MS-E2177 Seminar on Case Studies in Operations Research

Interim report: Disaggregation of electricity data

Client: Fortum

Project manager: Mihail Douhaniaris
Team members: Samuel Marisa, Matias Peljo, Johan Salmelin

28.02.2017

Contents

1 Overview

Fortum is interested in energy research and energy related venturing. Fortum operates in both energy generation and sales, and has access to vast amounts of energy consumption data. Consequently, Fortum is currently interested to evaluate whether these datasets could be used to build new products and services. More specifically, our high-level objective is to provide Fortum understanding of the possibilities and limitations of currently available power disaggregation technologies.

In this project the main objective is to develop and implement an unsupervised power disaggregation algorithm. In addition, Fortum has specified three subgoals related to the main objective: separation of electric heater signals, detection of boiler switch events and detection of recurring signals. The idea behind the subgoals is to provide direction: they are used in guiding the development of the disaggregation model such that it can be effectively used to solve the given test cases. That is, the subgoals are not goals per se but inspiration for the designing and tools for the verification of the model.

Our efforts began in the form of an extensive review of research in the field. The review resulted in the identification and selection of a model that seems to match the goals of the project. In addition, we discovered a NILM (Non-Intrusive Load Monitoring) research toolkit that we decided to integrate to our model [1]. The toolkit is used in the NILM research community and will allow us to compare our data and model with previously published datasets and NILM algorithm implementations.

We have been able to follow our original project schedule pretty accurately. However, we decided to streamline the schedule plan such that instead of starting with a simple prototype we immediately started to develop a more advanced model and preprocessing the data to work with NILMTK's standards. NILMTK was too complex to learn to use properly even for simple prototypes in such a short time. The updated schedule is presented in table 1. The tasks in the schedule are explained in the tasks section. Currently we have finished the following tasks or phases: conception and initiation, exploratory data analysis, literature review, scoping and planning, model comparison, model specification, and model implementation. The following tasks are in progress or further ahead: model testing, model refinement, model verification, business case ideation, reporting.

The chosen model is a Nonparametric Factorial Hidden Markov Model (NFHMM) model based on the state-of-the-art research of [2, 3, 4]. The model is designed specifically for unsupervised disaggregation and is likely to be a useful tool in solving test cases 1 and 3 given by Fortum. However, we have realized that the second test case, finding out reoccurring patterns in the consumption, is not on the same horizon as the other two and will not be facilitated by the other work. Since the model and toolkit have proven to be rather complex to develop and use we decided to discard the subgoal from the scope of the project.

As reflected in the schedule below, our current plan is to test the model by integrating it into NILMTK after which we proceed to test it with available datasets and finally, verify its usefulness regarding test cases 1 and 3. Along with testing, model refinement will be done until the end of the verification phase. It is difficult to estimate the performance of the model as not much testing has been done yet. This means that it is difficult to project the quality of the final output of the project at the moment. Notable risks are presented in section 4.

2 Schedule

The updated project schedule is presented in table 1. The tasks in the schedule are explained in the tasks section.

Table 1: Updated project schedule. The original schedule is represented with the 'o' symbols on the respective weeks where the task was originally scheduled. Some tasks listed in the original schedule were replaced to account for the decision to change from prototype oriented development to a more waterfall method. The tasks prototype, prototype evaluation, and model improvements are now represented with model implementation and model testing.

Task \ Week	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Conception and initiation	o	o																	
Exploratory data analysis		o	o																
Literature review			o	o	o														
Scoping and planning					o	o													
Model comparison						o	o												
Model specification								o	o										
Model implementation								o	o	o									
Model testing									o	o									
Model refinement											o								
Model verification												o							
Business case ideation													o	o					
Reporting and finalizing														o	o	o	o	o	o

current week

3 Accomplished tasks

This chapter describes contributions that were made before the interim report development. We have made an extensive literature review by distributing publications containing promising information and disaggregation algorithms along all the team members to study. This gave us a good sense of what is already achieved on the field and what are the limitations. According to these findings we chose the algorithm implemented to meet the overall objective of constructing a disaggregation model.

Conception and initiation

In the beginning of the project we focused our efforts in fully understanding the assignment given by Fortum and its context. This was done through discussion with the client and further study of the field of energy disaggregation.

Exploratory data analysis

In exploratory data analysis our plan was to go through the data to find possible errors and to understand for which purposes is it possible to utilize the data.

The data was given to all team members and also additional data was provided by Fortum according to our needs. There have not been problems related to security and confidentiality. The data is proven to be free of major errors but the data did contain lots of minor errors such as missing values, duplicate values etc. Some data parsing and convertion logic was developed to more effectively explore the data as well as to convert data from the Fortum dataset to work with NILMTK, the open source disaggregation toolkit. Exploratory data analysis was mostly done using Python (scipy/matplotlib) and R.

Literature review

Literature review was regarded as an important task not only since it is part of the assignment given by Fortum but also we could not have chosen sufficient approaches or models let alone develop a satisfactory model with which to begin to solve the problem of power disaggregation without a thorough understanding of the field. The literature review included studying of scientific journal articles and other academic publications as well as searching possible open source projects relating to power disaggregation. The goal was to find methods that have been applied to derive results in similar problems.

The literature review proved to be very rewarding in terms of learning experience and it was relatively easy to find academic publications relating to power disaggregation. The area of disaggregation proved to be much more studied in the literature than what was expected. In general starting from 1990’s the interest towards disaggregation has been gradually rising and recent development in the field of internet of things shows in the quantity of research being made. Based on the articles and reviews of different disaggregation algorithms we found hidden markov model based approaches matching our objectives well.

During the review we also found NILMTK and began to explore whether we should learn to use it and attempt to build and integrate our model into it as well as whether it could facilitate the testing and verification of the model.

Scoping and planning

After having an understanding of the field of power disaggregation we decided to concentrate on implementing a state of the art disaggregation algorithm, meanwhile, developing a parser that can convert our data to be compatible with NILMTK. Focusing on NILMTK ensured that we will have some valuable tools to offer even if we can not implement a satisfactory algorithm. Namely, NILMTK provides some disaggregation algorithms and the comparison of different disaggregation methods is possible since there is disaggregated data available for testing. There are also articles that have used to NILMTK to benchmark and compare disaggregation algorithms.

Model comparison

We analyzed and compared the most promising methods identified during the literature review and continued with the models that best fit our project purposes.

We decided to concentrate on unsupervised models because gathering disaggregated training data is impractical, expensive and not in Fortum’s intentions. Literature review showed that methods based on Hidden Markov Models (HMM) are considered as state of the art methods in power disaggregation, especially in the case of low sampling rate. It seemed that there is no simple and easily implemented disaggregation method that could provide satisfactory results. We chose

Nonparametric Factorial Hidden Markov Model (NFHMM) as our model, since it has shown some promising results and requires minimal prior knowledge of the appliances. NFHMM does not even require prior knowledge of the number of appliances in the household which makes it suitable for our purpose.

Model specification

After choosing the model, we studied it in detail to fully understand its functioning and possible limitations that we were not able to notice in the literature review.

The chosen model, NFHMM, is a Hidden Markov Model, where the states are distributed so that we can model each device in household as an independent Markov chain. Each device has its own power level and transition matrix. It is assumed that the power level of each device is constant. The states of the devices in different times are stored in a matrix.

Learning in the algorithm is performed by using a non-parametric Bayesian method, the Indian Buffet Process (IBP). Understanding of the model and the algorithm took quite much time since the procedure required understanding of many different schemes such as IBP, combination of blocked Gibbs sampling and Forward Filtering Backward Sampling (FFBS) and Adaptive Rejection Sampling (ARS).

During the model specification phase, we studied NILMTK and worked to represent the first Fortum dataset in it according to the NILM Metadata specification.

Model implementation

We implemented a first version of NFHMM algorithm in R based on [2, 3, 4]. We run into a few challenges that made the algorithm not work properly. The main challenges were time consumption and that the algorithm did not yet work in an expected way. However, the algorithm is not complete and adding the missing parts in it may change its performance. For example, the conjugate priors of hyperparameters are not yet considered in the R code.

During the model implementation phase, we continued to study NILMTK and explore how it can be used to analyze and disaggregate data. It was discovered what the NILMTK developers meant by emphasizing that it is still not a dissaggregation tool but a research toolkit: Although developed, the code in the toolkit is immature and buggy and learning to fully utilize it has proven to take much more time than expected. To facilitate debugging and future verification a purely synthetic dataset was created. This helps in evaluating whether the statistical and descriptive dataset analysis tools work as expected.

4 Future tasks

This chapter describes project tasks that will be completed after the interim presentation. These are model testing, refinement and verification, as well as business case ideation and working on the final report. We describe our plans and approaches for each future task below.

Model testing

In this task we work on testing and evaluating the model performance. The testing will be done on generated simple datasets, so that the disaggregation accuracy can be compared to the ground truth data.

During this phase, we will try to integrate our model into NILMTK such that it can be tested with Fortum's dataset and other previously published open datasets.

Aim to test the disaggregation with Fortum datasets, test cases 1 and 3 as well as data from Juhani's house.

Model refinement

This task will be carried out in parallel with the model testing. Herein, we will work on optimizing the performance of our model and implementing the integration of our disaggregation model to NILMTK.

Model verification

In this task we will work on applying our disaggregation model to the chosen two test cases given by Fortum, the boiler switch event and electric heater signal detections. In addition to electric heater signals open source disaggregation datasets which provide both the aggregate and disaggregated data, are used to verify the model. Finally, we verify that our product meets the specifications imposed by our client.

Business case ideation

Main contribution for this task, the idea generation session and reporting, is scheduled to take place in the end when most of the work with the model is already accomplished. However we have already gathered information about current commercial solutions and business case ideas that have come along while working together with the team and discussing the motivations of this project so far.

Reporting and finalizing

Work on writing the final report and presentation slides.

5 Risks

This section contains the updated risks of the project. The identified risks are shown in table 2.

Table 2: Updated project risks.

Risk	**Probability**	**Impact**	**Actions**
Model runtime not satisfactory	Medium	Model cannot be used in real time disaggregation	Model will be used for historical disaggregation
Model disaggregation accuracy not reliable	Medium	Model cannot be utilized in Fortum's functions	Use heuristics and simplifications to try improve accuracy
Model implementation proves to be too complex for the scope of the course	Low	Workload grows too large and implementation may remain incomplete	Narrowing the scope along the course if needed
Unexpected team member inactivity	Low	Imbalanced workloads between members	Transparency in scheduling and working together
Team member dropout	Low	Workload grows too large for the remaining members	Transparency in scheduling
Confidential information spread	Low	Legal consequences for Fortum and students	Data is kept only at specified storage places

References

[1] Nipun Batra, Jack Kelly, Oliver Parson, Haimonti Dutta, William Knottenbelt, Alex Rogers, Amarjeet Singh and Mani Srivastava. *NILMTK: An Open Source Toolkit for Non-intrusive Load Monitoring*. 5th International Conference on Future Energy Systems (ACM e-Energy), Cambridge, 2014.
https://arxiv.org/pdf/1404.3878.pdf

[2] Jurgen Van Gael and Zoubin Ghahramani. *Bayesian Nonparametric Hidden Markov Models*. PhD thesis, University of Cambridge, 2011.
https://jvangael.github.io/assets/thesis.pdf

[3] Ruoxi Jia, Yang Gao and Costas J Spanos. *A Fully Unsupervised Non-intrusive Load Monitoring Framework*. In Proceeding of the IEEE International Conference on Smart Grid Communications (SmartGridComm), pages 872–878, 2015. https://ruoxijia.github.io/assets/papers/sgc2015_final.pdf

[4] Yee Whye Teh, Dilan Görür and Zoubin Ghahramani. *Stick-breaking Construction for the Indian Buffet Process*. AISTATS, 2007.
http://mlg.eng.cam.ac.uk/zoubin/papers/TehGorGha07.pdf