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:

- 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:

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"

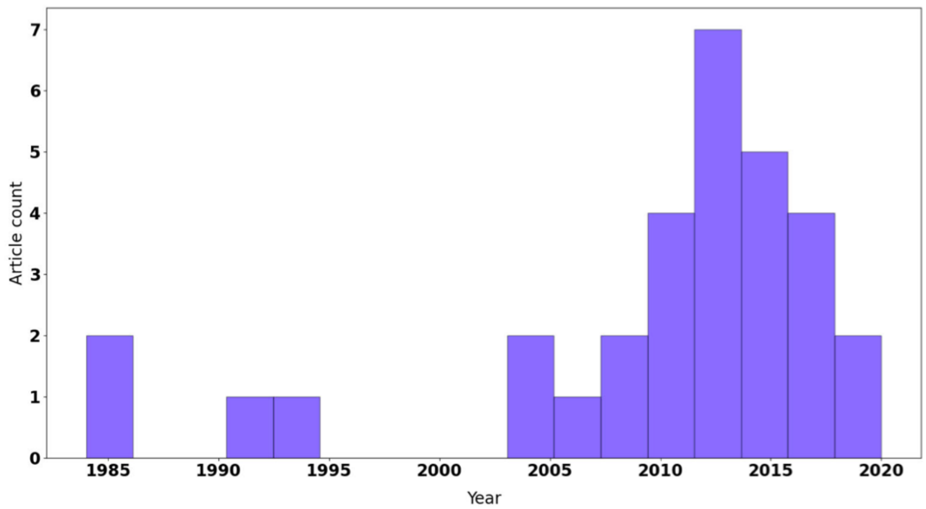
0.4.1 Load profiling

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

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 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 direction. 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 paper was by Azizi, Beheshti, and Bolouki, 2021... insert descriptions

Castangia et al., 2021 used disaggregated sub meter data to detect anomalies in use consumption. They used 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. Authors first pre-processed the data by aggregating input load int Hourly energy consumption, second derived additional features, which are 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.

0.4.4 Possible use cases

Load profiling method has a lot of different use cases across different fields.

Energy saving

As mentioned before many applications for load profiling could be used in order to reduce energy use and increase energy efficiency. With emerging EV-market and ever-increasing installation of heat pumps, more and more energy is being used via electricity. Meaning, most of the current power grids would have to be upgraded in order 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". DER 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. Devices mentioned above, with smart management could be used in a way that would reduce net flow on energy and alleviate the load on power grid. A way to achieve this is via load profiling, and load modeling. Besides that a control system would have to be put in place in order to control devices that are using the most energy. An actual use case would be a user with EV that works from home on occasions. In this case two profiles would be developed. Normal work day and work from home day. Information about which day is coming would be extracted from users work calendar, in case the system is not periodical. In case of normal work day users profile would suggest that all PV energy can be sent into grid, whereas in case of work-from home day his energy would be used to fill up his car during the peak production and not during the night. In case where users battery is full, and grid would additional power in evening hours his car could inject few percent of its power instantly. With ever-increasing power capacity and increasing range of EVs, more and more of battery capacity could be used in order to load-balance the grid. If users usual commute is 100 km, and EVs range is 500 km, at least 250 km worth of capacity could be used to balance the grid. If users used a battery pack, the profiling job would be even easier. One other use case could be using heat pump and heat storage, where besides users use profile system would also obtain weather forecast from the internet. Heat pumps are more efficient when temperature differences are smaller, using weather forecast info, heat pump could store energy when warm and release the energy when cold. One other case would be that energy distributors could use the user load profile in order to optimally control the use of electricity and heat. By signing user would pay less for the heating of his house and user more of renewable sources. Minimal change if his habits would be achieved by using his load profile. Energy could be localy trasfered similar to how p2p netowrks operate, including load profile data and many peers, system could work without user even noticing.

Many papers have been published, where authors exploed ways to reduce energy consumption of users by studying their user load profiles. Energy saving is done trogh instant feedback, recuction goals and by comparing their use profile to the average user.

Eldery care

Demographic changes i.e agging population is facing issuses when staying at home alone for extened periods of time. Accidents, such as falls, or in-ability to do choirs due to health related issues or even dementia induced issues such as leaving appliances on for long periods of time could all be detected using user load profiling. To detect falls or other issues a normal daily appliance use profile could be developed. It would involve routine behavior of users such as turning on coffee machine and stove in the morning, turning on stove, oven and kitchen vent in the noon, tuning on microwave or a kettle in the evening. All these routines could be measured and tracked. Using mentioned data a profile would be developed and using probabiliy and a treshold system could detect an issue or an anomaly. Such as coffee machine not turning on in the morning or stove and vent not being used at the noon. This could be detected if user is using less than usual, another anomaly could be detected if user is using the appliance too much. Stove or oven has been on for long period of time with high power consumption it could indicate that user forgot to turn it off, the same could be detected lights and fridge in case user left it open. In case of fridge, duty cycles would drastically increase which could be detected. After an anomaly would be detected a care-giver would be notified to check on that person. (find source here)

Anomaly detection

The use case of anomaly detection was already mentioned above. One more thing that could be detected using load profiling would be altered operation of appliances. In case of fridge system would detect that its duty cycles are too long and that there is an issue with these appliances. Increased duty cycle can be caused by cooling liquid leakage, fridge being open or compressor motor malfunction. Heat pumps work on same principle as fridges and same anomalies could be detected here. Same malfunction could be detected in heating element appliances such as toaster or boiler. Since mentioned appliances are one of the largest consumers in a household, early enough detection could lead to large energy saving benefits.

Grid managment

As mentioned earlier increasing percentage of DER appliances is causing troubles to energy distributors, due to increased energy flow. I was talking about energy saving benefits in case of smart managed systems that would be used by users, independent of energy distributors. Joint actions between user and energy management company would benefit both end-user and the company. If user allowed the installation of energy meters and controllers on few appliances that use most electricity and their use can be allocated (fridge cannot be allocated, whereas heat pump can be), grid management company could control the use of main appliances so that load on power grid is as uniform as possible, with as little peaks as possible. This would introduce a statistical multiplex, similar to what is done in internet traffic. Benefit of user would be lower cost of charging and heating the building. This is already done trough so called small and high tariifs, More details user load profiles would enable energy distribution companies to introduce real time tariifs. User would have three options. To these appliances as free as he wants i.e turning them on at times he desireds to, this would lead to higher tariifs. Second option would be to use the appliances as regularly as possible, this would lead to lower tariifs. Third option would be to leave use of appliances such as washing machine, heat pump and EV to managmet company and use them charge them when real time market price is the lowest. This would lead to free or even being negative price of electricity since ditribution companies have to load the grid somw how in order to keep the frequency steady. Load shedding is already a commond practice that dcs use, in order to keep the frequenct at 50hz. Load shedding is when dc disconets the whole neighbourhood in order to keep the frequency from drifting. Using user load profiles of users, dc cooul diconect loads in a way that would minimaly affect end-user, without the need to disconnect the whole neihgbourhood.

Research

0.5 Possible additions

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