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Quantifying flexibility of commercial and residential loads for demand response using setpoint changes

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HIGHLIGHTS

- Presents a novel demand response estimation framework for residential and commercial buildings.
- Applies a combination of EnergyPlus and two-state models for thermostatically controlled loads.
- Regression models are fit to each dataset for predicting DR potential quickly without any computational burden.
- Regression model equations are based on key inputs, including hour of day, set point change and outside air temperature.
- Models are validated for DR measurement in commercial buildings.

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ABSTRACT

This paper presents a novel demand response estimation framework for residential and commercial buildings using a combination of EnergyPlus and two-state models for thermostatically controlled loads. Specifically, EnergyPlus models for commercial and multi-dwelling residential units are applied to construct exhaustive datasets (i.e., with more than 300M data points) that capture the detailed load response and complex thermodynamics of several building types. Subsequently, regression models are fit to each dataset to predict DR potential based on key inputs, including hour of day, set point change and outside air temperature. For single residential units, and residential thermostatically controlled loads (i.e. water heaters and refrigerators) a two-state model from the literature is applied. For commercial office building and Multiple Dwelling Units (MDUs) building, the fitted regression model can predict DR potential with 80–90% accuracy for more than 90% of data points. The coefficients of determination (i.e. R^2 value) range between 0.54 and 0.78 for the office buildings and 0.39–0.81 for MDUs, respectively. The proposed framework is then validated for commercial buildings through a comparison with a dataset composed of 11 buildings during 12 demand response events. In addition, the use of the proposed simplified DR estimation framework is presented in terms of two cases (1) peak load shed prediction in an individual building and (2) aggregated DR up/down capacity from a large-scale group of different buildings.

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1. Introduction

With penetration of intermittent renewable energy generation positioned to increase in the coming years, there is a growing need for ancillary services (AS) to absorb renewable related disruptions and support power grid operation. Demand Response (DR), in the form of direct load control, interruptible/curtailable programs, and time-of-use rates, is emerging as a low-cost alternative to conventional fast-ramping generation resources [1,2]. This emergence is made possible partly because of the technological advances in communication and control systems, and partly because of decreasing costs of hardware. These advances make it possible for fast, automated DR assets to be aggregated and to participate in the wholesale market. Demand response in the wholesale market can facilitate Regional Transmission Organizations (RTOs) and Independent System operators (ISOs) in balancing supply and demand, and thereby, help maintain stable energy prices [3]. Demand response has been recognized as a low-cost and practical solution to allow more penetration of intermittent renewable energy generation in bulk electric power systems [4]. More specifically, this study indicates that the inter-hourly demand response

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Nomenclature

α	TCL thermal parameters, e^{-h/C_iR_i}
α_1, α_2	regression coefficients
β_1, β_2	intercepts of the regression model
δ	deadband width (°C))
ϵ	individual TCL model noise (°C)
η_i	coefficient of performance
γ	setpoint adjustment (°C)
$\theta^a_{i,t}$	ambient temperature at time t (°C) or (°F)
θ^g_i	heat gain (kW)
$\theta^s_{i,t}$	thermostat setpoint (°C)
$\theta_{i,t}$	interior temperature (°C) or (°F)
A_i	area of zone surface i (m^2)
C^Z	zone capacitance (W h/°C)
C_i	thermal capacitance (kW h/°C))
C_p	zone air specific heat (J/kg k)
DR^p	demand response potential (%)
h_i	heat transfer coefficient of zone surface i (W/m^2 K)
$m_{i,t}$	switch parameter representing ON/OFF state of the TCL, 1/0
m_{inf}	mass flow of infiltration of outside air (kg/h)
m_{sys}	mass flow of supply air from air systems (kg/h)
$P^{base}_{i,h}$	power consumption of the baseline (kW)
$P^{DR}_{i,h}$	power consumption during the DR event hours (kW)
P^r_i	rated power (kW)
Q_i	convective internal loads (W)
R^2	R squared, coefficient of determination
R_i	thermal resistance (°C/kW)
T_{sup}	supply air temperature (°C)
T_s	zone surface temperature (°C)
T_Z	zone temperature (°C)
h	time step
U	U-value (W/m^2 °C)

magnitude is not as useful as intra-hourly demand response for promoting additional renewable energy resources. On the other hand, demand response has also been used to integrate with customer-side distributed energy resources to enable optimal grid transactions [5].

1.1. Demand response for ancillary services

There are various types of AS in the power system, including frequency control, voltage control, spinning reserve, standing reserve, operating reserve, black start capability, remote generation control, grid loss compensation and emergency control actions. Among these AS products, two types have been identified as products that fast DR can participate in: contingency and operating reserves [6]. Contingency reserves are allocated in response to a major generator or transmission outage within 10 min holding for 30 min or less. Operating reserve is the generating capacity available to the system operator within a short interval of time to meet demand, such as regulation service, load following and fast energy market. Depending on the type of AS required, DR can be requested to respond quickly in a similar manner as an AS generator. Over the past decade, DR has become increasingly capable of providing AS in bulk power systems [7]. Some studies [8,9] have argued that a number of small DR resources are well suited to provide AS to the grid. A smart appliance model was developed to utilize the cycle delay and interruption for providing reserve services [10]. Non-thermostatic loads, such as washing machines, dish washers and dryers, were modeled with multiple discrete power phases. A comprehensive modeling framework of a smart grid system was developed to integrate with demand-side flexible resource and renewable energy resource, which includes non-thermostatic loads (e.g. appliances) and thermostatic loads (e.g. air-conditioning units) [11]. Furthermore, a number of field studies have been conducted to show the capability of DR for providing AS [6,12,13]. The authors of [14] described generalized DR product definitions for load participation in AS, energy, and capacity markets.

1.2. Demand response potential from buildings

Residential and commercial building sectors account for approximately 37% and 36% of total U.S. electricity consumption respectively. Together, these sectors account for 73% of national electricity consumption [15]. In particular, heating, ventilation and air-conditioning system (HVAC) in buildings are well-suited to load shedding and shifting on timescales of seconds to minutes. Within the comfort bounds of building indoor temperature, the power use of building HVAC systems are highly flexible and can be controlled with temperature setpoint changes. Targeting building HVAC, as well as other thermostatically controlled loads (TCLs) within these sectors can potentially provide DR resources across different scales of DR products including regulation, flexibility, contingency, energy and capacity services. These load types can be an excellent resource for DR for several reasons:

1. HVAC systems accounts for a substantial electric load in commercial buildings, often more than 1/3 of the total load.
2. The "thermal flywheel" like behavior of indoor environments allows HVAC systems to be temporarily unloaded without immediate impact to the building occupants.
3. It is common for HVAC systems to be at least partially automated with energy management and control systems (EMCSs).

In the residential building sector, thermostatically controlled loads (TCLs) such as air conditioners, refrigerators, and water heaters have been deployed to provide power system services [16–20]. To accommodate the need of real-time demand response, a recent study developed a new thermostat for real-time price demand response to allow reliable aggregate demand response for ancillary services [21]. A few pilot studies were conducted to better understand demand response potential and flexibility of residential appliances [22,23].

1.3. Current approaches to quantifying building DR potential

Various research studies have investigated the modeling, control and aggregation of TCLs through a variety of methods. A simplified equivalent thermal parameters (ETP) model is well-suited for simulating DR potentials in residential and small commercial buildings [24,25]. The use of two-state RC (resistance–capacitance) is commonly used in the aggregation of residential TCL loads to provide demand response in the market [9,17,26]. A recent study presents a physical–statistical approach to simulate and forecast energy consumption for heterogeneous buildings [27]. Uncertain stochastic parameters are introduced into the physical model and are derived based on the comparison with measurements. A similar combined physical and behavioral approach was also proposed to simulate office building consumer load [28]. This bottom up