

An online disaggregation algorithm and its application to demand control

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The increase of renewable energy has made the supply-demand balance of power more complex to handle. In [1], the authors designed randomized controllers to obtain ancillary services to the power grid by harnessing inherent flexibility in many loads.

However these controllers suppose that we know the consumption of each device that we want to control. This introduce the cost and the social constraint of putting sensors on each device of each house. Therefore, our approach was to use Nonintrusive Appliance Load Monitoring (NALM) methods to solve a disaggregation problem. The latter comes down to estimating the power consumption of each device given the total power consumption of the whole house.

We started by looking at the Factorial Hierarchical Dirichlet Process - Hidden Semi-Markov Model (Factorial HDP-HSMM) introduced in [2]. In our application, the total power consumption is considered as the observations of this state-space model and the consumption of each device as the state variables. Each of the latter is modelled by an HDP-HSMM which is an extension of a Hidden Markov Model.

However, the inference method used in [2] is based on Gibbs sampling and has a complexity of $\mathcal{O}(T^2N + TN^2)$ where T is the number of observations and N is the number of hidden states. As our goal is to use the randomized controllers with our estimations, we wanted a method that does not scale with T . Therefore, we developed an online algorithm based on particle filters. Because we worked in a Bayesian setting, we had to infer the parameters of our model. To do so, we used a method called Particle Learning which is presented in [3]. The idea is to include the parameters in the state space so that they are tied to the particles. Then, for each (re)sampling step, the parameters are sampled from their posterior distribution with the help of Bayesian sufficient statistics.

We applied the method to data from Pecan Street. Using their Dataport, we have collected the power consumption of each device from about a hundred houses. We selected the few devices that consume the most and that are present in most houses. We separated the houses in a training set and a test set. For each device of each house from the training set, we estimated the operating modes with a HDP-HSMM and used these estimations to compute estimators of the priors hyperparameters. Finally we applied the particle filters method to the test houses using the computed priors.

The algorithm performs well for the device with the highest power consumption, the air compressor in our case. We will discuss ongoing work where we apply the "Thermostatically Controlled Loads" example of [1] using our estimations of this air compressor's operating modes.

References

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