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ROBUST CONTROL OF RESIDENTIAL DEMAND RESPONSE NETWORK WITH LOW BANDWIDTH INPUT

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ABSTRACT

This preliminary work is concerned with low sample rate control of a residential Demand Response network. Residential Demand Response networks are very high order nonlinear stochastic systems. We provide a methodology for dealing with this complicated type of system. Then we examine the performance and robustness of potential controllers. To date, only sliding mode control has been examined, but further work will compare sliding mode control to other robust controllers.

INTRODUCTION

This preliminary work is concerned with the control of residential Demand Response networks with low input bandwidth. It is nearly impossible to exactly model a very high order nonlinear stochastic system such as a residential Demand Response Network, because it is rarely possible to even recognize every state. Unfortunately, much traditional controller design is rooted in accurate system modeling. Additionally, low input bandwidth makes control difficult because the input cannot keep up with the output fluctuations. These types of systems present considerable controller design difficulty. In order to deal with this difficult type of plant, we propose the following methodology:

1. Based on input/output data, identify the system as a fast sample rate low order linear system with arbitrary states.
2. Discretize the system at the actuator sampling rate.
3. Design a controller with good robustness characteristics in the presence of model uncertainties.

In this continuing work, we first designed a sliding mode controller for a residential Demand Response network. Further work will compare the performance and robustness of sliding mode control with robust linear design techniques like H_∞ and different input bandwidths. Preliminary results indicate that the design methodology has great promise.

BACKGROUND

Our research is primarily focused on residential Demand Response (DR). The goal of Demand Response technology is to manipulate the load on the electricity grid to achieve an arbitrary goal. Residential DR looks solely at personal residences which account for a large portion of the peak load. Even after removing most components of the grid, the system remains daunting because of its inherent randomness, geographical dispersion, and maintaining customer acceptance.

From a control systems standpoint, it is difficult to model the power consumption of a group of homes. The system is effectively a huge order stochastic nonlinear multi-input system. To see this, first consider that *each* home contains numerous interdependent states that act to define the overall power consumption. Then consider that every house is built differently with different inhabitants. Further, thermostatically controlled devices – refrigerators, water heaters, and HVAC systems – are one of the primary energy consumers, and they usually use nonlinear hysteresis control algorithms.

Obviously, customer acceptance of the DR technology is needed in order to obtain high penetration, but this places another demanding constraint on the control – cost. In order to

reduce expense, we consider using an RDS digital sub-band on an FM radio broadcast to transmit the DR message with a slow data rate of about 300 baud. The low data rate forced us to limit the input bandwidth to 15 minutes.

RESIDENTIAL SIMULATION

Because of the cost and complexity of real world experiments, we constructed a large simulation that embodies most of the challenges of large scale Demand Response systems. It consists of a large number (e.g. 1000) of independent and random simulated homes capable of responding to DR events.

A major portion of a home's energy use comes from thermostatically controlled devices such as room heat, air conditioning, water heaters, and refrigerators, and therefore a large number of residential Demand Response technologies focus on this type of appliance. For this simulation, we modeled the energy consumption of air conditioning in homes subject to environmental effects in a similar manner as [1, 2]. Each of the simulated homes has five states. Heat inputs come from conduction through the walls, solar radiation, infiltration of outdoor air, and directly into (or out of) the HVAC system.

What sets this simulation apart from other similar models is each of the HVAC systems is controlled by actual programmable thermostat software capable of processing and responding to many different types of Demand Response messages. We developed Cost Ratio Demand Response for this simulation, and it provides a framework for autonomously using energy price to control the consumption of a house. The first key idea is representing the energy price as a normalized quantity that allows straightforward temporal comparison of energy costs. The second is introducing the concept of a cost tolerance that numerically illustrates a customer's cost/comfort preferences. Using historical energy costs, normalized price, and a prediction for future energy consumption, the thermostat can decide how best to cool (in the case of AC) the home while still meeting the cost tolerance relative to past consumption.

With Cost Ratio DR in mind, normalized energy price is the input to the system, and for the reason of overall cost, the input sample rate was fixed to 15 minutes. The output from the system is the aggregated instantaneous power consumed by every house, and for this simulation, we only look at the power consumed by the HVAC systems.

CONTROLLER DESIGN

In order to deal with this difficult type of plant we used the methodology described in the Introduction.

System Identification

We started with a simulation of 1000 houses subject to outside temperature variation as well as cost variations. The actual system is comprised of 4000 states and 1000 nonlinear regulators. Exactly identifying this system is completely intractable,

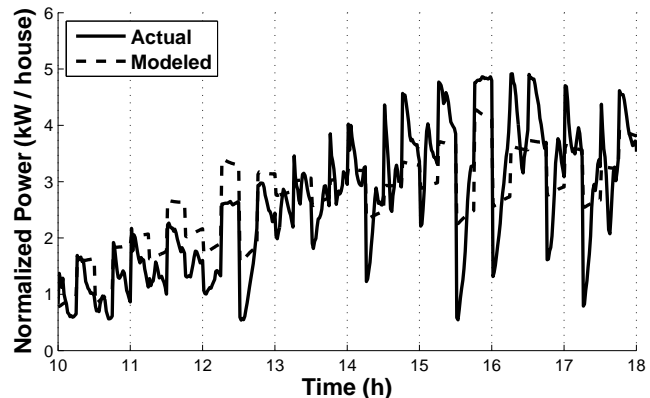


Figure 1. MODEL COMPARISON

but the output looks approximately linear with stochastic disturbances. Therefore, we chose to identify the system as a linear model with two inputs (outdoor temperature and cost) and one output (aggregate normalized power) at a fast sample time of 60 seconds. We identified the system using a fast sample rate because the dynamics of the cost ratio DR system are fast and to facilitate future studies relating input bandwidth to performance. A second order ARX representation offered the best trade-off between residual and peak error, and no higher order system was able to obtain a whiter residual due to the inherent periodic nonlinearities like saturation. Equation 1 shows transfer function.

This drastically simplified model results in large modeling errors. Figure 1 shows a comparison between the actual system and the simplified model.

$$P(z) = \frac{-0.2016z + 0.1923}{z^2 - 0.9771z + 0.0387} C(z) - \frac{0.213z - 0.2063}{z^2 - 0.9771z + 0.0387} T_{out}(z) \quad (1)$$

Reduced Sample Rate Model

The next step in the process involves discretizing the system at the input sample rate. The DR message can only change every 15 minutes, so the system was discretized with this sample rate. Equation 2 shows the new system in state space form.

$$P(k) = CX(k)X(k+1) = AX(k) + BU(k)X(k) = [X_T(k) X_C(k)]^T; X_T, X_C \quad (2)$$

Controller Design

The identified model is multi-input single output, but the cost is the only input that can be manipulated. The outdoor temperature (T_{out}) cannot be modified, but it can be measured. Therefore, the system can be reduced to single input single output with a known disturbance. Unfortunately, the model is not in canonical form, and to cope with this, we extended the system so that the cost is a state ($C_{ost} = \zeta$) with a fictitious input ($r(k)$)

and τ chosen as a fast first order time constant. Equation 3 details the new model with uncertainties. The unmodified variables (like $P(k)$) represent the actual values, as before the *hatted* variables are estimated variables, and the *tilded* variables (like \tilde{A}_C) indicate error bounds.

$$\begin{aligned}
 P(k) &= P_C(k) + d_T(k) + d_{un}(k) \\
 P_C(k) &= \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} X_C(k) \\ \zeta(k) \end{bmatrix} \\
 \begin{bmatrix} X_C(k+1) \\ \zeta(k+1) \end{bmatrix} &= \begin{bmatrix} A_C + \tilde{A}_C & B_C + \tilde{B}_C \\ 0 & \tau \end{bmatrix} \begin{bmatrix} X_C(k) \\ \zeta(k) \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} r(k) \quad (3) \\
 d_T(k) &= \begin{bmatrix} 1 & 0 \end{bmatrix} X_T(k)
 \end{aligned}$$

$$X_T(k+1) = (A_T + \tilde{A}_T) X_T(k) + (B_T + \tilde{B}_T) T_{out}(k)$$

Following standard sliding mode control design, the error term is defined in Equation 4, and the sliding surface is given by Equation 5 with $|\lambda| < 1$ chosen to meet convergence criteria.

$$\epsilon(k) = P(k) - P_{ref}(k) \quad (4)$$

$$S(k) = \epsilon(k+1) - \lambda \epsilon(k) \quad (5)$$

$$|S(k+1)| < |S(k)| \quad (6)$$

To guarantee stability and error convergence the controller should be constructed in the method described by [3] so that Equation 6 is always true. To date, proper error bounds have not been determined because of the difficulty of comparing the low order model to the high order system. Our future work will attempt to find these error bounds so as to guarantee stability.

The control law is given by Equation 7. Notice that $d(k+2)$ depends on future values of the outdoor temperature, but since the sample rate is relatively fast in comparison to the change in outdoor temperature, $T_{out}(k)$ is used instead.

$$\begin{aligned}
 r(k+1) &= -\frac{1}{h(k+1)} \left(f(k+1) + d(k+2) - P_{ref}(k+2) \right. \\
 &\quad \left. - (1+\lambda)\epsilon(k+1) + \lambda\epsilon(k) + \phi \operatorname{sgn}(s) \right) \\
 h(k+1) &= B_{C(1)} \\
 f(k+1) &= A_{C(1,1)} X_{C(1)}(k+1) + A_{C(1,2)} X_{C(2)}(k+1) \\
 &\quad + B_{C(1)} \tau \zeta(k) \quad (7)
 \end{aligned}$$

RESULTS

The controller is only used intermittently. It is switched on when the power rises above the reference power (P_{ref}), and it switches off when the price drops below a preset value (C_-). For this testing, P_{ref} was set to 3.5kW per house and C_- was 0.5.

Figure 2 shows the results of testing on the large residential simulation with $\lambda = 0.01$ and $\phi = 0.15$. The controller performed rather well considering the very slowly updating control signal.

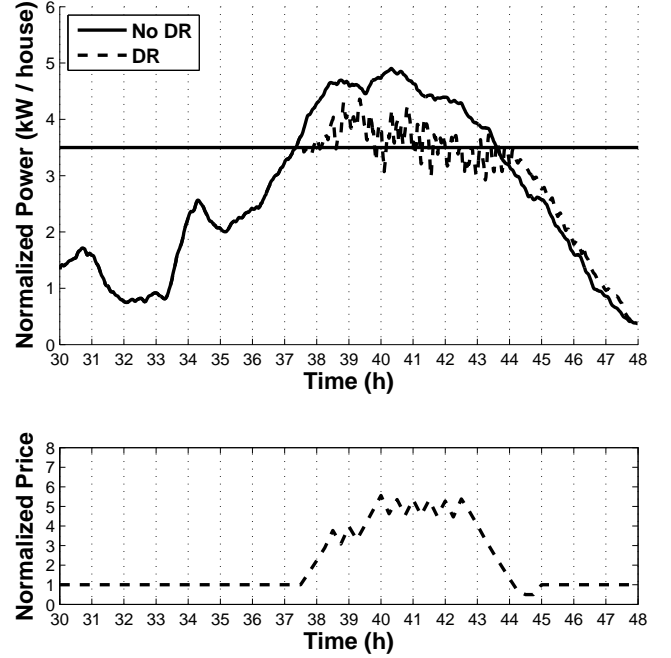


Figure 2. SLIDING CONTROL RESULTS

CONCLUSIONS

Discrete sliding mode control is an excellent fit for large order uncertain systems like residential Demand Response networks because of the guaranteed robustness with model uncertainties. Further, it yielded quite good performance considering the low input bandwidth.

There are still a number of open questions that will be answered in the continuing work. First, what is the exact robust stability bounds that can be placed on our system using sliding control? Additionally, how does this control compare to other types of robust control such as H_∞ ?

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