THE UNIVERSITY OF SYDNEY

Non-Instrusive Load Monitoring for Demand Response in Future Power Grid

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Introduction

Background

- Global ambition of integrating renewable energy sources (RES) into energy consumption sector
- Challenges of RES intermittent nature such as power balancing and stability are prominent
- Demand Response (DR) is one of the most proposed solutions to accommodate higher RES penetration
- Lack of accurate load models which can describe the DR potential of DR program participants

Summary

- We investigate the feasibility of modelling and assessing DR potential for residential electricity customers by using current smart meter infrastructure
- We also demonstrate how to model home appliances with Hidden Markov Model (HMM) and fit the HMM by using kmeans algorithm
- Finally, promising results of appliance identification by merely providing (1Hz Smapling) aggregate load profile with learned HMMs are shown.

Demand Response for Future Grid

Utilising Smart Meters To Evaluate Real-time Demand Response Potential

- Smart meters provide half hourly readings of total household electricity consumption
- Different appliances have different potential to participate in demand response programs. E.g., air conditioners have greater potential than electric stoves
- Can we assess real-time total demand response potential by utilising Advanced Metering Infrastructure (AMI)?

High DR Potential

Low DR Potential

Identifying DR Potential

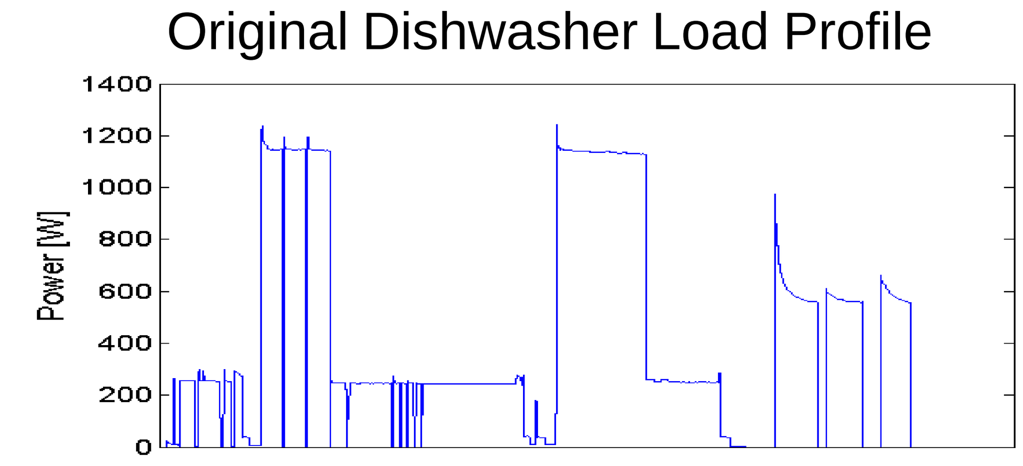
- The answer is true: we can use prior knowledge of appliance load profiles to identify whether high DR potential appliances are in operation from the aggregate total load profile. **This solution is also known as Non-Instrusive Load Monitoring (NILM)**.

Modelling NILM

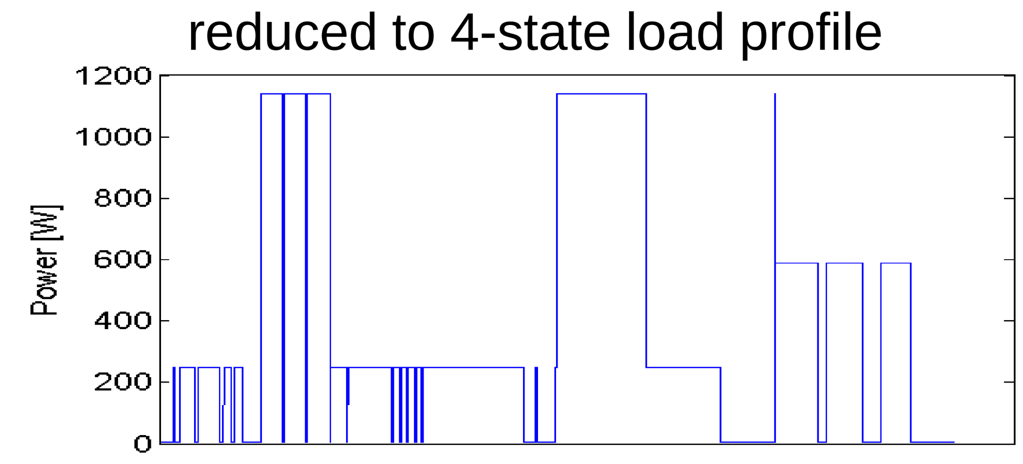
Hidden Markov Model

- Each appliance can be modelled as a Hidden Markov Model with *k* hidden states
- Using a dishwasher load profile as an example, we can represent a dishwasher's load profile as a hidden Markov model with 4 states (piecewise constants) by running **kmeans algorithm**

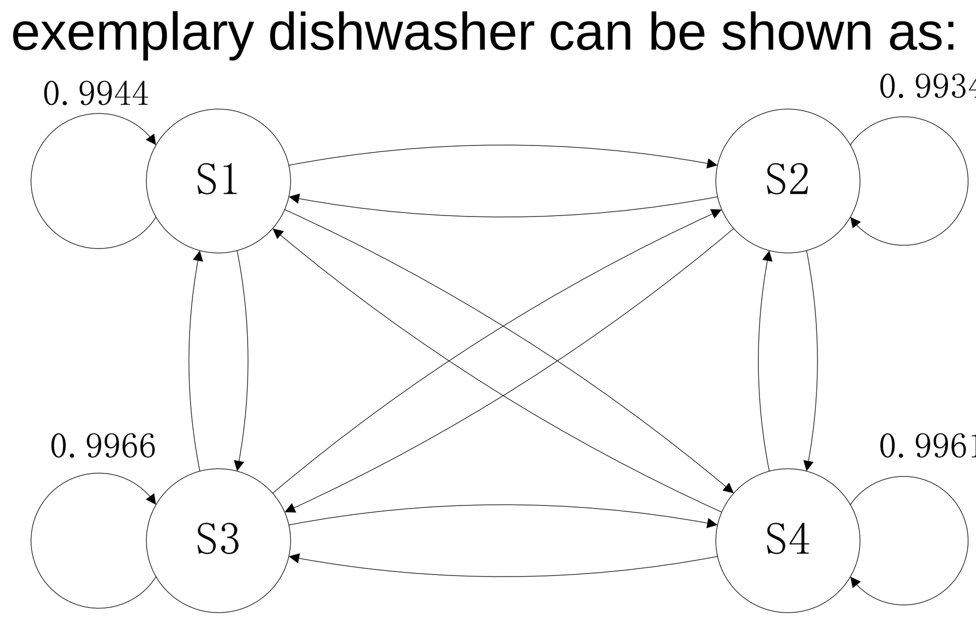
Original Dishwasher Load Profile



Pre-processed using Kmeans, reduced to 4-state load profile

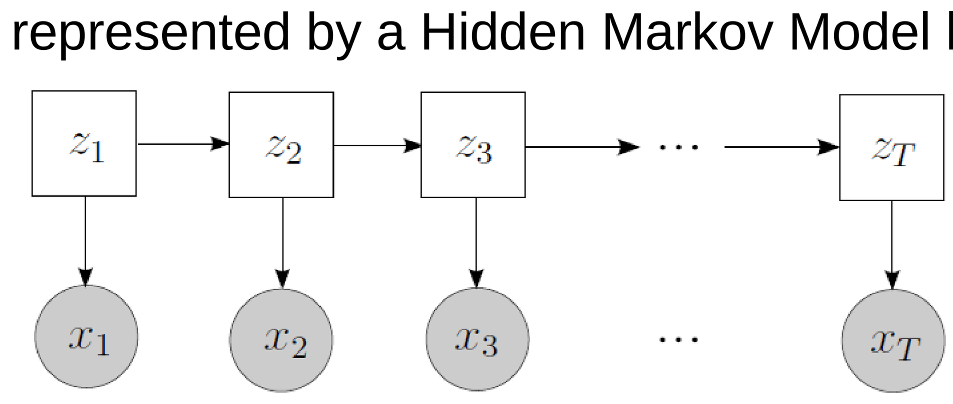


- The hidden state transition diagram for exemplary dishwasher can be shown as:



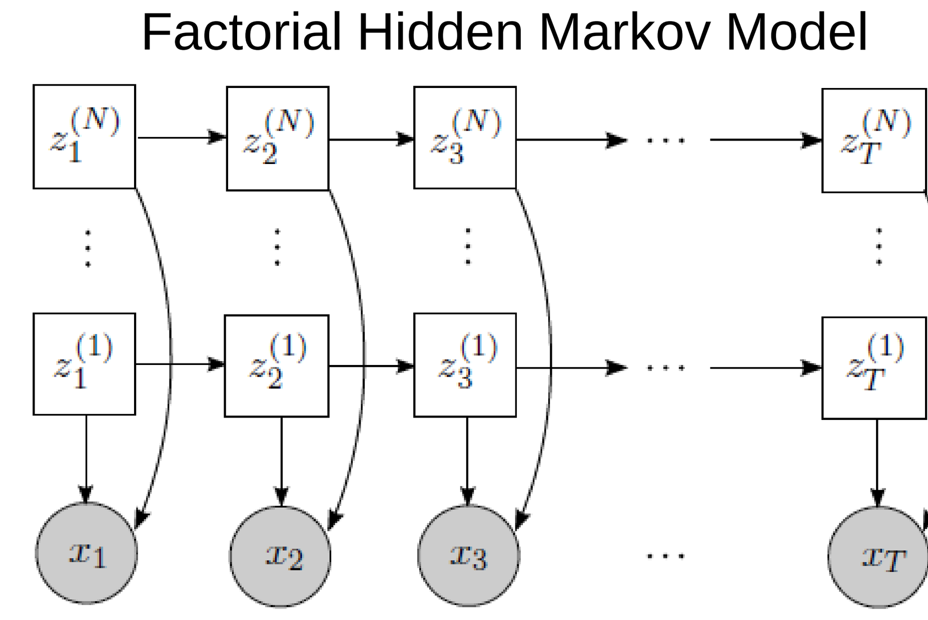
Z1 = 5W, Z2 = 249W, Z3 = 588W, Z4 = 1141W (For simplicity, only the probabilities of remaining the same state at the next time step are shown.)

- With that, a sequence of power readings for an appliance can be represented by a Hidden Markov Model like:



- Considering there are *N* appliances at a household, and we only have observation of a sequence of aggregate power consumption readings, the NILM problem can be represented as a Factorial Hidden Markov Model as shown below:

Factorial Hidden Markov Model



Case Study

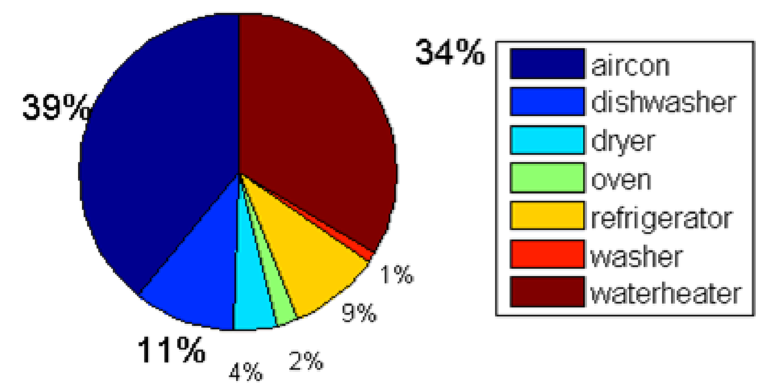
Disaggregate Load Profile with 7 Major Home appliances

- 7 major home appliance load profiles including air-conditioner, dishwasher, clothes dryer, oven, refrigerator, clothes washer and water heater are included [1]
- Kmeans algorithm is applied to learn the hidden Markov model of each appliance
- Randomly construct a sequence of total household power consumption reading using domestic load profile generator [2]
- Apply approximate inference to find the appliance operation sequence which best explain the sequence of reading observation (maximum likelihood).

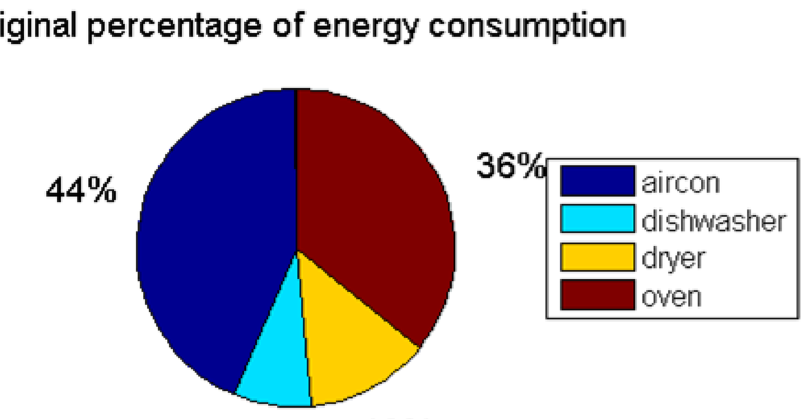
Results

- Comparison diagram below shows that NILM estimated successfully identifies most appliance operations and even simultaneous operations

NILM percentage of energy consumption



Original percentage of energy consumption



- Comparison diagram on the right shows the energy breakdown from the NILM. Even there are minor mis-classification to non-operated appliances, the percentages of energy consumption for individual appliances are closed to real values.

NILM estimated results

Ground True labels

[1] M. Pipattanasomporn, M. Kuzlu, S. Rahman, and Y. Teklu, "Load Profiles of Selected Major Household Appliances and Their Demand Response Opportunities," *Smart Grid, IEEE Transactions on,* vol. 5, pp. 742-750, 2014.

[2] W. Kong, Z.Y. Dong, Y. Jia and G. Chen, "A Rule Based Domestic Load Profile Generator for Future Smart Grid", AUPEC2014, Perth.

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