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Using Hidden Markov Models for Non-intrusive Appliance Monitoring

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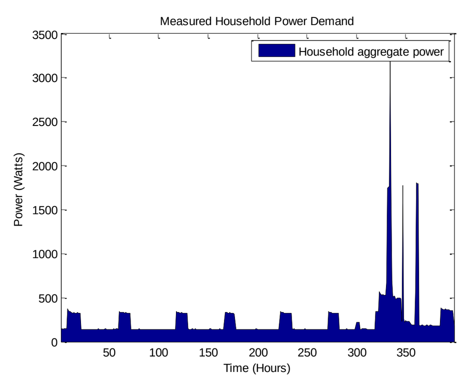
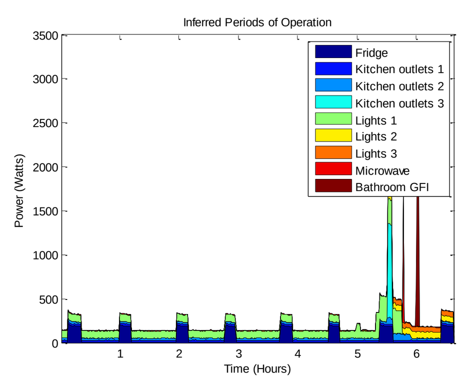
Scenario

Smart meters are being deployed by many countries on national scales (all houses in the UK by 2020)

In home displays have access to low resolution data from smart meters (5 second intervals in UK)

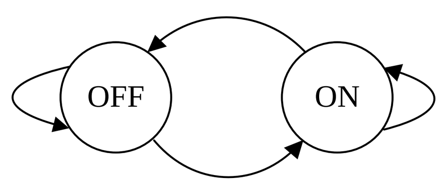




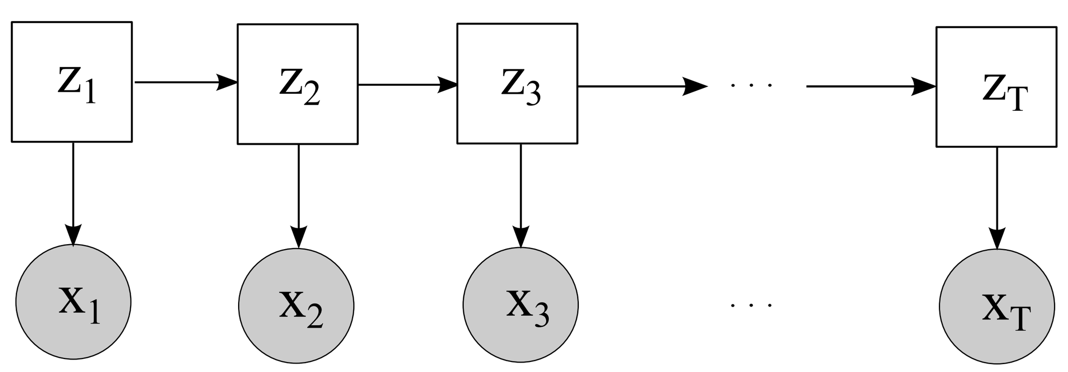
Provide disaggregated feedback of the energy usage of individual appliances to the household occupants empower them to optimise their energy use

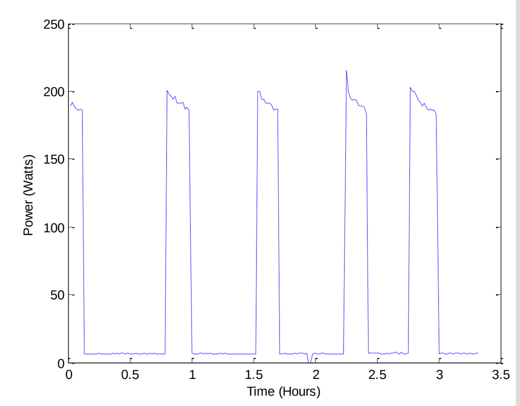
Appliance Modelling using HMMs

Appliances modelled as probabilistic NFAs in which states produce Gaussian distributed observations

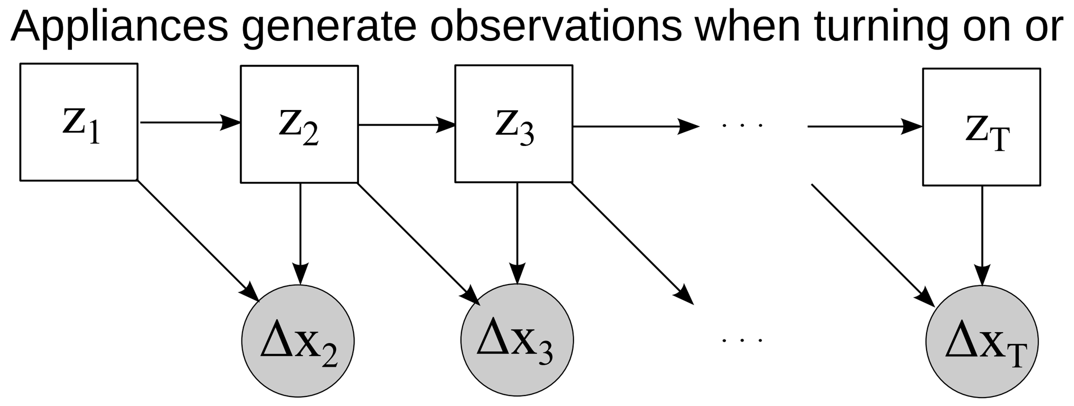


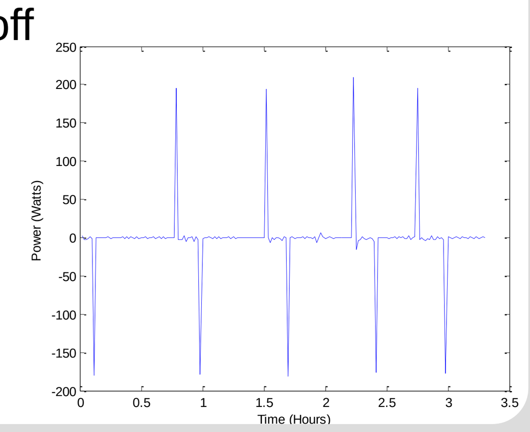
1. Observations are power demand
   Appliances generate observations during operation





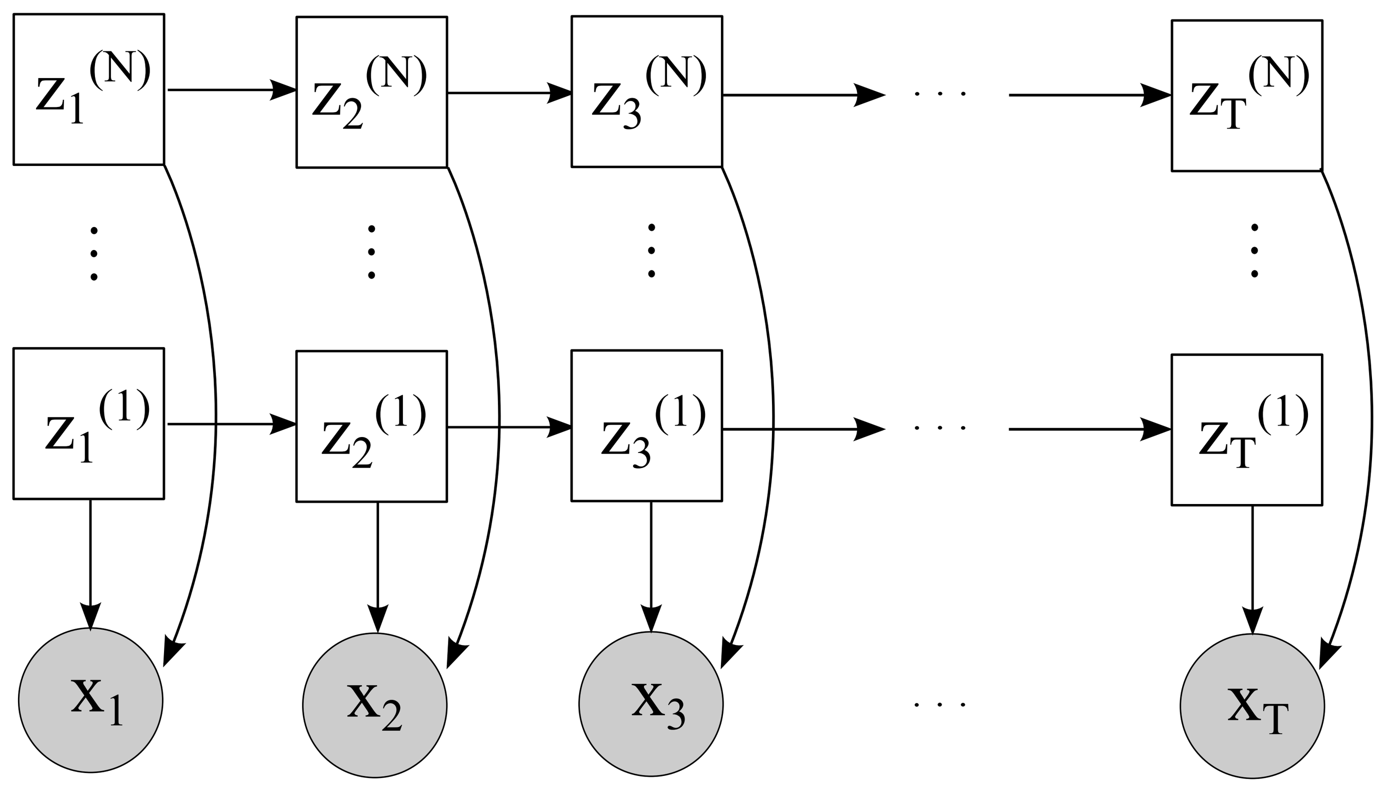
2. Observations are change in power demand
   Appliances generate observations when turning on or off





Household Modelling via Factorial HMM

We want to infer the state of each appliance in each time slice, given the sum of their emissions



$z_t^{(n)}$ – hidden state of appliance n in time slice t

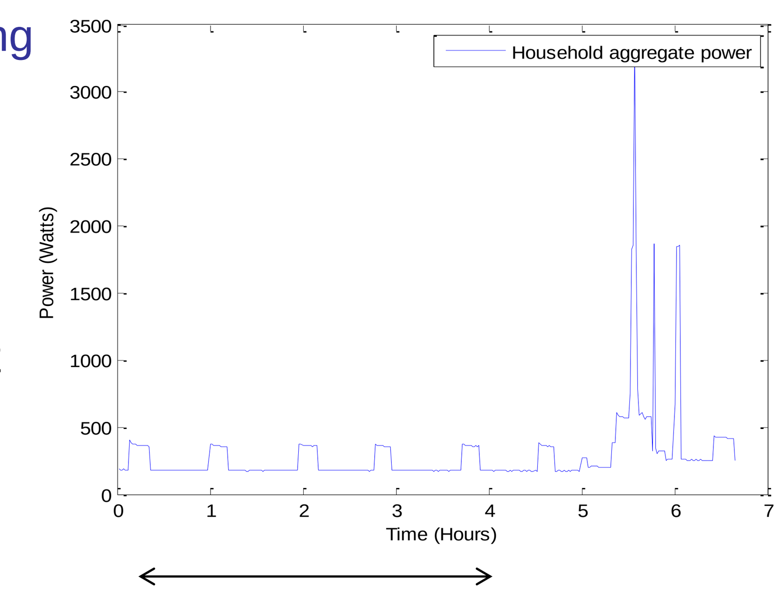
x_t – observed sum of emissions in time slice t

However, we only have prior knowledge of subset of appliances!

Learning FHMM Parameters

We decouple FHMM into individual HMMs for parameter learning

1. Identify periods during which only one appliance is operating
   - We use Expectation-Maximisation to find such periods
   - We initialise EM with our prior to restrict the behaviour it can represent
2. Use the identified periods of operation to train the model using a single application of EM

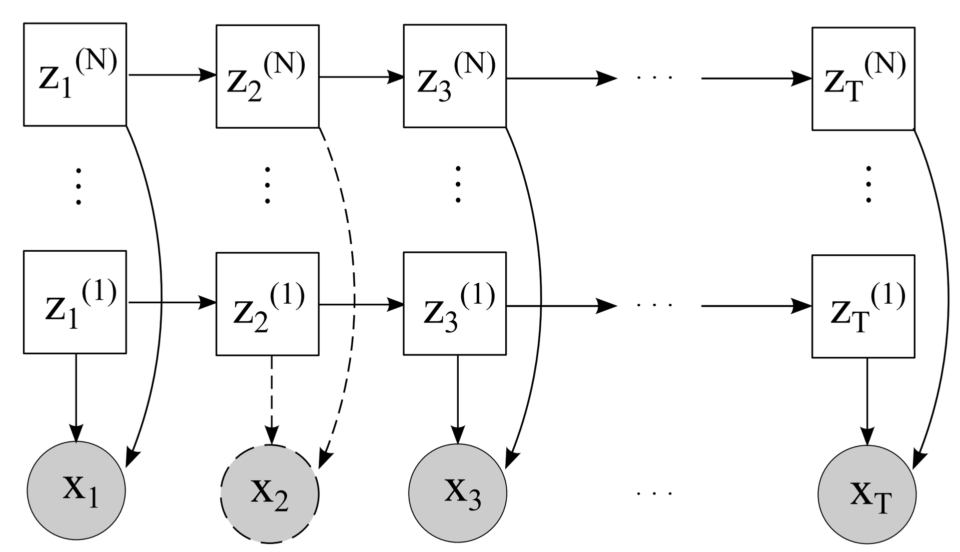


Fridge operating

Inference of FHMM Hidden Variables

We show that some appliances can be disaggregated without modelling all appliances

1. Filtering
   - Want to remove observations generated by unmodelled appliances
   - Remove observations with low probability according to: $P(x_t \mid z_t^{(1:N)}) <$ threshold
2. Inference
   - Gibbs sampling used to infer appliance states given household aggregate
   - Observations which cannot be explained by the trained model are filtered out



Results

We evaluated our approach using the REDD data set:

Appliance	No training	Aggregate training	Sub-metered training
Refrigerator	38%	21%	55%
Microwave	63%	53%	38%
Clothes dryer	3469%	55%	71%
Air conditioning	57%	77%	65%

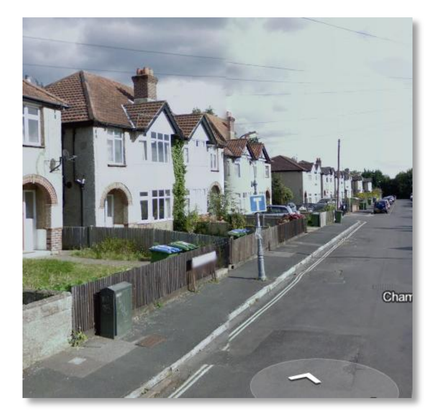
- Our approach which uses aggregate data to train the model outperforms a variant in which the prior is not trained
- The disaggregation accuracy of our approach is comparable to when using sub-metered data for training

Future Work

1. Reference Energy Disaggregation Data set (MIT)
   - 6 houses monitored
   - 10-25 circuits monitored per house

alertme

2. Smart home data set (Southampton)
   - 6 houses monitored



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