LIST OF ACCEPTED PAPERS

http://nilmworkshop.org/2018/

ABOUT NILM 2018

The 4th International Workshop on Non-Intrusive Load Monitoring (NILM) will be held at the University of Texas, Austin, in **Austin, Texas** on **March 7 to 8, 2018**. The exact date is still being confirmed, and will be announced on our website at the end of November 2017. As in 2014, this workshop will be co-located with the Pecan Street Annual Research Conference. Last workshop was held June/2014 at Simon Fraser University in Vancouver, Canada.

ORAL PRESENTATIONS

A Practical Discussion of Lessons Learned

Leesa Lee, Bidgely; Alex Shyr, Bidgely; Shishir Saraiya, Bidgely

ABSTRACT Deploying Disaggregation at Broad Scale Bidgely has over two years of practical experience deploying disaggregation in the field with utilities in the North America, Europe, and Asia Pacific regions. This paper will outline the lessons learned in transitioning disaggregation from the lab and early pilots to full-scale deployments. Particular attention is paid to the cost and technology trade-offs that are required to build a commercially-viable solution.

An Experimental Comparison of Performance Metrics for Event Detection Algorithms in NILM

Lucas Pereira, M-ITI; Nuno Nunes, Técnico, University of Lisbon

ABSTRACT In this work, we analyse experimentally the behaviour of 23 performance metrics when applied to event detection algorithms in Non-Intrusive Load Monitoring, identifying relationships and clusters between the measures. Our results indicate that when applied to this type of problems, the performance metrics will evidence some considerable differences in behavior when compared to

other more traditional machine learning problems. Our results also suggest that most of the differences in behavior are due to the naturally unbalanced nature of the event detection problem in which the number positive cases (True Positives and True Negatives) is much higher than the number of false cases (False Positives and False Negatives).

Data augmentation for dealing with low sampling rates in NILM

Tai Le Quy, L3S Research Center; Sergej Zerr, L3S Research Center; Eirini Ntoutsi, L3S Research Center; Wolfgang Nejdl, L3S Research Center

ABSTRACT Data plays a crucial role in evaluation the performance of NILM algorithms. The best performance of NILM algorithms is achieved with high quality evaluation data. However, many existing real world data sets come with a low sampling quality, and often with gaps, lacking data for some recording periods. As a result, in such data, NILM algorithms can hardly recognize devices and estimate their power consumption properly. An important step towards improving the performance of these energy disaggregation methods is to improve the quality of the data sets. In this paper, we carry out experiments using several methods to increase sampling rate of low sampling rate data. Our results show that augmentation of low frequency data can support the considered NILM algorithms in estimating appliances' consumption with a higher F-score measurement.

FactorNet: Learning to Factorize Intractable and Multi-Modal Posterior Distributions for Energy Disaggregation

Henning Lange, Carnegie Mellon University; Mario Bergés, CMU

ABSTRACT Factorial Hidden Markov Models (FHMM) have emerged as a prominent modeling approach for energy disaggregation. However, because latent variables become dependent conditioned on the observation, reasoning about the posterior is usually intractable which is required for inference as well as learning. Recent approaches try to deal with these intractable posterior distributions by applying Variational Inference with an auxiliary distribution that assumes independence between latent states of the posterior. However, because posterior distributions in the context of energy disaggregation are often multi-modal, independent auxiliary distributions fail to capture \emph{either}-\emph{or} relationships between appliance states. In this paper, we introduce an auxiliary distribution over posterior states that, in principle, can approximate any multivariate Bernoulli distribution arbitrarily well, while at the same time offering a functional form that allows obtaining independent samples as well as the mode required for inference in $ \mathcal{O}(N)$ where N is the number of parallel Hidden Markov chains. On top of that, training the distribution requires solely samples of the joint distribution which are typically easy to acquire. We conduct experiments in the context of waveform disaggregation illustrating the superior capacity of the proposed distribution in comparison to independent auxiliary distributions trained on minimizing the forward or backward KL-divergence.

On the Feasibility of Generic Deep Disaggregation for Single-Load Extraction

Karim Barsim, University of Stuttgart; Bin Yang, University of Stuttgart

ABSTRACT Recently, and with the growing development of big energy datasets, data-driven learning techniques began to represent a potential solution to the energy disaggregation problem outperforming engineered and hand-crafted models. However, most proposed deep disaggregation models are load-dependent in the sense that either expert knowledge or a hyper-parameter optimization stage is required prior to training and deployment (normally for each load category) even upon acquisition and cleansing of aggregate and sub-metered data. In this paper, we present a feasibility study on the development of a generic disaggregation model based on data-driven learning. Specifically, we present a generic deep disaggregation model capable of achieving state-of-art performance in load monitoring for a variety of load categories. The developed model is evaluated on the publicly available UK-DALE dataset with a moderately low sampling frequency and various domestic loads.

Post-processing for Event-based Non-intrusive Load Monitoring

Kanghang He, University of Strathclyde; Dusan Jakovetic, University of Novi Sad; Vladimir Stankovic*, University of Strathclyde; Lina Stankovic, University of Strathclyde

ABSTRACT Most current non-intrusive load monitoring (NILM) algorithms disaggregate one appliance at a time, remove the appliance contribution towards the total load, and then move on to the next appliance. On one hand, this is effective since it avoids multi-class classification, and analytical models for each appliance can be developed independently of other appliances, and thus potentially transferred to unseen houses that have different sets of appliances. On the other hand, however, these methods can significantly under/over estimate the total consumption since they do not minimise the difference between the measured aggregate readings and the sum of estimated individual loads. By considering this difference, we propose a post-processing approach for improving the accuracy of event-based NILM. We pose an optimisation problem to refine the original disaggregation result and propose a heuristic to solve a (combinatorial) boolean quadratic problem through relaxing zero-one constraint sets to compact zero-one intervals. We propose a method to set the regularization term, based on the appliance working power. We demonstrate high performance of the proposed post-processing method compared with the simulated annealing method and original disaggregation results, for three houses in the REFIT dataset using two state-of-the-art event-based NILM methods.

Power Signature Obfuscation using Flexible Building Loads

Kyri Baker, University of Colorado, Boulder; Kaitlyn Garifi, University of Colorado, Boulder

ABSTRACT This work provides a indication of the potential of using intelligent load shifting to increase the privacy of building occupants. Unwanted interception of smart meter communications and subsequent load disaggregation by third parties can potentially reveal private information about building occupants such as occupant demographics and occupancy/appliance schedules. Shifting loads and exploiting flexibility in appliance usage in a way that minimally impacts occupants can obfuscate revealing information in the aggregate power signature of a building. Unlike security measures such as encryption, the techniques proposed here use a building's inherent resources, removing the value from disaggregating the signal in the first place.

Real-Time Itemized Electricity Consumption Intelligence for Military Bases

Omid Jahromi, Belkin International Inc

ABSTRACT This paper outlines the methodology and the interim findings of a NILM demonstration project that Belkin and LBL have been conducting with a grant from the Department of Defense. More detailed findings including accuracy statistics and achieved energy savings will be presented at the workshop.

Scalable Energy Breakdown Across Regions

Nipun Batra, University of Virginia; Yiling Jia, University of Virginia; Hongning Wang, University of Virginia; Kamin Whitehouse, University of Virginia

ABSTRACT Providing an energy breakdown – energy consumption per appliance, can help homes save up to 15% energy. Given the vast differences in energy consumption patterns across different regions, existing energy breakdown solutions require instrumentation and model training for each geographical region, which is prohibitively expensive and limits the scalability. In this paper, we propose a novel region independent energy breakdown model via statistical transfer learning. Our key intuition is that the heterogeneity in homes and weather across different regions most significantly impacts the energy consumption across regions; and if we can factor out such heterogeneity, we can learn region independent models or the homogeneous energy breakdown components for each individual appliance. Thus, the model learnt in one region can be transferred to another region. We evaluate our approach on two U.S. cities having distinct weather from a publicly available dataset. We find that our approach gives better energy breakdown estimates requiring the least amount of instrumented homes from the target region, when compared to the state-of-the-art.

Using the Wisdom of Neighbors for Energy Disaggregation from Smart Meters

Nikolay Laptev, Stanford University; Yuting Ji*, Stanford University; Ram Rajagopal, Stanford University

ABSTRACT The problem of disaggregating the household electricity demand into appliance-level consumption is considered. A deep neural network, based on the long short term memory model, is developed to jointly predict all appliances by leveraging information of neighboring homes. The proposed technique is evaluated on a real-world data set with over 300 homes and more than 20 appliances. Numerical results show significant improvement of the proposed technique over the baseline without joint training and using the wisdom of neighbors.

POSTER SESSION PAPERS

Detection and Classification of Refrigeration Units in a Commercial Environment: Comparing Neural Networks to Unsupervised Clustering. Jérôme Van Zaen, CSEM

Disaggregating Smart Meter Data to Identify Electric Loads and Control Opportunities. Xin Jin, National Renewable Energy Laboratory; Dane Christensen, National Renewable Energy Laboratory

Electricity Usage Profile Disaggregation of Hourly Smart Meter Data. Bochao Zhao, University of Strathclyde; Lina Stankovic, University of Strathclyde; Vladimir Stankovic, University of Strathclyde

Energy Disaggregation for Commercial Buildings: A Statistical Analysis. Simon Henriet, Telecom Paristech

Estimating Power Loads from Partial Appliance States. Nicolas Roux, INRIA; Baptiste Vrigneau , Univ. Rennes ; Olivier Sentieys, INRIA-Univ. Rennes

Improving Appliance Detection and Energy Disaggregation based on Power-line Topology Information. Shiao-Li Tsao, National Chiao Tung University

Load Disaggregation of Industrial Machinery Power Consumption Monitoring Using Factorial Hidden Markov Models. Pedro Martins, GreenAnt; Pedro Bittencourt, GreenAnt; Raphael Pinto, GreenAnt

NILM Power Disaggregation via Artificial Neural Networks. Daniel Pacheco, The Institute for Complex Additive Systems Analysis (ICASA)

Self-configuring Event Detection for Electricity Disaggregation. Farrokh Jazizadeh, Virginia Tech; Milad Afzalan, Virginia Tech; Jue Wang, Virginia Tech