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Publication Date
2016-05-31

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Lawrence Berkeley National Laboratory

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To be Published in the Journal of Applied Energy

May 2016

The work described in this study was performed and coordinated by the Grid Integration Group of Lawrence Berkeley National Laboratory and supported by the State Grid Corporation of China Project (DZN17201300197, Study on Key Technologies for Power and Frequency Control of System with Source-Grid-Load Interactions).

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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. 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.

Keywords: demand response, thermostatically controlled loads, regression models, two-state model, simplified DR potential estimation.

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, $[^{\circ}C]$
ϵ	Individual TCL model noise, $[^{\circ}C]$
η_i	Coefficient of performance
γ	Setpoint adjustment, $[^{\circ}C]$
$\theta^a_{i,t}$	Ambient temperature at time t, $[^{\circ}C]$ or $[^{\circ}F]$
θ^g_i	Heat gain, $[kW]$
$\theta^s_{i,t}$	Thermostat setpoint, $[^{\circ}C]$

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$\theta_{i,t}$	Interior temperature, $[^{\circ}C]$ or or $[^{\circ}F]$
A_i	Area of zone surface i, $[m^2]$
C^Z	Zone capacitance, $[Wh/^{\circ}C]$
C_i	Thermal capacitance, $[kWh/^{\circ}C]$
C_p	Zone air specific heat, $[J/kg \cdot k]$
DR^p	Demand response potential [%]
h_i	Heat transfer coefficient of zone surface i, $[W/m^2 \cdot K]$
$m_{i,t}$	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, $[kg/h]$
$P_{i,h}^{base}$	Power consumption of the baseline, $[kW]$
$P_{i,h}^{DR}$	Power consumption during the DR event hours, $[kW]$
P_i^r	Rated power, $[kW]$
Q_i	Convective internal loads,[W]
R^2	R squared, coefficient of determination
R_i	Thermal resistance, $[^{\circ}C/kW]$
T_{sup}	Supply air temperature, $[^{\circ}C]$
T_s	Zone surface temperature, $[^{\circ}C]$
T_Z	Zone temperature, $[^{\circ}C]$
h	Time step
U	U-value, $[W/m^2 \cdot^{\circ} C]$

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. 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 [1]. 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 [2]. More specifically, this study indicates that the inter-hourly demand response 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 [3].

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 [4]. Contingency reserves are allocated in response to a major generator or transmission outage within 10 minutes holding for 30 minutes 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 [5]. Some studies [6, 7] 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 [8]. Non-thermostatic loads, such as washing machines, dish washers and dryers, were modelled 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) [9]. Furthermore, a number of field studies have been conducted to show the capability of DR for providing AS [4, 10, 11]. The authors of [12] 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 [13]. 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 [14, 15, 16, 17, 18]. 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 [19]. A few pilot studies were conducted to better understand demand response potential and flexibility of residential appliances [20, 21].

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 [22, 23]. 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 [7, 15, 24]. A recent study presents a physical–statistical approach to simulate and forecast energy consumption for heterogeneous buildings [25]. 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 [26]. This bottom up simulation model that includes electricity usage behaviours with the physical building model can generate load profiles with reasonable accuracy. The use of this model approach can be used to simulate building dynamics to provide demand response in the power system. In the commercial building sector, modeling methods of building thermal dynamics are generally categorized into three groups: 1) physical (white box) models, 2) empirical (black box) models, and 3) gray box models.

To capture the detailed building thermal dynamics, especially for DR, physical models are developed to simulate each building and HVAC system component and their interactions between sub-systems. Software tools such as EnergyPlus, DOE-2, ESP-r, and TRNSYS, are used to create physical models for building energy simulation. A number of studies demonstrated the use of physical models for predicting DR performance of various control strategies in both commercial and residential buildings [27, 28, 29, 30, 31]. Overall, physics based energy models, such as whole-building EnergyPlus models, capture sufficient details to simulate the effect of DR strategies such as thermostat setpoint or fan speed adjustment in individual buildings. Given an adjustment of zone temperature setpoint, EnergyPlus performs the integrated and simultaneous simulations of building loads, HVAC system, plant and other associated system components for each simulation time step. While this approach is suitable for single buildings, when applying it to aggregations of large populations of building loads, the computational burden can quickly become prohibitive, particularly when results must be generated quickly for specific weather conditions and building population characteristics. A recent study demonstrates the use of physical modeling tools to generate a mega database of simulation results for energy efficiency retrofit analysis [32]. This study simulates different building types with six vintages in 16 climates, and also 100 energy measures into the database. Users can use the tool to estimate the energy performance without creating physical models. Similarly, a very large database of building energy use at the national level is presented to support empirical comparison of energy use and data-driven savings analysis and help users identify the energy saving potentials [33]. Those studies provide insight into the use of physical models and large datasets in the most efficient manner.

Data-driven models such as ARMA (autoregressive moving average) models are also used for simulating the building thermal dynamics to estimate DR potentials [16, 34]. Generally, this modeling approach requires expanded datasets including HVAC power usage, indoor and outdoor air temperature, temperature setpoint and other data to train the model [35, 36]. Recently a data driven probabilistic graphic model is presented to predict building energy performance by capturing relationships among variables (i.e., outside air temperature and energy use) [37]. Gray-Box models for transient building load prediction range from purely empirical or "black-box" models to purely physical or "white-box" models.

A number of studies have deployed the purely physical models such as EnergyPlus to achieve reduced-order RC (resistance–capacitance) models for simulating thermal dynamics and DR performance in commercial buildings [17, 38, 39, 40, 41, 42, 43]. Fast power demand response strategies that involve HVAC systems in commercial buildings were evaluated based on the RC model [44, 45], which demonstrate that building HVAC systems are quite suitable for demand response. Pavlak et al. [38] demonstrated the use of RC model for model predictive control (MPC) function optimization that required hours of computation time for day-ahead planning of DR participation in energy and ancillary service markets. With respect to those different approaches, the challenges to accurately quantifying building DR potential include:

1. the model should be capable of capturing the complex thermal dynamics of their interacting energy systems
2. the model can be applied to large scale populations comprised of many buildings
3. the computation time for large population simulations should be fast enough to provide day-ahead, hour-ahead, and real-time estimation of DR potential

1.4. Motivation

The objective of this study is to develop a framework for estimating theoretical DR potentials in commercial and residential buildings that satisfies the aforementioned criteria. The framework proposed in this investigation utilizes a regression based prediction strategy to estimate the DR potential of a large scale aggregation of building loads, as a function of a number of key inputs. These variables include changes to thermostat setpoints, time of the day, seasons of the year, weather condition, and building envelope and HVAC characteristics. This novel approach captures the building thermal response to these inputs with high accuracy by leveraging a collection of previously generated detailed simulation results from physical models. This eliminates the high computational time required by physical building models used to estimate the DR potential of a large heterogenous load population. Each regression model is generated based on the following process:

1. Physical models or representative buildings are used to simulate HVAC and other thermostatically controlled load setpoint adjustments at various timesteps.
2. The load difference due to setpoint changes are determined for the period of the setpoint adjustment.
3. Linear regression models are fit to the simulated load changes based on other input variables (e.g. outside air temperature) for each hour of the day.

DR potentials from the observed load changes are characterized into two groups of AS product: contingency and operating reserves. DR potentials with similar response characteristics are aggregated from each sector to quantify the total DR resource available to grid operators. The request from the grid operator can be a DR control signal (e.g. thermostat setpoint reset, frequency regulation signal) or an amount of power change (e.g. ΔP).

The paper is organized as follows: Section 2 describes the methodology of the proposed DR estimation model and presents the model framework for evaluating DR potentials and response characteristics of commercial and residential sectors. Section 2.1 introduces the model development of commercial and residential building sectors. Section 3 presents the results of the DR flexibility estimation and model validation, and two use cases of the proposed simplified DR estimation framework. Finally, Section 4 concludes the findings of this study and suggests the future work.

2. Methodology

Under the proposed methodology, physical models of a variety of thermostatically controlled loads are created, then the hourly DR potential of these loads are calculated, finally a simplified DR potential estimation strategy for each load type is constructed. Table 1 outlines the scope of the study. In the following sections, the methodology employed for different load categories are described as given in Table 1 (i.e. HVAC and additional TCLs). For each load type, individual models used for different loads in this category are introduced, then the DR potential calculation methodology is described, finally the simplified DR potential methodology is introduced.

In this study, we deployed EnergyPlus models for 16 commercial building types. Specifically, we used reference model of each building category under each building type. In addition, we developed a suite of RC models for residential A/C units, refrigerators, and electric water heaters. In the current scope, we simulated these loads in different climate zones. Under each building category, we parametrized the prototype reference model into six groups of building energy codes (pre-1980, 1980 to 2004, 2004-2007, 2007-2010, 2010-2013, 2013 to 2016). Table 2 presents the number simulations of each building category in this study. The total number of simulation models with different physical properties is 288. Together with the setpoint changes (degrees of changes) of each hour of the day, day of week, and week of season,as a result, there are over 300M data points in the database. By using the outcome of this study, users don't need to create the detailed EnergyPlus models unless they want to simulate the demand response performance of other building types (e.g., data centers).

2.1. Calculating DR Potential for Thermostatically Controlled Loads

2.1.1. Modeling HVAC Loads

There are various methodologies proposed to accurately model the thermal dynamics of buildings. One of the most commonly used physical modeling tools in the literature is EnergyPlus [46]. In this study, EnergyPlus is used for modelling the thermal response of commercial buildings and the multi-dwelling

<table>
<tr><td>Building Segment</td><td colspan="3">Commercial</td><td colspan="4">Residential</td></tr>
<tr><td>Load Category</td><td colspan="5">Heating, Ventilation and Air Conditioning</td><td colspan="2">Additional TCLs</td></tr>
<tr><td>Loads</td><td>Small</td><td>Medium</td><td>Large</td><td>Multi-Dwelling Unit</td><td>Single Unit</td><td>Water Heaters</td><td>Fridges</td></tr>
<tr><td>Thermal Model</td><td colspan="4">Detailed Physical Models</td><td colspan="3">Two-State RC Models</td></tr>
<tr><td>DR Potential Calculation</td><td colspan="7">Bottom-up Setpoint Adjustment Simulations</td></tr>
<tr><td colspan="8">Simplified DR Potential Estimation</td></tr>
</table>

Table 1: Overall scope and methodology of the study

residential units. For the single residential units, water heaters and refrigerators a two-state RC model commonly used in the literature is applied. The reason for this is two-folds: (i) Modeling of commercial building thermodynamics is a very complex task that considers building envelope, geometry, interactions between perimeter and internal thermal zones, heat flow of air/water side HVAC systems, control system component, etc. and (ii) the operational on/off state change of TCLs is simple, the interval of compute time step is small at the second to minute level, and the number of HVAC units is large. Aggregation of thousands of TCLs in residential sector requires such a two-state RC model to capture the on/off state change with a short compute time.

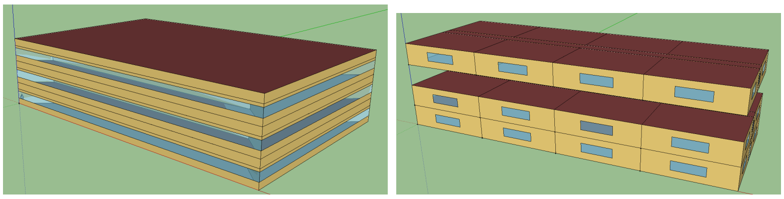
In this section, we select two building categories (1) commercial office buildings and (2) mid-rise apartments to demonstrate the DR potential estimation framework. For small, medium and large commercial buildings, EnergyPlus model includes thermal zones, HVAC, and plant models. Small and medium commercial office buildings are equipped with packaged direct expansion (DX) variable air volume (VAV) cooling systems. A large commercial office building has a chilled water VAV system. Figure 1a shows the building examples of a medium office building and a mid-rise apartment building. For commercial building sector, the number of floors can be changed to model different sizes of building floor area. The availability of DR potential from building HVAC systems is determined by HVAC operational schedules, which varies along with building types. Typically, it operates from 6AM to 6PM in small commercial buildings, and 6AM to 10PM in medium and large commercial buildings.

Among DOE developed prototype building models, mid-rise apartment building model was used to represent the common multiple dwellings, as shown in Figure 1b. It is a 4-story apartment building, 31 apartments plus an office at the first floor. Each apartment is equipped with a single speed DX cooling unit and a gas furnace system. The building is assumed to operate HVAC systems 24 hours a day, which indicates that it is capable to provide 24 hours' DR resources to the grid. To be consistent with the modeling framework of commercial sector, the same duration from 6AM to 10PM is selected to quantify the flexibility of DR potentials from residential HVAC systems.

In EnergyPlus [46], the method of heat balance solution is applied to solve the energy and moisture balances for the zone air, as follows:

Building Sector	**Building Type**	**Number of Different Physical Properties**	**Climate Zones**	**Total Number of Data Points [in Millions]**
Office	Small, medium and large offices	54	6	60M
Retail	Stand-alone Retail and strip mall	36	6	40M
Education	Primary and secondary school	36	6	40M
Hospital	Hospital and health care	36	6	40M
Hotel	Small and large hotels	36	6	40M
Warehouse	Warehouse	18	6	20M
Restaurant	Quick Service and full service restaurants	36	6	40M
Residential	Mid- and high-rise apartments	36	6	40M

Table 2: Number of simulations based on DOE Prototype Building Models



(a) Medium Commercial Office Building (b) Mid-rise Apartment Building

Figure 1: Render of DOE prototype building models

$$C_Z \frac{dT_Z}{d_t} = \sum_{i=1}^{N_{si}} Q_i + \sum_{i=1}^{N_{surface}} h_i A_i (T_{si} - T_Z) \\ + m_{inf} C_p (T_{si} - T_Z) \\ + m_{sys} C_p (T_{sup} - T_Z) \tag{1}$$

where $\sum_{i=1}^{N_{si}} Q_i$ is the sum of the convective internal loads, $\sum_{i=1}^{N_{surface}} h_i A_i (T_{si} - T_Z)$ is the convective heat transfer from the zone surfaces, $m_{inf} C_p (T_{si} - T_Z)$ is the heat transfer from the outside air infiltration, $m_{sys} C_p (T_{sup} - T_Z)$ is the HVAC air system load.

In order to represent different building characteristics, the parameters representing the building envelope, HVAC system, and plant efficiency were considered to vary with known distributions and used to initialize the prototype thermal model in each sub-category of buildings, as shown in Figure 2. Specifically, the parameters representing building envelope, building HVAC system and plant efficiency are tied with the built year in association with building energy standards and codes. In this study, the range of model parameters that include building envelope, thermal mass level, internal loads, HVAC system and plant efficiency were defined to simulate different levels of building stocks, as presented in Table 3.

In order to model the thermal behavior of single residential home AC units, refrigerators and water heaters a two-state model previously proposed and commonly used in the literature [14, 15] is used. The individual two-state model that captures the underlying thermal dynamics of each TCL, i, is given as follows:

$$\theta_{i,t+1} = \alpha_i \theta_{i,t} + (1 - \alpha_i)(\theta^a_{i,t} - m_{i,t} \theta^g_i) + \epsilon_{i,t} \tag{2}$$

where $\theta_{i,t}$ is the interior temperature, $\theta^a_{i,t}$ is the ambient temperature at time t, θ^g_i is the heat gain, $m_{i,t}$ is a switch parameter representing ON/OFF state of the TCL. The temperature gain, θ^g_i, is dependent on the *resistance* R_i and the *rated power* P^r_i of the appliance and is given as:

$$\theta^g_i = \begin{cases} R_i \eta P^r_i, \textit{ for cooling devices} \\ -R_i \eta P^r_i, \textit{ for heating devices} \end{cases} \tag{3}$$

where η is the coefficient of performance. α is a parameter that captures the thermal parameters of each TCL as follows:

$$\alpha_i = e^{-h/C_i R_i} \tag{4}$$

where R_i and C_i are thermal resistance and capacitance respectively.

2.1.2. Obtaining the DR Potential Using Individual Thermal Models

To obtain DR potential values from the EnergyPlus simulation environment, the control library of HVAC based DR strategies is used. Specifically, the "Global Temperature Adjustment" (GTA) strategy is applied. The component of thermostat setpoint schedule in EnergyPlus is used to manipulate the change

Model Parameters	Range of Values from Each Period of Building Energy Codes and Standards
Exterior Wall U-value ($W/m^2 \cdot ^\circ C$)	0.35-1.07
Roof U-value ($W/m^2 \cdot ^\circ C$)	0.37-0.44
Thermal Mass Level	Low, medium and high
Windows U-value ($W/m^2 \cdot ^\circ C$)	1.02-2.04
Windows SHGC	0.25-0.71
Lights(W/m^2)	8.6-19.4
Electric plug loads(W/m^2)	8.6-16.1
Occupancy ($person/m^2$)	18.58 in office areas and 2.5/per apartment, see others in [47]
HVAC system	PSZ-AC in small commercial buildings and VAV with electric reheat in large commercial buildings
Cooling plant efficiency	2.5-2.8 (Air-cooled) and 3.8-6.2 (Water-cooled)
HVAC operation schedule	6AM to 10PM in most commercial buildings and 24 hours in mid- and high-rise apartments

Table 3: Simulation parameters for EnergyPlus Models (Part of DOE Prototype Building Models)

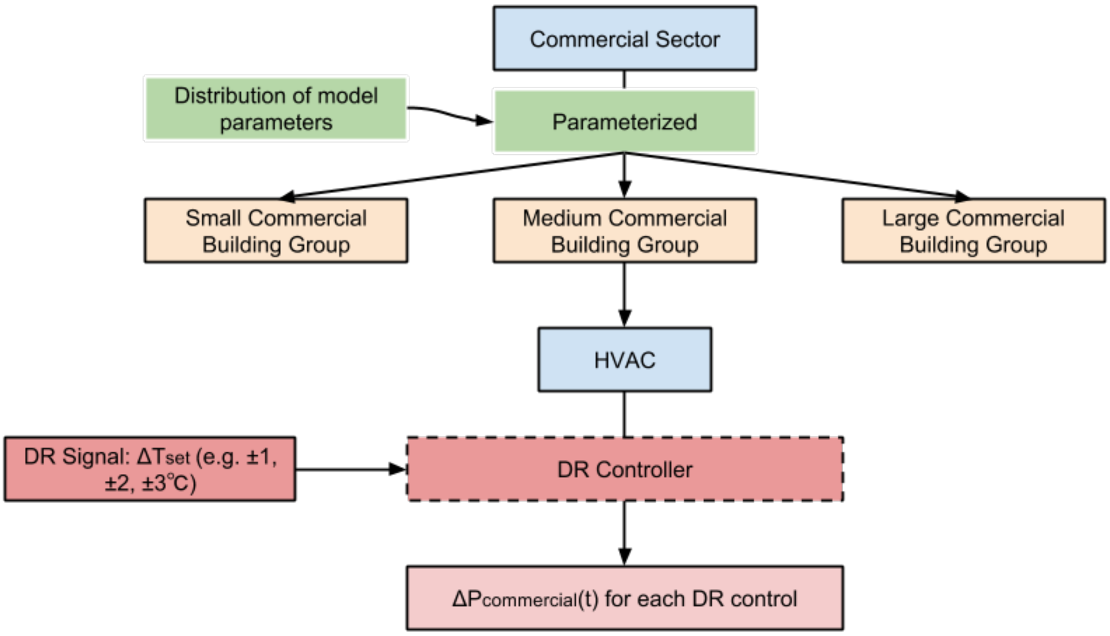


Figure 2: Modelling Framework of DR Estimation from EnergyPlus Model Simulations

of thermostat setpoint to receive the power change from building HVAC systems. This strategy is previously tested to evaluate the response characteristics in terms of depth, duration, and ramping of load change. The deployment of GTA in commercial buildings can achieve 15-30% of the whole building peak demand during the peak period and last for 4-6 hours with zone temperature in the comfort range [29, 27]. Kiliccote et al. [4] demonstrated fast DR capabilities to provide ancillary services using a few residential and commercial buildings. In particular, GTA in a large commercial building can receive the load response less than 5 minutes. Similar work has also proposed using zone setpoint adjustment to allow building participation in energy and ancillary markets [38, 48]. GTA is a feature that allows commercial building operators to adjust the space temperature setpoints for an entire facility with a single command from a single control location. It is most effective because it reduces the load of all associated air handling units and cooling equipment. Figure 3 shows examples of HVAC response to GTA in two types of prototype building models: a medium commercial building (left) and a midrise apartment (right). Notice that the building HVAC system load can be reduced by increasing thermostat temperature setpoint.

In two-state models, at any given point in time t, a TCL's operation can be interrupted by a setpoint adjustment. When used to trigger demand response events, setpoint adjustments result in TCLs switching OFF or ON due to the change in thermostatic control bounds governing their interior temperature. Once the TCL is switched, it remains in its new state until the interior temperature reaches the new thermostatic control bound that triggers switching back. To formalize this concept, one can define $\theta^s_{i,t}$ as the setpoint for TCL i at time t and δ as the deadband width of the ith TCLs thermostatic bound. Due to a setpoint adjustment of γ, $\theta^s_{i,t+1}$ can be defined as follows:

$$\theta^s_{i,t+1} = \theta^s_{i,t} + \gamma \tag{5}$$

For single unit residential building ACs, water heaters and refrigerators, one can use the equation for individual thermal dynamics, input parameters obtained from literature, and the proposed setpoint adjustment strategy similar to commercial buildings to simulate a population of TCLs to estimate the DR potential. For each TCL, two consumption profiles are calculated: baseline setpoint profile and a DR setpoint profile in order to estimate the change in load within the hour h a DR event is called. Formally,the average baseline

Figure 3: Example of zone thermostat setpoint adjustment and the power response in a medium commercial building (left) and a midrise apartment (right)

power consumption of a TCL within the DR event hour h is defined as $\hat{P}_{i,h}^{base}$, and the power consumption of a TCL i using the DR setpoint profile as $\hat{P}_{i,h}^{DR}$. The DR potential for individual TCL i DR_i^p can now be estimated as follows:

$$DR_i^p = \frac{\hat{P}_{i,h}^{base} - \hat{P}_{i,h}^{DR}}{\hat{P}_{i,h}^{base}} \tag{6}$$

As it can be seen in above equation DR_i^p captures the hourly load shed potential of each TCL with respect to its rated power consumption. Also notice that a positive DR potential refers to a "load shed" capacity, where as a negative DR potential refers to a "load increase" capacity. Using this definition and parameters obtained from the literature on heterogeneous load characteristics, a population of TCLs composed of individual models can be simulated in a bottom up fashion. The parameters used to simulate TCLs are given in Table 4.

As it can be seen in Table 4, the only TCLs subjected to outside air temperature are the air conditioners. Similar to the commercial and multi-dwelling unit DR potential estimation framework, outside air temperature data from 2015 is used to simulate these loads. For the refrigerators and water heaters, it is assumed that the ambient temperature is within the range of the AC setpoint. The motivation behind this is as follows: typically water heaters and refrigerators are located within conditioned environments, hence the variation in the ambient temperature can be modeled by the comfort zone of the AC units.

2.2. Simplified DR Potential Estimation Strategy

As previously noted, it is computationally expensive to run simulations of individual load models to estimate the DR potential of TCL populations. In particular, the detailed HVAC load models in EnergyPlus can be burdensome to re-run when a reassessment of DR potential is needed. Although HVAC's electrical load is dynamic and sensitive to weather conditions, occupancy, and other factors, previous research and field demonstration have found that HVAC demand and DR potential tend correlate positively with outside air temperature until the system limits are reached [28, 30, 49]. Motivated by this, the proposed model of

Table 4: TCL parameters used in this study

Parameters	**ACs**	**Refrigerators**	**Water Heaters**
Ambient temperature, $\theta^a_{i,t}$ [$°C$]	Outside Air Temperature	18-27	18-27
Deadband width, δ, [$°C$]	0.25-1	1-2	2-4
Temperature setpoint, $\theta^s_{i,t}$, [$°C$]	18-27	1.7-3.3	43-54
Thermal resistance, R_i, [$°C/kW$]	1.5-2.5	80-100	100-140
Thermal capacitance, C_i, [$kWh/°C$]	1.5-2.5	0.4-0.8	0.2-0.6
Rated power, P^r_i, [kW]	4-7.2	0.1-0.5	4-5
Coefficient of performance, η_i	2.5	2	1
Time step, h, [minutes]	2	2	2

DR potential of TCLs uses outside air temperature as the predictor. Since it is expected that the occupancy schedule will play a crucial role in these estimations, separate models are built for each hour of day h and the DR potentials DR^p. These are estimated using EnergyPlus simulations. For the two-state models for single residential AC unit, water heaters and refrigerators the only exogenous input that is time dependent is the ambient temperature. The change in occupancy and use cannot be captured in these models explicitly. Hence, a single model is built based on OAT for these loads.

When building a model of DR^p as a function of ambient temperature OAT one would suspect non-linear behavior due to complex thermal dynamics of the system. It is expected that this impact will be more obvious for the HVAC and TCL loads due to (i) occupancy patterns (when modeled), (ii) more variation in the ambient temperature, and (iii) more complex thermal dynamics. Figure 4 depicts the average outside air temperature and the $\pm 3\sigma$ range around the mean value.

If one wants to model the relationship between the ambient temperature OAT and DR potential using linear models, it may be apparent that for different ranges of OAT, different linear relationships occur. In these cases, a single linear model may not provide an adequate description of the dynamics of the DR potential. Piecewise linear regression is a form of regression that allows multiple linear models to be fit to the data for different ranges of OAT. Breakpoints are the values of OAT where the slope of the linear function changes. The value of the breakpoints may or may not be known before the analysis, but typically it is unknown and must be estimated. The regression function at the break point may be discontinuous, but a model can be written in such a way that the function is continuous at all points including the breakpoints. When there is only one break point, at $OAT = T$, the model can be written as follows:

$$DR^p = \alpha_1 + \beta_1 \times OAT, for\ OAT \leq T \tag{7}$$

$$DR^p = \alpha_2 + \beta_2 \times OAT, for\ OAT \geq T \tag{8}$$

Previous studies focusing on modelling building thermal dynamics using piecewise linear regression have suggested that different linear behavior can be expected at different breakpoints: OAT=75°F (24°C) and OAT=95°F (35°C) [50]. For the purposes of this study, these breakpoints will be used when training piecewise linear regression models to model the DR potential using OAT. Overall, a total of 16 piecewise linear regression models are trained from 6 AM to 10 PM for small, medium and large commercial buildings, and 24 hour models for the multi-dwelling. In addition, it is expected that applying the model to data from the entire summer season will avoid overfitting due to a wide range of outside air temperature values from the typical meteorological year (TMY) weather data.

For the refrigerators and water heaters, it is expected that a standard linear regression model is sufficient to capture the DR potential as a function of OAT. This is due to the simplicity in their operations and

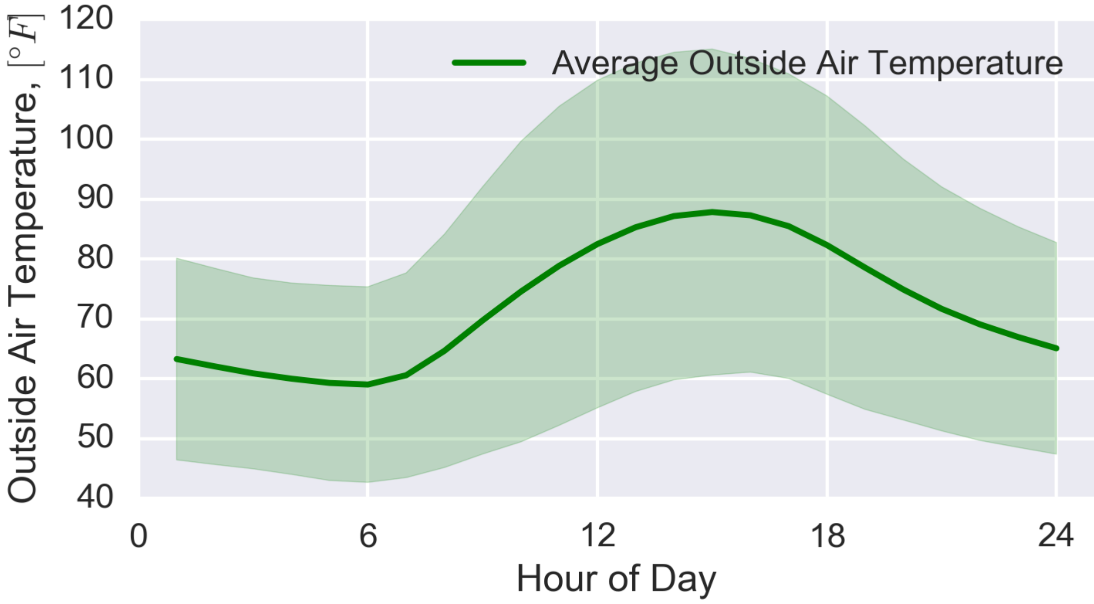


Figure 4: Outside air temperature from typical methodological year of 2015 in a California hot climate zone, solid line represents the average and the shaded area represents the $\pm 3\sigma$ range.

the controlled ambient temperature profile. For the ACs we use the piecewise linear regression model with respect to the outside air temperature OAT.

3. Results

3.1. Commercial HVAC results

For all piecewise regression models trained in this study, the default break points were defined as 75°F (24°C) and 95°F (35°C) [50]. During the summer season (e.g. May to October), the building HVAC systems' power demand can be changed as long as zone temperatures are within the comfort range. Figure 5 shows the piecewise linear regressions at each hour during the peak period from 12PM to 6PM in a medium commercial office building. It is possible to see that the selected break points are in agreement with the slope changes observed in the simulated dataset.

Similar to the regression models of commercial sector, results in Figure 6 show piecewise linear regression models fitted from each hour's potential percentage and outside air temperatures. There was no significant difference between each model's slope except for each hour's range of outside air temperatures. In comparison with commercial sector's models, it was noted that the DR potential during hot weather conditions can get saturated and then start to drop when exceeded a certain point of outside air temperature. It was caused by the cooling capacity at the design condition. Typically, the cooling system is sized to meet the cooing load requirement on the summer design day. When the outside air temperature reaches or exceeds the design weather condition, AC units will be running at their full capacity to maintain the thermostat setpoints, and sometimes they can't. Therefore, there is very limited room for AC units to reduce their power uses even though thermostat setpoints raise a couple of degrees. This finding indicates that the sizing factor of cooling capacity is an important parameter to be considered when modeling residential buildings.

As shown in Figure 7, each hour's DR potentials were averaged to show the impact of degrees of thermostat setpoint adjustment between 12PM to 6PM. It can be seen that: 1) the effect of the load response to the same degree of thermostat setpoint adjustment was not symmetric, 2) HVAC systems have more load potential for regulation up and down corresponding to the hot and cool weather conditions and, 3) when the

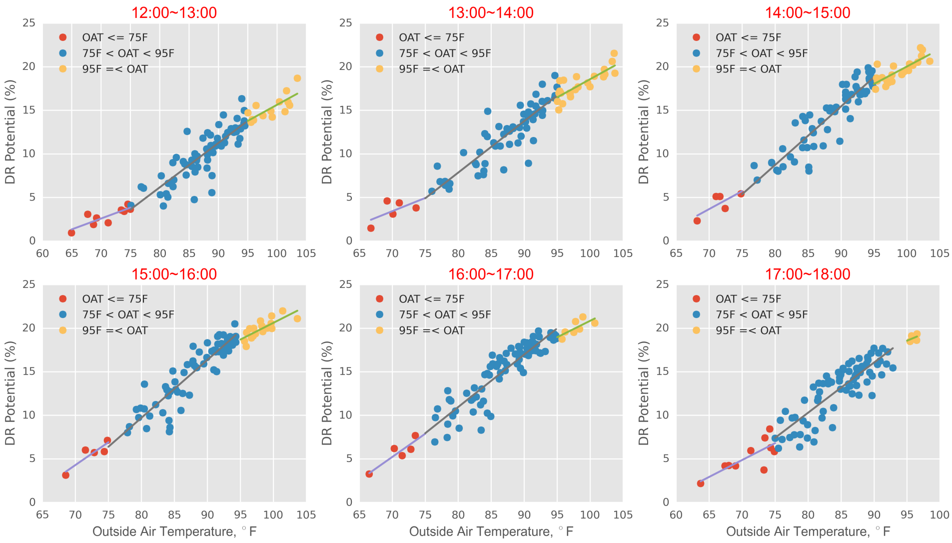


Figure 5: Example of piecewise linear regression for DR potential of 2 degrees setpoint change at different ranges of the outside air temperature between 12PM to 6PM

	$OAT \leq 75°F$				$75°F < OAT < 95°F$				$95°F \leq OAT$			
Time	α_1	β_1	R^2	ϵ	α_1	β_2	R^2	ϵ	α_3	β_3	R^2	ϵ
12-1PM	-99.26	1.70	0.93	0.16	-40.28	0.92	0.49	0.12	6.99	0.39	0.70	0.10
1-2PM	-92.78	1.60	0.90	0.20	-34.38	0.85	0.41	0.13	48.04	-0.03	0.01	0.10
2-3PM	-110.28	1.86	0.76	0.61	-30.58	0.81	0.38	0.13	62.44	-0.18	0.21	0.08
3-4PM	-103.24	1.77	0.73	0.61	-24.21	0.73	0.35	0.13	81.32	-0.39	0.43	0.10
4-5PM	-73.14	1.31	0.72	0.46	-25.93	0.68	0.41	0.10	87.35	-0.53	0.44	0.15
5-6PM	-59.30	1.12	0.84	0.29	-9.62	0.46	0.32	0.08	137.29	-1.09	0.71	0.31

Table 5: Regression model parameters of multi-dwelling unit HVAC systems

outside weather is extremely hot, there is very limited DR potential for load increase, but a huge potential for load shed.

The goal of this study is to achieve simple and sufficiently accurate models for predicting DR potentials from building HVAC systems. The validations of regression models against EnergyPlus predictions are presented in Figure 8 (commercial office building) and Figure 10 (Multiple Dwelling Units) in terms of cumulative distribution of absolute relative errors between regression model results and EnergyPlus data. Regression models of residential sector show better performance in comparison with that of commercial sector. The fitted regression model can predict DR potential within ±10% and ±20% in more than 90% of all data points for commercial office building and Multiple Dwelling Units building, respectively. In addition, as shown in Figure 9, the distribution of absolute relative error at each hour in the office building indicates that larger errors are observed during the early morning and late night hours when the building power usage is not sensitive to the outside air temperature as in other periods. More details of model parameters can be found in Table 5.

3.2. *Results Obtained for Residential Loads*

In Figure 11, it is possible to see the results obtained for a 2 $°C$ setpoint increase for residential AC units in single residential buildings.

For AC units in single residential buildings, a DR potential estimation methodology similar to the multidwelling units and commercial buildings was followed. Specifically, an aggregation of 1000 AC units

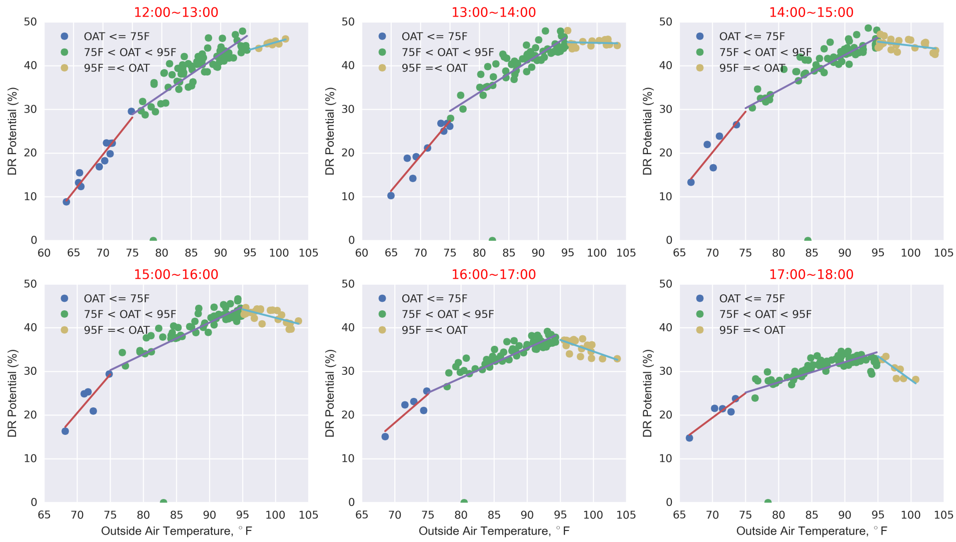


Figure 6: Example of piecewise linear regression at different ranges of the outside air temperature between 12PM to 6PM - multiple dwellings

are simulated during summertime, and the DR potential is estimated using equation 6. Then the piecewise linear regression model is fit to explain the DR potential with outside air temperature.

For the refrigerators and water heaters, we also simulate an aggregation of 1000 units for each load type. Then, a linear regression model is used to predict the DR potential using ambient temperature OAT as discussed in Section 2. The model parameters for ACs, water heaters and refrigerators can be found in Table 6.

In Figure 12, notice that an increase in setpoint of refrigerators results in a positive DR potential value. This is because an increase in the setpoint is expected to result in a decrease in load in cooling loads. The opposite is true for the water heaters (i.e. heating loads).

As it can be seen in Figure 12, decreasing the setpoints for water heaters by 1 to 3 $^{\circ}C$ does not result into significant DR potential. There are several reasons behind this observation. First and foremost, the water heaters have high thermal capacitance, high thermal resistance and high rated power. Thus, they are designed to heat up very quickly, and keep heat for a longer periods of time. Hence, the likelihood of them being OFF at any given point in time is more than them being ON. Hence, the likelihood of being able to turn them OFF with a thermostatic setpoint adjustment is lower than vice versa. Also, notice that the proposed breaking points for the AC aggregations represent the observed behavior in the simulations.

Load Type	α	β	R^2	ϵ
AC, $OAT \leq 75^{\circ}F$	-18.94	0.30	0.48	0.02
AC, $75^{\circ}F < OAT < 95^{\circ}F$	-111.70	1.55	0.78	0.05
AC, $95^{\circ}F \leq OAT$	23.01	0.11	0.18	0.05
Refrigerator	-34.25	1.01	0.87	0.06
Water Heater	-30.08	0.16	0.64	0.02

Table 6: Regression model parameters of Residential AC Units, refrigerators and water heaters for 2 $^{\circ}C$ setpoint increase

As previously expressed by many researchers, the law of large numbers plays a significant role in DR potential of aggregations of loads such as TCLs [51, 14]. To emphasize the impact of population size on the estimated DR potential, we simulated 100,000 refrigerators and water heaters with a constant ambient temperature of 20$^{\circ}C$. Then, the expected DR potential per TCL are calculated using equation(6). Following that, aggregations are created of varying population sizes $N \in [10, 100, 250, 500]$. In Figure 13, the estimated DR potential is shown for each setpoint change value for refrigerators and water heaters with varying number

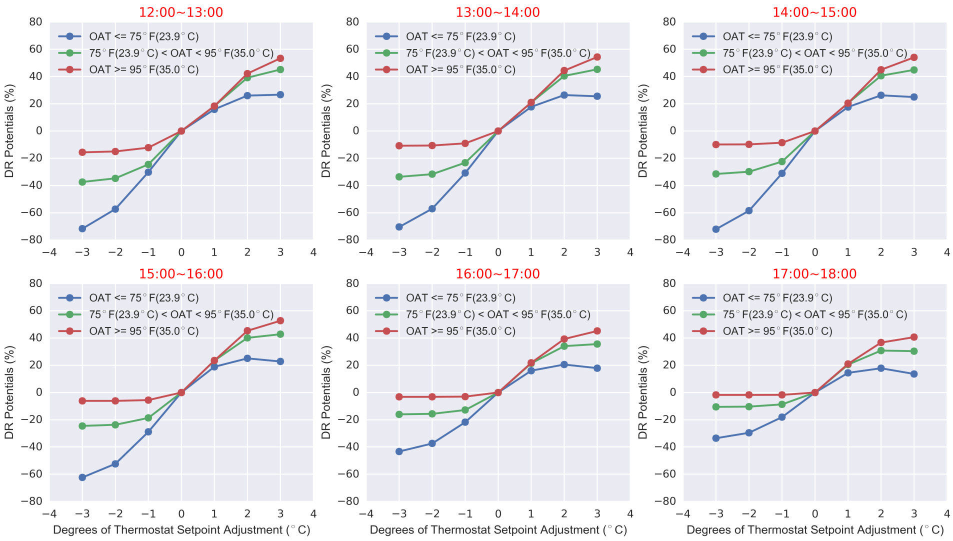


Figure 7: Impact of the degrees of thermostat setpoint adjustment on the DR performance of multiple dwelling units

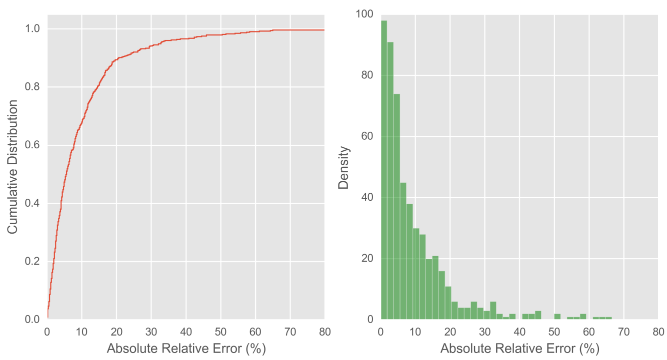


Figure 8: Medium Commercial: Cumulative Distribution of Absolute Relative Error of Regression Models between 12PM to 6PM

of units in the TCL population. The solid marked lines represent the mean value of the DR potential for each population of size N. The shaded areas represent the 0.1%-99.9% percentile range of DR potential.

Although, there is no significant variation in the mean values of DR potential of refrigerators and water heaters with increasing number of units, it is possible to see that the variation decreases significantly for most of the cases.

3.3. Discussion

Figure 14 shows the impact of the degrees of global temperature adjustment on the DR performance at different ranges of outside air temperature. It can be seen that the DR potential increases along with the degrees of the zone temperature setpoints adjustment when the outside air temperature exceeds 75°F (24°C). However, when the outside air temperature is less than 75°F (24°C), the DR potential decreases for the adjustment of 3 degrees over the normal thermostat setpoint 75°F (24°C). It is also noted that commercial building HVAC systems have less DR potential percentage for regulation up when the outside weather is very hot (above 95°F (35°C)). The lower DR potential could be caused by the saturate cooling capacity when the outside air temperature exceeds the design weather condition. Under such a weather condition, building HVAC systems always run at their full capacity with less or no room to increase power use when thermostat setpoints are set to be cooler.

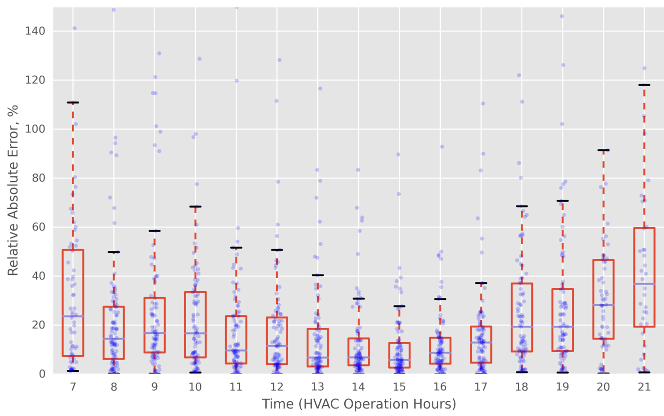


Figure 9: Distribution of Absolute Relative Error of Regression Models at Each Hour during HVAC Operational Period

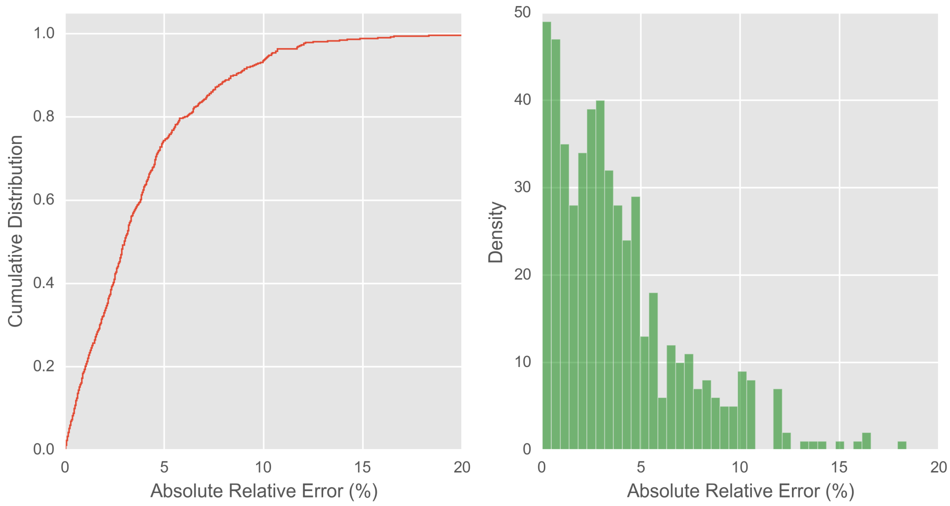


Figure 10: Multi Dwelling Units: Cumulative Distribution of Absolute Relative Error of Regression Models between 12PM to 6PM

1. To reduce the number of regression models, the low dimensional parameters such as building envelope, COP, and degrees of thermostat setpoint adjustment are taken into account by adding a matrix of weighting factors.
2. At the end, there will be 16 model equations for each hour during the period of 6am to 10pm.
3. For each group of buildings, a set of model equations is generated to estimate the DR potential at each hour.

As summarized in Figure 15, there are large variations of the DR potential at each time step of the building HVAC operational period. Most of those variations are caused by the weather conditions, such as the outside air temperature in particular. With respect to this, the rule of thumb is that 1 degree of the thermostat setpoint adjustment can save 2.5% of the HVAC power use. Actually, this percentage of the HVAC power savings is dynamic along with the outside weather condition.

3.4. Model Validation With Available Field Test Measurements

As discussed in the section of model development and validation, the model was validated against the prediction of DR potential from EnergyPlus simulations. Results indicate that the model fits the EnergyPlus

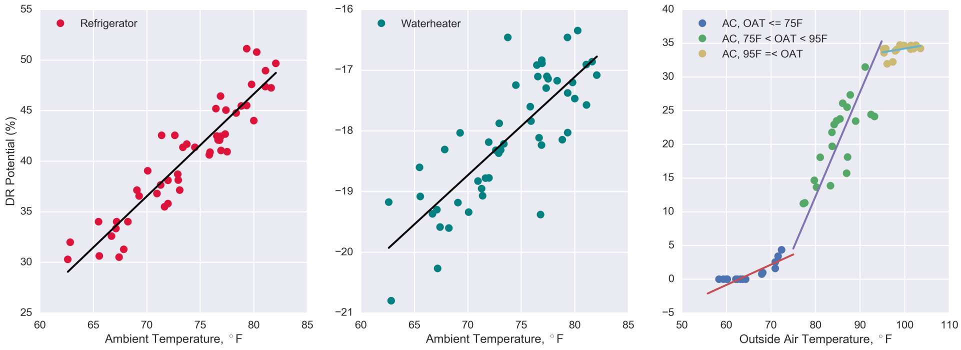


Figure 11: DR potentials estimated for waterheaters, refrigerators and AC units for a 2 $°C$ setpoint increase

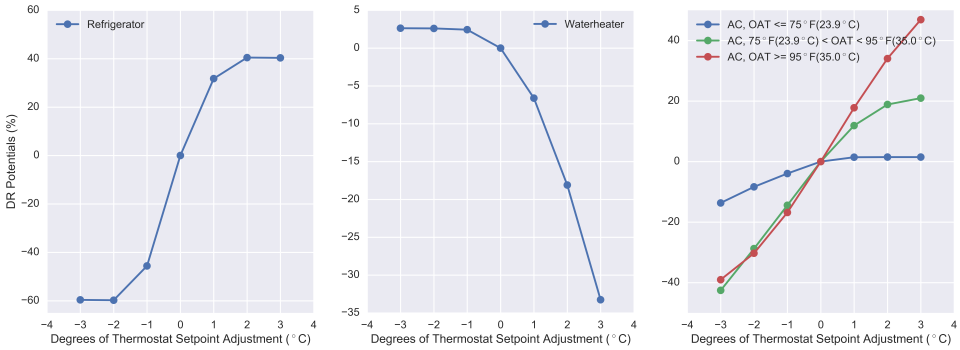


Figure 12: Average DR potential estimated for different set point changes for ACs, water heaters and refrigerators

data well for both commercial and residential sectors, especially for weather sensitive hours. In order to be considered for real implementation, the predictions from those regression models were also validated against the actual DR performance in buildings. In the previous Auto-DR demonstrations, various DR control strategies of setpoints adjustment were tested in a number of small, medium and large commercial buildings [52]. In this study, the regression model was validated by predicting the building HVAC response to same changes in temperature setpoints that were tested in eleven commercial buildings located in Southern California, US. Building floor areas range from 3605 m^2 to 11057 m^2. Two of those commercial buildings are characterized as large commercial buildings with chilled water plant systems. Rest of buildings are characterized as medium commercial buildings with rooftop DX systems. Internal loads such as occupancy, lighting, and plug loads are typical internal load densities and operating schedules. Each building has packaged rooftop units with VAV systems and the HVAC systems operate between 7AM and 6PM on weekdays. The normal zone temperature setpoints were about 24-25$°C$ in the summer season.

First, all the EnergyPlus models were parameterized from the modeling framework to be close to the field test, such as normal thermostat setpoints, setpoint changes during the DR events. TMY weather data of the test location was used to simulate all the cases and regression models were fitted as a result. Table 7 presents the measured and predicted DR potentials of eight DR events at 12PM-1PM, 1PM-2PM, 2PM-3PM following a setpoint change. The predicted DR potentials were calculated from the piecewise linear regression models with the actual outside air temperature. Results indicate that the model predictions match to the measured DR performance in a good agreement, with mean bias errors of 0.11 and 0.25 during the first two hours. Difference between the model prediction and the measured data increases at the third hour (2PM-3PM), as shown in Figure 16. There are several reasons for this result: 1) building HVAC system operation and control issues may cause the disordered DR performance; 2) Too many variables need to be considered to modify the prototype building models; 3) Transient thermal response from building thermal mass causes the overestimation of DR potential from models at the independent basis. On the other hand, it

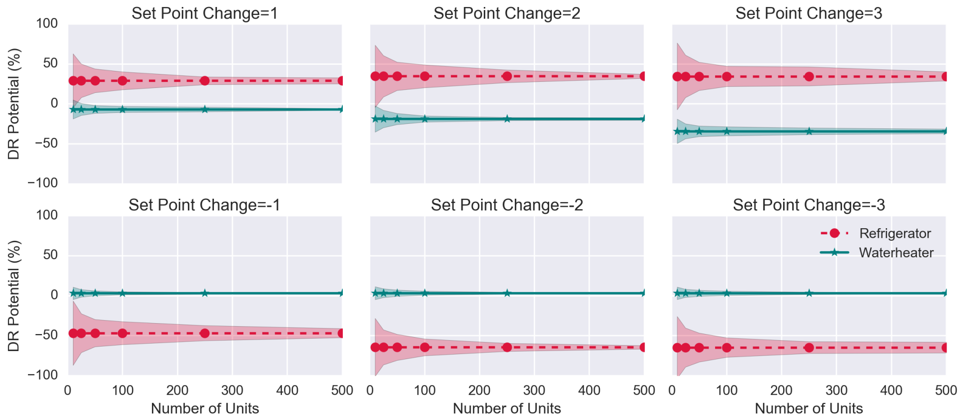


Figure 13: DR potential for water heater and refrigerator aggregations with changing aggregation population size. The shaded areas show $+-3\sigma$ range for potential values.

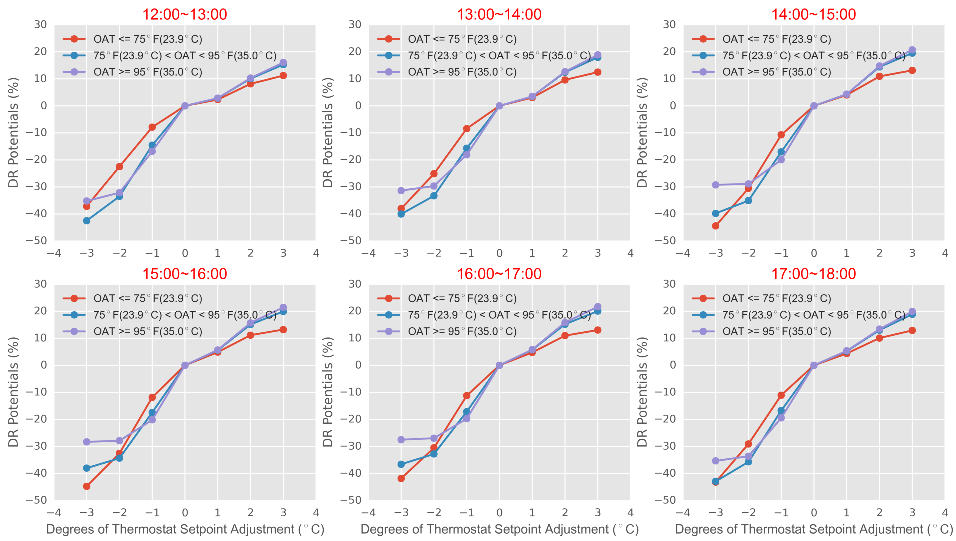


Figure 14: Impact of the degrees of thermostat setpoint adjustment on the DR performance of commercial buildings

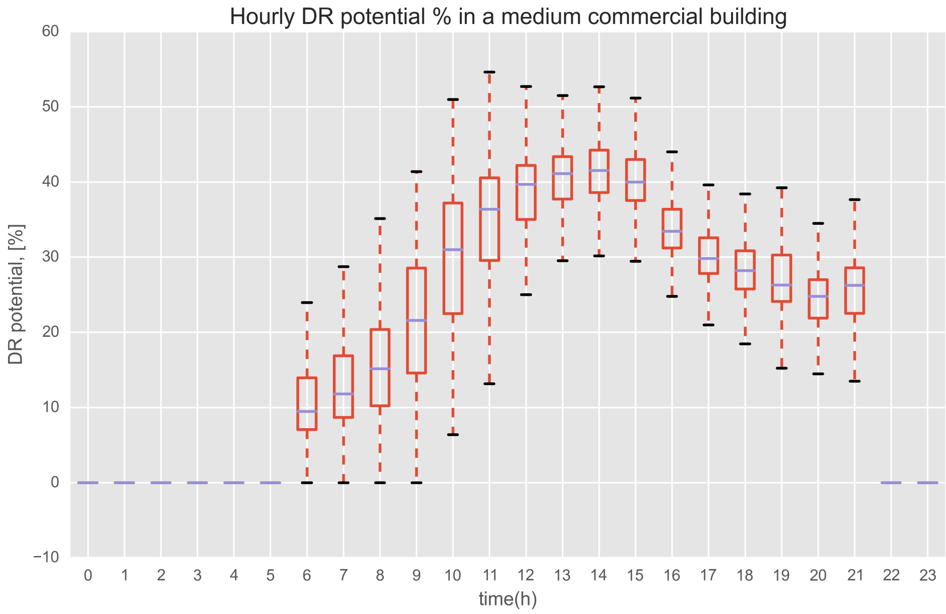


Figure 15: Summary of hourly DR potential % in the summer season

provides us an insight to develop similar models for use in frequency regulation following continuous setpoint changes in building HVAC systems. To solve this problem, the same modeling framework and simplified DR estimation method can be used to predict the DR potential over longer period than an hour.

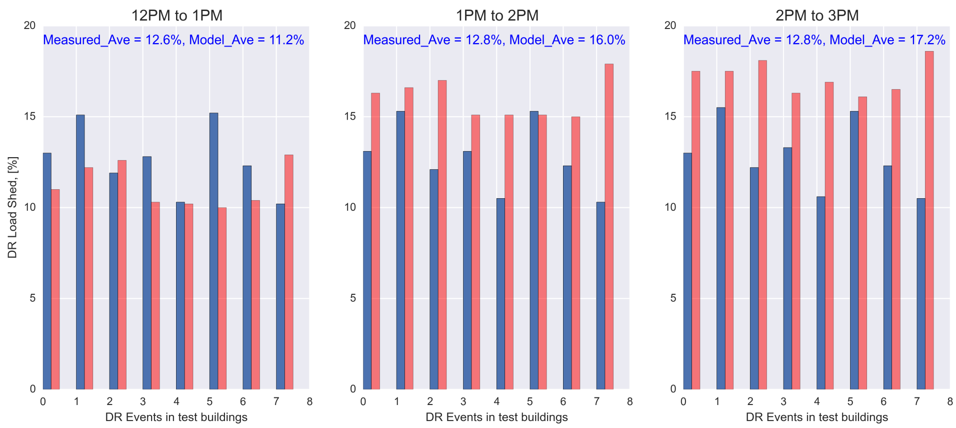


Figure 16: Model Validation against Measured DR Performance in field commercial buildings

3.5. Use of the Framework for Individual and Large-Scale of Customers' DR Estimation

Both of the results of model validation against EnergyPlus results and measured DR performance show that the simplified DR estimation framework performs very well in the prediction of DR potential and flexibility as well. To be specific, we present two examples of the use of the DR estimation framework for individual customers and a large-scale group of customers in the substation of the grid.

From the perspective of customers, their interests are load shed potentials from various DR strategies (e.g., duration and depth of precooling and thermostat setpoint adjustment) and the associated cost benefits before participation in DR programs. Therefore, it is very valuable to provide such information to customers.

	$DRPotential(12-1PM)$			$DRPotential(12-1PM)$			$DRPotential(12-1PM)$		
Event	OAT	$Measured$	$Model$	OAT	$Measured$	$Model$	OAT	$Measured$	$Model$
1	89.4	13.0	11.0	94.3	13.1	16.3	97.4	13.0	17.5
2	91.8	15.1	12.2	95.3	15.3	16.6	97.4	15.5	17.5
3	92.6	11.9	12.6	96.3	12.1	17.0	98.9	12.2	18.1
4	88.2	12.8	10.3	92.3	13.1	15.1	94.2	13.3	16.3
5	87.9	10.3	10.2	92.2	10.5	15.1	96.1	10.6	16.9
6	87.6	15.2	10.0	92.3	15.3	15.1	94.0	15.3	16.1
7	88.4	12.3	10.4	92.1	12.3	15.0	94.7	12.3	16.5
8	93.2	10.2	12.9	98.3	10.3	17.9	100.0	10.5	18.6

Table 7: Model Validation against Measured DR Performance

On the other hand, utilities can also utilize this framework to allocate DR resources to reach out new customers with the most cost-effective DR potentials. Using the typical meteorological year (TMY) weather data and the customer's meter data, Figure 17 shows an example office building's DR potentials across the range of outside air temperature from 60 ˚F (16˚C) to 90 ˚F (32˚C) and above. This example building is located at a relative warm climate zone, a large office building with peak power around 1,100 kW. Each point of the DR shed estimates is the average kW shed by applying 2 degrees (˚F) of precooling and 4 degrees (˚F) of thermostat setpoint setback during the peak hours from 2PM to 6PM. It represents the available DR capacity that customer can bid into the DR market.

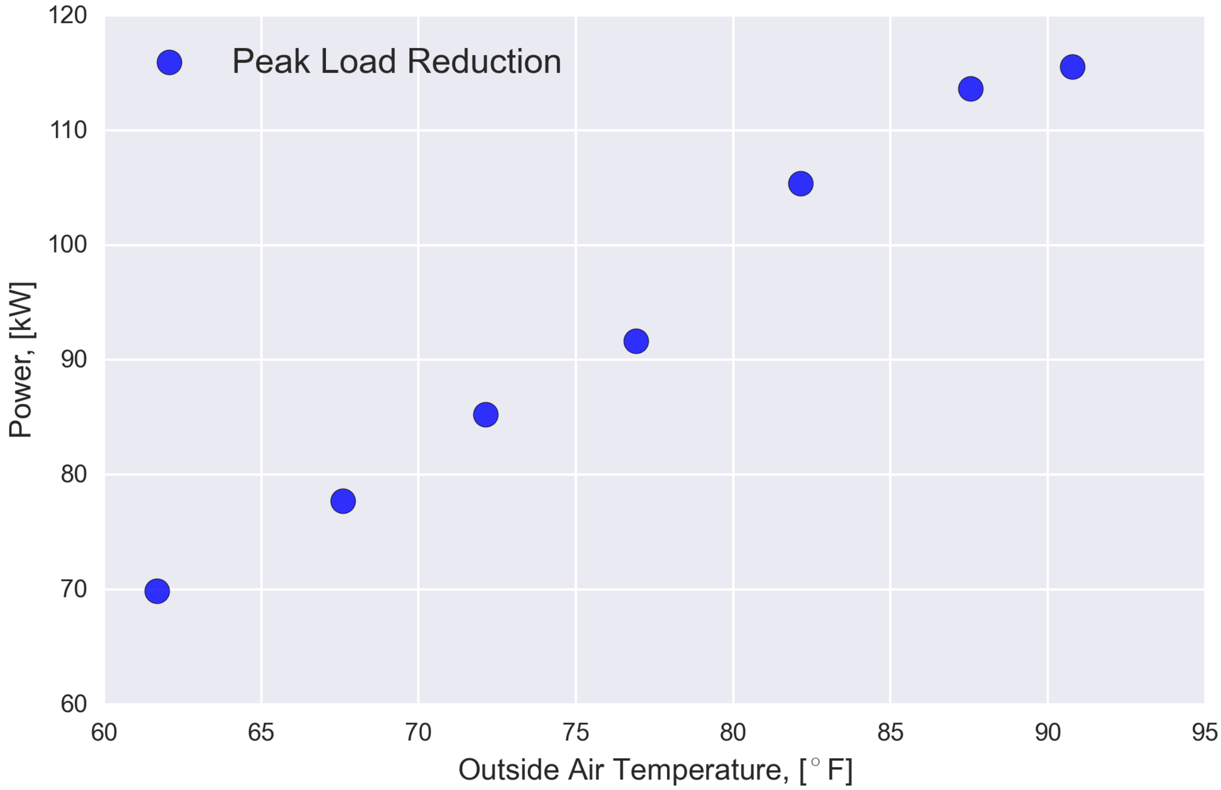


Figure 17: DR Shed Estimates (kW) for Different Peak Temperatures

In the second case, we use the proposed framework to quantify the aggregated DR potential and flexibility of a large scale group of customers at the substation level in the grid. Here we assume a large scale group of customers which is composed randomly by 11 small offices, 12 medium offices, 24 large offices, 20 hotels, 18 restaurants, 7 hospitals, 300 mid-rise apartments, and 200 houses. Given a day of weather data and each building's load profile, the aggregated DR estimates (up/down capacity) at this substation are presented in Figure 18. During the building HVAC system operational period from 6AM to 10PM, the adjustment of ± 2 $°C$ degrees are applied to the normal thermostat setpoint. From what we demonstrate the use of the framework above, it would be very straightforward for utilities to estimate the DR potential and flexibility by using each customer's meter data and the weather forecast data.

4. Conclusions and Future Work

In this study, Detailed physical building (white-box) model and two-state RC (gray-box) model were used to simulate complex thermal dynamics of commercial buildings and TCLs in residential buildings, separately. Afterwards, the hourly DR potential from building HVAC systems were calculated for various strategies of thermostat adjustment at each type of building. Last,a simplified DR potential estimation method was introduced to quantify the DR potential from commercial and residential sectors, in particular HVAC systems and TCLs. The developed regression models eliminate the need for high-level and time consuming modeling work, reduce significant time and resource for computing a large scale of physical building models. The new approach is very well suited for predicting hourly DR potential along with the weather prediction to utilize the demand-side resource to participate into the electricity grid market. It is also very valuable for use in the planning and scheduling of DR resources for different DR products in the market, such as day-ahead, day-of peak load curtailment, and even hourly dispatch for ancillary services.

Previously, the rule of thumb from engineering estimation is that the load response from thermostat setpoint change is static, for instance, 2.5% saving of the HVAC power use from 1 degree of the thermostat setpoint change. However, it is known that this response is dynamic along with time of day, day of week, outside weather condition, and so on. There are some interesting findings in this study: 1) decreased DR potentials for aggressive change of thermostat setpoint when the outside air temperature is less than 75°F (24°C); 2) decreased DR potential when the HVAC system exceeds its capacity; 3) similar regression model break points at 75°F (24°C), 95°F (35°C) for both detailed physical model and two-state RC model.

In addition, two phases of model validation work were performed in this study. First, the developed regression equation models were validated against physical model predictions. It was found that the fitted regression model can predict DR potential within $\pm 10\%$ and $\pm 20\%$ in more than 90% of all data points for commercial office building and Multiple Dwelling Units building, respectively. Second, the predictions of DR potential from commercial building HVAC system were also compared with the measured DR performance in a number of DR events from 11 commercial buildings. Results indicates that the model predictions match to the measured DR performance in a good agreement at the first two hours. Due to the transient thermal response from building thermal mass, the model overestimates the DR potential on the third hour from the independent hourly DR action over continuous DR sequences. This issue can be solved by performing the same modeling framework and method with longer period of setpoint change experiment.

Last, we present two examples of the use of the DR estimation framework for individual customers and a large-scale group of customers at the substation level in the grid. Future work will include the development of such a simplified method for predicting the load response from continuous DR sequences, which will be extremely valuable for using the demand response resource for providing ancillary service such as regulation up/down product to the grid.

5. Acknowledgement

The work described in this study was coordinated by the Grid Integration Group of Lawrence Berkeley National Laboratory and was supported by the State Grid Corporation of China Project (DZN17201300197, Study on Key Technologies for Power and Frequency Control of System with 'Source-Grid-Load' Interactions).

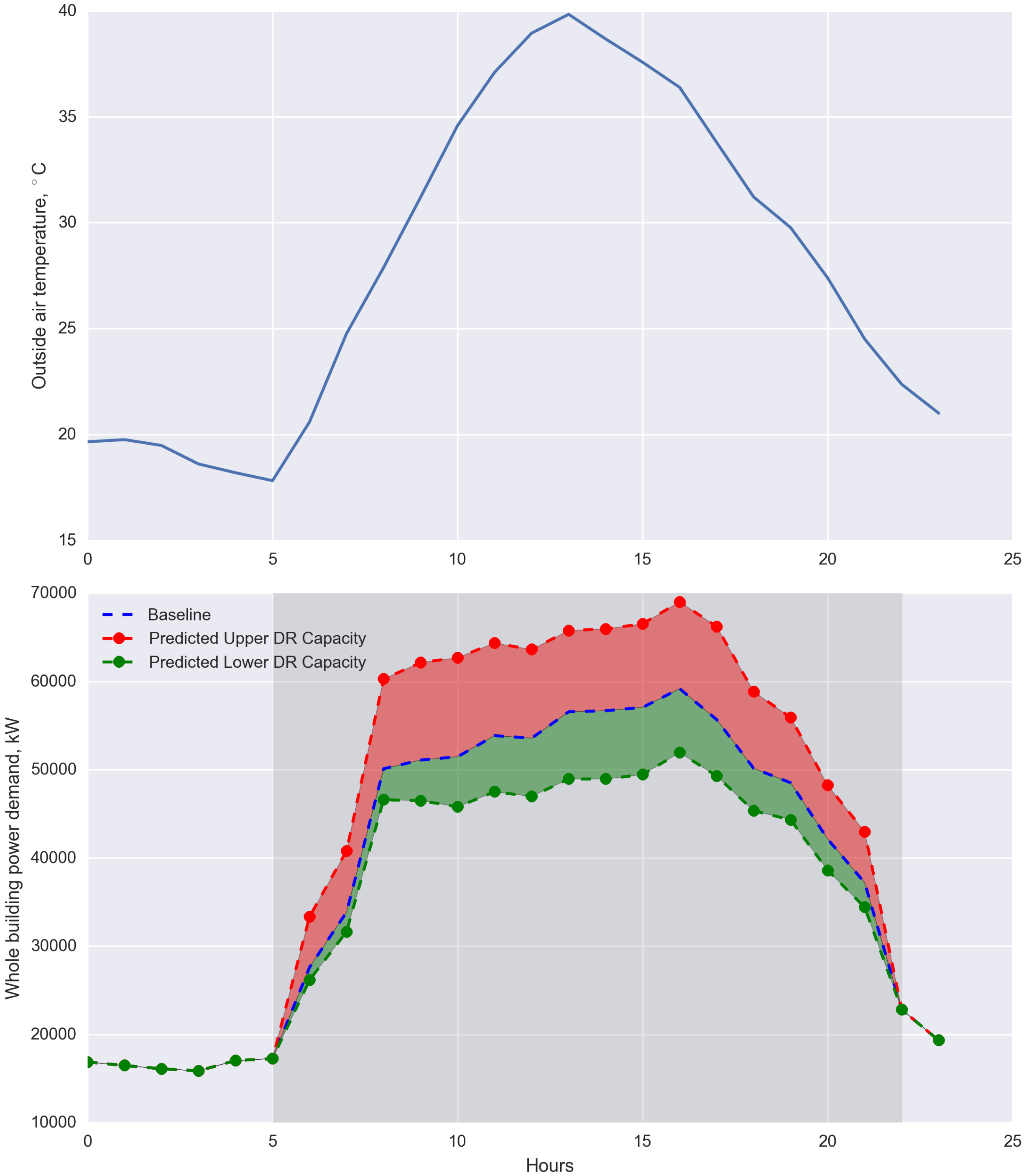


Figure 18: Aggregated DR Estimates (kW) for A Large Scale Group of Customers at the Substation Level

6. References

[1] D. Kathan, J. Kwok, M. Lee, L. Medearis, P. Sporborg, M. Tita, and D. Wight, "Assessment of Demand Response and Advanced Metering," tech. rep., Federal Energy Regulatory Commission, 2011.

[2] S. Behboodi, D. P. Chassin, C. Crawford, and N. Djilali, "Renewable resources portfolio optimization in the presence of demand response," *Applied Energy*, vol. 162, pp. 139–148, jan 2016.

[3] G. Ghatikar, S. Mashayekh, M. Stadler, R. Yin, and Z. Liu, "Distributed energy systems integration and demand optimization for autonomous operations and electric grid transactions," *Applied Energy*, vol. 167, pp. 432–448, 2016.

[4] S. Kiliccote, S. Lanzisera, A. Liao, O. Schetrit, and M. A. Piette, "Fast DR : Controlling Small Loads over the Internet," in *2014 ACEEE Summer Study on Energy Efficiency in Buildings*, pp. 196–208, 2014.

[5] P. Cappers, J. MacDonald, C. Goldman, and O. Ma, "An assessment of market and policy barriers for demand response providing ancillary services in U.S. electricity markets," *Energy Policy*, vol. 62, no. March, pp. 1031–1039, 2013.

[6] B. J. Kirby, "Load response fundamentally matches power system reliability requirements," in *Power Engineering Society General Meeting, 2007. IEEE*, pp. 1–6, IEEE, 2007.

[7] D. S. Callaway, "Tapping the energy storage potential in electric loads to deliver load following and regulation, with application to wind energy," *Energy Conversion and Management*, vol. 50, pp. 1389–1400, may 2009.

[8] S. Nistor, J. Wu, M. Sooriyabandara, and J. Ekanayake, "Capability of smart appliances to provide reserve services," *Applied Energy*, vol. 138, pp. 590–597, jan 2015.

[9] T. Broeer, J. Fuller, F. Tuffner, D. Chassin, and N. Djilali, "Modeling framework and validation of a smart grid and demand response system for wind power integration," *Applied Energy*, vol. 113, pp. 199–207, jan 2014.

[10] J. H. Eto, J. Nelson-Hoffman, E. Parker, C. Bernier, P. Young, D. Sheehan, J. Kueck, and B. Kirby, "The demand response spinning reserve demonstration–measuring the speed and magnitude of aggregated demand response," in *System Science (HICSS), 2012 45th Hawaii International Conference on*, IEEE, 2012.

[11] J. Macdonald, S. Kiliccote, J. Boch, J. Chen, and R. Nawy, "Commercial Building Loads Providing Ancillary Services in PJM," in *2014 ACEEE Summer Study on Energy Efficiency in Buildings*, pp. 192–206, 2014.

[12] O. Ma, N. Alkadi, P. Cappers, P. Denholm, J. Dudley, S. Goli, M. Hummon, S. Kiliccote, J. MacDonald, N. Matson, D. Olsen, C. Rose, M. D. Sohn, M. Starke, B. Kirby, and M. O'Malley, "Demand Response for Ancillary Services," *Ieee Transactions on Smart Grid*, vol. 4, no. 4, pp. 1988–1995, 2013.

[13] DOE, "Buildings Energy Data Book," tech. rep., U.S. Department of Energy, 2011.

[14] J. L. Mathieu, S. Koch, and D. S. Callaway, "State estimation and control of electric loads to manage real-time energy imbalance," *IEEE Transactions on Power Systems*, vol. 28, no. 1, pp. 430–440, 2013.

[15] E. Kara, M. Bergés, and G. Hug, "Modeling thermostatically controlled loads to engage households in the smart grid: Lessons learned from residential refrigeration units," in *Computing in Civil and Building Engineering (2014)*, pp. 2032–2039, ASCE, 2014.

[16] E. C. Kara, M. D. Tabone, J. S. MacDonald, D. S. Callaway, and S. Kiliccote, "Quantifying flexibility of residential thermostatically controlled loads for demand response: a data-driven approach," in *Proceedings of the 1st ACM Conference on Embedded Systems for Energy-Efficient Buildings*, pp. 140–147, ACM, 2014.

[17] P. Zhao, G. P. Henze, S. Plamp, and V. J. Cushing, "Evaluation of commercial building HVAC systems as frequency regulation providers," *Energy and Buildings*, vol. 67, pp. 225–235, dec 2013.

[18] M. Sullivan, J. Bode, B. Kellow, S. Woehleke, and J. Eto, "Using Residential AC Load Control in Grid Operations: PG&E's Ancillary Service Pilot," *IEEE Transactions on Smart Grid*, vol. 4, no. 2, pp. 1162–1170, 2013.

[19] D. P. Chassin, J. Stoustrup, P. Agathoklis, and N. Djilali, "A new thermostat for real-time price demand response: Cost, comfort and energy impacts of discrete-time control without deadband," *Applied Energy*, vol. 155, pp. 816–825, oct 2015.

[20] R. D'hulst, W. Labeeuw, B. Beusen, S. Claessens, G. Deconinck, and K. Vanthournout, "Demand response flexibility and flexibility potential of residential smart appliances: Experiences from large pilot test in Belgium," *Applied Energy*, vol. 155, pp. 79–90, oct 2015.

[21] K. Vanthournout, B. Dupont, W. Foubert, C. Stuckens, and S. Claessens, "An automated residential demand response pilot experiment, based on day-ahead dynamic pricing," *Applied Energy*, vol. 155, pp. 195–203, oct 2015.

[22] N. Lu, "An evaluation of the HVAC load potential for providing load balancing service," *IEEE Transactions on Smart Grid*, vol. 3, no. 3, pp. 1263–1270, 2012.

[23] W. Zhang, J. Lian, C.-Y. Chang, and K. Kalsi, "Aggregated Modeling and Control of Air Conditioning Loads for Demand Response," *IEEE Transactions on Power Systems*, vol. 28, pp. 4655–4664, nov 2013.

[24] J. L. Mathieu, M. Kamgarpour, J. Lygeros, and D. S. Callaway, "Energy Arbitrage with Thermostatically Controlled Loads," *European Control Conference*, pp. 2519–2526, 2013.

[25] X. Lü, T. Lu, C. J. Kibert, and M. Viljanen, "Modeling and forecasting energy consumption for heterogeneous buildings using a physical–statistical approach," *Applied Energy*, vol. 144, pp. 261–275, 2015.

[26] C. Sandels, D. Brodén, J. Widén, L. Nordström, and E. Andersson, "Modeling office building consumer load with a combined physical and behavioral approach: Simulation and validation," *Applied Energy*, vol. 162, pp. 472–485, 2016.

[27] R. Yin, P. Xu, M. A. Piette, and S. Kiliccote, "Study on Auto-DR and pre-cooling of commercial buildings with thermal mass in California," *Energy and Buildings*, vol. 42, pp. 967–975, jul 2010.

[28] R. Yin, S. Kiliccote, and M. A. Piette, "Linking measurements and models in commercial buildings: A case study for model calibration and demand response strategy evaluation," *Energy and Buildings*, oct 2015.

[29] P. Xu, P. Haves, M. A. Piette, and L. Zagreus, "Demand Shifting With Thermal Mass in Large Commercial Buildings : Field Tests , Simulations and Audits," no. LBNL-58815, Lawrence Berkeley National Laboratory, 2006.

[30] P. Xu, R. Yin, C. Brown, and D. E. Kim, "Demand Shifting with Thermal Mass in Large Commercial Buildings in a California Hot Climate Zone," Tech. Rep. LBNL-3898E, Lawrence Berkeley National Laboratory, 2009.

[31] X. Li, J. Wen, and E.-W. Bai, "Developing a whole building cooling energy forecasting model for on-line operation optimization using proactive system identification," *Applied Energy*, vol. 164, pp. 69–88, feb 2016.

[32] T. Hong, M. A. Piette, Y. Chen, S. H. Lee, S. C. Taylor-Lange, R. Zhang, K. Sun, and P. Price, "Commercial Building

Energy Saver: An energy retrofit analysis toolkit," *Applied Energy*, vol. 159, pp. 298–309, 2015.

[33] P. A. Mathew, L. N. Dunn, M. D. Sohn, A. Mercado, C. Custudio, and T. Walter, "Big-data for building energy performance: Lessons from assembling a very large national database of building energy use," *Applied Energy*, vol. 140, pp. 85–93, 2015.

[34] A. Rabl, "Parameter Estimation in Buildings: Methods for Dynamic Analysis of Measured Energy Use," *Journal of Solar Energy Engineering*, vol. 110, p. 52, feb 1988.

[35] I. Korolija, Y. Zhang, L. Marjanovic-Halburd, and V. I. Hanby, "Regression models for predicting UK office building energy consumption from heating and cooling demands," *Energy and Buildings*, vol. 59, pp. 214–227, apr 2013.

[36] S. Horowitz, B. Mauch, and F. Sowell, "Forecasting residential air conditioning loads," *Applied Energy*, vol. 132, pp. 47–55, nov 2014.

[37] Z. O'Neill and C. O'Neill, "Development of a probabilistic graphical model for predicting building energy performance," *Applied Energy*, vol. 164, pp. 650–658, 2016.

[38] G. S. Pavlak, G. P. Henze, and V. J. Cushing, "Optimizing commercial building participation in energy and ancillary service markets," *Energy and Buildings*, vol. 81, pp. 115–126, 2014.

[39] J. E. Braun and N. Chaturvedi, "An Inverse Gray-Box Model for Transient Building Load Prediction," *HVAC&R Research*, vol. 8, pp. 73–99, mar 2011.

[40] H. Hao, A. Kowli, Y. Lin, P. Barooah, and S. Meyn, "Ancillary service for the grid via control of commercial building HVAC systems," in *2013 American Control Conference*, pp. 467–472, IEEE, jun 2013.

[41] W. J. Cole, K. M. Powell, E. T. Hale, and T. F. Edgar, "Reduced-order residential home modeling for model predictive control," *Energy and Buildings*, vol. 74, pp. 69–77, 2014.

[42] Y. Lin, P. Barooah, S. Meyn, and T. Middelkoop, "Demand side frequency regulation from commercial building HVAC systems: An experimental study," in *2015 American Control Conference (ACC)*, pp. 3019–3024, IEEE, jul 2015.

[43] V. Harish and A. Kumar, "Reduced order modeling and parameter identification of a building energy system model through an optimization routine," *Applied Energy*, vol. 162, pp. 1010–1023, jan 2016.

[44] B. Cui, D.-c. Gao, S. Wang, and X. Xue, "Effectiveness and life-cycle cost-benefit analysis of active cold storages for building demand management for smart grid applications," *Applied Energy*, vol. 147, pp. 523–535, jun 2015.

[45] X. Xue, S. Wang, Y. Sun, and F. Xiao, "An interactive building power demand management strategy for facilitating smart grid optimization," *Applied Energy*, vol. 116, pp. 297–310, mar 2014.

[46] D. B. Crawley, C. O. Pedersen, L. K. Lawrie, and F. C. Winkelmann, "Energyplus: Energy simulation program," *ASHRAE Journal*, vol. 42, pp. 49–56, 2000.

[47] U.S. DOE, "DOE Commercial Prototype Building Models."

[48] I. Beil, I. Hiskens, and S. Backhaus, "Round-trip efficiency of fast demand response in a large commercial air conditioner," *Energy and Buildings*, vol. 97, pp. 47–55, jun 2015.

[49] S. Kiliccote, M. a. Piette, J. Mathieu, and K. Parrish, "Findings from Seven Years of Field Performance Data for Automated Demand Response in Commercial Buildings," in *2010 ACEEE Summer Study on Energy Efficiency in Buildings*, no. August, 2010.

[50] P. N. Price, N. Addy, and S. Kiliccote, "Predictability and Persistance of Demand Response Load Shed in Buildings," tech. rep., LBNL-187399, Lawrence Berkeley National Laboratory, 2015.

[51] D. Callaway and I. Hiskens, "Achieving Controllability of Electric Loads," *Proceedings of the IEEE*, vol. 99, no. 1, pp. 184–199, 2011.

[52] M. A. Piette, D. S. Watson, N. Motegi, and N. Bourassa, "Findings from the 2004 fully automated demand response tests in large facilities," Tech. Rep. October, Lawrence Berkeley National Laboratory, 2005.