Demand Response Supply Estimation with Smart Meter Data

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Overview

Demand flexibility is viewed as an integral and crucial part of a reliable future electricity system with high penetration of intermittent generation. Capturing and activating demand response depends in part on the contracts for flexibility available to households and firms. Designing effective contracts require knowledge about individual consumption patterns over time as well as the heterogeneity of consumption patterns at a fine geographical granularity. One possible source for learning about, and monitor, consumption patterns is smart meter readings. Smart meter readings represent a detailed data source for electricity system management and operation. We argue that it is possible to leverage meter data into valuable information about the extent and cost of demand response.

This paper applies a variety of statistical and machine learning methods to smart meter readings with the aim of detecting and decoding specific consumption patterns. Although there are many generic machine learning methods that can provide excellent consumption predictions, the focus on demand response and flexibility require additional understanding and details about consumption. A structural modeling approach in combination with machine learning algorithms allows us to detect and decode consumption patterns that are relevant for assessing the extent of demand response and the opportunity cost of load shifting or load shedding. As the opportunity costs and the volume of available demand response varies with external factors such as time and temperature we can construct supply functions for demand flexibility conditional on these external factors.

Methods

Smart meters provide detailed meter data recording aggregate electricity consumption in a housing unit at short time intervals. These records are matched with meteorology data from nearby weather stations. The electricity consumption is modeled as a continuous non-negative real number, is conditional upon the current state of (unobserved) household activities and a function of time and weather conditions. As the household's activities are changing over time so are the states and the relevant consumption functions. The actual states are unobserved (using only meter data) and may include states such as "heating", "cooling", "sleeping", and "away".

The transition between states are modeled as a time-varying hidden Markov chain where the time-varying transition probabilities depends on outdoor temperature and time of day and year. The observed consumption is modeled as a switching regression model with state specific parameters for temperature and time of day and year. The resulting model is an Input-Output Hidden Markov Model with state transition probabilities specified as multinominal logit models and output specified as switching Tobit regression models. The joint estimation of the model parameters relies on a customized Baum-Welch version of the EM algorithm.

In order to get reliable detection of relevant states for demand response we utilize data from households with detailed information about behind-the-meter usage of electricity for specific purposes. This allows us to utilize supervised learning of regression trees for as classifiers of the hidden states. Training the classifier on a set of meter data with known states improves the predictions as compared to a situation with unsupervised learning. We implement the classifier as a fast-and-frugal tree.

With meter readings without known states we first estimate the IOHMM and then predict loads in all time periods and all states. Utilizing the classifier we identified a state at some time *t* as, say "heating", and then block this state in time *t*. The multinominal logit model for state transition probabilities will now give revised probabilities for the other states, and we calculate the restricted predicted load as well as the net expenditure for access to the restricted state. This predicted cost allows for estimation of willingness-to-pay for access using standard methods, that is, we have an estimate for the reservation price for changing the electricity consumption. We aggregate these results over the relevant segment of the population (smart meters) thus resulting in a supply function for demand response.

Results

We use detailed meter readings from the Pecan Street experimental houses in Austin, TX, and identify AC usage. A random subset of observation with the detected states from the IOHMM model and observed electricity usage are used to train the classifier. The classifier is then applied to the IOHMM result for each individual house. The combination of the IOHMM model and the classifier identifies AC states for 18 out of 22 houses. For the houses with identified AC states the reservation price for not using AC is estimated and the associated reduction in electricity load. Valid reservation prices are obtained for 15 of the houses. On the basis of this we get estimates for the average probability of AC units being active at any point in time, the expected volume of electricity used for AC, and the reservation price for AC usage, and hence the supply curve of demand response.

Conclusions

The availability of meter data with high time resolution at the household level represents a new data source about consumption at the household level. We have developed a structural model embedded in a hidden Markov chain and a classifier for electricity use that enables us to predict electricity use for specific purposes and estimate the opportunity cost of reducing electricity consumption for specific purposes. The results from this modeling framework is used to predict the demand response following certain interventions in the consumption patterns. We utilized detailed data from behind-the-meter reading. The model has been applied to experimental data, but can be applied to community wide data in order to assess the overall potential and cost of demand flexibility.

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