamic appliances have a much clearer presentation of their activity. One other observation is that there are many empty LPs for certain appliances. This is because we have no data for these appliances for this household. This is likely one of the biggest weak points of this LP.

The Bag of appliances was not shown on the Table of profiles 2.8, as it is a special case of the per-building per-appliance profile shown in Figure 4.11.

4.5 Summary

This chapter demonstrated how some activation profiles from Table 2.2 present real-world data, analyzed the presentations and further elaborated on their use-cases.

It was possible to see how each LP presents its unique user activation pattern. Figure 4.1a offered us a unique look into how users behave on a daily basis and Figure 4.1b how this behavior changes over a year. Next, with Figure 4.2, we presented how combining these figures presents new features, that were otherwise hidden. Further on it was shown how the very same presentations can be used on appliance data, for example, Figure 4.10 showed how this yearly change could be affected by the seasons. Finally, we have shown how more detailed profiles 4.11 could be used for practical applications such as elderly care.

Chapter 5

Exploratory data analysis of LPs using t-SNE

5.1 Introduction

LPs can be used to understand the consumption patterns of appliances or buildings. The one thing they do not offer is a comparison between activation patterns. To achieve this, we can utilize various dimensionality reduction algorithms. In the process of dimensionality reduction, these algorithms map similar LPs closer together compared to dissimilar LPs. This enables us to have an insight into similar activation patterns across various entities. It enables us to visualize and compare LPs of buildings and appliances, to find the differences and similarities in their activation patterns.

In this chapter, we will explore the use of t-distributed stochastic neighbor embedding (t-SNE) for Exploratory Data Analysis (EDA) on LPs. The t-SNE is a nonlinear dimensionality reduction algorithm, used to visualize high dimensional data in usually two or three dimensions. We will delve into the details of what t-SNE is and how it can be applied to the LPs.

To achieve this goal, we will first provide a brief overview of t-SNE and its application to LPs. Next, we will describe our methodology for using t-SNE to analyze LPs and compare activation patterns. Finally, we will present the results of our analysis and discuss their implications for understanding energy consumption patterns.

The clustering of similar LPs has been researched many times before, as it was described in related work Chapter 2. We will be working with dimensionality reduction, where clusters are usually formed as a side product. The following clustering publications are worth mentioning. We have seen that authors [28], [36] and [1] have clustered regular one-dimensional LPs, as well as with 2D image-based load profiling in publications published by authors [52].

The publication by authors [3] compared various dimensionality reduction techniques for clustering and visualization of LPs. Their goal was to compare Principal Component Analysis, Isometric Feature Mapping, Sammon Mapping, Locally Linear Embedding and Stochastic Neighbor Embedding. They used daily power LPs from residential and industrial areas. This publication was the closest in resemblance to our goals, that we were able to find.

In all cases, work has been done with the power LP, whereas in this case, we will try to find similarities between activation profiles using a t-SNE algorithm. Most of the publications used single-time dimensions, whereas we will use two-time dimensions.

Although the use-cases were presented in-depth in Chapter 2, it is worth mentioning one specific use case. The increasing price of energy resources could lead to excessive saving and living in cool homes. By using similarity metrics between profiles across different buildings, it would be possible to detect outliers when it comes to heating. With this approach, it would be possible to detect users who are living in below-average cool homes and offer them cheaper plans.

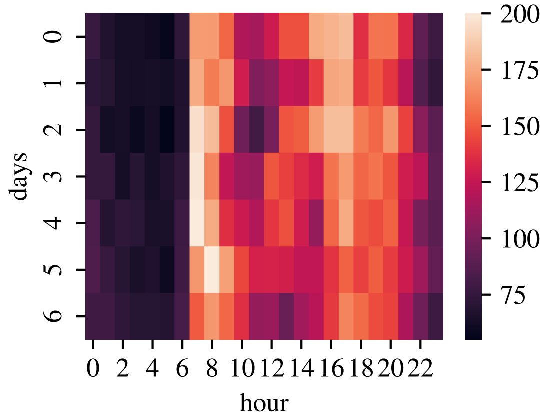
5.2 Methodology

5.2.1 LPs

Weekly-Daily LP

During testing, a weekly-daily LP constructed from a month of data will be used. Y-axis will present the days in a week and X-axis will present the hours in a day. Weekdays are labeled from 0 to 6, and hours from 0 to 23. Since we are working with images, the origin is placed in the upper-left corner. This means that a pixel in the upper-left corner represents the first hour of a week, this would be a Monday from midnight to one o'clock. The lower-right corner represents the last hour of the week. Since there are roughly 4 weeks in each month, each pixel will represent 4 samples. One such example of profiles that we will use, was already presented in Chapter 4 with Figure 4.8. For practical reasons, we are presenting it again here with Figure 5.1.

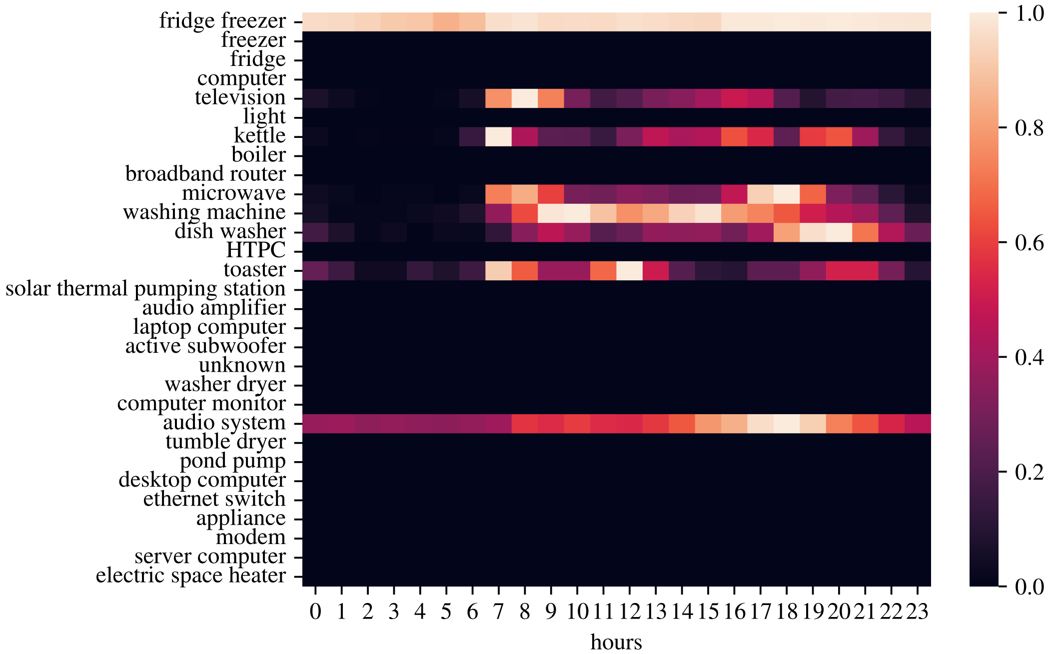
FIGURE 5.1: Weekly per-appliance LP



Bag of Appliances LP

Another LP that will be used at the end of this Chapter will be the bag-of-appliances LP. The profile was presented and analyzed in depth in Chapter 4 and was presented in Figure 4.13. But again, for ease-of-use purposes, we will summarize the profile here.

FIGURE 5.2: Universal presentation of per-building per-appliance LP



To build the profile seen in Figure 5.2, we used the data from all 5 datasets and made a list of the most commonly used appliances. Only the top 30 appliances were selected. This enables us to have the same LP for all buildings and thus enables us to see how the usage differs across them.

One problem that arises here is the missing appliances. These appliances present themselves as a black line. A lot of missing appliances may cause the image to be primarily black, which could cause trouble for the algorithm processing this as an image.

5.2.2 Normalisation

Activations portrayed in a heatmap must always be normalised in order for color (heat) to be properly mapped. We need to ensure that the LPs fed into t-SNE match our perception in order to achieve meaningful results we can interpret. To achieve this, we will use min-max scaling seen in Equation 5.1 below.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{5.1}$$

Where x is the value being scaled, x_{min} is the minimum number of activations in the LP, x_{max} is the maximum number of activations in the LP, and x_{norm} is the output normalised value.

5.2.3 Measuring LP Similarly

The similarity of the LPs will play an important role in the analysis, as it will be used as a base of the t-SNE cost function. The activations in LPs can also be thought of as n-dimensional vectors, where each bucket is the nth dimension and the activation magnitude is their length. Once LPs are presented as a vector, we can use tools from linear algebra to calculate their similarity.

One way to calculate the similarity between two points is by calculating the Euclidean distance, where we calculate the square root of the sum of squared differences.

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{5.2}$$

Where x and y are n-dimensional vectors. The result of the Euclidian distance is not limited and can be anywhere from 0 to infinity. Alternatively, we can use the cosine similarity Equation 5.3, where the results are limited between -1 and 1. 1 would mean that both vectors point in the same direction, 0 that they are orthogonal, and -1 means they point in opposite directions.

$$cosSimilarity(X,Y) = \cos(\theta) = \frac{X \cdot Y}{\|X\|\|Y\|} = \frac{\sum_{i=1}^{n} X_i Y_i}{\sqrt{\sum_{i=1}^{n} X_i^2}\sqrt{\sum_{i=1}^{n} Y_i^2}} \tag{5.3}$$

In the above equation, X and Y are n-dimensional vectors. The dot product of X and Y is divided by the product of their magnitudes to obtain the cosine similarity. The magnitude is also known as $L2$ Euclidian normalization. An important feature of cosine similarity is that it's not affected by the magnitude of the vectors. To include the magnitude, we can use Pearson's correlation coefficient seen in Equation 5.4.

$$corr(X,Y) = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \tag{5.4}$$

Where X and Y are n-dimensional vectors. The correlation is calculated with the summation of the product of the centered vectors, obtained by subtraction of the mean of the vectors X and Y. This is divided by the product of their standard deviations to obtain the Pearson correlation coefficient. As mentioned, an important feature of correlation is that it measures the strength as well as the direction of two vectors. Correlation values range between -1 and 1, where the interpretation follows the same logic as cosine similarity.

What is most interesting here is that equations 5.3 and 5.4 look very similar. The main difference is that 5.3 takes into account individual vectors, whereas 5.4 first centers the vector using the mean value of all vectors and then computes the similarity. Another difference is the naming of elements in the denominator. In cosine similarity, we used $L2$ Euclidian normalization whereas, in the correlation equation, we used standard deviation. While these two are not the same, they play the same role of normalizing the numerators.

5.2.4 Data

We have on average roughly one year of data per building. In some cases a few weeks and in others up to 5 years for some appliances. By slicing this data into 1-month-long intervals and converting them to LPs we were able to obtain 5218 samples.

More detailed methodological approaches were discussed in Section 3.1.

5.2.5 T-SNE Algorithm

The t-SNE [46] or t-distribution stochastic neighboring embedding is a method for portraying high dimensional data in low dimensional space. This process is also known as dimensionality reduction.

One of the well-known dimensionality reduction algorithms is PCA. The key difference between the two is that one is linear, and the other is non-linear. PCA, linear, projects data in new space and finds the one with the least variance between data points. SNE [32], non-linear, is composed of two main parts. The first one is converting the high-dimensional Euclidean distances between data points into conditional probabilities that represent similarities [32]. The pairs with high similarity have a high probability, and pairs with lower similarity have a low probability. Second, it uses Kullback-Leibler divergence to minimize it with respect to a location on a map. To achieve this, it uses gradient descent to minimize the cost function. Over many iterations, similar data points should be close together and far away from dissimilar objects. Similar data points usually form clusters. t-SNE uses SNE as a basis, except that it uses a t-student distribution instead of normal to calculate the similarity.

A good example that showcases the non-linearity of t-SNE can be seen in Figure 5.3. In this simple task, projecting all data points to the y-axis would leave us with a different solution than the one we can see on the right.

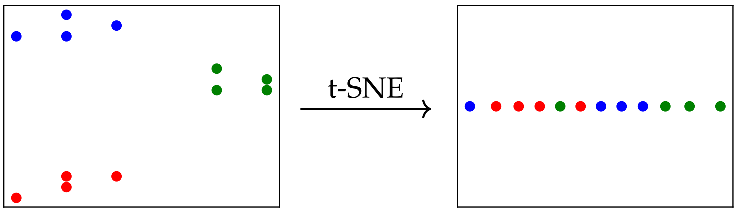


FIGURE 5.3: 2D data point transformed into 1D data point using t-SNE

In order to calculate the t-SNE for a set of data points, we first need to calculate the conditional probability. This is calculated based on the Equation 5.5 below. The author of t-SNE, Van der Maaten [46], states: "The similarity of datapoint x_j to datapoint x_i is the conditional probability, p_{ij}, that x_i would pick x_j as its neighbor if neighbors were picked in proportion to their probability density under a Gaussian centered at x_i."

$$p_{ij} = \frac{\exp(-\|x_i - x_j\|^2/2\sigma_i^2)}{\sum_{k \neq l} \exp(-\|x_k - x_l\|^2/2\sigma_i^2)} \tag{5.5}$$

In Equation 5.5, x_i and x_j are two data points and $|x_i - x_j|$ is the Euclidean distance between the two. The numerator in Equation 5.5 is equal to the similarity between two points normalized by the variance $2\sigma_i^2$. The whole expression is run through the $exp()$ function to ensure the value stays positive and within boundaries. The denominator in Equation 5.5 serves as a normalization factor, to ensure that the sum of probabilities for data point x_i will sum to 1.

The σ_i, also known as Gaussian bandwidth, Gaussian kernel, or just variance, is picked for each data point based on the number of neighbors in its vicinity. In areas where data points are more crowded, σ_i is usually smaller than in less crowded areas. It is pre-calculated for every point using binary search. A search is complete when σ_i outputs probability distribution P_i that matches user-defined perplexity $Perp(P_i)$.

$$Perp(P_i) = 2^{H(P_i)}$$

Here, $H(P_i)$ is the entropy of the conditional probability distribution P_i. The entropy of the conditional probability distribution is a measure of perplexity. Perplexity is one of the parameters defined by the user, and it's used as a measure of the number of effective neighbors, between which we will compute similarities. High perplexity means that the distribution of the Gaussian kernel will be wide and contain more data points between which similarity will be computed. Low perplexity means that the kernel will be narrow, so fewer data points will fit into it and therefore fewer data points will be compared.

The output of the algorithm is a map of every data point y_i. These points are low-dimensional counterparts of x_i. Usually, these data points contain a comprehensible number of dimensions where $y_i \in \mathbb{R}^2$ or $\mathbb{R}^3$. Similarly, as in Equation 5.5, we can now use low-dimensional data points y_i and y_j to calculate probability q_{ij} in Equation 5.6. Here, t-student distribution with one degree of freedom is utilized to calculate the similarities.

$$q_{ij} = \frac{(1 + \|y_i - y_j\|^2)^{-1}}{\sum_{k \neq l}(1 + \|y_k - y_l\|^2)^{-1}} \tag{5.6}$$

q_{ij} is again a conditional probability of finding y_i and y_j near each other but for fewer dimensions.

Setting up a cost function, which tries to minimize the difference between q_{ij} and p_{ij}, should result in a low-dimensional map where similar points should be near each other. The cost function is also known as Kullback-Leibler divergence seen in Equation 5.7. The equation is the sum of all pairwise similarities between low and high-dimensional data points. The smaller the C, the closer the similar data points are in the low-dimensional space

$$C = \sum_{i \neq j}^{n} p_{ij} \log \frac{p_{ij}}{q_{ij}} \tag{5.7}$$

The similarity is achieved over many iterations where we use gradient descent to minimize the Kullback-Leibler divergence seen in Equation 5.7. The process can be seen in Figure 5.4.

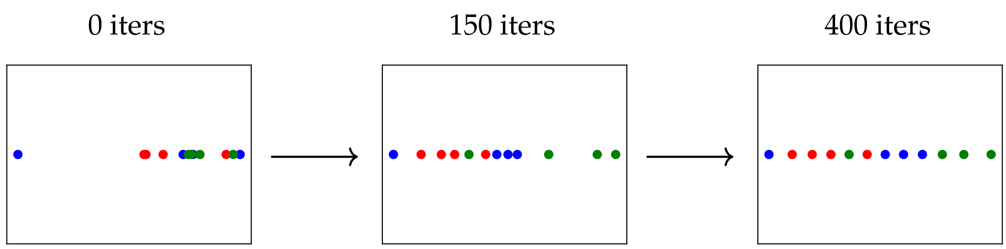


FIGURE 5.4: Iterations of t-SNE
The input data can be seen in 5.3

In our case, two dimensions will be used. Since this is a non-linear dimensionality reduction, the axes usually represent dimensions that are hard to comprehend by the brain. It is important to keep in mind that the resulting low-dimensional representation is not necessarily interpretable in the same way as the original high-dimensional data. This also means that the axes labels on the graphical presentations are meaningless. In our case, we labeled the two axes as $dimension - 1$ and $dimension - 2$.

5.3 Results

The results will be presented in three subsections

- Per-building LP
- Per-appliance LP
- Per-building per-appliance LP

The following figures are best viewed in color and in a digital format. In the analysis, the reader can use the first figures to identify buildings and the second to identify the patterns and actual LPs. Readers reading the digital version should have the ability to zoom into each cluster and see the actual samples. Readers reading a paper version can still explore the high-resolution figures online via the provided link below every figure.

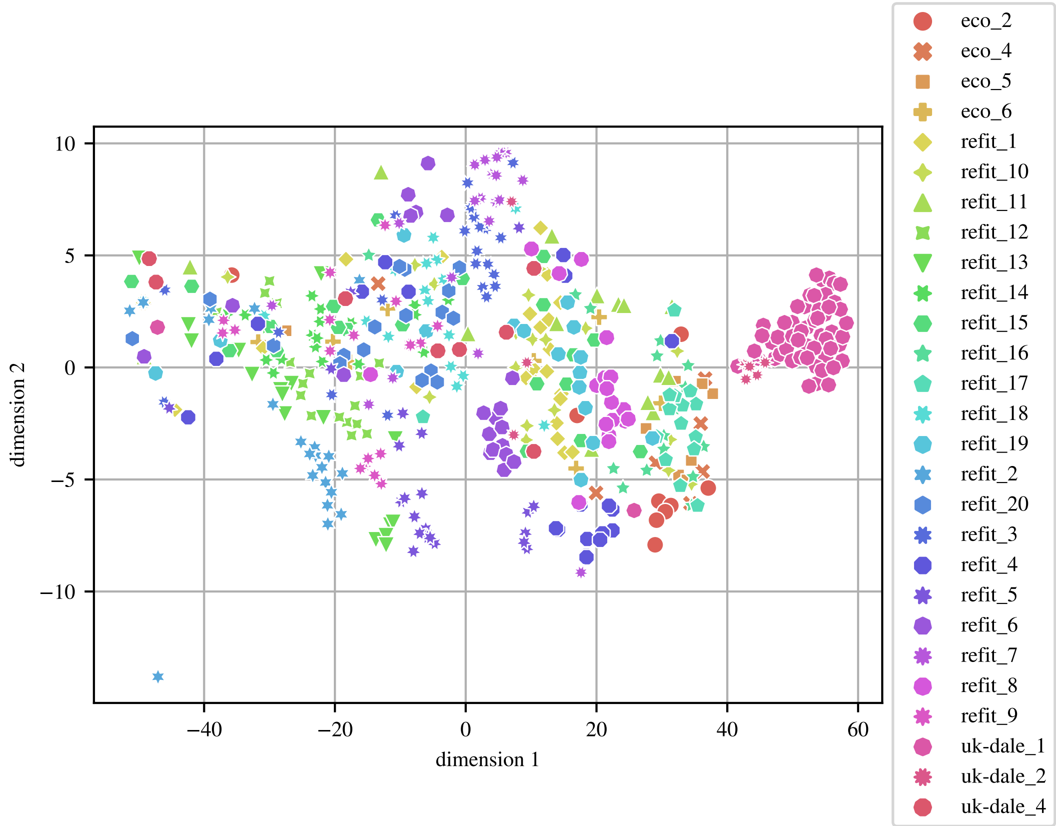
5.3.1 Results for Per-Building LPs

This LP is useful when it comes to comparing how activation patterns change over buildings and datasets. Per-building data uses combined activations of all appliances to present the aggregated usage pattern.

This section will first address non-normalized LPs and later move on to normalized LPs. We have already addressed the methodology on normalization in Section 5.2.2. By normalizing the data, we are essentially removing information from the LP. This information contains knowledge of the number of appliances in a building and their usage intensity. Knowing the two could be useful in scenarios where we are analyzing the magnitude of usage and not the patterns themselves.

Figure 5.5 uses non-normalized data, meaning the number of appliances in a building will affect the end LP. The algorithm could pick up on how many and how much appliances are being used. In some cases, such as energy poverty detection, this information is useful, as we are searching for buildings that exhibit reduced activation patterns.

FIGURE 5.5: Projection of per-building LPs



Full resolution figure: `https://github.com/jenkoj/msc/tree/main/Figures/TSNE/TSNE_per_building/scatter_per_building.pdf`

FIGURE 5.6: Projection of per-building LPs with actual samples

Full resolution figure: `https://github.com/jenkoj/msc/tree/main/Figures/TSNE/TSNE_per_building/img_scatter_per_building.png`

Figure 5.6 displays the LP for each sample. T-SNE provides an intuition of how LPs are connected in higher-dimensional space, and through analysis, we can find clusters with similar usage patterns. Figure 5.6 shows that the left side has mostly samples with little activity, and the right side has more activity.

When looking at Figure 5.5, we can observe a clear pink colored cluster of LPs from UKDALE 1 and UKDALE 2, which contain plenty of appliances and may explain why they have many activators. Some less obvious clusters formed in the bottom section for REFIT buildings 2, 3, 5, 6, 4, and 8.

There are no recognizable patterns in the central part of the plot. Since there are no patterns, such LPs do not form clusters. The reason behind non-recognizable patterns is possibly because appliances like fridges contributed the majority of activations, which are not affected by the dweller, leading to random activations. Similarly, there are no clusters in the far-left part of the plot because those profiles lack enough information to distinguish them.

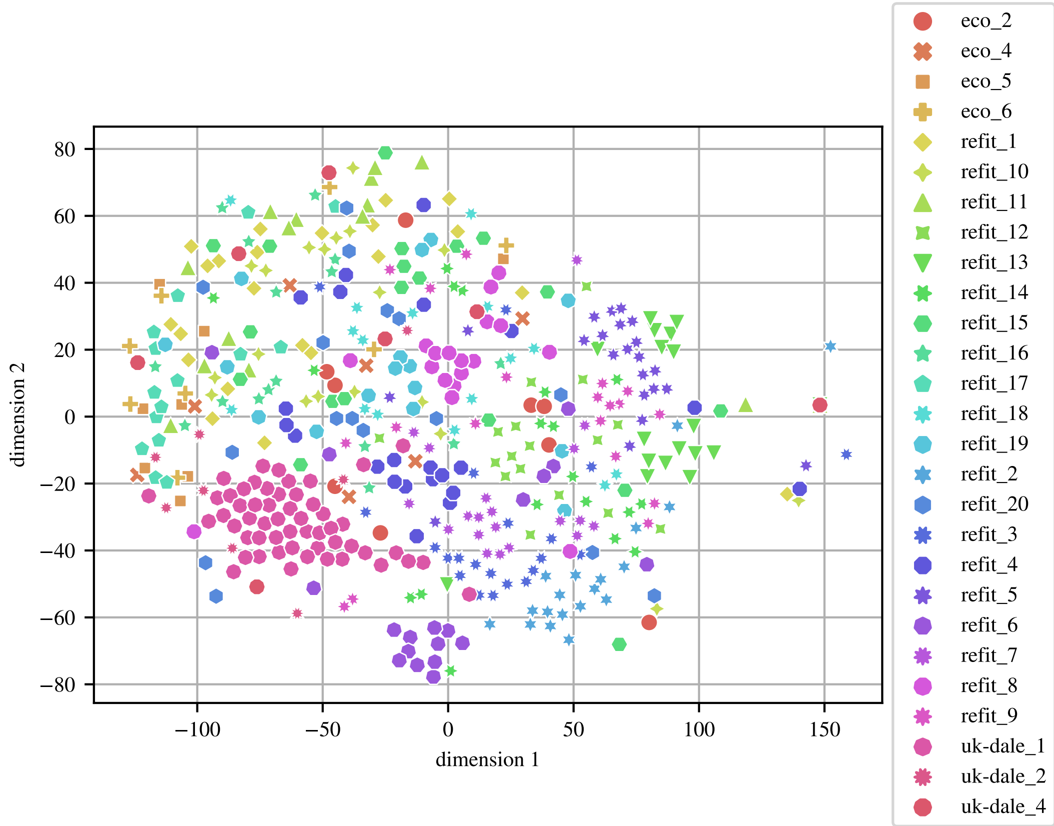
Even though the activations of LPs contained non-normalized activations, some clusters of buildings are quite close to each other. Here we have to keep in mind the fact that through current presentations we can only observe usage patterns and not usage intensity, which was used as an input to t-SNE. This implies that these buildings have similar usage intensities but not necessarily usage patterns. We can confirm this, by looking at Figure 5.6, where it is hard to find what similarities between buildings and clusters that are close together.

Normalized LPs

The issue mentioned in the previous Section 5.3.1 can be addressed by normalizing the data between 0 and 1 as mentioned in methodology Section 5.2.2. The normalization should enable t-SNE to focus on finding similarities between the usage patterns.

Figure 5.7 illustrates how normalization affects the algorithm. By comparing Figures 5.5 and 5.7, we can observe that the samples in the latter are much closer to each other, while still retaining the individual clusters. This outcome is expected because normalization removes information regarding the number of appliances in the building. With a reduced amount of information, LPs become more similar, and therefore clusters are closer together.

FIGURE 5.7: Projection of normalized per-building LPs



Full resolution figure: `https://github.com/jenkoj/msc/tree/main/Figures/TSNE/TSNE_per_building/scatter_per_building_norm.pdf`

When observing the LPs in Figure 5.8, we can confirm that similar clusters are closer together. In this case, the input of the algorithm was the same as our perception of the LPs. Upon closer look, we can see a gradual and smooth change in patterns as we move across the plot. If we recall from before, that was not the case in Figure 5.6, where we were analyzing non-normalized LPs. This observation is important, as it is visual proof, that normalization did help the t-SNE to focus on the usage patterns.

FIGURE 5.8: Projection of normalized per-building LPs with actual samples

Full resolution figure: https://github.com/jenkoj/msc/tree/main/Figures/TSNE/TSNE_per_building/img_scatter_per_building_norm.png

Upon closer inspection of Figure 5.8, we can see that the general pattern is that there is less activity during the night, with one peak in the morning and evening hours. Some buildings are more active during the week, and again, some are more active during the weekend. A significant amount of the data is from UK-DALE 1, colored pink. It is possible to see that the building has one large cluster where activations are generally similar, with few outliers where the pattern completely changes. This phenomenon occurs due to events such as vacations, holidays, or weather-induced behavioral changes.

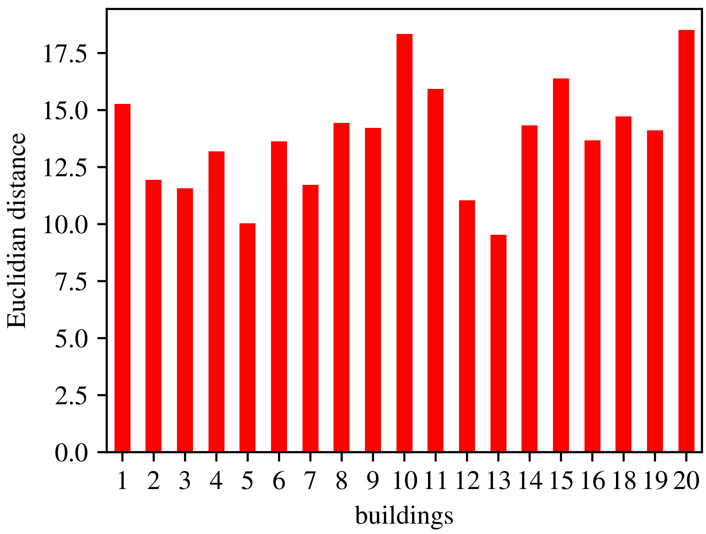
The key difference between non-normalized and normalized LPs is that non-normalized LPs enable t-SNE to identify similarities in the number of appliances and their usage intensity. In contrast, normalized LPs force t-SNE to focus on similarities in the actual usage pattern. Normalized LPs provide information about when appliances are likely to be used throughout the day, while non-normalized LPs offer insight into the magnitude of appliance usage.

Based on the above observations, we could infer that usage patterns are more similar than the number of activations across buildings.

Euclidian distance of samples for every building

A significant observation is that LPs closer together have more similar consumption throughout each month. By measuring the distance between LPs of the same building, we can estimate the strength of the household's routine. Figure 5.9 presents the Euclidean distance between samples for a given building. The larger the value, the longer the distance and the less similar the consumption through each month is.

FIGURE 5.9: Euclidean distance of samples for every building on normalized LPs



The methodology and the equation for calculating Euclidean distance were thoroughly discussed in Section 5.2.3. Since t-SNE uses Euclidean distance as its basis, we essentially measured the values of the last t-SNE iteration.

As we will use the Euclidean distance plot in the next Chapter, 6, for comparison, we have used only samples from the REFIT dataset. A more detailed analysis will follow in this chapter as well. For now, we can observe that the buildings with the most similar consumption patterns are 5 and 13. They both lie on the right side of the plot and have a similar activation pattern, with very few activations throughout the weekdays. This observation could suggest that people with steady jobs have very steady consumption patterns.

5.3.2 Per-Appliance

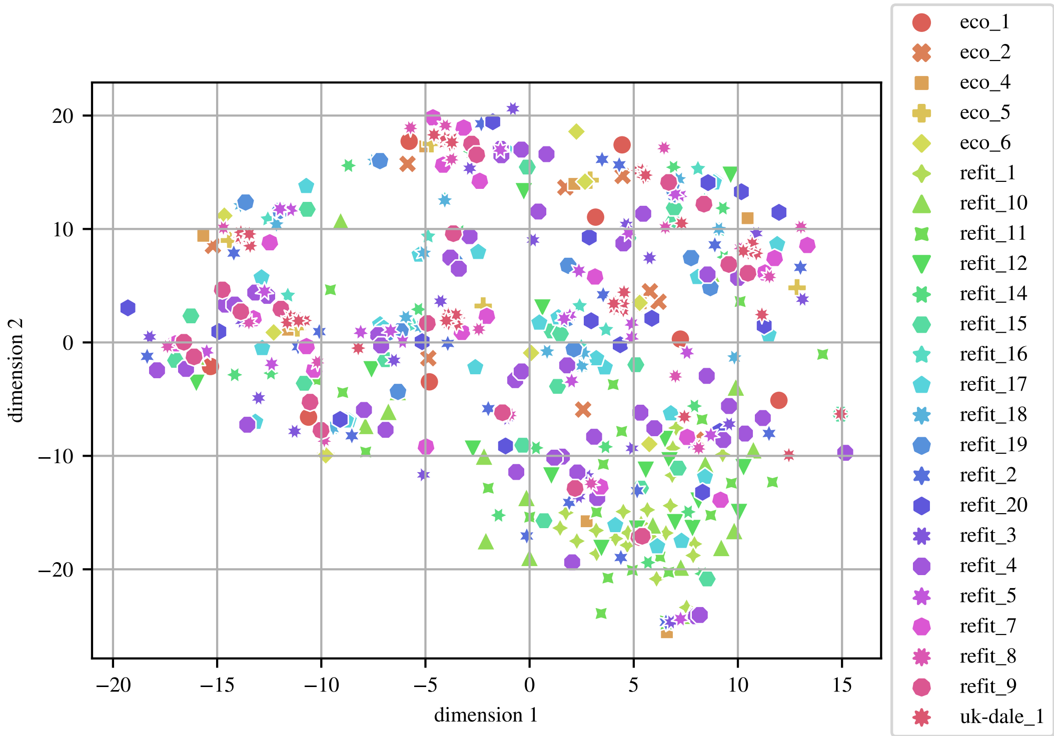
We can use per-appliance LPs to examine how different appliances are used in a single building, how a single appliance is used across various buildings, or how many appliances are being used in many buildings. Per-appliance LPs are built using sub-meter data, meaning each LP should represent each appliance.

Single Appliance Over Many Buildings

Using one appliance and the building as a label allows us to examine how the same type of appliance is being used across different buildings.

Fridges are generally a poor indicator when it comes to user behavior since the user does not significantly affect its operation. The only case when the user interacts with it is when opening the door and turning on the light inside. Usually, this event is dwarfed by the activations of a compressor. This also implies that the usage pattern should be the same across all buildings. This can be observed in Figure 5.10, where, apart from REFIT buildings 1 and 11, there are no distinct clusters.

FIGURE 5.10: Projection of fridge LPs for various buildings

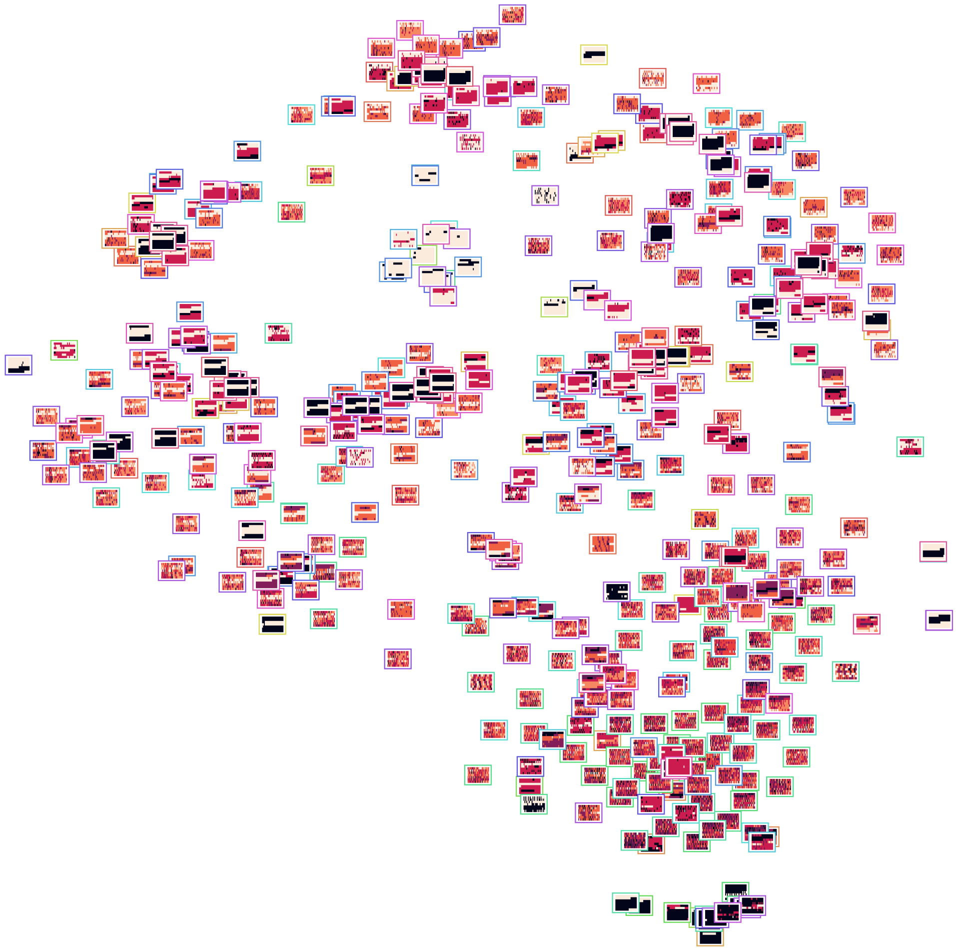


Full resolution figure: `https://github.com/jenkoj/msc/tree/main/Figures/TSNE/TSNE_per_appliance/scatter_refit_fridge_freeezer_fridge_freezer.pdf`

Figure 5.11 shows mostly bright images, apart from a few outliers. LPs scattered in a circle are generally less dynamic than the ones at the bottom.

Figure 5.11 is a good example of how LPs, with little to no human interaction, can look a lot different. This could be due to the different makes of the appliances, malfunctions of the appliance, or the meter measuring it.

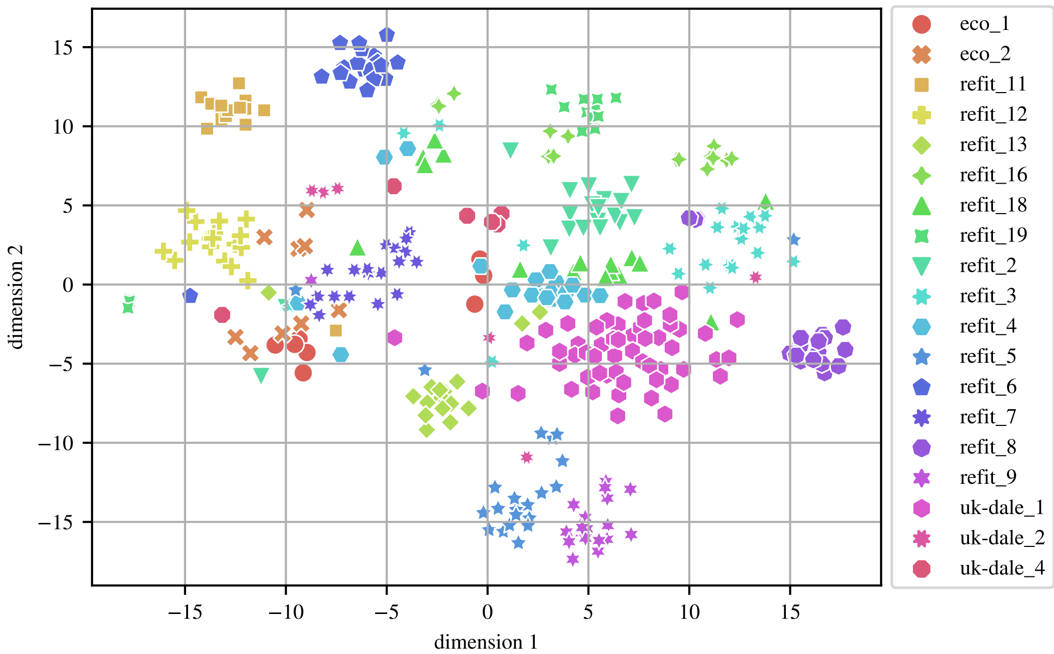
FIGURE 5.11: Projection of fridge LPs for various buildings with actual samples



Full resolution figure: `https://github.com/jenkoj/msc/tree/main/Figures/TSNE/TSNE_per_appliance/img_scatter_refit_fridge_freeezer_fridge_freezer.png`

Figure 5.12 shows how, compared to fridges, kettles have many clear clusters that are spaced out from each other. This could mean that every household uses a kettle a bit differently. These clusters are a good example where we can observe the strength of a user's routine. The closer together the samples in individual clusters are, the higher the routine, since samples are more similar to each other.

FIGURE 5.12: Projection of kettle LPs for various buildings

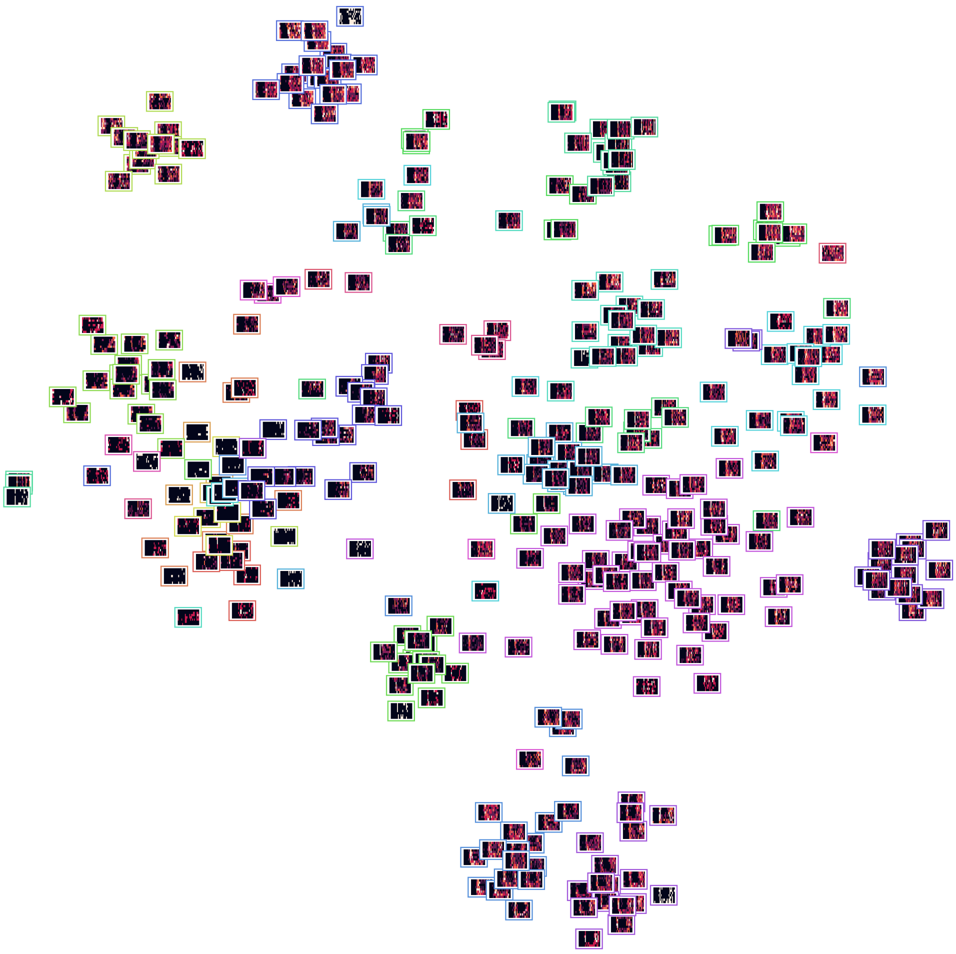


Full resolution figure: `https://github.com/jenkoj/msc/tree/main/Figures/TSNE/TSNE_per_appliance/scatter_refit_kettle.pdf`

Figure 5.13 shows us that images on the lower part of the plot contain less activity than the others. LPs that are closer together have more similar activation patterns. Similar activation patterns are caused by similar behavior, which is essentially a routine. This means that this projection could be used to calculate how much behavior varies in time for each building. This could be calculated by measuring the scattering of samples (variance) for each building.

If we find samples that always activate in the same morning buckets, we would see that they form a straight line on the y-axis. This is the daily routine. One such example can be seen in Figure 5.12 in cluster REFIT 5 and REFIT 9, where we can see the lines and the pattern throughout the day. Since the routine is present, the samples look more similar and are therefore closer together. This does not necessarily mean that the closer the samples, the higher the routine. They could also be together in the case of "ordered chaos," such as can be seen in Figure 5.12 for buildings REFIT 16 and REFIT 8, where there is no pattern throughout the day. So, scattering is not a precise metric when it comes to routine, but it gives us a rough idea of its presence. As mentioned earlier in this chapter, the strength of a routine is an important feature that will be used in Chapter 6, where we will build an elderly care anomaly detection system.

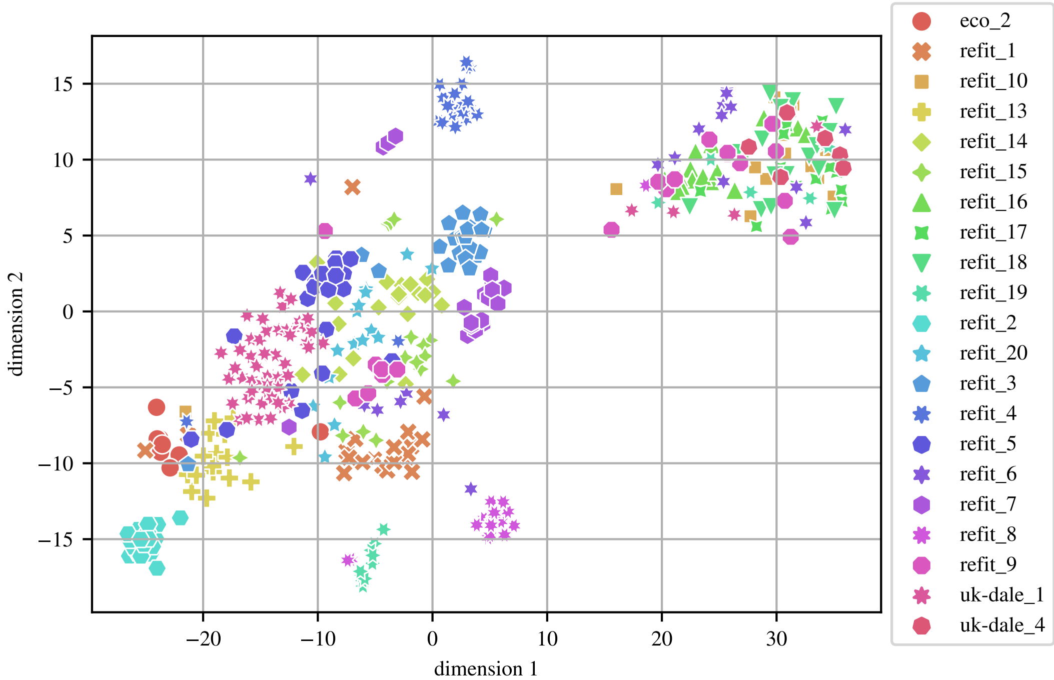
FIGURE 5.13: Projection of kettle LPs for various buildings with actual samples



Full resolution figure: `https://github.com/jenkoj/msc/tree/main/Figures/TSNE/TSNE_per_appliance/img_scatter_refit_kettle.png`

The last per-appliance example is a television presented in Figure 5.14. Television was chosen since it is the most commonly occurring appliance. Interestingly enough, televisions form nice clusters with a few outliers. Clusters are separated but close together; this could mean that usage patterns across buildings are unique but not that different from one another. The LPs in some clusters are also close to each other, which could also indicate a higher routine.

FIGURE 5.14: Projection of TV LPs for various buildings



Full resolution figure: `https://github.com/jenkoj/msc/tree/main/Figures/TSNE/TSNE_per_appliance/scatter_refit_television.pdf`

The images in Figure 5.15 prove the fact that outliers' consumption is significantly different. Again, the bright images could be the results of faulty appliances, faulty meters, or simply unusual behavior. Figure 5.15 also enables us to see that TVs are primarily used in the evening hours. Outliers from the main cluster show slightly different behavior. One such example is the blue cluster (building REFIT 4), where appliances are mostly used in the morning hours. Another interesting observation can be made when looking at the purple cluster. This is the far low cluster for building REFIT 8. Here, the TV is being consistently used every day in the early morning hours. This is portrayed as a straight line. There could be two possible explanations for this. The first is a high routine of a user, who turns on the TV every morning to listen to the news. The other is that the TV updates itself every morning. This is probably not the case since updates do not occur on a regular basis. What is also interesting, is that the same pattern can be observed in a few other buildings, one example being building REFIT 19.

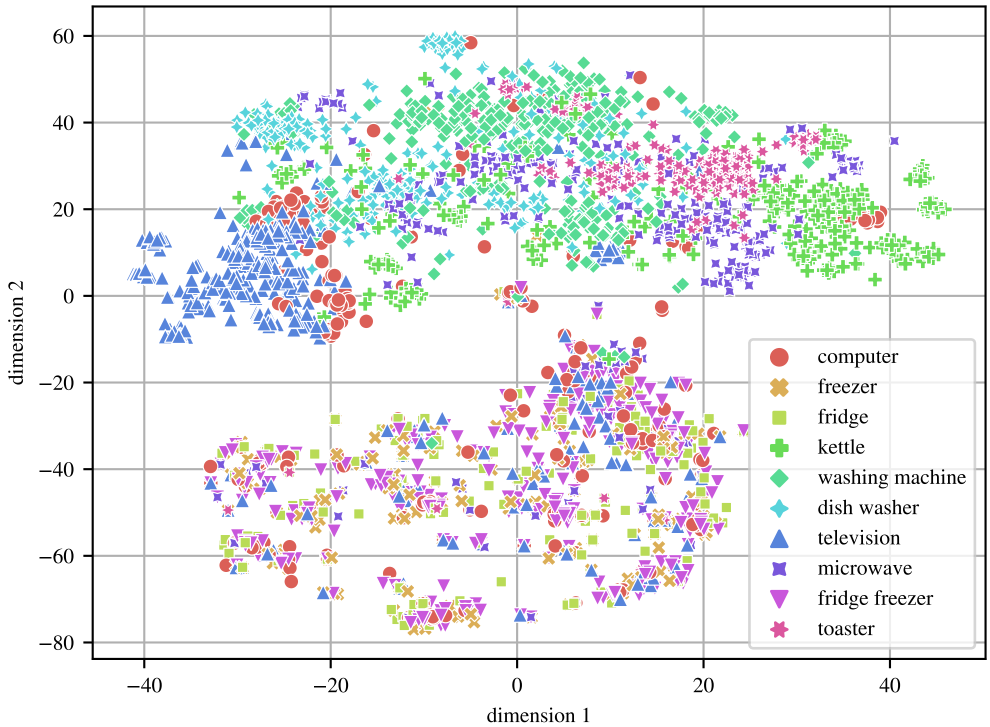
FIGURE 5.15: Projection of TV LPs for various buildings with actual samples.

Full resolution figure: https://github.com/jenkoj/msc/tree/main/Figures/TSNE/TSNE_per_appliance/img_scatter_refit_television.png

Per-Appliance LPs - Comparing Appliances

To get a general idea of where each appliance group lies, let's filter out all appliances that have less than 150 samples. Applying this filter yields Figure 5.16.

FIGURE 5.16: Projection of filtered per-appliance LPs



Full resolution figure:
https://github.com/jenkoj/msc/tree/main/Figures/TSNE/TSNE_PHPA/phpa_reduced_15.pdf

Figure 5.16 shows how these 10 appliances are connected in high-dimensional space. Kettles, microwaves, and toasters are quite similar when it comes to usage patterns. They are operated for a short amount of time and are typically used in users' routines in the morning or evening. These appliances are located in the upper-left part of the plot. The second group of appliances that are quite near each other is white goods (excluding fridges) such as washing machines, dishwashers, and dryers. We can refer to them as white goods with a program. This group of appliances is located in the upper-right part of the plot. The third group of appliances is white goods with a compressor. They are usually not affected by human interaction and are, therefore, harder to cluster. They are located in the lower part of the plot. The final group of appliances is televisions and computers. They lie on a bridge between the fridges and other groups.

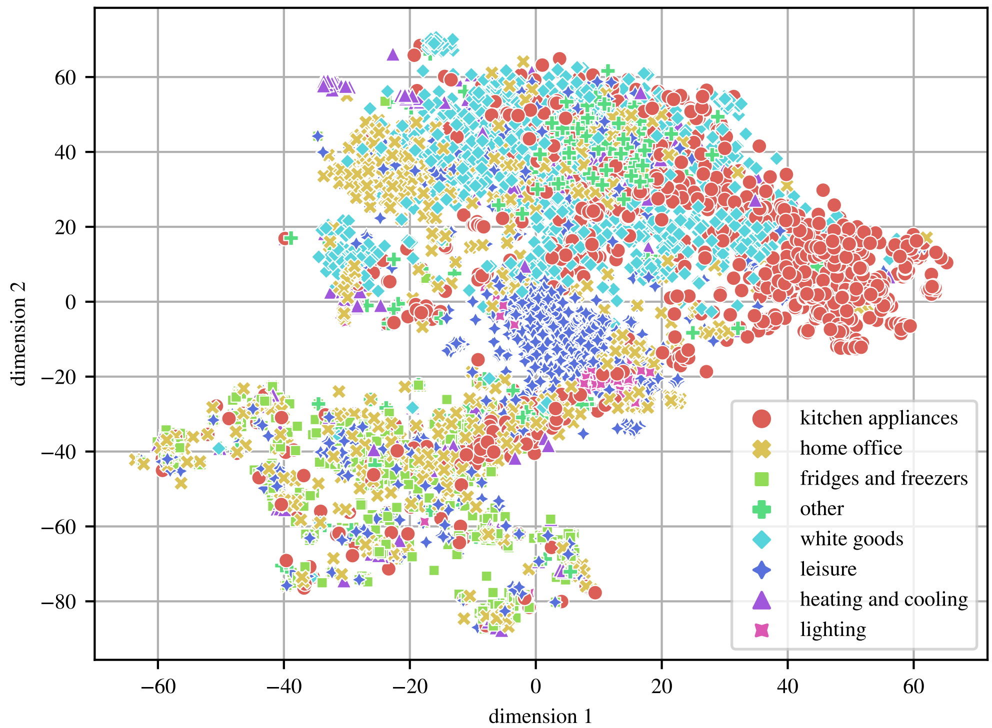
Knowing that a pattern exists, we can use the newly found group to define new appliance groups. The following 8 groups will be defined

- Kitchen appliances - toasters, ovens, microwaves, etc.
- Fridges and freezers - contains fridges, freezers and fridge freezers or white goods with a compressor
- White goods - washers, dryers, dishwashers i.e. white goods with a program
- heating and cooling - Electric radiators, dehumidifiers and HVACs
- leisure - Living room appliances such as TVs, games consoles, audio amps, HTPCs, etc.
- home office - Computer, laptops, printers, network equipment, chargers, etc.

- lightning - lights and lamps
- Others - unknown and unlabeled appliances

Applying these groups yields Figure 5.17. The new plot shows that, although appliances might be used by different users, or even by users in a different part of the EU or world, they can be grouped in high-dimensional space.

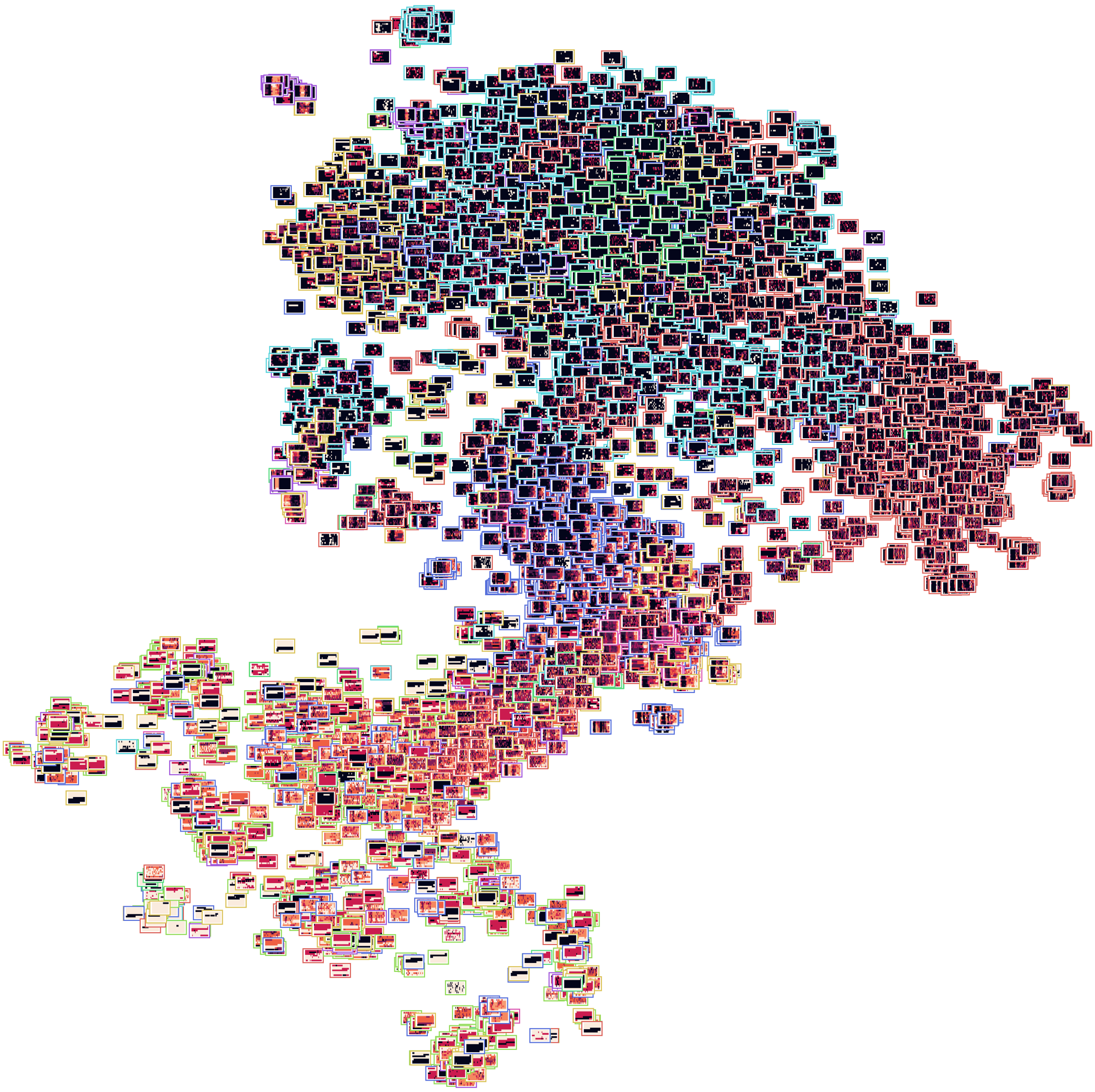
FIGURE 5.17: Projection of grouped per-appliance LPs



Full resolution figure:
`https://github.com/jenkoj/msc/tree/main/Figures/TSNE/TSNE_PHPA/phpa_grouped_15.pdf`

The Figure 5.18 below is the same as the Figure **??**, except it is easier to use color to see the appliance they present

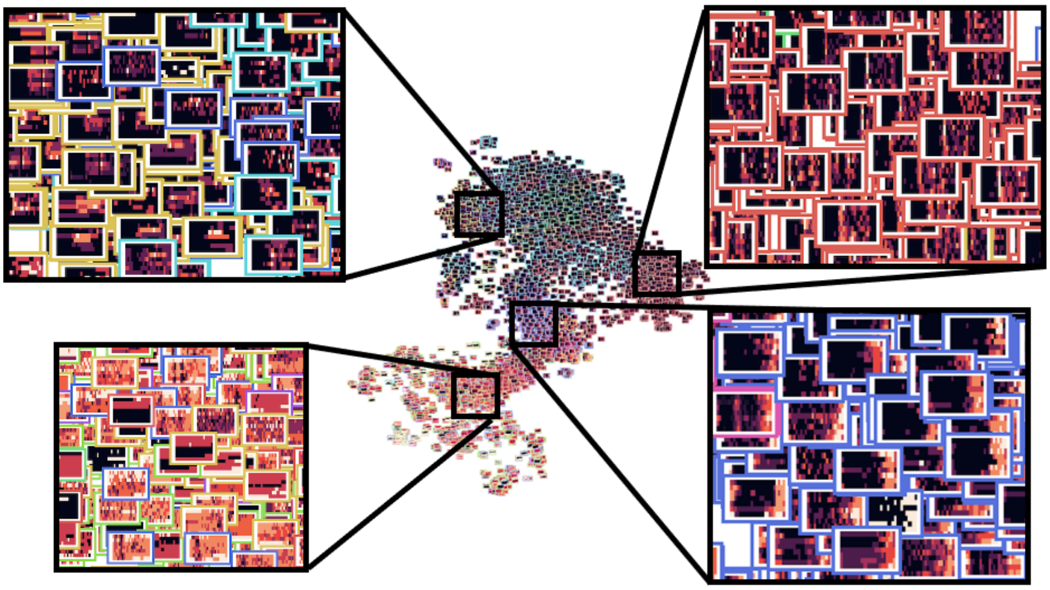
FIGURE 5.18: Projection of grouped per-appliance LPs with actual samples



Full resolution figure: `https://github.com/jenkoj/msc/tree/main/Figures/TSNE/TSNE_PHPA/img_scatter_all_all_groups.png`

To better emphasize the details from Figure 5.18 and 5.17 we present zoomed-in areas of key locations with Figure 5.19.

FIGURE 5.19: Projection of grouped per-appliance LPs with actual samples



Full resolution figure:
`https://github.com/jenkoj/msc/tree/main/Figures/TSNE/TSNE_PHPA/t-sne_zoomed.png`

5.3.3 Per-Appliance Per-Building

To be able to study the usage by comparing all appliances between buildings, we must use one of the proposed LPs; in this case, it is the Bag of Appliances.

Bag of Appliances

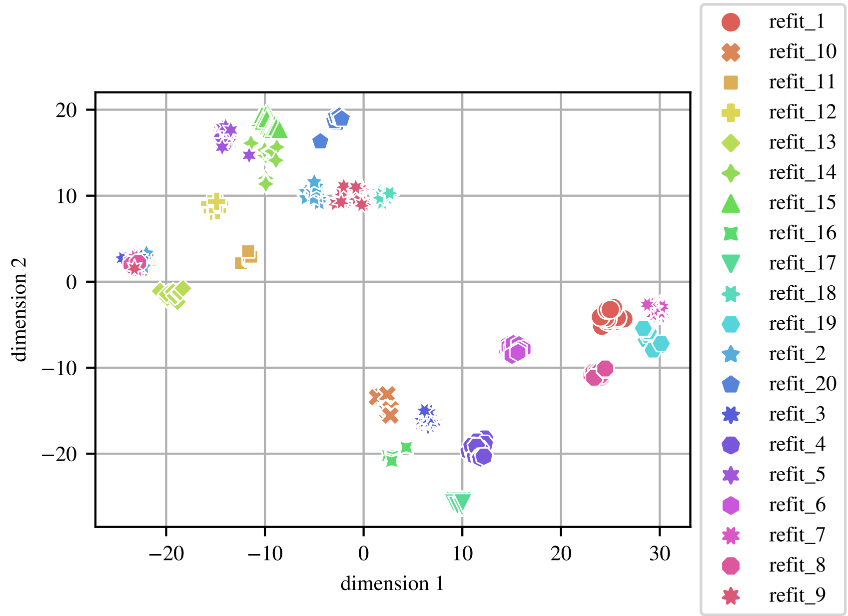
This LP is a combination of the LPs mentioned above, except it provides a greater detail when observing groups of appliances. Since we are using one dimension for appliances, we will use only the daily dimension.

To construct such a profile, we need a universal way of constructing it. This is done by measuring how many times each appliance occurs in the datasets, then this list is sorted from most common to least common, and finally, the top 30 are selected.

The problem with such a comparison is that it is best if all buildings would use the same appliances. Since that is not the case, missing appliances are portrayed as always off.

This is the main reason why we can see in Figure 5.20 that the clusters are separated quite a bit. We can still see that some clusters are closer than others, meaning they are more similar.

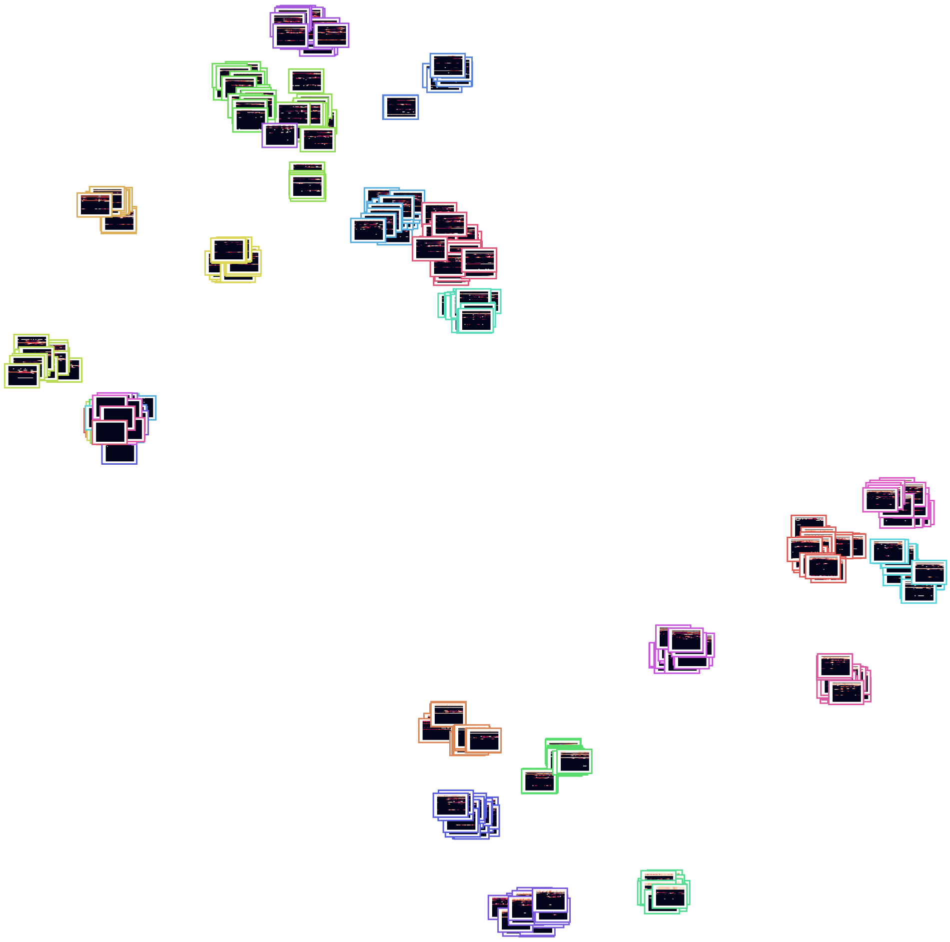
FIGURE 5.20: Projection of a bag of appliances LPs for various buildings



Full resolution figure:
`https://github.com/jenkoj/msc/tree/main/Figures/TSNE/TSNE_BOA/scatter_refit_boa.pdf`

Figure 5.21 shows that LPs are split between two poles. By observing the Figure, it is possible to see that all the bottom clusters have more than one active white good with a compressor (fridges and freezers), while the top ones have only one. In general, the bottom buildings have more appliances, with more activity than the top ones.

FIGURE 5.21: Projection of a bag of appliances LPs for various buildings with actual samples



Full resolution figure:
`https://github.com/jenkoj/msc/tree/main/Figures/TSNE/TSNE_BOA/img_scatter_boa.png`

5.4 Discussion

We used t-SNE to show how LPs are related in high-dimensional space by mapping them into two-dimensional space. We used three different types of LPs: per-building, per-building per-appliance, a bag of appliances, and per-appliance. Per-building load profiles offered a look into how activation patterns differ across different buildings and datasets. Per-building per-appliance and bag of appliance load profiles offered the same thing, but in greater detail. Per-appliance load profiles were the most versatile and were utilized in the most various ways: First, we showed how the same type of appliance is being used across various buildings. Next, we compared appliances with each other. Since the plot was hard to comprehend, we defined appliance groups. These new groups formed clusters, which further revealed the relationship between LPs. Finally, we compared how appliance load profiles are connected in a single building.

One of the main findings of this chapter was the formation of appliance groups. Such groups enable us to look into the similarity of their activation profiles and understand which groups have similar usage patterns. Another important piece of information these groups provide is the strength of the user's routine. The closer the samples, the more similar their activation is, which means the user has a stronger routine. Such a routine will be useful in the next Chapter 6, where we will try to evaluate if it is strong enough to detect anomalies.

We found that by calculating the Euclidean distance between points on the t-SNE map, we could detect the presence of a routine, which in turn would allow us to detect anomalies. As mentioned, this will be explored in greater detail in the next Chapter 6. The advantage of this method is that we used the main meter data, which significantly increases the applicability of this approach. The ease of installation of the system is essential for the successful adoption of emerging technologies. In this light, the evaluation and development of such a system would be of high importance and one of the possible directions for future research.

In addition to t-SNE, it would be interesting to examine other dimensionality reduction methods such as PCA or the more advanced UMAP method. The use of both developed and new profiles with these methods could improve the current approach or even reveal new use-cases.

5.5 Summary

The analysis provided a look into the relationships between LPs and their consumption patterns. We were able to group appliances into categories and found the presence of routine in the LPs. These findings will be valuable in the next chapter where we continue to explore the potential applications of LPs.

Chapter 6

Elderly Care Assisted Living System

6.1 Introduction

Elderly care has been addressed by many EU-funded research projects since the aging population is one of the main issues facing the EU. There are many solutions to this problem. One approach is invasive, such as the use of wearables, sound sensors, and IR occupancy detectors, among others. This approach has been discussed in numerous publications. Reviews [13], [65], and [5] present and discuss this method.

Authors [9] and [24] tried to solve this issue using a non-invasive approach with NILM algorithms. In the case of a non-invasive approach, no additional meters need to be installed, as per-appliance usage can be disaggregated. While this is practical from the "no additional equipment needed" side, it is a bit less practical from the efficiency and accuracy side, especially for larger buildings.

There is a middle ground between invasive and non-invasive approaches, as explored by the authors of papers [71] and [54]. It is possible to use sub-meters for each appliance and indirectly observe the usage pattern. The advantage of this approach is that the elder does not need to wear a device. The disadvantage is that new meters need to be installed for the most commonly used appliances. Our approach will use the latter.

6.2 Goal

The chapter will focus on building an elderly care system that will use users' periodic usage patterns to detect anomalies. Anomalies could be anything from a fall, stroke, or altered usage pattern due to dementia. The algorithm will be designed based on the LP 4.11, which we discussed in Chapter 4. The figure shows that the first appliances used in the morning are a kettle and toaster, and with a delay of one hour, the microwave and TV. If none of these appliances are used within that hour, then that hour is considered anomalous. This means that the algorithm will be able to detect an anomaly within 1 hour of its occurrence.

6.3 Methodology

6.3.1 Defining an Anomaly

Since the elderly care system is based on anomaly detection, we first have to define it. In our case, an anomaly occurs when something that should operate, does not. Based on this definition, we will develop an anomaly detection algorithm.

6.3.2 Building Anomaly Detection Algorithm

The following section presents the steps taken while designing this algorithm.

Step One

To detect the anomalies, one first needs to build a daily activation profile for each appliance, such as the one previously shown in Figure 4.11. In this specific case, we will be using 2h buckets, yielding a total of 12 buckets.

Step Two

The second step is to ignore appliances that are always on by calculating the standard deviation of activations for each bucket. The activations are normalized between 0 and 1. This step is important so that appliances that are always on, such as fridges or freezers, get ignored. These appliances are detected based on the width of their activation normal distribution. Periodic (on an hourly basis) appliances should have narrow distributions, and the more dynamic ones should have wider distributions. This can be seen in examples from building 2.

866	842	810	772	868	854	859	854	864	887	889	883

FIGURE 6.1: Daily activations for fridge σ = 0.036

86	77	75	74	100	118	113	127	168	202	171	121

FIGURE 6.2: Daily activations for audio system σ = 0.2

9	4	4	3	212	122	85	80	102	260	134	48

FIGURE 6.3: Daily activations for microwave σ = 0.3

Based on results from all appliances a threshold of σ = 0.1 was set. This method will also get rid of appliances that are always on due to their specific nature such as server computers or fridges.

Step Three

Next, appliances that trigger together must be grouped. This means we must find parts of the day when they are operating together. Due to the filtering in the previous step, we are left with appliances whose usage varies throughout the day. Some appliances are on even when the user is not necessarily using them, this can be seen in Figure 6.2. One of many ways to do this grouping is to normalize the activations, which yields a metric that tells us the probability of that appliance being turned on compared to the rest of the day. If we apply this to the microwave and audio system appliances, the result is the following:

0.43	0.38	0.37	0.37	0.5	0.58	0.56	0.63	0.83	1.	0.85	0.6

FIGURE 6.4: Daily activations for audio system σ = 0.2

0.03	0.02	0.02	0.01	0.82	0.47	0.33	0.31	0.39	1.	0.52	0.18

FIGURE 6.5: Daily activations for microwave $\sigma = 0.3$

Finally, a suitable threshold must be selected. The threshold of 0.5 was selected, which yields the following vectors:

0	0	0	0	0	1	1	1	1	1	1	1

FIGURE 6.6: Daily activations for audio system

0	0	0	0	1	0	0	0	0	1	1	0

FIGURE 6.7: Daily activations for microwave with one usage peak in the morning and the other in the evening

The vectors show us that the microwave has two usage peaks, where the audio system can be used anytime throughout the day. It is possible to do this for all appliances, which results in a 2D matrix. Using this matrix we can build rules for which appliances are being used together. Figure 6.8 uses rows for appliances and columns for buckets. If we use terminology from image processing the matrix 6.8 is essentially a highly saturated LP 4.11, which can be easily processed by computer algorithms due to binary encoding.

0	0	0	0	0	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	1	1	1
0	0	0	0	0	0	0	0	1	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	1	1	1	1	0
0	0	0	0	1	1	0	0	1	0	0	0
0	0	0	0	1	1	0	1	0	0	0	0
0	0	0	0	1	0	1	0	0	0	1	0
0	0	0	0	0	1	1	1	1	1	0	0

FIGURE 6.8: Activation matrix

It is possible to display the matrix 6.8 as an image. The Figure below shows how the LP is transformed.

(A) Input data (B) Figure 6.8 as an image

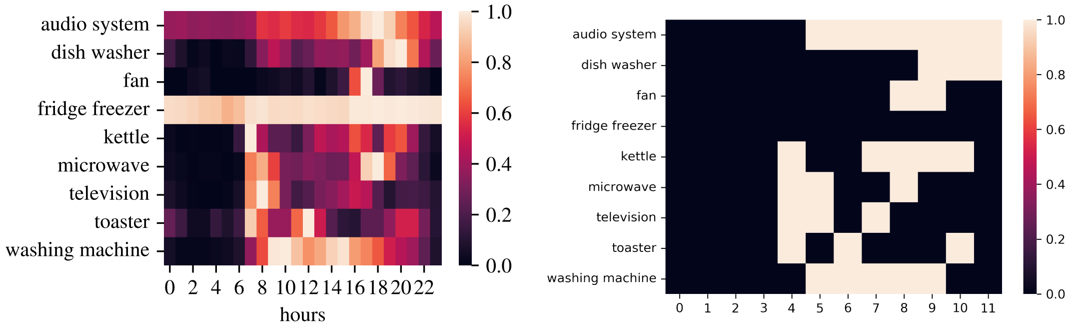


FIGURE 6.9: Transformation of source LP to black and white

Step Four

Previously, we defined an anomaly as an event where something that should activate does not. Using the matrix from Figure 6.8, we can compile an algorithm that detects the anomaly by testing current activations and comparing them to the adjacent column in the matrix seen in Figure 6.8. Let's use the fifth bucket as an example, which includes data from 8 to 10 o'clock.

The tested sample is considered normal if at least two appliances that are normally used are activated. Otherwise, the tested sample is considered anomalous. Our implementation multiplies the adjacent matrix column by the tested sample. We sum the elements of the resulting array and check if the sum is larger or equal to 2. In cases where this rule is not met, the samples are considered anomalous.

	profile		sample		result	
audio system	0		1		0	
dish washer	0		0		0	
fan	0		0		0	
fridge freezer	0		0		0	
kettle	1	X	1	=	1	IF SUM >= 2 not an anomaly
microwave	1		0		0	
television	1		0		0	
toaster	1		1		1	
washing machine	0		0		0	

FIGURE 6.10: The evaluation of the test sample compared to the adjacent column from the matrix. An example is for a fifth bucket or fifth row from the matrix.

This process is done for all samples, where we count normal and anomalous samples for each bucket. The important thing to note here is that we are evaluating the samples from train data, from which the profile was built.

472	469	468	466	57	153	288	187	123	84	75	281

FIGURE 6.11: Aggregated anomalies for each bucket

0	0	0	0	409	312	181	280	342	384	394	188

FIGURE 6.12: Aggregated normal samples for each bucket

Step Five

The next step is to combine these two arrays so that we calculate the percentage of anomalous samples for each bucket with an equation.

$$\frac{N_{anom}}{N_{anom} + N_{norm}} \tag{6.1}$$

Where N_{anom} is a number of anomalous samples and N_{norm} is a number of normal samples.

We can modify Equation 6.1 so that it measures a number of normal samples out of the total samples. The result is the Equation 6.2 In other words, we are measuring the strength of a routine that the user maintains in each bucket.

$$R_{outine} = \frac{N_{norm}}{N_{anom} + N_{norm}} \tag{6.2}$$

Using Equation 6.2, we can populate the array in Figure 6.13.

0.0	0.0	0.0	0.0	0.88	0.7	0.39	0.6	0.74	0.82	0.84	0.4

FIGURE 6.13: Aggregated anomalies for each bucket

In other words, the array in Figure 6.13 indicates the persistence of the user's routine in each bucket or part of the day. The higher the metric, the stronger the routine. Since routines are detected based on appliance usage, they cannot be detected during the night.

It is possible to see that the routine is quite high during the morning and evening hours. The anomaly detection algorithm will perform best when the metric is high. A notable characteristic of the elderly is that their routine is typically high even during the day.

Another thing to do is to ignore the parts of the day when the user has no detectable routine. This is accomplished by using the array in Figure 6.13 and setting a threshold of 0.7.

A threshold of 0.5 would imply that we could detect false positive anomalies every other day. By setting the rate to 0.7, this is reduced to every third day. Compromises must be made here; the lower the threshold, the more accurate the algorithm will be. This also implies that it will be less sensitive. In our case, there is not much harm in false positive detections, as the caregiver can call the elder to check if everything is okay.

0	0	0	0	1	1	0	0	1	1	1	0

FIGURE 6.14: Using the above-mentioned threshold a new mask is made, to check only buckets with high routine.

Step Six

The last step is to repeat Steps 4 and 5 with the test data. When using the test data, we skip the buckets with low routine rates by using the mask from Figure 6.14. Since the profile has never seen the data being used, this should give us a good representation of actual performance in a real-world scenario.

6.3.3 The metric - routine rate

Due to the lack of ground truth data on actual accidents, it is hard to determine the exact accuracy of this algorithm. Every anomaly detected is not necessarily an actual accident, it could be that the user decided to lie in bed a bit longer, or decided to go to bed early in the evening. One metric that we can use to determine how well the algorithm functions is the routine rate metric 6.13. The reason behind this is that if the routine rate is high, it means that it will be easier to detect the actual anomaly.

- A routine rate of 0 would mean that for that bucket, the household has no routine at all.
- A routine rate of 0.5 would mean that the routine is broken every second day.
- A routine rate of 0.8 would mean that the routine is broken on average every fifth day.
- A routine rate of 1 would mean that this household has a routine that is never broken.

An example of when a user's routine rate is close to 1: When a true anomaly occurs such as a fall, the dweller, though he had maintained the same strong routine for the past year, would not be able to continue it, and the algorithm will be quite sure that this is an actual anomaly. Therefore, the lower the routine rate, the less sure we are that an actual anomaly such as a fall occurred. This is a good alternative measurement, which tells us how well this algorithm will perform. Since sometimes it is easier to read when results are presented as percentages, we will sometimes present them in this way.

6.4 Results

Results were obtained for 3 datasets. The REDD and iAWE datasets were not used, since they were too small. They contained less than a month of data.

6.4.1 The Routine Rate Over a Period of Time

In the following sections, we will present how the metric changes over given periods of time. This will enable us to see the patterns that this metric helps reveal. Since we have more than a year of training data, this will allow us to observe how the metric changes over years. This allows us to see how the routine changes over the year. We cannot use testing data in this case, as there is not enough of it.

The Routine Rate Through the Week

As the behavior of the dweller changes, so does the accuracy of the algorithm. One observation that was made was that the routine was higher during the week than during the weekends, as can be seen in Figure 6.15 below. The only exception is Figure 6.15d, which shows that the observation does not hold for all houses.

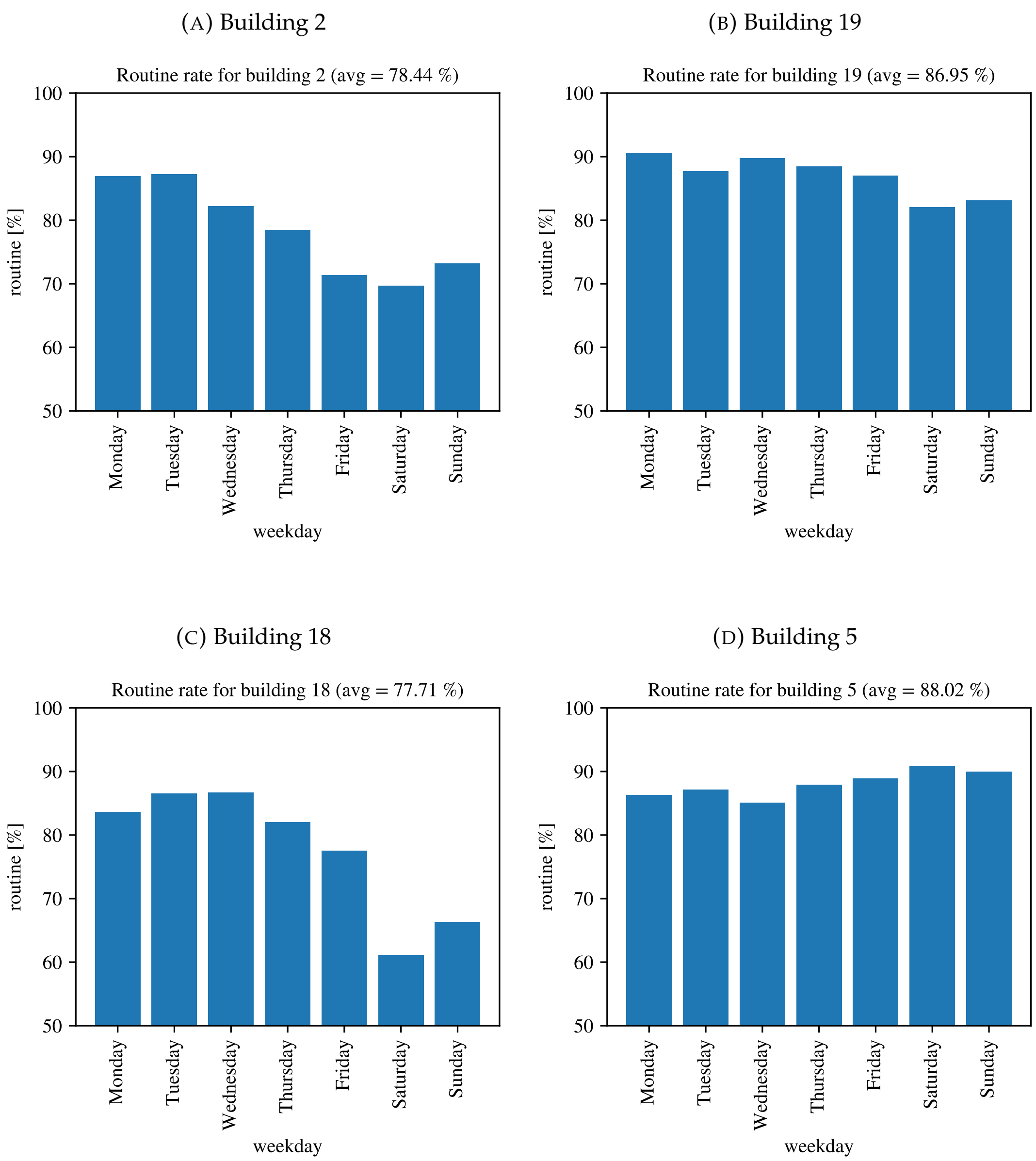
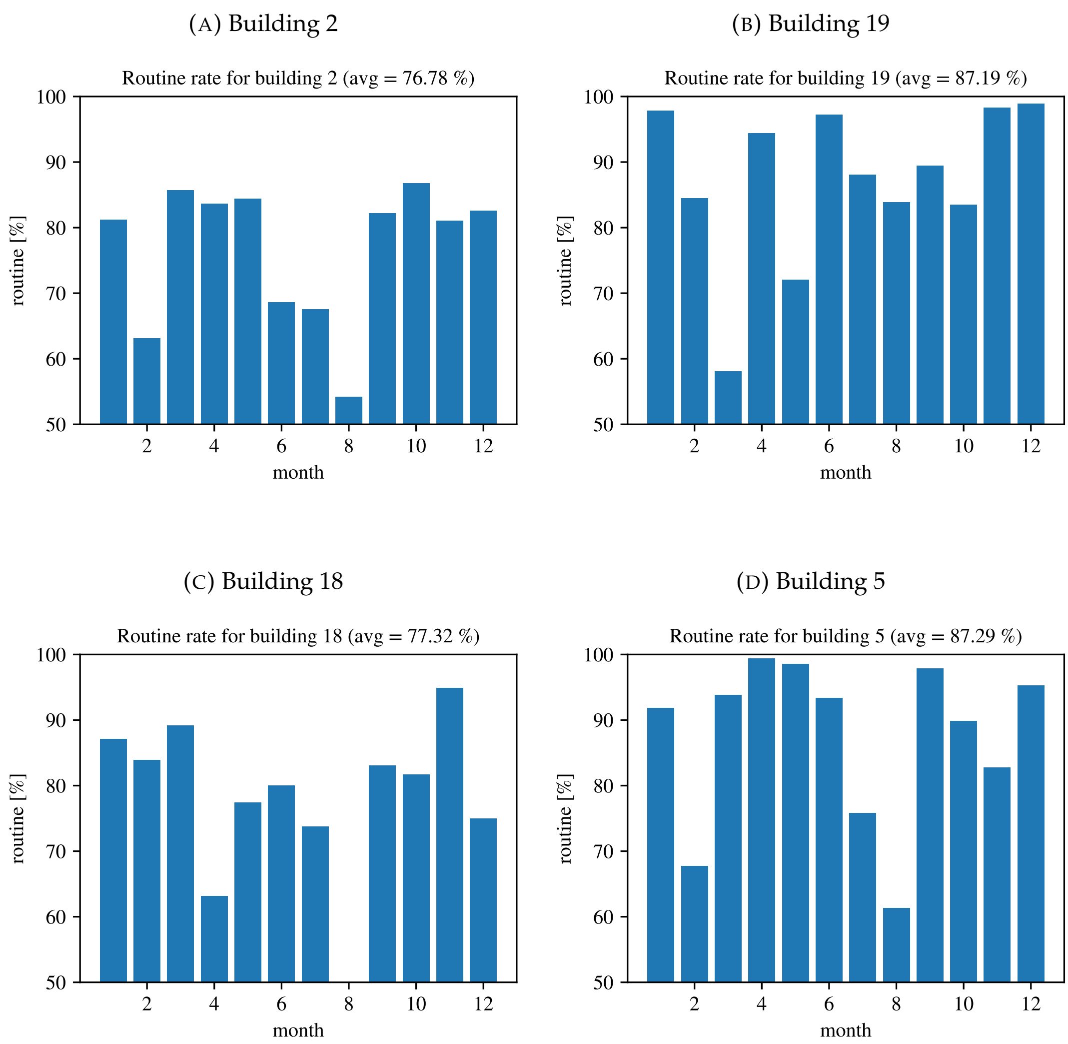


FIGURE 6.15: Routine rate through the week (train data)

Since we are dealing with the elderly, they have a consistent routine, and it does not vary significantly during the weekends. Usually, assisted living systems are put in place because elders are alone in the dwelling. Taking all of this into account, we could assume that the routine of the elderly remains the same throughout the week and simply ignore the weekends. This should yield more relevant results.

Routine Rate Through a Year

The rate at which the routine is practiced also changes over a year. While on average the routine rate is higher during the winter, spring, and fall, it is lower during the summer, due to vacations. This can be seen in Figure 6.16 below. It is possible to observe dips in the routine. In some cases, these dips occur in the summer and others in the springtime. Without metadata, we cannot know for sure what was the event behind these dips. There is a high chance that most of them are due to vacations or other events where one or more dwellers are away from home for extended periods of time.



(A) Building 2

(B) Building 19

(C) Building 18

(D) Building 5

FIGURE 6.16: Routine through the year (train data)

Effectiveness of Anomaly Detection Through the Day

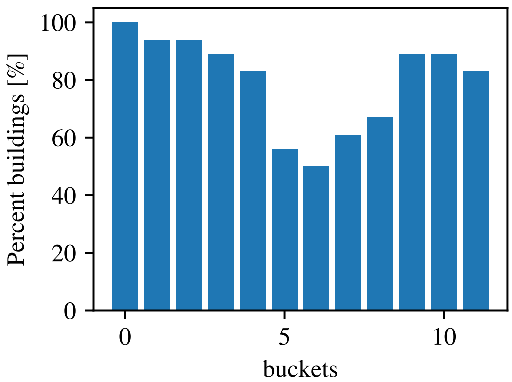
The following subsection will show how the effectiveness of anomaly detection changes throughout the day.

One thing to keep in mind is that this algorithm can detect anomalies only when the routine is high, and when more than two appliances are used in given buckets.

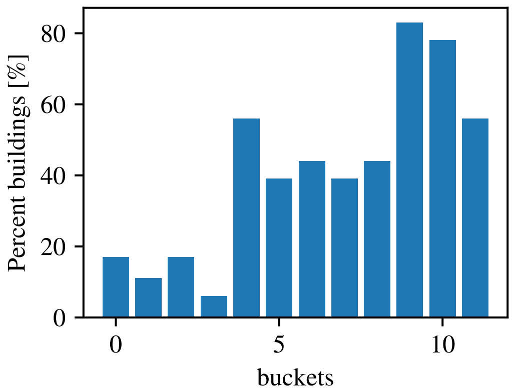
Figure 6.17a shows which buckets are most commonly used for the detection of an anomaly. The figure includes averaged values from all buildings and datasets. In other words, the figure presents the strength of the average routine throughout the day.

This means that the higher the routine, the higher the chance that this bucket will be used for anomaly detection. During the night, it is possible to see that the average routine rate is quite high. This can be seen in Figure 6.17a, this is because most users are routinely sleeping during this period. As we can see in Figure 6.17a, a high routine rate does not necessarily mean the buckets are useful.

(A) Effectivity of anomaly detection through the day



(B) Actual effectiveness of anomaly detection through the day



To find the usable buckets, an additional filter must be applied. The rule is that at least two appliances must be commonly used in each bucket. After applying this rule, the following Figure emerges 6.17b.

Figure 6.17b shows that there are two peaks: one in the morning and a wider one in the evening.

This means that, on average, the algorithm would perform best in the morning and evening because the average person is at school or work during noon. Elderly individuals, who are usually at home at noon, could extend the effective detection window.

The Anomaly Detection During the Night

We have observed that anomalies can be detected throughout the day, but are hard to detect during the night, since appliances are typically off.

In our current state, an anomaly occurs when something that should operate does not. When the user is sleeping, an anomaly occurs when something that shouldn't operate does. To implement this additional rule, we would have to build two models: one that operates during the day, and another that operates when the user is asleep.

To obtain information about the user's sleep schedule, we could either request a schedule from the user or extract it based on the usage pattern of appliances. We can detect when most of the appliances are inactive and build a sleep profile based on this information.

Using the sleep schedule, it is possible to switch between the two operating modes. This new implementation would further extend the time windows within which we can detect anomalies and thus further improve users' safety.

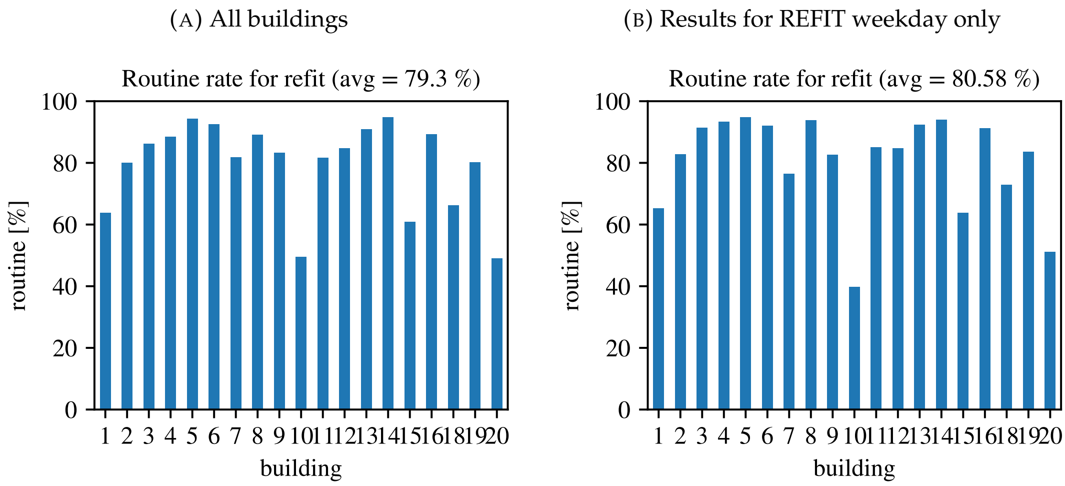
The main issue is not the detection itself but efficiently determining when the user is asleep.

The examples above serve as a demonstration and a look into data and metrics. The examples shown were trained and evaluated on the same data. To show true performance, we will use test data to determine actual performance.

6.4.2 Per-Building Results

REFIT

Results show that the method is, on average, **79.3** % efficient for REFIT. In Figure 6.18a, we can see that buildings 10 and 20 yield much worse results than the rest. The overall routine pattern is very similar to Figure 5.9 from the t-SNE chapter where we calculated the final Euclidean distance between samples of the t-SNE plot. We will make a deeper analysis of this connection in the final Section 6.7 of this Chapter.



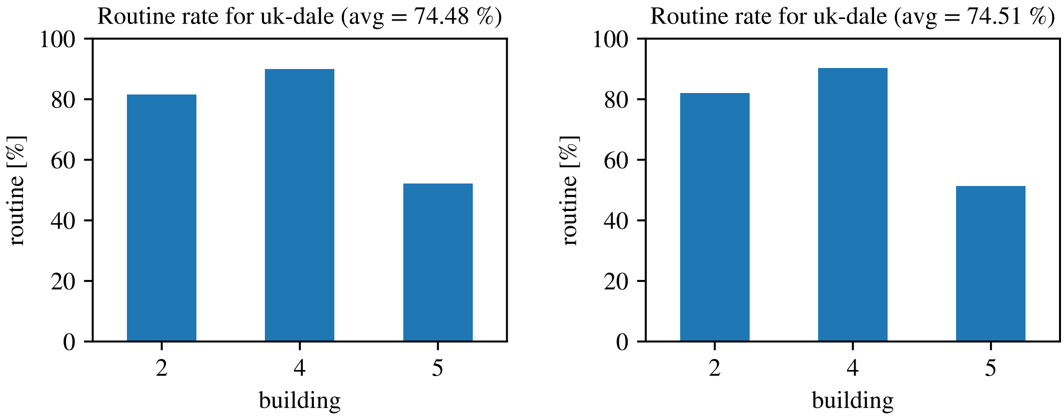
As mentioned in Section 6.4.1, the average routine varies between weekdays and weekends. The assumption was that the routine of elderly people does not change significantly throughout the week, therefore, results should be more relevant if we exclude the weekends. Figure 6.18b shows that the result improved to **77.08** %. By removing the weekend data, the results improved by **1** %.

UK-DALE

As mentioned in Section 3.1.4, the UK-DALE is not as big and clean of errors as the previous dataset, so the results could be less relevant. The results in Figure 6.19a, show that the average result is **74.48** %.

(A) Results for UK-DALE

(B) Results for UK-DALE omitting weekends



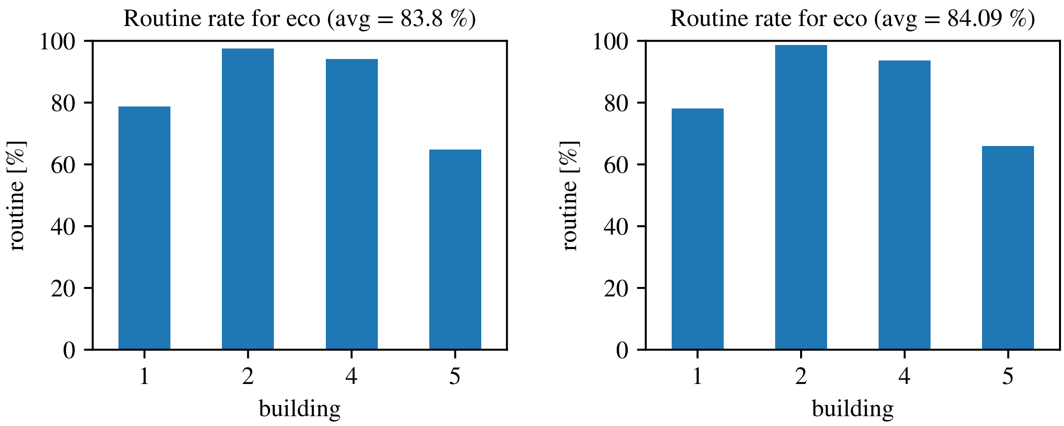
In this case, omitting the weekend data improves the routine slightly, increasing it to **74.51** %. There are many reasons behind this small improvement, one of which is, that the existing routine of these buildings does not change over the weekend.

ECO

ECO is of similar quality as UK-DALE when considering the number of buildings and the length of data, as can be seen in Section 3.1.4. The results in Figure 6.20a show that this dataset has the highest average routine rate of **83.80** %. As before, we can exclude the weekend data, which can be seen in Figure 6.20b. This brings the result up to **84.09** %.

(A) Results for ECO

(B) Results for ECO omitting weekends



6.4.3 Combined Results

After combining results from all 26 buildings, Table 6.1 can be populated. It shows that the algorithm is **79.43** % efficient at detecting true anomalies. On average, the algorithm would label **20.5** % of samples as false positives, in other words, every fifth sample could be a false positive.

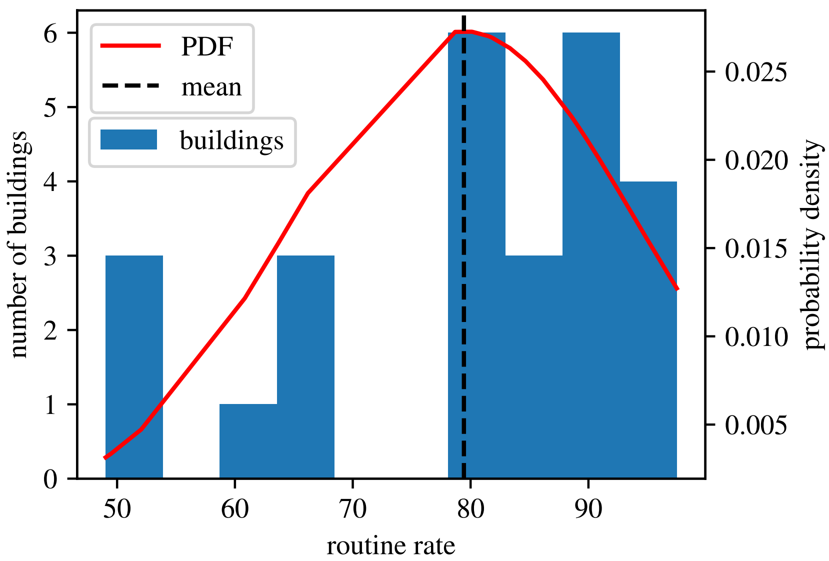
To understand the results a bit better, Figure **??** presents the distribution of the samples. It is possible to observe that the distribution is not normal as there is no

TABLE 6.1: Combined percentage [%] of routine rate for 26 buildings

including weekend data	test	train
mean	79.43	84.55
median	82.58	84.40
standard deviation	14.62	9.05

bell-shaped pattern. Such a distribution makes it hard to statistically analyze the results and makes it difficult to draw meaningful conclusions. However, this issue can be addressed by visually analyzing and interpreting the data. In this case, it is possible to see that a large portion (74 %) of the samples fall in the interval above the mean, more specifically above the 80 % routine rate. This observation is important, as it adds another dimension to our understanding of the results.

FIGURE 6.21: Histogram of results overlayed with a probability density function



If we assume that the average building in our dataset has altered routine during the weekend as can be seen in Figure 6.15, and assume that the average elder has roughly the same routine throughout the week, we can remove the weekend data to obtain more relevant results. Table 6.2 shows the results after removing the weekend data. We can observe that the mean test routine is **80.42** %, which is slightly higher compared to the results from the previous Table 6.1.

TABLE 6.2: Combined percentage [%] of routine rate for 26 buildings not including weekend data

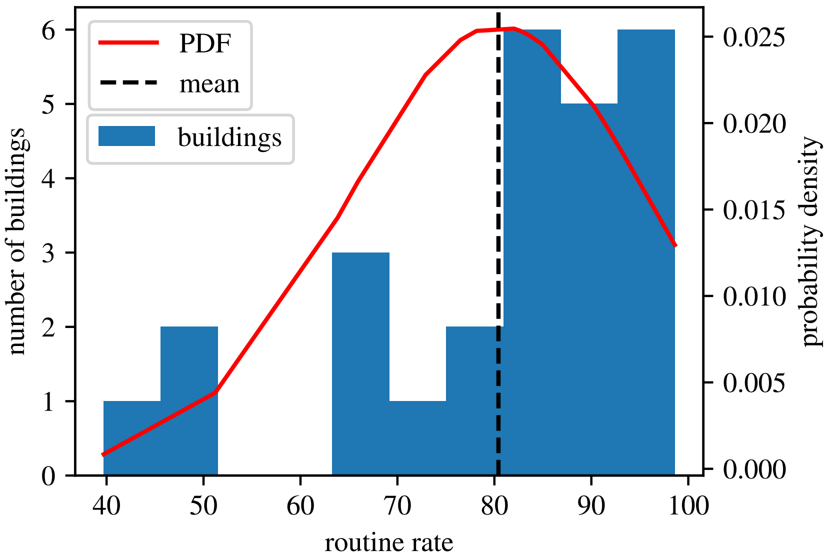
not-including weekend data	test	train
mean	80.42	85.88
median	84.15	86.35
standad deviation	15.58	8.25

The last rows in Tables 6.2 and 6.1 show the standard deviation of our measurements, which is 14.62 % for weekend data and 15.58 % for data that does not include weekends. Even though the standard deviation is lower when excluding weekend data for the train data, it is higher for the test data, which was unexpected.

The reason can be seen in Figures 6.21 and 6.22, where we have already observed the non-normal distribution, and mentioned that statistical methods should be analyzed with caution.

Visual analysis of Figure 6.22 reveals that the general distribution did not change compared to Figure 6.21. However, there are fewer samples above the 80 % line and fewer samples with very low routine. This could mean that not including weekend data may improve the overall score by aiding the worst performers, but it may also lower the score of the best performers.

FIGURE 6.22: Histogram of results not including weekend data overlayed with a probability density function



When comparing the differences between the train and test data, it can be clearly observed that the train data performed better. The difference in performance can be attributed to the changed user behavior after the model was trained. It would be beneficial if we managed to update the model over time to include the small changes in users' routines. This will be addressed in the next section 6.6.

6.5 Discussion

The main goal of our system is to detect anomalies when they occur. The nature of this system is that there is more harm done if we do not detect an anomaly than if we detect a few false positives. On the other hand, too many false positives could lead to caregivers ignoring detections altogether. In this regard, we must find a balance between the two. A false positive once a week is a good balance, especially since the caregiver is only a phone call away from checking the status of the patient. Since the validation is so simple, we can claim that the performance of the system is adequate to be used in a real-world setting.

When analyzing these results, one important to keep in mind is, that we do not have metadata available to know what kind of socio-economic status dwellers have. Socio-economic status encompasses attributes such as age, income, number of children, geolocation, etc. They may also encompass the age of the building, type of insulation, number of dwellers in the buildings, etc. Since datasets do not provide them, it is hard to make any other conclusions other than the algorithm works well on an average building.

We know that the reason for installing such a system is that the user is left alone. We can assume that on average there is more than one dweller living in the buildings we tested on. Since this system would usually be used by a single dweller, this would be in favor of our algorithm, as it would be easier to extract the routine.

One other thing that would be in our favor is, that the average person spends less time at home than an elderly person. If we take a look at the results, it is possible to see that, the average home has a low routine during the noon. This is because the average person is not at home during noon, which can be observed in Figure 6.17a. Since the elderly are usually home at that time, this would increase the time windows where we can detect the accident.

We could also assume that the older the dweller, the higher the routine. The nature of the elderly is that they are more conservative when it comes to changes, and prefer to stick to their routine. Since the algorithm works better when usage is periodic, this would also be in our favor. Taking all of these assumptions into account, there is a possibility that this algorithm would work better on the elderly due to their nature. Since the results on the average building are promising a real-world setting test study should be performed. This would also prove our assumption that this algorithm works better on the elderly.

6.6 Iterative Learning System

In the case of the practical use of this algorithm, it is important that the system is put online as fast as possible and that it improves over time. This can be achieved with the implementation of iterative learning. The algorithm will build an LP based on the first month of data. Using this LP, the system can be immediately put online. At the end of the month, it can use this data to improve the model, which can then be repeated indefinitely.

6.6.1 Methodology

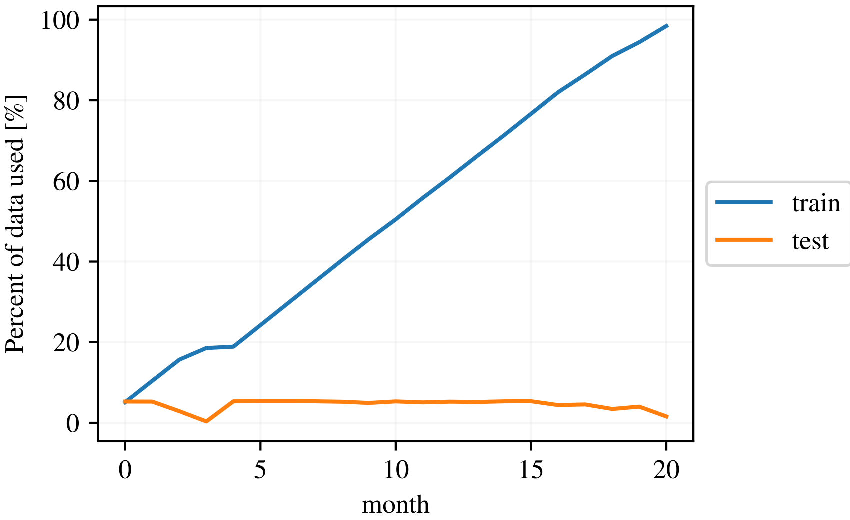
The tools, metrics, and other methodologies are the same as in a normal learning system. The only change that was made was on the data preparation side.

Data Preparation

For this evaluation, only REFIT ([57]) data was used. As it can be seen in Figure 3.1, Refit buildings have long and relatively similar timelines compared to other datasets.

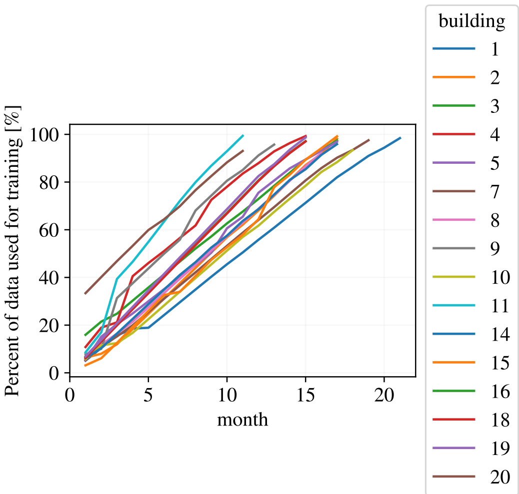
In Figure 6.23, it is possible to see how the amount of training and testing data changes over 16 months.

FIGURE 6.23: Data for building 1 over 16 months

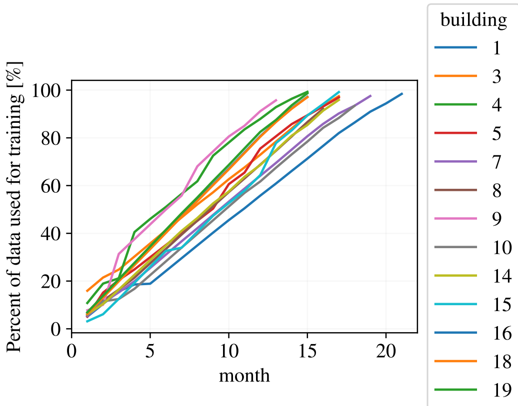


We can also plot how the amount of data changes for all buildings. This can be seen in Figure 6.24a.

(A) Data used for training

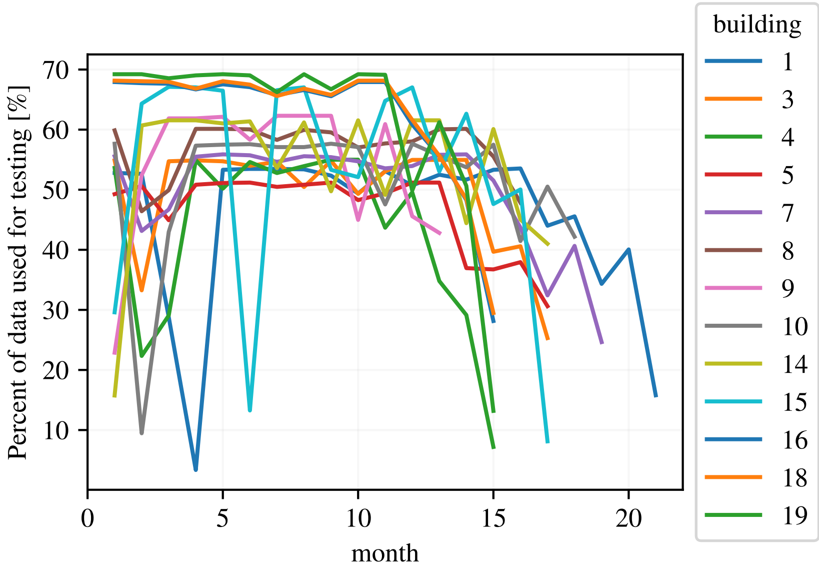


(B) Data used for training, with removed buildings



To analyze the results, at least 1 year of usable data should be available. Figure 6.24b shows only buildings containing at least one year of data. Similarly, we can check how test data changes over the months. In this case, data is not being aggregated, but only one month of it is used at a time. Figure 6.25 shows that after one year, the amount of data used for training starts to decline. To get more accurate results, we will only observe the performance using one year of data.

FIGURE 6.25: Data used for training, with removed buildings



6.6.2 Results

To show the effect of training data on the metric, Figure 6.26 is presented. Figure 6.26 contains 12 months of data for each building.

FIGURE 6.26: Effect of new data on metric

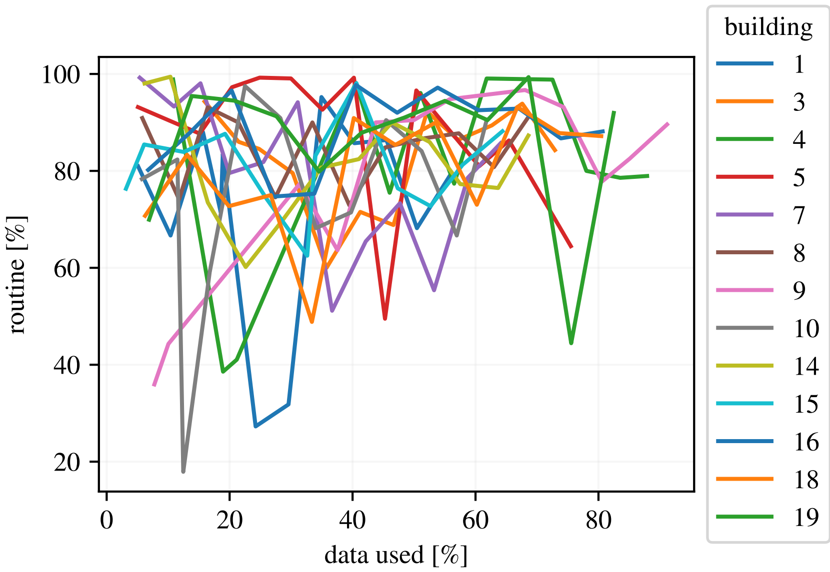


Figure 6.26 shows, that in most cases, results converge towards **80** %. In some cases, the results are good from the beginning, but sooner or later the routine rate will dip. With more data, these dips become smaller and less frequent. If the behavior in the household radically changes, it can still lead to a dip.

FIGURE 6.27: Metric over 12 months

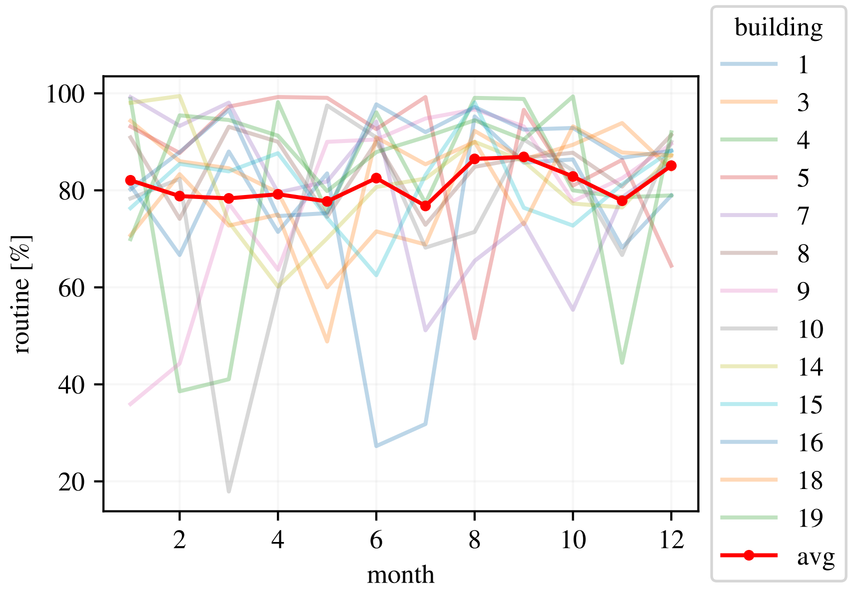


Figure 6.27 shows how the same data can also be presented so that it shows how the metric changes over a year. The same as in the previous Figure 6.26 we can observe the dips getting less frequent and smaller. Here we can also observe the average line. The average value seems to be on average at around **80 - 85** %,

6.6.3 Discussion

It is hard to compare these results from iterative learning to the ones from non-iterative learning. Even though the same data was used, different sections of it were used.

Let us consider the last point in Figure 6.27, where the average is at the 85 % mark, as an example. Here, the amount of training data is different since we limited it to one year. The training set is also different as only the last month was used, not 20 %. There are many differences between the train and test sets, so we cannot compare them. The results do prove that the method works, and the true performance is around the expected 80 %.

By increasing the amount of data, the algorithm becomes more stable. In some cases, where users' behavior does not change, the algorithm could work from the first month onward. In other cases, where behavior is more dynamic, the algorithm needs a month or two to stabilize.

It is important to note that the longer the observation, the higher the chance there is that the routine of the user will change. When such changes do occur, the algorithms must have methods in place that enable them to adjust to the new routine. The simplest approach would be to use weights that put more attention on more recent data and less attention on older data.

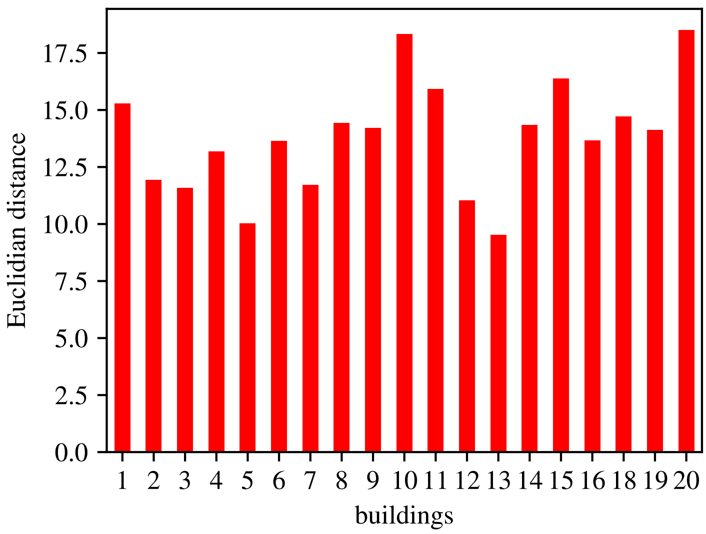
Future research in this area offers many open opportunities to improve the current approach. For more accurate results, a method could be used where several synthetic anomalies are modeled and incorporated into existing data. Additionally, the system could be set up in a real-world setting where elderly people live on their own. Real anomalies would allow us to fully evaluate the system. As mentioned, similar approaches already exist, so it would be essential to compare the accuracy of our method with other publications. Additionally, we could compare our method to a more invasive method where the user wears a sensor such as a smart bracelet.

6.7 Correlation Between t-SNE Plot Euclidean Distance and Routine Rate

In Section 5.3.1, we first observed the presence of periodic behavior in the formed t-SNE clusters. We speculated that the scattering of LP clusters could be correlated to a routine; the smaller the scattering, the better the routine. We calculated the scattering using Euclidean distance, which is the same metric used as a cost function in t-SNE.

Figure 6.28 was already presented in Section 5.3.1, but it makes sense to reuse it here in this context. As mentioned, this Figure shows the Euclidean distance between samples for per-building LPs for every building.

FIGURE 6.28: Euclidean distance of samples for every building using normalized LPs



To reveal the connection between the two, we plotted both on the same Figure 6.29, where the routine rate is reused from results Figure 6.18a.

FIGURE 6.29: Plot of results from REFIT and t-SNE Euclidean distance

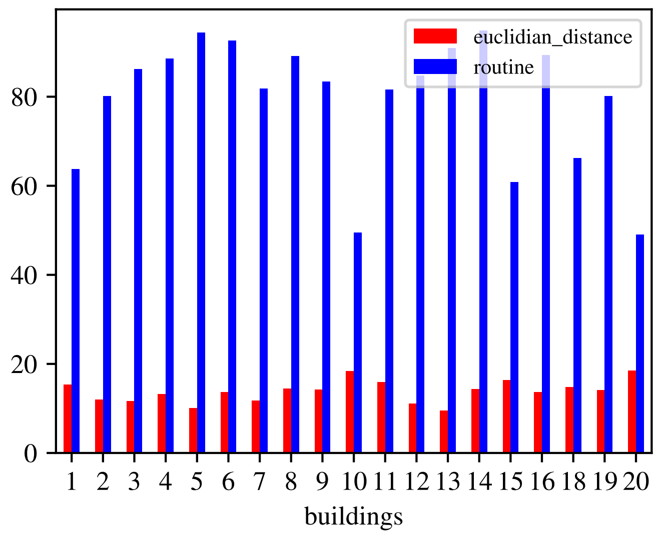
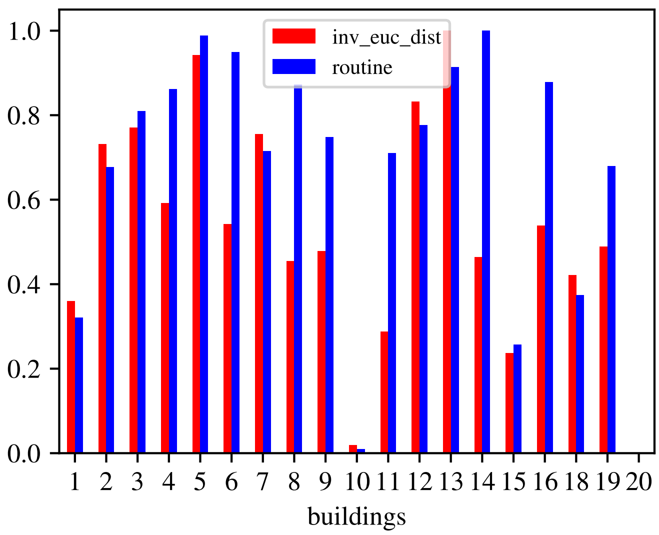


Figure 6.30 shows the same data as the Figure above, but it's normalized using a min-max scaler. Additionally, we have inverted the values of Euclidean distance, since values seem to be inversely correlated. Looking at the Figure it is clear that there is some similarity between the two columns, especially for the best and worst-performing buildings.

FIGURE 6.30: Normalized values



To further prove the similarity, we have used the methodological approaches for calculating similarity that we explained in Section 5.2.3. The results can be observed in Table 6.3. First, we calculated cosine similarity using Equation 5.3, which yielded a cosine similarity of **0.94** for the data seen in the second Figure 6.29 and **0.86** for the data seen in the third Figure 6.30. Second, we calculated Pearson's correlation coefficient using Equation 5.4, which yielded a result of **-0.76** for the data seen in the second Figure 6.29 and **0.76** for the data seen in the third Figure 6.30. These values present that there is a connection between the t-SNE plot and the routine of the households.

TABLE 6.3: Similarity and correlation results

Method	**Figure 6.29**	**Figure 6.30**
Cosine similarity	0.94	0.86
Pearson's correlation coefficient	-0.76	0.76

When analyzing these results, we must keep in mind that the methodological approaches were very different for the two experiments. In the case of t-SNE, we used normalized per-building LPs with very little preprocessing, whereas in the elderly care algorithm, we used per-building per-appliance LPs with extensive preprocessing to extract appliances that could help us detect the routine. Another thing we must keep in mind is that elderly care enables us to detect anomalies on hourly intervals, whereas our t-SNE approach requires a minimum of a week of data to construct the LPs. In this regard, t-SNE could be used to evaluate the routine rate of a household.

6.7.1 Discussion

This connection is an important demonstration that confirms our statements from Chapter 5 that the dispersion of samples in the t-SNE plot is related to routine. This also means that we can rely on t-SNE to evaluate the routine of a household. While it may not be as precise and fast as an elderly care algorithm, it is simple to use. Apart from implementation being easily available, it uses per-building LPs, which can be built from most existing residential power meters.

This leads us to privacy issues, as almost all households use power meters for utility billing tracking. Before processing this data to build per-building LPs, the user should be informed and agree to the use of their data. It should also be made clear that their data will be handled according to GDPR.

6.8 Summary

The results show that our approach can detect changes in routine and can improve over time. Due to a lack of ground truth data, we were not able to measure the exact accuracy of the system, but rather evaluate if the behavior of residents is sufficiently periodic. Even the best algorithm would not be able to detect anomalies in a stochastic system. With that, we also proved that such a system is sufficiently deterministic for such applications.

Furthermore, we have demonstrated the existence of a connection between the t-SNE plot and the routine obtained from the elderly care anomaly detection algorithm. While t-SNE cannot be directly used in the setting of elderly care, as it's too slow, it could be used to determine if the routine of the household is strong enough before a more complex system is put in place.

Chapter 7

Conclusion

In the introduction of Chapter 1, we stated that the goal of the thesis would be achieved by contributing the following:

1. Surveying the state-of-the-art LPs (Chapter 2)
2. Developing multidimensional activation LPs (Chapter 4)
3. Conducting exploratory data analysis of activation LPs through t-SNE (Chapter 5)
4. Proposing a new anomaly detection method for elderly care (Chapter 6)

With the first contribution, we have found new, previously unused ways of presenting the data. This was achieved by building a detailed table of profiles such as we have seen in Chapter 2. This table presented the missing gaps, and which presentations were not used by the community. We knew that not all unused profiles were useful, by using other publications we classified them based on their impact. We have selected the few with the highest impact and used them in the following chapters.

Furthermore, we presented all the LPs in high detail, enabling the reader to understand what the LPs look like and what they represent. While doing so, we discussed possible use-cases for the LPs and showcased our plans on how we intend to utilize some of the previously unused activation LPs.

The third contribution was made in Chapter 5, where we have shown how data is connected in high-dimensional space using t-SNE for dimensionality reduction. Here, we show that some buildings have more similar activation patterns than others. Furthermore, we identified which appliances are used similarly. We grouped the appliances into appliance groups and showed that appliances from different datasets are used similarly, and how this method and groups can help us label unlabeled data. The formed clusters revealed that a routine and persistent usage pattern does indeed exist. This laid the groundwork for elderly care, where we have used this routine at the center of the algorithm.

The last contribution was made in Chapter 6, by building functioning elderly care assisted living system. The results confirmed that we successfully used one of the proposed LPs in a real-world scenario. The main goal was to efficiently extract the routine and then build a working system around it. The results show that we have succeeded in doing so and that the algorithm is adequate for use in the real world. To further prepare the algorithm for the real world, we have implemented an iterative learning system. The system could be put online a month after the installation, and it continues to improve over time. Furthermore, we have shown a correlation between t-SNE Euclidean distance and the calculated routine rate, which proves our statement from Chapter 5 that formed clusters represent routine.

The sole purpose of the load profiles is to reveal patterns, contextual features and information itself in the vast sea of data. With the proposed load profiles, we have hopefully contributed new tools that will help researchers to uncover the truths held within data. We have applied these tools to improve the independence and well-being of the elderly and discussed how they can be used in numerous use-cases one of them being energy efficiency. There is still much more to learn about how and which LPs can be used to improve our lives, and the proposed table of profiles can serve as a good starting point for such research. While we have filled in a few gaps in the table of profiles, it is up to the scientific community to fill in the rest.

Appendix A

The Source Code, High-Resolution Figures and Datasets

The following appendix contains mostly links that point to GitHub. GitHub should be a valid repository for such projects, where links should persist indefinitely. In case the links do eventually break, you can find the repository of thesis and demos under the username "jenkoj", under "msc" and "appliance-profiling".

A.1 The source code

The source code used in this chapter can be found in a GitHub repository:
`https://github.com/jenkoj/appliance-profiling`

Individual scripts can be found in the following Jupyter Notebooks:

The source code for generating the figures can be found at:
`https://github.com/jenkoj/appliance-profiling/blob/main/profilng_slices.ipynb`

The source code for t-SNE can be found at:
`https://github.com/jenkoj/appliance-profiling/blob/main/t_SNE.ipynb`

the source code for elderly care can be found at:
`https://github.com/jenkoj/appliance-profiling/blob/main/elderly_care_demo.ipynb`

A.2 High resolution figures

High-resolution figures can be found in the thesis repository `https://github.com/jenkoj/msc`.
More precisely in the "figures" subfolder `https://github.com/jenkoj/msc/tree/main/Figures`.

A.3 Data and datasets

We cannot share the data since it is not ours to share, but we can share the spreadsheet that points to each dataset. The spreadsheet includes other datasets that could be used for the very same purpose. The spreadsheet can be found here.

`https://github.com/jenkoj/msc/blob/main/Appendices/datasets_and_sources.pdf`

An overview of the data in the datasets was made, and it can be seen in the following spreadsheet.
`https://github.com/jenkoj/msc/blob/main/Appendices/dataset_overview.pdf`

The sliced hourly datasets can be found here.
`https://drive.google.com/drive/folders/1tIsG-bqxoJdbU1p8xa_LCTaKNSk_LylZ?usp=sharing`

Appendix B

Expanded General Table

TABLE B.1: Expanded general table of load profiles

	frequency	appliances	number of activations	power (avg)	operating time
appliances		X	X	X	X
number of activations	X	[16] [39]	X	X	X
power (avg)	X	[62]		X	X
power (array)	[39]	X	X	X	X
power (histogram)			X	X	X
operating time	X	[37]	[59] [58] [4]	[4]	X
time array	X	X	[16] [39]	[20] [23] [12] [38] [72] [28] [27] [36] [1] [40] [59] [58] [35] [4] [17] [41] [20] [15] [52] [39] [27]	[26]

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