Aggregated Modeling and Control of Air Conditioning Loads for Demand Response

Wei Zhang, *Member, IEEE*, Jianming Lian, *Member, IEEE*,
Chin-Yao Chang, *Student Member, IEEE*, and Karanjit Kalsi, *Member, IEEE*

***Abstract*—Demand response is playing an increasingly important role in the efficient and reliable operation of the electric grid. Modeling the dynamic behavior of a large population of responsive loads is especially important to evaluate the effectiveness of various demand response strategies. In this paper, a highly accurate aggregated model is developed for a population of air conditioning loads. The model effectively includes statistical information of the load population, systematically deals with load heterogeneity, and accounts for second-order dynamics necessary to accurately capture the transient dynamics in the collective response. Based on the model, a novel aggregated control strategy is designed for the load population under realistic conditions. The proposed controller is fully responsive and achieves the control objective without sacrificing end-use performance. The proposed aggregated modeling and control strategy is validated through realistic simulations using GridLAB-D. Extensive simulation results indicate that the proposed approach can effectively manage a large number of air conditioning systems to provide various demand response services, such as frequency regulation and peak load reduction.**

***Index Terms*—Demand Response, Aggregated load modeling, Direct Load Control, Thermostatically Controlled Loads.**

I. Introduction

One key feature of the smart electric grid is the ability to shift or directly control the demand to improve system efficiency and reliability under challenging operation scenarios. To achieve this, many pricing strategies, such as Real Time Pricing (RTP), Time of Use (TOU) pricing, and Critical Peak Pricing (CPP) have been studied [1–4]. Many validation projects [5] have been carried out to demonstrate the performance of different pricing strategies in terms of peak shaving and/or demand shifting.

In addition to price, local frequency signal also provides valuable real-time information about the grid. Allowing the load to respond to local frequency measurement can dramatically improve the reliability and stability of the grid. Many decentralized load control methods have been developed in the literature to stabilize frequency deviation, especially for primary frequency regulation [6, 7].

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W. Zhang and C-Y Chang are with the Department of Electrical and Computer Engineering, The Ohio State University, Columbus, OH 43210. Email:`zhang@ece.osu.edu` and `chang.981@osu.edu`

J. Lian and K. Kalsi are with the Advanced Power and Energy System Group, Pacific Northwest National Laboratory, Richland, WA 99354. `{jianming.lian,karanjit.kalsi}@pnnl.gov`

Direct load control (DLC) is another important paradigm for demand response. It is often employed to achieve faster and more predictable response. While transitional DLC strategies are mainly for peak shaving applications during high demand period [8–10], recent DLC paradigms often focus on real-time coordination of a large number of small residential loads [11–21]. It is typically operated by a centralized aggregator representing Load Serving Entities or Curtailment Service Provider; and it mostly employs Thermostatically Controlled Loads (TCLs), such as HVACs (Heating, Ventilation, and Air conditioning) and water heaters.

Despite the extensive recent studies in this area, a formal way to design demand response strategies with systematic consideration of their impact on the efficiency and reliability of the bulk power system is conspicuously missing. One main challenge is on characterizing the aggregated dynamic behavior associated with demand response programs. The goal of this paper is to address this challenge by focusing on one of the most important types of responsive loads, namely, the HVAC systems. Specifically, we aim to develop highly accurate aggregated modeling and control strategies for a large population of HVAC loads for various demand response applications.

Aggregated load modeling and control have been studied extensively in the literature, especially for TCLs such as HVACs and water heaters [17, 18, 22, 23]. The key idea of aggregated load modeling is to characterize the temperature density evolution of the population. This can be done through deterministic fluid dynamics approach [5] or stochastic differential equation approach [17, 24], both leading to the same Fokker-Planck type of Partial Differential Equation (PDE). An analytical solution to the equation in a much simplified setting is derived in [17], which can provide insight into the transient dynamics. Aside from the first-principle-based approach, data-driven type of approaches based on Markov chains have also been studied in the literature [15, 20, 23]. Such methods compute the transition probability between discrete temperature bins based on simplified first-order TCL models or directly from the simulated training data. Both the PDE-based approach and the Markov chain based method are essentially characterizing the temperature density evolution. Several non-density based methods have also been proposed [14, 25], whose main objective is to represent the aggregated dynamics using simple linear state-space or transfer function models. Once a good model is obtained, many well established control methods can be directly applied to regulate the aggregated power response. Examples include open-loop control [26], Model Predictive Control [15], Lyapunov-based control [18], or simple inverse control [20] that computes the control action so that the predicted output matches the given reference signal.

The aforementioned approaches have several limitations that need to be addressed for realistic demand response applications. First of all, most of them adopt first-order differential equations for individual load models. Although such models may be appropriate for small TCLs such as refrigerators, they are not appropriate for residential HVAC systems. HVAC systems have a large heat capacity due to building materials and furnishing requiring the consideration of both air and mass temperature dynamics. Unfortunately, second-order TCL dynamics have not been adequately studied for load aggregation in the literature. Secondly, many aggregate models assume homogeneous loads. It is well known that diversity in load parameters is crucial to obtain realistic aggregated responses [15, 18, 19, 21]. The method proposed in [21] considered heterogeneous thermal capacitances for first-order TCLs, while the other parameters are still assumed to be homogeneous. Although the Markov chain model developed in [15, 23] can be applied to general heterogeneous loads, it is essentially a homogeneous approximation and can not accurately capture the true heterogeneous dynamics as admitted by the authors [15, 23]. Lastly, the aggregated control strategies developed in the literature often involve frequent interruptions of the temperature-deadband-based operations of the participating TCLs. These methods can not be directly applied to HVAC loads for which compressor time delay relays are often installed to prevent short cycling of the device. New modeling and control methods need to be developed to systematically deal with the compressor time delay constraint.

This paper will develop a general aggregated modeling and control framework for HVAC loads that can systematically address the aforementioned challenges. In particular, the proposed aggregated model is based on a general second-order Equivalent Thermal Parameter (ETP) model [27, 28], which considers both the air and mass temperature dynamics of individual HVAC systems. A clustering technique is employed to deal with load heterogeneity. A novel way to incorporate compressor time delay constraint in the aggregate model is also proposed. Numerical simulations indicate that the model can accurately capture both the transient and steady state responses over a long prediction horizon under realistic compressor time delay restrictions and various demand response scenarios. Such a result represents a significant improvement over most existing works in the literature. In addition, a simple aggregate control method is also proposed based on the developed aggregate model. Simulation results indicate that the controller can make the aggregated power accurately follow realistic frequency regulation signals, even under compressor time delay constraints. Application in peak power reduction is also studied, for which the total power is shown to be reduced by 30% without violating users' temperature preference. All the modeling and control validations are performed using GridLAB-D, which is an agent-based simulation tool for distribution systems developed by the Department of Energy (DOE) of the United States [29].

The paper is organized as follows. A second-order ETP model of an HVAC system is introduced in Section II. A general aggregated modeling framework is developed in Section III. In Section IV, we propose a simple aggregated control scheme and incorporate compressor time delay in the aggregated model to accurately capture the closed-loop dynamics. The proposed modeling and control strategies are validated using GridLAB-D in Section V. Finally, some concluding remarks are given in Section VI.

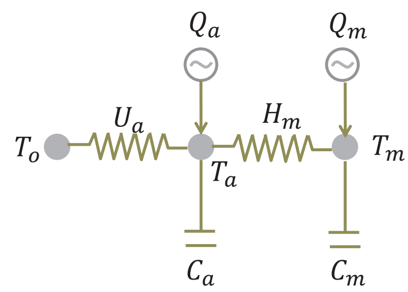

Fig. 1. The Equivalent Thermal Parameter (ETP) model of home heating/cooling system

II. Dynamics of HVAC Systems

The individual device model is the basis for developing an aggregate load model. In this paper, we adopt the popular Equivalent Thermal Parameter (ETP) model (see Fig. 1) to describe the thermal dynamics of each individual load [27–29]:

$$\begin{cases} \dot{T}_a(t) = \frac{1}{C_a}\left[T_m H_m - (U_a + H_m)T_a(t) + Q_a + T_o U_a\right] \\ \dot{T}_m(t) = \frac{1}{C_m}\left[H_m(T_a(t) - T_m(t)) + Q_m\right] \end{cases} \tag{1}$$

Here, T_a is the indoor air temperature, T_m is the inner mass temperature (due to the building materials and furnishings), U_a is the conductance of the building envelope, T_o is the outdoor temperature, H_m is the conductance between the inner air and inner solid mass, C_a is the thermal mass of the air, C_m is the thermal mass of the building materials and furnishings, Q_a is the heat flux into the interior air mass, and Q_m is the heat flux to the interior solid mass. The total heat flux Q_a consists of three main factors: Q_i, Q_s and Q_h. Here, Q_i is the heat gain from the internal load, Q_s is the solar heat gain, and Q_h is the heat gain from the heating/cooling system. Depending on the power state of the unit, the heat flux Q_a could take the following two values:

$$Q_a^{\text{on}} = Q_i + Q_s + Q_h \text{ and } Q_a^{\text{off}} = Q_i + Q_s$$

The power state of an HVAC system is typically regulated by a simple hysteretic controller based on a temperature deadband $[u_{\text{set}} - \delta/2, u_{\text{set}} + \delta/2]$, where u_{set} is the temperature setpoint and δ is the deadband size. When operating in air conditioning mode, the system turns on when the air temperature T_a reaches the upper boundary $u_{\text{set}} + \frac{\delta}{2}$, and turns off at the temperature $u_{\text{set}} - \frac{\delta}{2}$.

As an example, Fig. 2 shows the evolution of the air and mass temperatures of a HVAC unit subject to a setpoint change from 74 $^{\text{o}}$F to 75 $^{\text{o}}$F at time $t = 1$ hour. It can be seen that it takes a much longer time for T_a to increase from 74