UNIVERSITY OF LJUBLJANA

MASTERS THESIS

Load Profiling of Home Appliances Using Load Classification

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in the

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ICT

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Declaration of Authorship

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

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

Signed:

Date:

Chapter 1

Introduction

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

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

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

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

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

1.1 Structure

M.Sc. degree will be composed of the following parts. In the first part, I will define what is load profiling, appliance level load profiling, non-intrusive load monitoring, intrusive load monitoring, and anomaly detection. Then I will review related research work done to date. Next, I will elaborate on existing ideas on where load profiling is being used to date and what are its possible applications. Then, I will present used datasets, and finally, I will present a working demo using appliance classification and simple load profiling. The demo will present the possible use of one of the previously mentioned applications.

The rough outline of chapters:

- Abstract?
- Introduction
- Define load profiling
- Anomaly detection (how it fits in) maybe?
- Related work
- Define contributions and goals
- Present "Demo"
- Methodology
  - Datasets (used)
  - Load classification
    - Mention my work on images?
    - Machine learning
  - Load profiling method
- Results
- Use cases
- Privacy
  - Concerns
  - Sharing and transparency
  - Solutions
- Datasets
  - Issues
  - Load profiling
  - Solutions
- Future research directions
  - Map of current work
  - Where does NILM load profiling lay on the Map
- Discussion
- Conclusions

Chapter 2

Definitions

Author Proedrou, 2021 defines terms as following

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

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

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

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

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

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

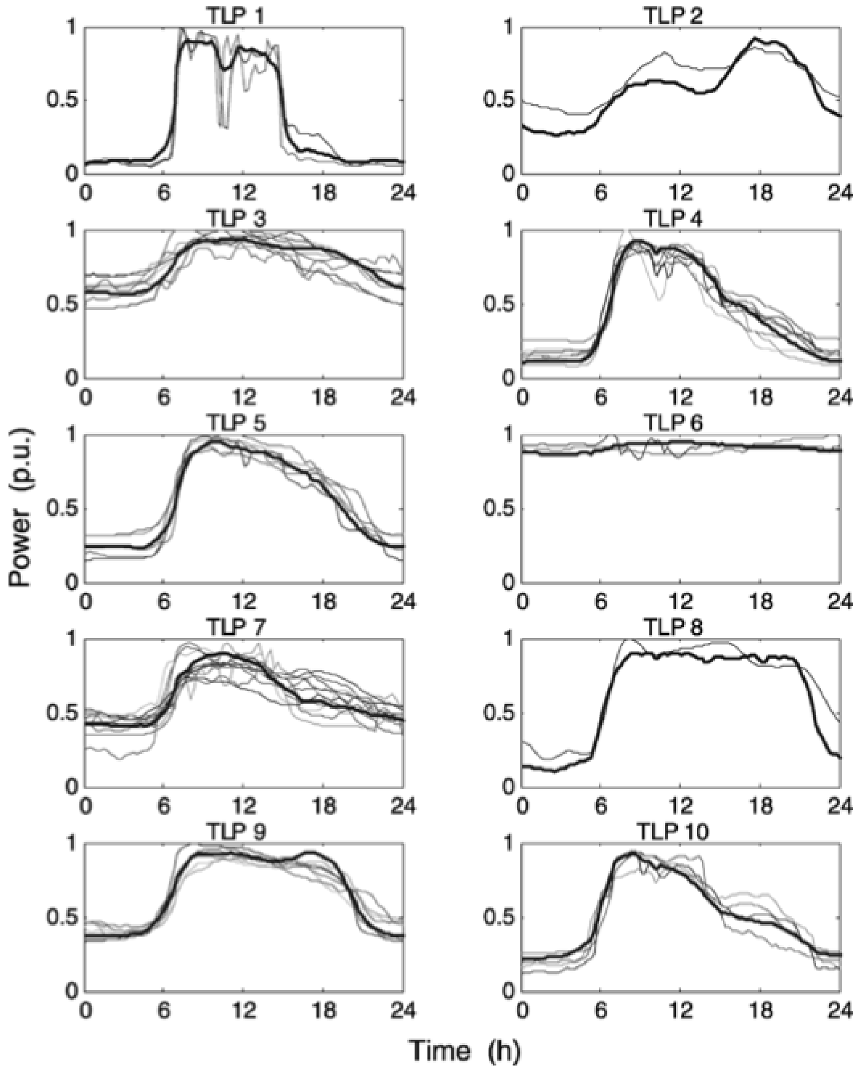


Figure 2.1 depicts 10 clusters of daily load profiles. This is not the only way to present it, for example, author Park and Son, 2019 used an image-based presentation.

Chapter 3

Related work

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

3.1 Load profiling

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

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

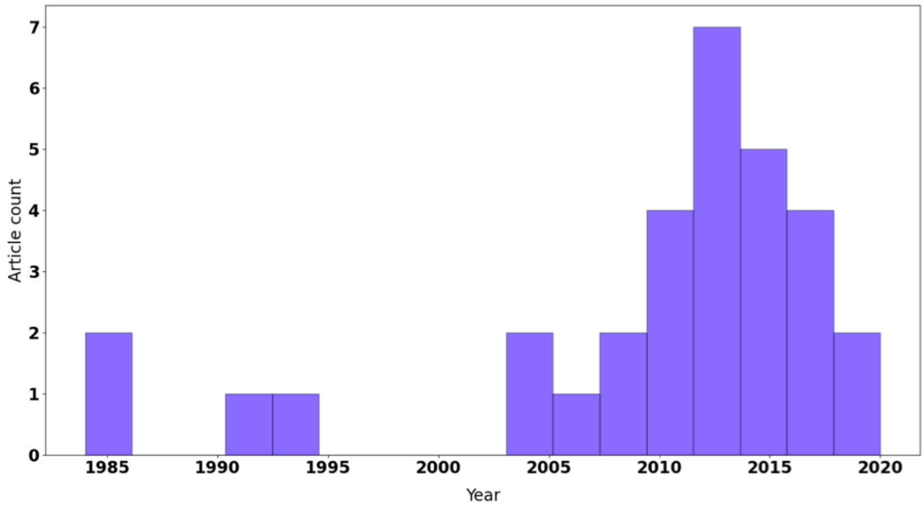
Proedrou, 2021 did a comprehensive review on load profiling. The author defined various load-profile application subgroups such as demand-side management, planning and control design of energy systems, and residential load profiles. The author also grouped modeling techniques as probabilistic models,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

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

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

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

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



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

Gao, Liu, and Zhu, 2018 makes use of the bottom-up method to build a forecasting framework for household load profiling, that takes into account consumption patterns of residents. A model falls into the demand-side management subgroup. They developed a "similar day extraction model", that is designed to extract similar days by comparing environmental factors and household factors, that influence on energy consumption. Using that, they improved the prediction accuracy of residents consumption behavior.

They have had developed a "single-day extraction model", designed to select the same days by comparing environmental and household factors, which influence energy consumption. By using this approach, they have improved the accuracy of predicting behavioral patterns of dwellers.

This method falls into the probabilistic method subgroup. Results show that their method successfully modeled daily usage.

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

Csoknyai et al., 2019 analyse energy consumption habits, trends, and intervention strategies in residential buildings. This is mainly done through the serious game approach, with a combination of direct consumer feedback through smart metering. Application or serious game as they call also offers advice, comparisons, savings, reductions goals, and monitoring. They measure almost all dimensions of electricity usage as well as heating. Their results show that their serious game was not able to induce energy-saving behavior.

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

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

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

Whereas most of the above-mentioned papers focused on aggregated consumption of building to build a load profile, authors Issi and Kaplan, 2018 focused on appliance-level load profiling. Their main contribution is to create a realistic per appliance load profile. They developed a wireless measurement system with smart plugs that enabled them to obtain power signatures for each appliance. They evaluated the data and based on observations they determined working cycles for each appliance.

3.2 Anomaly detection in building energy consumption data

A review on Anomaly detection in building energy consumption data was written by Himeur et al., 2021. Here, the authors took a deep dive into detecting anomalies in energy consumption in buildings. The author first makes an overview of existing anomaly detection schemes and applications. Second, they perform a critical analysis and an in-depth discussion of the state-of-the-art. Next, they describe current trends such as NILM anomaly detection. Finally, they derive 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., 2019b authors propose an algorithm that functions on top of existing state-of-the-art NILM algorithms Hidden Markov model, combinatorial optimization, Latent Bayesian Modeling, and Graph-based Signal Processing. They focus on three appliances, a fridge, freezer, and heater. Their metric was the number of operation cycles and energy used within those cycles. They implemented sigma variables to represent standard deviation and used rule-based anomaly detection. So if energy or counts are significantly larger than the mean then the day is considered anomalous. Their rule had only one manual setting and that was a number of standard deviations before the sample was considered anomalous. Their results show that sub-meter anomaly detection works decently whereas NILM based anomaly does not work at all.

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

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

Chapter 4

Possible use cases

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

4.1 Energy saving

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

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

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

An actual use case would be an EV owner with an installed PV system and heat pump, who works from home on occasions. In this case, two profiles would be developed. Normal workday and work from home day. Additional information would be obtained from the calendar of a user. 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 day, the system would start charging the car with the morning sun, using only the PV energy. In the evening hours, when consumption rises and production falls, EV could inject the power back into the house. Again using appliance load profiles to mitigate net energy flow as close to zero as possible. 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.

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

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

Many papers have been published, where authors explored ways to reduce the energy consumption of users by studying their user load profiles. Energy saving is done through instant feedback, reduction goals, rewards, and by comparing their user profile to the average user as authors did in Csoknyai et al., 2019. All though authors did state that these measures did not reduce energy efficiency, other sources state that my smartly managing the consumption as much as 10 - 30 % of energy could be saved.

4.2 Grid management

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

The electricity provider could control the main appliances so that load on the power grid is as uniform as possible, with few peaks. For this to function, users would have to allow the installation of energy meters and controllers on appliances that use the most electricity, and their use can be allocated, the fridge cannot be allocated, whereas heat pump can be. This would introduce a statistical multiplex, similar to what is done with internet traffic, alleviating load off the grid.

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

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

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

4.3 Elderly care

Demographic changes i.e. aging population is an increasing socioeconomic issue. The elderly are facing many issues when staying at home alone for extended periods. Accidents such as falls or the inability to do choirs due to health-related issues or even dementia-induced issues such as leaving appliances on for long periods could all be detected using user load profiling.

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, turning on stove, oven, and kitchen vent in the noon, or using kettle and 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: coffee machine not turning on in the morning or stove and kitchen vent not being used at the noon. Another issue could be detected if the appliance would be used more frequently or for extended periods of time. This could indicate that the user forgot to turn off the stove, oven, or even a light. The same system could detect that fridge or freezer was left open since 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. (find source)

4.4 Anomaly detection

One use case of anomaly detection was already mentioned in the prior chapter. One more thing that could be detected, using load profiling, would be altered operation of appliances. In the case of a fridge, the system would detect that duty cycles are too long. The increased duty cycle can be caused by cooling liquid leakage, fridge being open or compressor motor malfunction. Heat pumps work on the same basis as fridges, meaning the same anomalies could be detected. The malfunction could also be detected in heating element appliances such as toasters or boilers. Since mentioned appliances are one of the largest consumers in a household, early enough detection could lead to large energy-saving benefits. (source)

4.5 Other

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

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

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