Deep Dis-aggregation: A CNN model to monitor appliance specific load consumption

Prajna Paramita Dash, *Member, IEEE,* Akshaya Mishra, *Fellow, OSA,*

***Abstract*—Estimating appliance specific power consumption using a single measuring device, known as non-intrusive load dis-aggregation, is a fundamentally challenging blind signal source separation problems. For past two decades, numerous mathematical and pattern recognition techniques, including fractional hidden Markov model, Gaussian mixture model and mean shift based clustering techniques have been proposed to decompose total power consumption of a house hold into appliance specific power signals. The measurement sampling rate, operating characteristic of individual appliance and unknown number of mixed signal, creates a big challenge to represent the mixed signal as a sum of individual signals. To address, these problem, Deep dis-aggregation, is taking a data driven deep learning approach to learn to estimate the individual appliance power signal from a mixture of power signals. Essential, deep aggregation, employs a multi-scale deep convolutional architecture to learn distinct power consumption characteristics of each appliance by a set of training samples derived from power consumption signature of different appliance. Dee-aggregation is trained using $60,000$ signal samples, consisting of four house-holds and five types of appliances. The dis-aggregation capability of deep-dis aggregation is tested using $20,000$ testing samples collected from 5 house holds and five appliance that are different from the training samples.**

***Index Terms*—Deep convolutional neural network, non-intrusive load dis-aggregation, blind source separation, mixture of Gaussian models, FHMM.**

I. Introduction

ENVIRONMENTALIST are striving to device policies to reduce the carbon emission from all possible energy sources. On, the other hand, the energy demand of consumers are increasing exponentially and the estimated energy demand is going to double by 2030. Therefore, a great amount of research have been proposed in effective management of power supply and demand. One of the most important innovations for minimizing house hold energy wastage is through measuring the energy consumption of individual loads. Monitoring of energy can be done at different levels; from energy dispatch centers or at consumer level. With advancement of smart meter technologies, consumers are aware of patterns of their energy consumption over days, weeks, or months. Adding features like appliance level energy consumption will make them "smart" user of energy. In addition to monitoring whole house energy consumption they can monitor energy usage of each appliance. Appliance level load monitoring can be measured in two ways, intrusive and non intrusive methods. In intrusive load monitoring (ILM), a sub-meter is attached to each appliances, which is an expensive and complex manual installation process. In non-intrusive load monitoring the total house hold energy consumption is decoupled into appliance specific measurements, without installing appliance specific sub-meters.

George W. Hart's seminal idea on Non-intrusive appliance monitoring (NALM) has provided a foundation to apply signal processing, pattern recognition and machine learning concepts to decompose total house hold energy consumption into appliance specific load. Hart followed an information theoretical approach by describing the total energy consumption of house hold is an additive mixture of individual loads. Where, he created a debase or(database??) of load signature of each devices and followed a constrained finite state machine approach to dis-aggregate the total house hold load into appliance specific loads. Following, Hart's approach numerous signal processing and classification based NLML (NALM???) approaches are proposed to estimate the transition state of appliance at lower frequency sampling rate. Where, waveform of time domain power signal of each appliance is measured at different time intervals, then a manual feature extraction and selection procedure is followed to describe them. Then, estimation or clustering techniques, such as Fractional Hidden Markov model (HMM), finite state-machines (FSM), Combinatorial Optimization, mean-shift, k-nearest Neighborhood, and kd-tree, uses those feature vectors to determine transition state of each device from the aggregated load signal. The complexity, signal non-uniformity and non-linearity, and noise statistic of aggregate power signal poses a great challenge for manual selection of appropriate appliance load feature vectors.

Rest of the paper is organized as follows. Section 2 provided a fundamental overview of Non-intrusive load monitoring methods. The NIALM method we developed for a low-frequency sensor is presented in Section 3. By using simulationexamples, we demonstrate that this method has the potential to outperform existent methods. In Section 4, we present our NIALM method for high-frequency sensors. The method combines together a multivariate statistical technique and a pattern recognition technique. The method is tested using our laboratory system. The two developed NIALM methods can be combined together in the future work, which is briefly discussed in Section 5.

II. NILM Background Theory

- Introduction of NILM by George W. Hart

M. Shell was with the Department of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA, 30332 USA e-mail: (see http://www.michaelshell.org/contact.html).

J. Doe and J. Doe are with Anonymous University.

Manuscript received April 19, 2005; revised August 26, 2015.

- Implementation of NILM
- Commercialization of NILM
- Recent application of deep learning in NILM

August 26, 2015

A. *Subsection Heading Here*

Subsection text here.

1) Subsubsection Heading Here: Subsubsection text here.

III. Problem Formulation

IV. Implementation

V. Case Studies

VI. Discussions and Future Work

VII. Conclusion

VIII. Conclusion

The conclusion goes here.

Appendix A
Proof of the First Zonklar Equation

Appendix one text goes here.

Appendix B

Appendix two text goes here.

Acknowledgment

The authors would like to thank...

References

[1] H. Kopka and P. W. Daly, *A Guide to LATEX*, 3rd ed. Harlow, England: Addison-Wesley, 1999.

PLACE
PHOTO
HERE

Michael Shell Biography text here.

John Doe Biography text here.

Jane Doe Biography text here.