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Tapping the energy storage potential in electric loads to deliver load following and regulation, with application to wind energy

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A B S T R A C T

This paper develops new methods to model and control the aggregated power demand from a population of thermostatically controlled loads, with the goal of delivering services such as regulation and load following. Previous work on direct load control focuses primarily on peak load shaving by directly interrupting power to loads. In contrast, the emphasis of this paper is on controlling loads to produce relatively short time scale responses (hourly to sub-hourly), and the control signal is applied by manipulation of temperature set points, possibly via programmable communicating thermostats or advanced metering infrastructure. To this end, the methods developed here leverage the existence of system diversity and use physically-based load models to inform the development of a new theoretical model that accurately predicts – even when the system is not in equilibrium – changes in load resulting from changes in thermostat temperature set points. Insight into the transient dynamics that result from set point changes is developed by deriving a new exact solution to a well-known hybrid state aggregated load model. The eigenvalues of the solution, which depend only on the thermal time constant of the loads under control, are shown to have a strong effect on the accuracy of the model. The paper also shows that load heterogeneity – generally something that must be assumed away in direct load control models – actually has a positive effect on model accuracy. System identification techniques are brought to bear on the problem, and it is shown that identified models perform only marginally better than the theoretical model. The paper concludes by deriving a minimum variance control law, and demonstrates its effectiveness in simulations wherein a population of loads is made to follow the output of a wind plant with very small changes in the nominal thermostat temperature set points.

1. Introduction

1.1. Motivation

Aggregated populations of thermostatically controlled loads (TCLs) can exhibit large collective dynamic responses in power demand when subjected to a common control signal. This is perhaps most well-known in the context of "cold load pickup," which occurs at the conclusion of a service interruption [1]. In this case, when service is restored, the entire population operates for a prolonged period at maximum capacity to restore the conditioned spaces to the desired temperature set points. This type of load synchronization is to be avoided because it requires generation to ramp quickly and may risk exceeding reserve margins.

In contrast, this paper focuses on using partial TCL synchronization to provide system benefits by directly controlling loads so that their aggregated power ramps both up and down, on hourly to sub-hourly time scales. Successful application of this method could allow loads to serve in place of conventional generation for ancillary services such as regulation, automatic generation control and load following [2,3]. The method is based on the fact that, although it would be challenging to track the state (i.e., temperature and power demand) of every load in a population subject to control, it is possible to accurately estimate the *probability* that each load in the population is in a given state. The results could be used to supply the increasing need for ancillary services associated with growing penetration of renewable electricity generators, especially wind turbines [4,5]. Wind plants are often far from other generation, and especially in situations with weak grids it would be desirable to locate some ancillary services in the vicinity of the plant. With the method presented here, it may be possible to identify and control nearby populations of electricity loads that could serve this purpose, thus avoiding the need to build new generation or for transmission upgrades.

As advanced metering infrastructure (AMI) and programmable communicating thermostats (PCTs) are introduced in growing numbers, system operators will have the ability to control TCLs by manipulating thermostat set points, rather than directly interrupting power, as is traditional in direct load control (DLC) programs.

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Although some TCLs are capable of continuously modulating electrical demand, they more commonly have only one power demand state and simply cycle on and off to maintain temperature within a prescribed deadband. This paper focuses on the latter, and demonstrates that small thermostat set point manipulations can be used to turn on and off only those loads that are approaching the limits of their thermostat temperature deadbands. The net result is a partial synchronization of TCLs, producing the desired aggregated power demand with minimal deviation from the original thermostat set points (thus avoiding conflicts with customer comfort).

There is a direct analogy between using conventional grid-connected energy storage devices – such as batteries and pumped-hydro – and controlling TCLs to provide ancillary services. In the former case, the storage device charges when excess generation is available, and discharges when generation is scarce. In the case of TCLs, the devices can 'charge' the conditioned thermal mass by operating when generation is in surplus, and 'discharge' by ceasing to operate during periods of scarcity. Just as increasing the storage capacity of a battery can increase the period of time over which it can supply (or consume) a given amount of power, if the thermal mass conditioned by a TCL has sufficient thermal capacitance, then prolonged 'charge' and 'discharge' periods can be enacted without significantly affecting the temperature of the thermal mass.

1.2. Previous work on load control

This paper builds on previous research in the area of physically-based models of TCLs and their application to cold load pickup and direct load control. These efforts most likely began with the independent work of Ihara and Scwheppe [6] and Chong and Debs [7], who introduced models of individual TCLs to describe the continuous evolution of temperature and discrete evolution of thermostat state. Mortensen and Haggerty [8] review most of the major categories of load models, in particular the diffusion approximation framework introduced by Malhamé and Chong [9] as well as the discrete-time simulation model previously developed by Mortensen and Haggerty [10] and later adapted to heterogeneous load populations by Uçak [11]. Although these models are physically meaningful, there have been few successful attempts to assign to the models parameters that represent the true characteristics of the population subject to control. Instead, most meaningful efforts have focused on identifying parameters for one load at a time [12,13]. Furthermore although the Malhamé and Chong framework is arguably the most impressive from an analytical point of view, most of its results require the limiting assumption that all loads in the control group are homogeneous.

Research on controlling TCLs prior to this paper focuses on reducing system demand to avoid shortages during peak hours or cold load pickup events. These efforts have focused primarily on dynamic programming and model reference adaptive control methods to identify DLC control laws. Some of the most innovative recent advances have dealt with the topic of balancing customer comfort with the need to reduce system load [14] as well as model predictive approaches [15,16]. The most commonly applied control signal is simply a discrete signal that turns off all loads in a group subject to control; multiple groups can be assigned [17,18]. Navid-Azarbaijani and Banakar [19] present a different control option that manipulates the duty cycle of units via a pulse-width modulated signal. More recently, Burke and Auslander [27] have explored the use of PCTs for peak load shaving.

1.3. Original contributions of this paper

Although the concept of using loads to provide ancillary services is not new [16,20], to the author's knowledge, this is the first paper to develop load models and control strategies to provide ancillary services like load following and regulation via thermostat set point manipulation. It will be shown that a simple linear model, with parameters justified on physical grounds, can be used to describe the aggregated dynamics of TCLs subjected to a common thermostat control signal. A simple but powerful result of this modeling exercise is that, in the case of homogeneous load groups, the number of TCLs that respond to thermostat set point manipulation is a function of only the size of the set point change and the width of the TCL temperature deadband. Because these parameters are effectively design variables, in principle system identification techniques are unnecessary for homogenous load groups. However, although the homogeneous model result remains a good approximation for limited amounts of heterogeneity, identified models ultimately perform better for high amounts of heterogeneity, though only marginally so. Data requirements for system identification are only the input signal (thermostat set point change) and the resulting change in aggregate demand from the population. It will be the subject of future research to demonstrate the feasibility of using this approach in an adaptive control framework.

A fundamental analytical contribution of this paper is an exact solution to the coupled Fokker–Planck equations (CFPE) originally developed by Malhamé and Chong [9] to describe the aggregated behavior of TCL populations. This solution provides the eigenvalues governing transient deviations from the steady state temperature distribution. The result will be directly applied to understanding the performance of the linear time series modeling approach. This information can in turn be used to identify load groups that are amenable to thermostat DLC. Although the CFPE formulation requires the assumption that load groups are homogeneous, it will be shown that load group heterogeneity actually improves the accuracy of the linear TCL model and associated control strategies, and that in fact some amount of heterogeneity is required to produce realistic dynamics.

Perhaps most importantly, this paper demonstrates the potential to provide ancillary services by remotely manipulating thermostat set points, specifically to balance fluctuations from intermittent renewable generators. To this end, the paper derives and shows the effectiveness of a minimum variance control law based on the linear time series model.

Although the simulations in this paper will use parameters that are typical for buildings, the analytical results are general and can in principle apply to other applications where electricity is used to control temperature in a thermal mass – for example cold storage and tank water heating (although in the latter case, water draw profiles would significantly complicate the analysis).

2. Model preliminaries: single and aggregated TCLs

2.1. Single TCL model

Two state variables are required to model the dynamics of a single TCL: the temperature of the conditioned mass and the discrete state of the thermostat (on or off). In this paper, temperature will be represented by θ (°C) and the thermostat state by m (a dimensionless discrete variable equal to 0 (off) or 1 (on)). This paper uses the following hybrid state discrete time model, originally developed in [10] and extended to heterogeneous systems in [11], to study the evolution of a population TCLs in time:

$$\theta_{i,t_{n+1}} = a_i\theta_{i,t_n} + (1 - a_i)(\theta_{a,i} - m_{i,t_n}R_iP_i) + w_{i,t_n} \tag{1}$$

$$m_{i,t_{n+1}} = \begin{cases} 0, & \theta_{i,t_n} < \theta_{s,i} - \frac{\delta_i}{2} = \theta_{-,i} \\ 1, & \theta_{i,t_n} > \theta_{s,i} + \frac{\delta_i}{2} = \theta_{+,i} \\ m_{i,t_n}, & \text{otherwise} \end{cases} \tag{2}$$

$$y_{t_{n+1}} = \sum_{i=1}^{N} \frac{1}{\eta_i} P_i m_{i,t_{n+1}} \tag{3}$$