Energy Disaggregation

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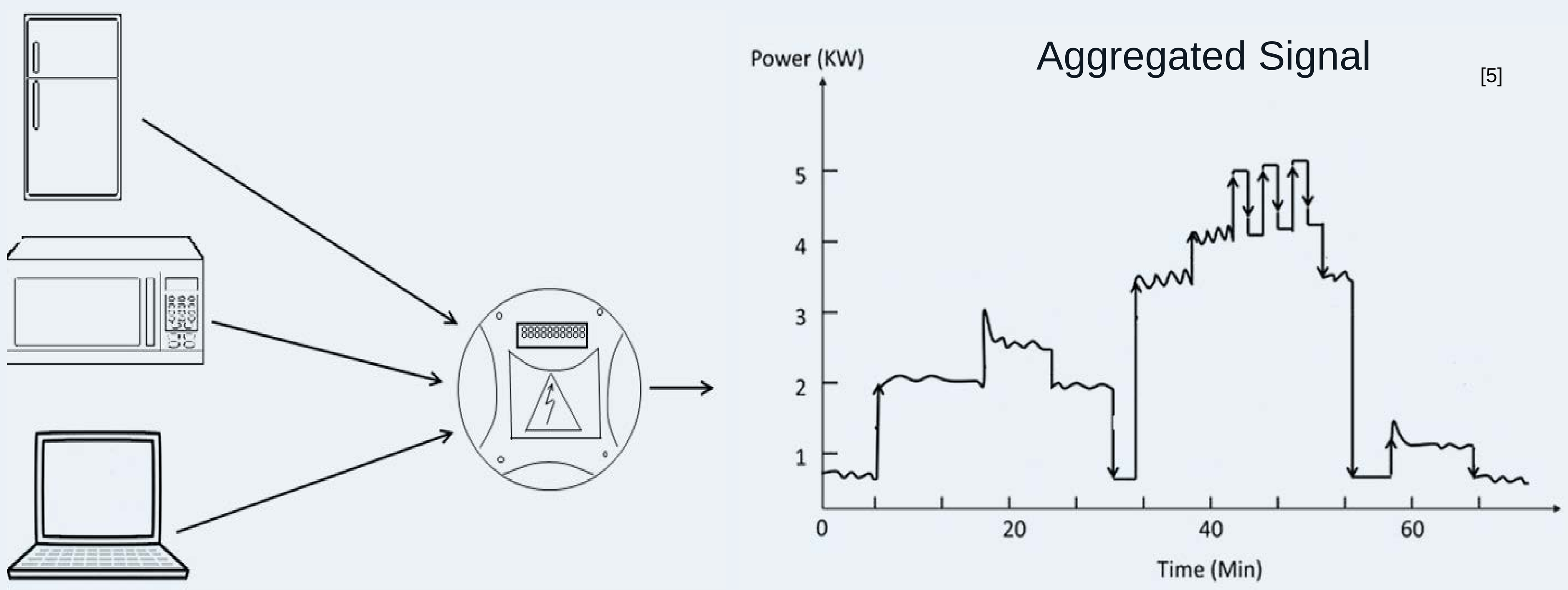
Introduction

Energy disaggregation, if solved, may be one of the most important contributions to energy conservation. Energy disaggregation will allow for greater control and optimization of our current energy grid, as well as naturally curb individual energy consumption. Energy disaggregation is the task of breaking up the whole energy signal of a home or business into its individual components. The method used translates a device's energy consumption pattern into a Hidden Markov Model. After the device models are created, they are joined together to create an Additive Factorial Hidden Markov Model. Then, inference over a household's energy consumption signal using the Viterbi Algorithm was performed. This in turn gives me the most likely devices consuming energy at any given time period providing the power usage. The method works over small datasets with a low number of devices. However, the approach proves too slow to be considered a complete solution.

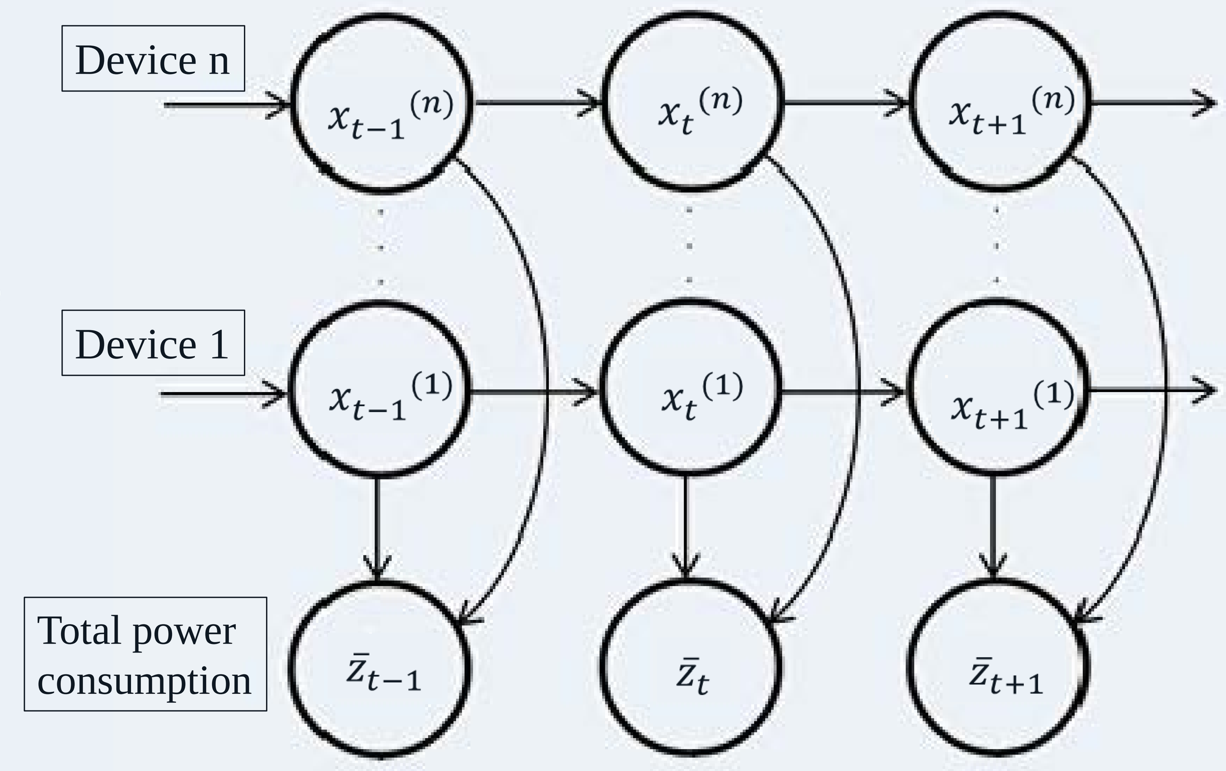
The Problem

- Energy Disaggregation seeks to take the combined power consumption of a house and break it up into individual device usage.
- In other words, given a meter reading, what devices in the house combined to give us that signal.



Additive Factorial Hidden Markov Model

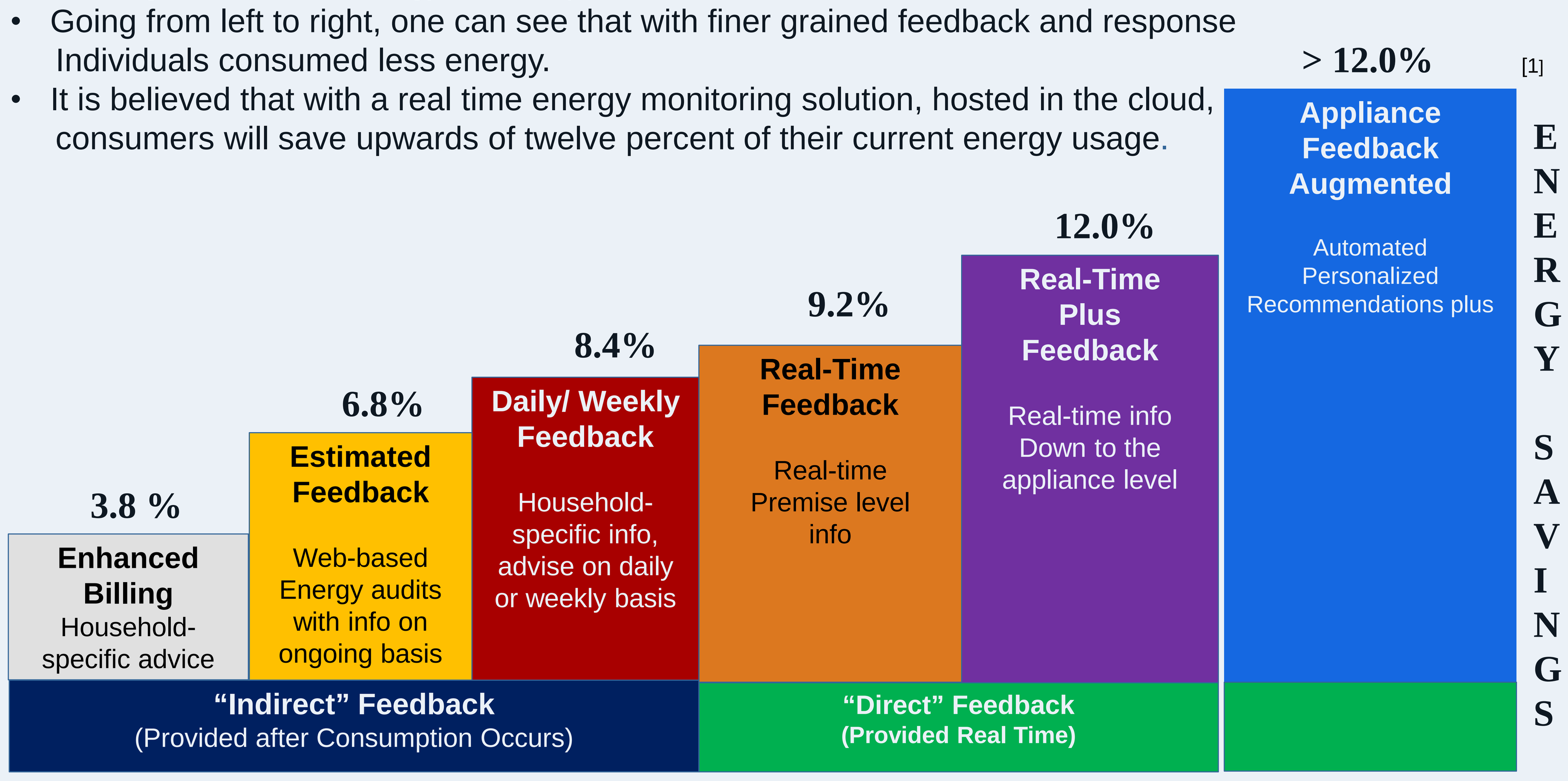
After developing the HMMs for different devices, I needed a way to simulate an entire household full of devices. In order to do this I combined the HMMs into an Additive Factorial Hidden Markov Model, where the emissions are the power consumption of each device at each time step. This proves useful in that I can use the same inference techniques used with HMMs on AFHMMs. This occurs from the states in an AFHMM being the combination of states from smaller HMMs. The inference technique I use is the Viterbi Algorithm.



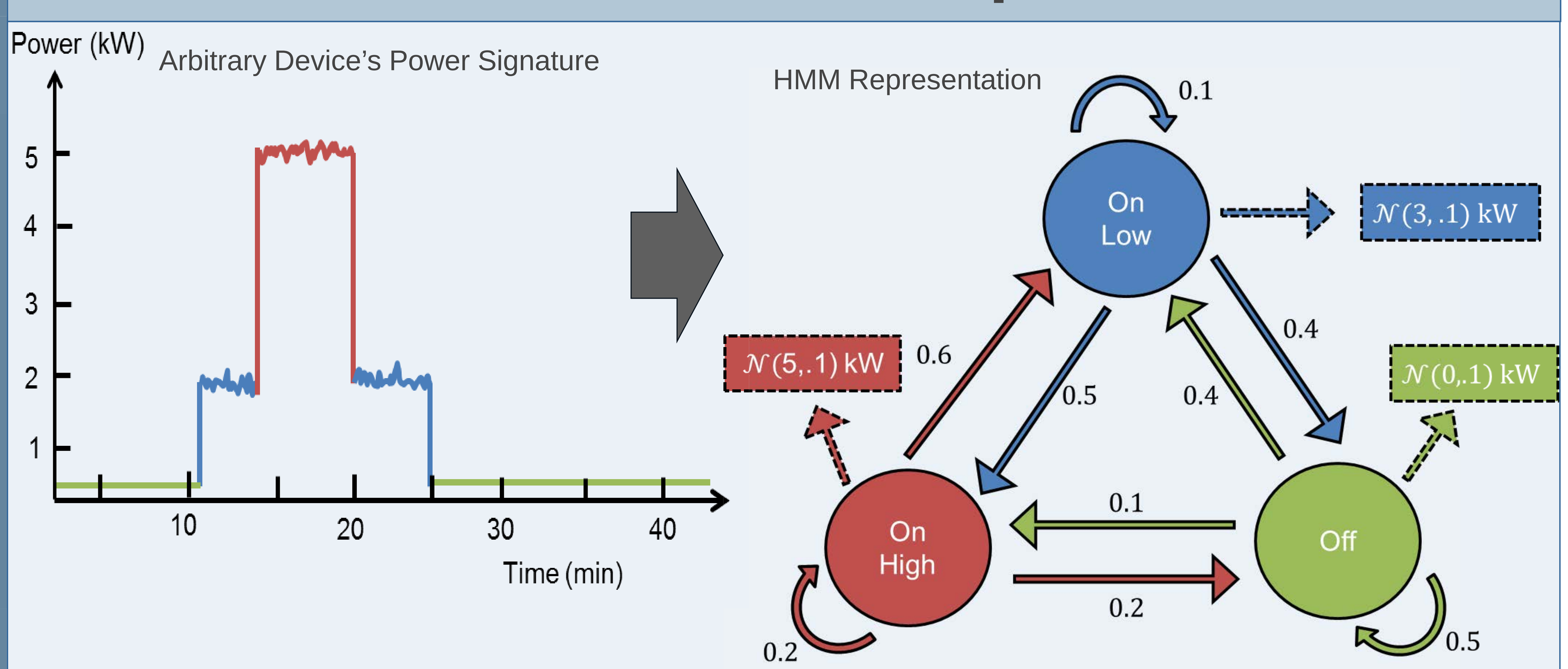
The Viterbi Algorithm is a dynamic programming technique that turns the current problem into a shortest path problem. I can then use the model's parameters to find the most likely sequence of states (devices) given a set of emissions (power consumption).

Motivation

- The graph below illustrates the work of over 60 studies done on household energy usage when given various energy consumption feedback. [3]
- Going from left to right, one can see that with finer grained feedback and response Individuals consumed less energy.
- It is believed that with a real time energy monitoring solution, hosted in the cloud, consumers will save upwards of twelve percent of their current energy usage.



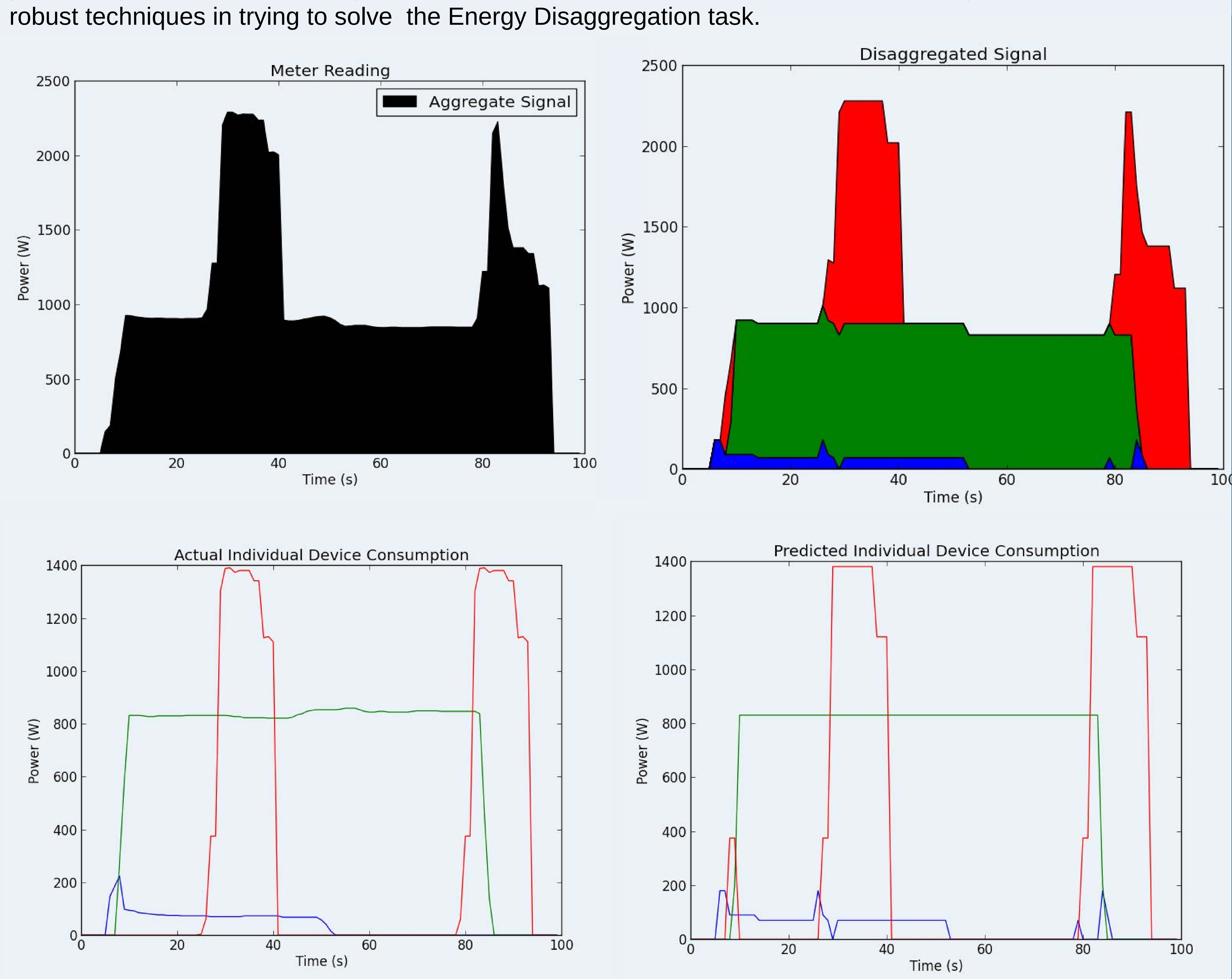
Hidden Markov Model Representation



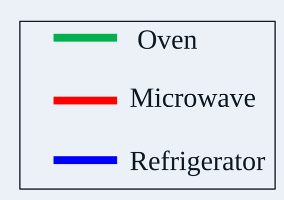
Generally, household devices consume power in a piecewise manner. As a result, I chose to model their operation as a stochastic process using Hidden Markov Models (HMM). HMMs are a Markov process in which we can not see what state the model is in, only the emission (power consumption). In the example above I have a device that operates in three states: On High, On Low, and Off. The solid arrows between them denotes the probability of the device transitioning from its current state into a different state. The dashed arrows denote the probability density function of the power consumption for each device given its state. In Modeling the devices this way it allows us to use various inference techniques for determining what sequence Of states most likely gave us a sequence of emissions (power consumption.)

Results and Conclusion

Below are the results of the tests using 3 devices over 100 time steps. The techniques I used work well for a small number of devices and time steps. However, they are slow and computationally expensive when performing inference over a large number of devices. For future work, I would like to explore faster more robust techniques in trying to solve the Energy Disaggregation task.



	Oven	Fridge	Microwave	Total
Actual (W)	63498	3718	32910	100126
Predicted (W)	61820	4030	33810	99660
Percent Correct	97.36%	92.26%	97.34%	95.65%



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Support Information
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