A Machine Learning Approach to Demand Response Supply Estimation

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Overview

Demand response is viewed as an integral and crucial part of the future electricity system. Activating demand response depends in part on the contracts available to households and firms. Designing effective contracts require knowledge about the individual consumption patterns over time as well as the heterogeneity of consumption patterns. One possible source for learning about consumption patterns is smart meter readings. Smart meter readings represent a new and very detailed data source for electricity system management and operation. One challenge in the analysis of high time resolution meter readings is the shear volume of data.

This paper applies machine learning methods to smart meter readings where the purpose is to detect and decode specific consumption patterns. Although there are many generic machine learning methods that can provide excellent consumption predictions, the focus on demand response requires additional understanding and details about consumption. A structural (econometric) modeling approach in combination with machine learning allows us to reveal and decode consumption patterns that may be relevant for assessing the extent of demand response and ultimately for the design of contracts. Furthermore, the decoded consumption patterns are used to predict the extent of demand response both as load shifting and load shedding.

Methods

We have available detailed meter data recording aggregate electricity consumption in the housing unit in each five minutes interval for a year. These records are matched with meteorology data from a nearby weather station. The consumption is modeled as a continuous non-negative real number, and is conditional upon the current state of household activities. As the household's activities are changing over time so are the states and the relevant consumption function. The 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 modeled as multinominal logit models and output modeled as Tobit models. The joint estimation of the model parameters relies on a customized Baum-Welch version of the EM algorithm.

From the IOHMM we predict loads in all time periods and all states for each meter (household). If the identified state at some time t is, say "heating", we 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. We aggregate these results over the relevant segment of the population thus resulting in a supply function for demand response. We use additional time-periods following the blocking of a particular state to assess the extent of load shifting vs load shedding.

Results

Consumption patterns at the individual unit level are heterogeneous. Our results from analyzing some 12 000 households show that for more than half the households the machine learning algorithm is capable of detecting discernible and specific consumption patterns. Our structural modeling approach allows us to draw specific conclusions about the factors influencing the observed consumption patterns. The presence of significant influence on certain state transition probabilities and consumption levels show that it is possible to identify, say, heating and cooling states. Furthermore, our approach allows us to predict the short-term demand response at any given time as well as assess the extent of load shifting and/or shedding following a shorter or longer period without access to, say, electric heating or cooling.

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 econometric model embedded in a hidden Markov chain. This model is capable of detecting specific consumption patterns, predict consumption with a high degree of precision, and reveals the underlying drivers for the consumption levels. The results from this modeling framework is used to predict the demand response following certain interventions in the consumption patterns.

References

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