Disaggregating Multi-State Appliances from Smart Meter Data

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1) Motivation

- Every house in the UK will have a smart meter by 2019
- Disaggregated, appliance-by-appliance information enables consumers to manage their electricity consumption effectively
- Reducing energy consumption is a good idea for multiple reasons

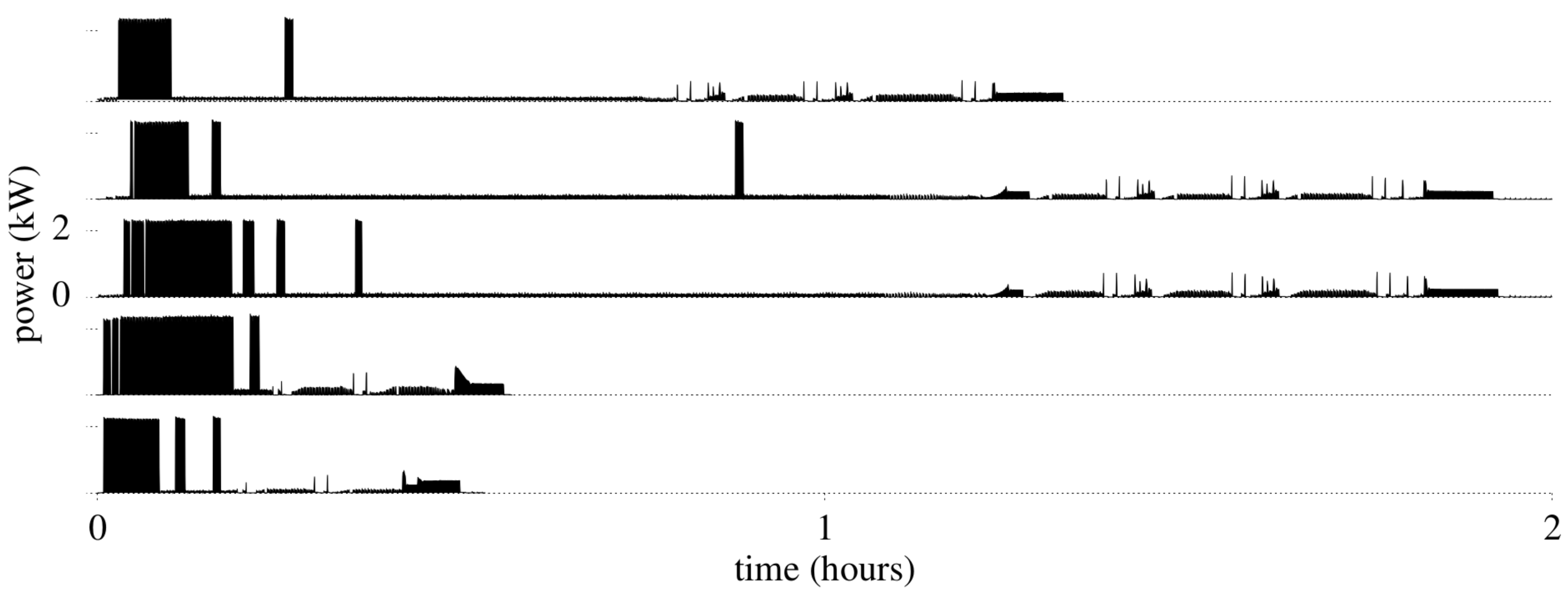
2) Aim

- Infer which appliances are active & energy used by each appliance given only the whole-house aggregate smart meter signal. Appliance-by-appliance submetering is not required.

3) Challenges

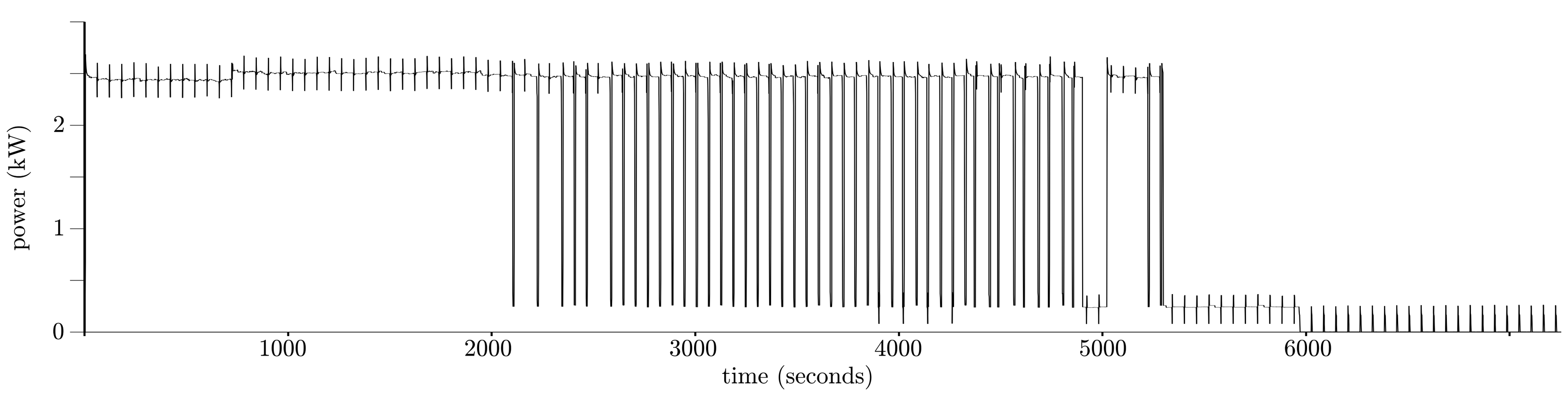
Challenge 1: modelling multi-state appliances

- The following figure shows five runs of the same washing machine. Note that:
- the washing machine has multiple states and
- the sequence of states varies from run to run



Challenge 2: rapidly changing appliance waveforms

- The figure below shows a tumble drier waveform
- Note the regular spikes in the waveform
- Most existing techniques start by simplifying waveforms into sequences of steady-states, hence ignoring these rather distinctive regular patterns.



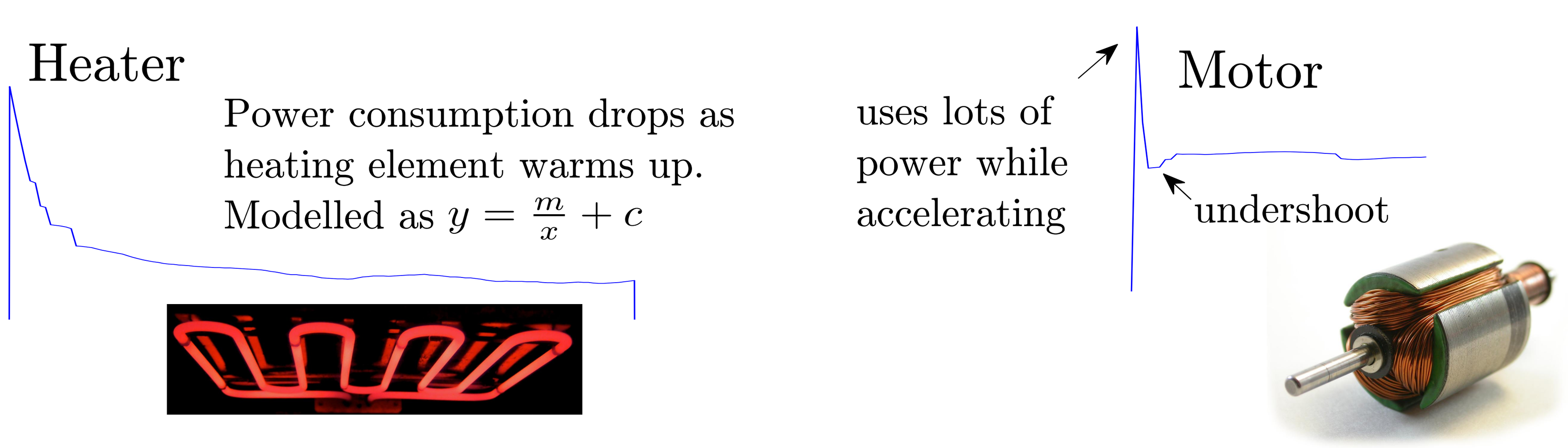
4) Our proposed solution

- Disaggregation will be a 4 step process:
  1) Process smart meter data with a bank of feature detectors
  2) Decode features into multiple probabilistic appliance hypotheses
  3) Refine hypotheses using a probabilistic graphical model representing higher-order relationships
  4) Further refine hypotheses by reconstructing appliance waveforms and fitting these reconstructed waveforms to the aggregate signal

- Appliances will be modelled using 3 hierarchical layers:

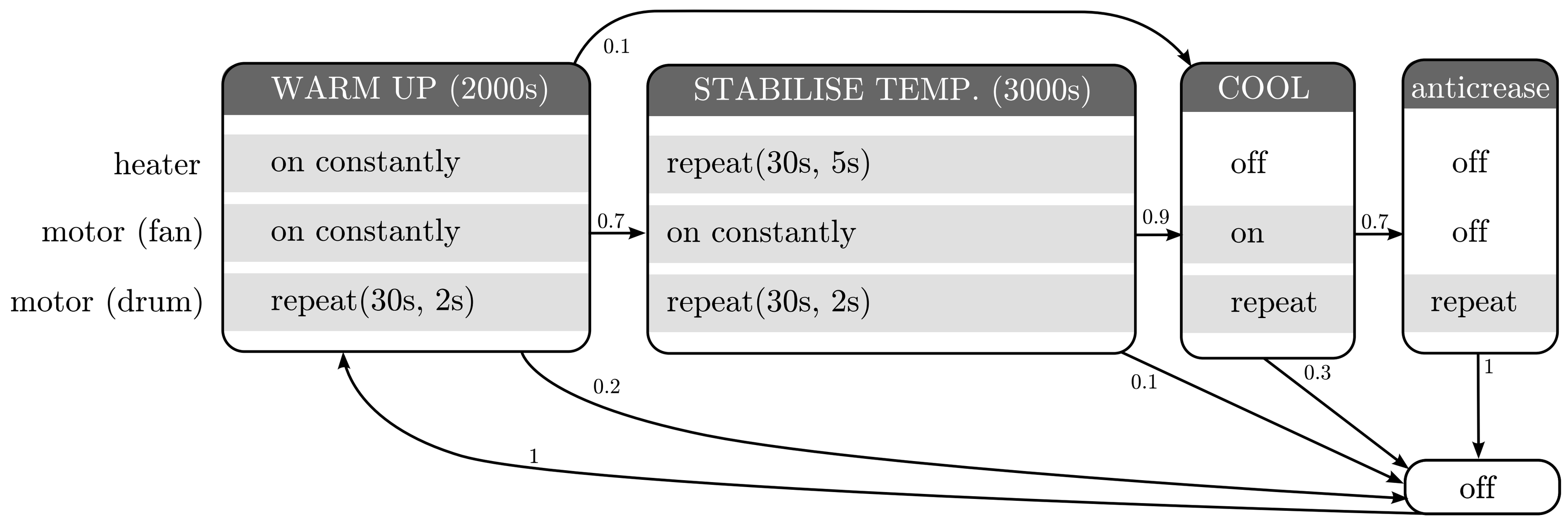
Layer 1: Parameterised models of appliance components

- All appliances are constructed from a set of components such as motors, heaters, compressors and plasma screens, for example:



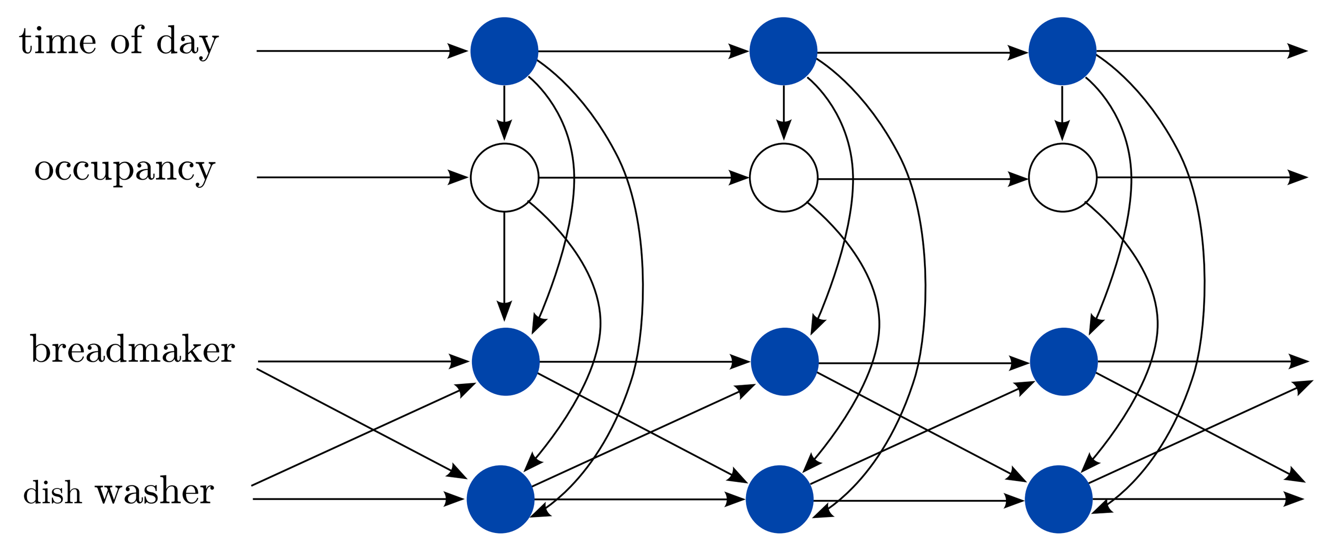
Layer 2: Finite Markov chain models of appliances

- The probability of observing a component state change will be represented by a graphical model. Each node represents the state (on, off, repeating or ramping) of each component in the appliance
- The figure below shows a cartoon example FMC for a tumble drier



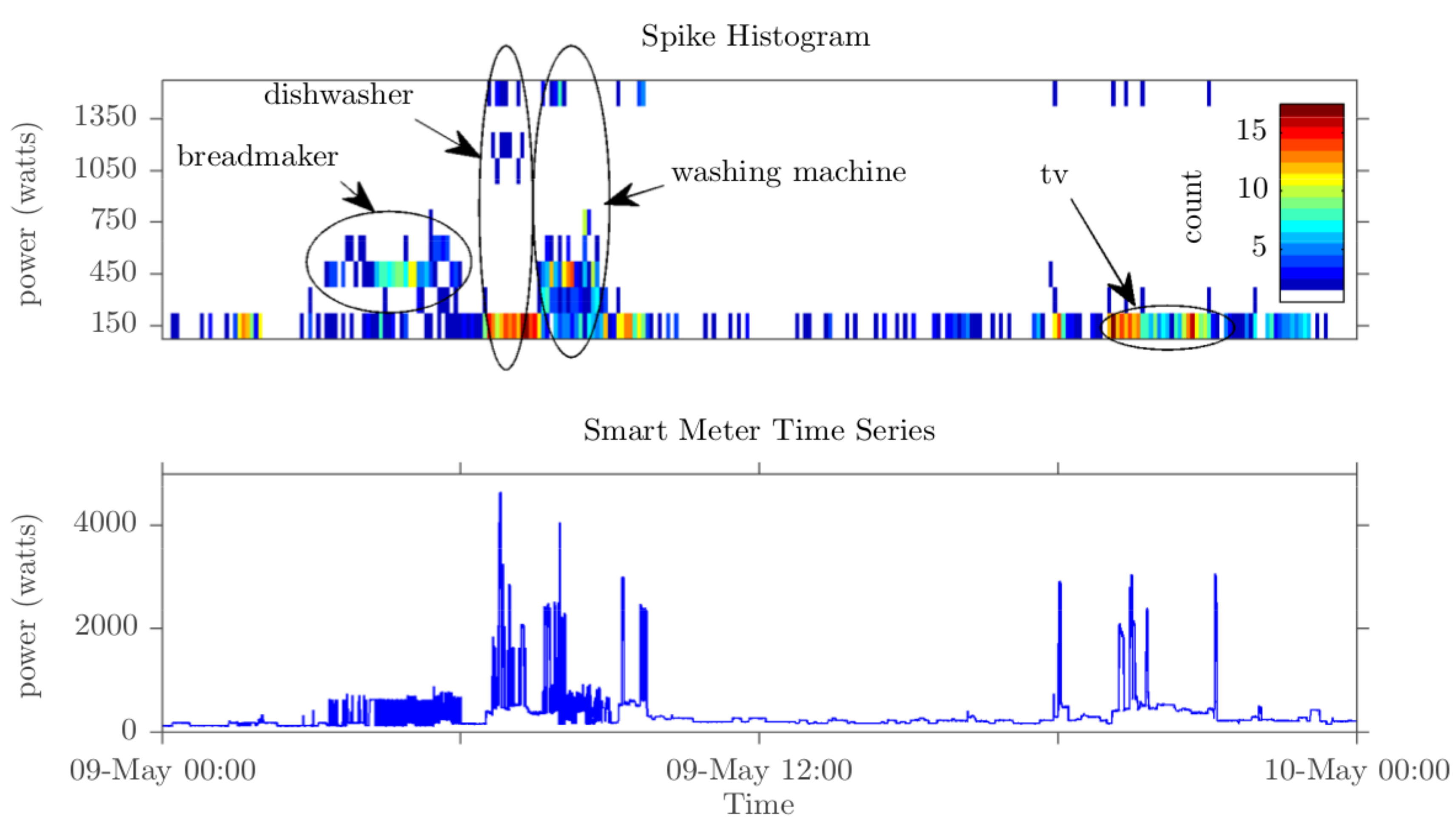
Layer 3: Higher-order relationships

- Correlations between appliances
- Hidden parameters e.g. occupancy



5) Preliminary results

- I have implemented a feature-detector designed to address challenge 2
- The figure below shows the output of my "spike histogram" feature detector in the top panel and the input smart meter time series in the lower panel
- The time series is broken into 3 minute slices. For each time slice, a histogram of the forward difference is calculated. Each column in the figure represents a time slice.
- This feature detector is capable of resolving the differences between several appliances (manually annotated in the figure below)
- This will be one of several feature detectors



6) Next steps

- Implement the design outlined above
- Characterise the performance of our disaggregation system using MIT's Reference Energy Disaggregation Data Set http://redd.csail.mit.edu and our own data (which will also be made public)