FAKULTETA ZA ELEKTROTEHNIKO

MASTERS THESIS

Msc Disposition

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Declaration of Authorship

I, Jakob JENKO, declare that this thesis titled, "Msc Disposition" and the work presented in it are my own. I confirm that:

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- 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.
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Load profiling of home appliances using load classification

0.1 Introduction

Climate change calls to shift to renewable energy and restructuring of electricity sector. Sources Eurostat, 2022 show as of time of reading this paper, 44 % of produced in Europe was from combustible sources such as gas, fuel and coal. Even thorough that is significant decrease of 10 % in last 10 years, it is a significant Co2 emitter. Same source Eurostat, 2022 also states that, third of energy is consumed by residential sector. It is estimated, that human population will reach 10 billion inhabitants in 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 human footprint.

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

This could be achieved trough various applications and methods that use load profiling and load monitoring as their core technology. Authors in Chuan, Rao, and Ukil, 2014 proposed 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 a use of distributed energy resources and manage them in such a way to decrease net output of energy flow such as authors describe in Moreno Jaramillo et al., 2021. All described methods would reduce and alleviate the load off the power grid.

Load profiling and load monitoring and anomaly detection in building energy consumption are not a novelty and had been in research since 1980s. While 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 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. Goal of these systems is to mitigate net energy flow to be as local as possible. Socioeconomic changes such as (work-from-home), also drastically reshaped the load profile curve.

Technology advancements in load monitoring and non-intrusive load monitoring and increased adoption of smart energy meters offer a new way of load profiling, that is NILM load profiling. Besides consumption reduction there are many applications of load profiling which I will later describe.

0.2 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 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. Demo will present possible use of one of previously mentioned applications.

0.3 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.

Besides above pre-defined terms I have defined few of my own:

- 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.

0.4 Related work

Work relating to load profiling can be found in two research verticals or topics. First one is load profiling and load profile models, that in most cases study the load profile curve of the building. There are few exceptions that study load profiles on appliance-level. Second vertical is anomaly detection in building energy consumption data. While first topic is closer, there are quite 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"

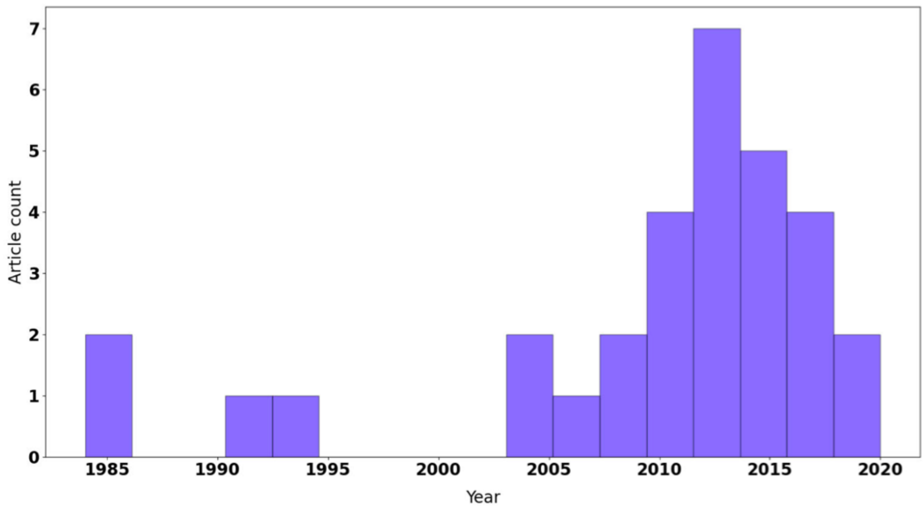
0.4.1 Load profiling

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

With 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 bottom-up approach, since it is more relatable.

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

FIGURE 1: "Distribution of publications on load profiling from 1985 to 2020. The graph was published by Proedrou, 2021"



Early years

One of the first publications on load profiling were published by Train, Herriges, and Windle, 1985. They used 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 are able to adjust the curve based on weather, dwelling size and income. In same year Walker and Pokoski, 1985 published paper where they used bottom-up approach with psychological factors to create probability models of when will 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 1 shows.

0.4.2 Main load profiles

Start of second was, among others, stared by our fellow researchers David Gerbec cite first paper. Another paper that they have published, that matches our topic was Gerbec et al., 2005. Where authors tried to assign typical load profiles to a particular group of consumers based on their activity. To achieve that, they used probabilistic neural networks as a way of classification. Their methodology was tested in real use scenario.

Gao, Liu, and Zhu, 2018 makes use of bottom-up method to build a forecasting framework for household load profile considering consumption behavior of residents. Model falls into demand side management subgroup. They developed a "similar day extraction model", that is formulated to select similar days by comparing external environmental factors and household internal influence factors on energy consumption in order to enhance prediction accuracy of residents consumption behavior. This method falls into probabilistic method subgroup. Results show that their method successfully modeled daily usage.

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

Csoknyai et al., 2019 analyze 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 advices, 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 appliance usage curve. Usually, the first usage peak is in morning, and the second one 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 image. Image is a grid of squares where y-axis contains monthly data with resolution of one day, x-axis contains daily data with resolution of one hour. Grid if color filled with algorithm that authors developed, where red means more activity and blue less. Using digital image filters they transform 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 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 for k-means resulting 5 clusters. Similar to other load profiling papers.

Whereas most of 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 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.

Maybe more usefull at use case Moreno Jaramillo et al., 2021 present the first systematic review of load modeling and identification technique applied to distributed energy resources on distribution networks.

0.4.3 Anomaly detection in building energy consumption data

Review on Anomaly detection in building energy consumption data was written by Himeur et al., 2021. Here, authors took a deep dive into detecting anomalies in energy consumption in buildings. Author first makes and 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, and 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 directions. Only one paper was published on NILM anomaly detection Rashid et al., 2019b. Here, 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, fridge, freezer and heater. Their metric was a Number of cycles taken by appliance and energy used in 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 mean then day is considered anomalous. Their rule had only one manual setting and that was a number of standard deviations before 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 similar approach, except that they used only compressor based appliances such as fridge and air conditioner. They also added additional rule to their anomaly detection algorithm, but results still showed that NILM algorithms are not there yet.

another anomaly detection

0.4.4 Possible use cases

0.5 Possible additions

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