Active Participation of Buildings in the Power Sector: the Case of Small Office Buildings

by

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Abstract

Under the broad context of decarbonization of the energy sector, commercial buildings are well-suited for providing ancillary services to the electricity grid and poised to transform from passive consumers to active electricity market participants. A data-driven multi-zonal thermal response model is formulated and fit to EnergyPlus simulation data from a Department of Energy Small Office Reference Commercial Building for the months of June, July and August. When validated and tested against EnergyPlus simulation data, the thermal response model performs well. The thermal response model is then used in a co-optimization of energy and ancillary provision for a small office building with a variable air volume system from [9] using summer wholesale electricity and ancillary services prices from ISO-NE. Under six different price cases, the individual small office building provides maximum hourly regulation and spinning reserve capacities of 3.2 and 4.4 kW respectively and daily total regulation and spinning reserve capacities of 51 and 46 kW respectively. When scaled up over similar building stock in New England, small office buildings can provide up to 9.5% of ISO-NE's daily regulation requirement and 8% of the daily spinning reserves requirement. From an economic perspective, a small office building's potential summer ancillary services' revenues are not sufficient to drive investment in installation of a building automation system, variable air volume system and associated metering. However, buildings may invest in the necessary equipment for energy cost reductions and to participate in other demand response programs. Increasing building participation rates in ancillary services markets requires addressing the principal-agent problem, building-specific concerns such as program controllability and convenience and targeted policies aimed at increasing availability of clear aggregator-enabled building participation avenues.

Thesis Supervisor: Leslie K. Norford
Title: Professor of Building Technology

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Chapter 1

Introduction

1.1 Motivation

A focus on decarbonizing the energy supply has motivated policy and regulatory decisions and voluntary behavior shifts in North America and Europe. Within the vast energy sector, the provision of electricity and grid-related services is no exception; decarbonization should be viewed as both a desired goal and an influencing factor on regulation that will impact how the energy sector will evolve. These policies have resulted in support for renewable generation sources through renewable portfolio standards, renewable energy incentives and a spotlight on the use of demand resources to meet peak demand and provide grid services.

In the next three decades, U.S. electricity demand is projected to increase with a low growth rate [77]. Assuming no change in efficiency standards, the U.S. Department of Energys Energy Information Agency (EIA) projects that 196 GW of new generating capacity is needed to accommodate electricity demand in 2040 [77]. Of the projected capacity additions, 58% is natural gas and 38% is renewable. Lower demand growth is possible if such factors as energy-efficient technology are combined with higher electricity prices and lower economic growth, though these conditions are not necessarily desirable [77]. Domestically, industrial energy consumption is projected to increase 0.7% per year, commercial consumption 0.5% per year and overall consumption 0.3% per year [77].

Simultaneously, traditional coal-based baseload and peaking generation are expected to retire within the next three decades, prompted by emissions-reduction policies. By 2040, a total of 90 GW of retirements are expected of which nearly half are baseload coal and nuclear [77]. Consideration of the EPAs proposed Clean Power Plan results in an additional 50 GW of coal-based generation retirements and additional retirements in oil and gas units [76]. Thus, in the U.S., we expect flat to low demand growth coincident with baseload retirements.

1.2 Distributed Energy Resources for Electricity Services

With the confluence of three important factors: a focus on decarbonization, expected generation retirements and constant-to-increasing future demand, the provision of energy, capacity and ancillary services will likely move into a different paradigm. Part of this transformation is an expected increase in decentralization of sources providing energy, capacity and other electricity services. The primary goal of the electricity system is to deliver energy when required at a given time and location. However, supply and demand of electricity must be in equilibrium at all times to maintain the system frequency within a narrow band. Agents (either supply or demand-side) who can change their generation or demand to maintain this balance provide frequency control services at timescales ranging from second-to-second to multi-hourly. Frequency control belongs to the category of ancillary services, or services that support grid stability and function. Today, the majority of ancillary services are provided by generation. At longer time scales, capacity guarantees installed generation or demand response committed to production or load reduction when called upon during times of system stress; use of the capacity service can enhance reliability in terms of both adequacy and/or firmness.

Trends of increasing distributed energy resources have the potential to disrupt the ways in which electricity services are currently provided. Distributed energy resources

(DER) encompass a variety of resources capable of modifying end user power flow patterns. DERs include distributed wind and solar generation, energy storage devices, electric vehicles and demand response from end users in industrial, commercial and residential buildings. An increase in DERs presents potentially large technical and regulatory challenges for distribution systems [28] [29] [37] [68]. DERs may generate and consume power atypically and affect how current distribution systems interact with the larger power system.

With policy and regulatory factors enabling growth, DER deployment is projected to increase in the U.S. and Europe. Decarbonization-motivated policies such as the U.S. Investment Tax Credit (ITC) and 29 states' renewable portfolio standards (RPS) have encouraged renewable generation, much of which is distributed. Additionally, higher electricity prices and decreasing costs of enabling technology have encouraged DER adoption. DER implementation is expected to be most attractive in regions with high electricity costs, such as Europe, California and Hawaii. Accordingly, public utilities commissions are increasingly requesting DER integration plans. The California Public Utilities Commission issued an order for utility-submitted Distribution Resource Plan Proposals addressing DER integration [33]. Hawaii's Public Utilities Commission published its vision for a new regulatory environment that included integration of distributed energy and reduction in older, fossil fuel generation [36].

Though much of the existing DER growth had centered around the deployment of solar PV with a global installed capacity of over 128 GW and U.S. installed PV capacity of over 18 GW, there is a spotlight on demand response's potential to provide a multitude of grid services [38, 74]. Demand response is provided by entities and structures that are largely pre-existing. For the 2014-2015 year, 48% of PJMs demand response registrations were from the industrial sector, 9% from the commercial sector and 16% from residential [44]. There is increasing interest in exploiting the energy storage capability of commercial buildings and coordinating large numbers of residential dwellings to provide electricity services. The use of demand response as an energy resource allows the grid to exploit pre-existing consumption flexibility and energy storage capabilities found in building thermal mass and supplemental technologies.

1.3 Commercial Buildings as a Distributed Energy Resource

The ability to rely on commercial buildings to assist in maintaining grid stability is predicated on the transformation of buildings from passive consumers to active market participants. For decades, industrial and commercial buildings have been providing demand response through peak reduction, load shifting and the capacity markets. Given the need for electricity services beyond energy and capacity, buildings' properties may enable them to succeed in providing ancillary services as well.

Our focus is on the commercial sector due to building qualities that render commercial buildings good candidates for demand response in energy, capacity and ancillary services markets. Commercial buildings consume large amounts of electricity, have large inherent thermal storage mass in the building structure, and increasingly, contain enabling software and technological components. As end-users, buildings in the U.S. use 32% of total electricity and almost half of building electricity consumption is from commercial buildings [77]. Within that breakdown, the amount of electricity devoted to heating, ventilation and air condition (HVAC) systems is the largest and frequently most variable category.

In addition, commercial buildings envelopes contain thermal mass that acts as energy storage when strategically heated or cooled. Methods such as model predictive control (MPC) allow buildings to calculate the optimal cooling strategy for exploiting thermal storage to minimize energy costs in addition to providing other services. Increasing knowledge and interest in acquiring enabling technologies and software combined with HVAC systems that can facilitate more flexibility in building operation may result in higher participation levels of commercial buildings in electricity markets. Advanced metering infrastructure (AMI) has been increasingly deployed across the

U.S. and a recent 2012 Commercial Building Energy Consumption Survey (CBECS) survey found that 24% of small (5,000 ft^2), 26% of medium (5,000-54,000 ft^2) and 63% of large commercial buildings contain variable air volume (VAV) HVAC systems [75].

Commercial buildings are well-suited for providing ancillary services to the electricity grid. Shorter service time scales are more easily matched to a buildings economic, operational and thermal comfort constraints. To begin, commercial buildings primary purpose is to provide a space for tenants to perform working functions within thermal comfort levels. Straying beyond thermal comfort levels may add risks of reduced productivity, tenant complaints and loss of long term revenue streams for building owners and operators. Among the sets of constraints for commercial buildings that limit their ability to provide electricity services, occupant thermal comfort is the most important.

Demonstrations and simulations have been exploring the potential that buildings have in providing ancillary services in addition to energy and capacity services within the context of building thermal comfort constraints. For example, while generators that provide regulation service may incur a high opportunity cost if they can sell the electricity to the wholesale market, buildings can experience periods where extra cooling capacity is available at no opportunity cost. Second-to-second regulation signals are close to energy neutral over short time periods; if signals are close to uniform in time spent up and down-regulating, occupant thermal comfort may not be impacted. Moreover, provided that average cooling over longer periods of time is enough to maintain comfortable temperatures, the building thermal mass storage capability can assist in curbing potential thermal effects of providing short time-scale ancillary services. Optimal pre-cooling of buildings in preparation for potential provision of ancillary services can enable buildings to minimize overall cost.

Exploring the possible resource potential from optimal control of building cooling for a variety of electricity services is most important in the larger context of decarbonization and the electricity supply. With the projected growth of DERs, it is important to simultaneously assess current capabilities and future potential of existing resources. From a grid-scale perspective, an increasingly decarbonized future requires changes in the transmission and distribution systems, generation and end-user roles. To move towards an end goal of identifying the optimal providers for each electricity service, it is necessary to explore the potential of one of those resources, commercial buildings, under a variety of conditions and tariffs.

Estimating ancillary services resource potential from commercial buildings requires examining not only the excess capacity that commercial buildings have when operating on an energy minimization goal, but including ancillary service provision in an optimization alongside energy consumption for the building's primary task of housing occupants comfortably. To do so, the preexisting building may require modifications. Practically, these may include additional equipment such variable speed or variable frequency drives, equipment to satisfy advanced telemetry requirements for verification and request signals, a method for determining the buildings optimal operating strategy and knowledgeable building operators.

1.4 Thesis Objectives

In the future, 'smarter' buildings will be able to do more than operate normally and use excess capacity for services provision. Instead, they will factor those potential services into their initial optimal operating strategies. Buildings will become active participants in electricity services markets as they consider provision of ancillary services along with electricity consumption. Because HVAC operation is the most flexible energy consumption source in buildings, and 97% of office-use commercial buildings use electric cooling but only 42% use electric heating, this work focuses on using building optimal cooling strategies that include provision of additional ancillary services [24]. Though there are additional challenges associated with integrating large numbers of commercial buildings into the electricity grid, it is necessary to first understand the potential of an individual commercial building, using optimal cooling strategies, to see what services might be provided.

Determining a buildings optimal cooling strategy requires being able to model the ability of the building to supply different ancillary services given the environmental conditions, building thermal response constraints, HVAC system and expected internal loads. Generally, this requires being able to model the building's thermal response and HVAC systems. Commercial buildings have multiple thermal zones in which the temperatures of adjacent zones mutually affect each other. In larger commercial buildings, more complex HVAC systems are a benefit since they are potentially more controllable and can provide ancillary services but a challenge in system modeling efforts.

The objective of this thesis is to determine the potential that a small office commercial building has in providing ancillary services to the grid when the individual building considers energy consumption and ancillary service provision in its optimal cooling decision. The thesis also wishes to review regulatory and policy decisions on both market operation and building industry sides that affect the ability of commercial buildings to participate in ancillary service markets. To do so, a process for fitting a data-driven inverse building thermal response model from EnergyPlus simulations of a multi-zonal DOE Small Commercial Reference Building is developed and validated. This thermal model is an extension of previous data-driven inverse model development for single thermal zones [6, 7, 31, 83]. The thermal response model is then used as an input in a co-optimization of energy and ancillary provision for a small commercial building with a VAV HVAC system from [9] to determine optimal cooling strategy and ancillary service provision. Scaling of small office buildings in the U.S. New England Census Division through the DOE's Commercial Building Energy Consumption Survey (CBECS) results in an estimate of resource potential. A regulatory review of buildings ability to participate in ancillary service markets, identification of key topics which could effect building sector participation rates are presented.

The thesis is structured as follows: chapter 1 serves as an introduction to the motivation and purpose of the thesis. Chapter 2 is a review of relevant literature about electricity markets, building thermal response models and MPC. Chapter 3 describes the development of a multi-zonal data-driven inverse building thermal response model fit to a small office reference building for summer months of June, July and August. Chapter 4 summarizes the co-optimization of energy and ancillary services used from [9] and resulting optimal cooling strategy. Chapter 5 describes scaling methodology and results, while chapter 6 discusses market insights and policy interactions.

Chapter 2

Background and Literature Review

2.1 Electricity Market Fundamentals

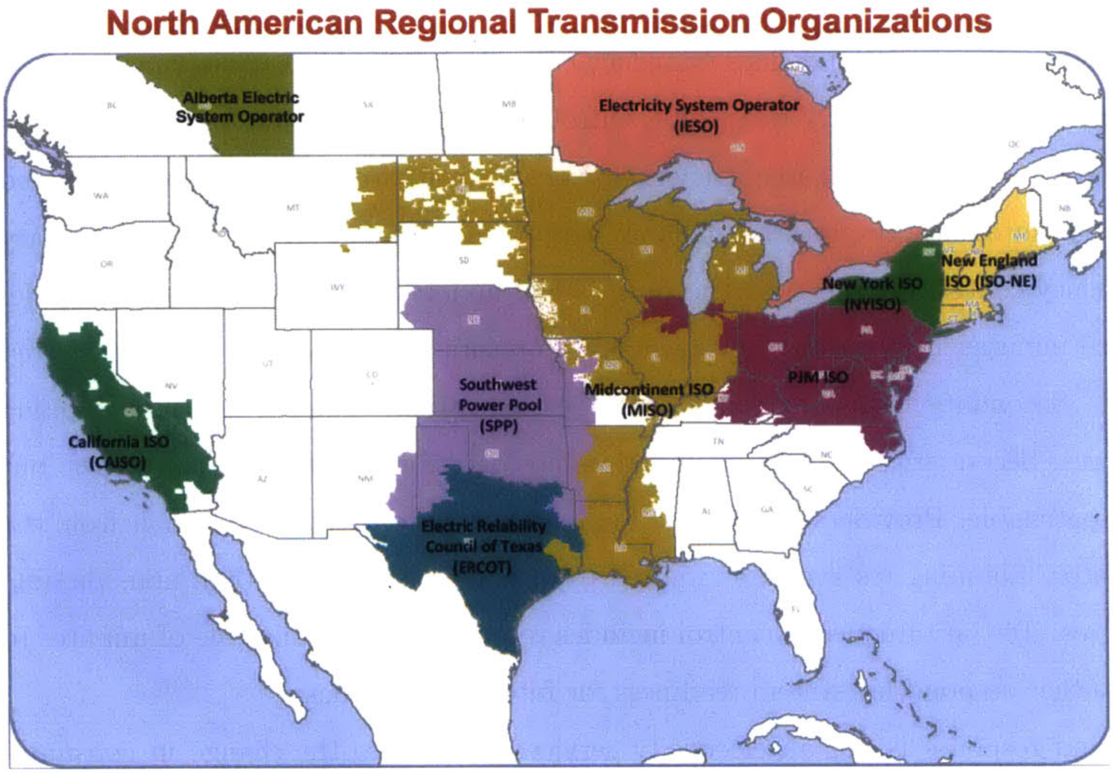
Electricity markets have historically been regulated industries where vertically integrated utilities could own generation, transmission and distribution companies and equipment. Now, there exists a range of market structures: large swaths of the U.S. are served by competitive wholesale markets and some states still have fully vertically integrated providers. In restructured electricity markets, competitive electricity services became unbundled from regulated natural monopolistic electricity services. Deregulated electricity services included generation and retail distribution, while naturally monopolistic services include transmission and distribution systems. Re-structuring and deregulation of some wholesale U.S. electricity markets began in 1978 when the Public Utilities Regulatory Policies Act (PURPA) allowed non-utility companies to own generation assets [4]. The Energy Policy Act of 2005 amended PURPA and conferred the Federal Energy Regulatory Commission (FERC) significant new responsibilities to establish and enforce grid reliability and administer restructuring incentives and policy instruments.

FERC Orders 888 and 889 led to the ultimate creation of both regional transmission operators (RTOs) and Independent System Operators (ISOs). RTOs/ISOs are operators mandated to coordinate and administer wholesale electricity markets, and maintain network reliability and stability at multiple time scales. Though similar to ISOs in role, RTOs must meet additional requirements. In function, RTO/ISOs administer wholesale electricity markets at timescales ranging from hourly to multi-yearly. In addition, the RTO/ISOs determine market-based mechanisms used to ensure supply reliability at multiple timescales.

Within the U.S., relevant RTO/ISO regions depicted in Figure 2-1 are California Independent System Operator (CAISO), the Electric Reliability council of Texas (ERCOT), Independent System Operator of New England (ISO-NE), the Midcontinent Independent System Operator (MISO), New York Independent System Operator (NYISO), the Pennsylvania-New Jersey-Maryland Interconnection (PJM) and Southwest Power Pool (SPP). Each RTO or ISO administers its own wholesale electricity market and reliability planning systems; though many include similar market operation and planning structures, there is also variability between ISOs. For instance, some U.S. ISOs do not use capacity markets (ERCOT, CAISO) as mechanisms to satisfy planning margins while others do (ISO-NE, MISO, PJM). Of particular note is the variation in ancillary services markets. ISOs are responsible for providing sufficient ancillary services; rules and requirements for participation, compensation methods and products vary amongst ISOs.

A variety of services related to the delivery of electricity (kWh) and maintenance of grid stability at different time scales are used to maintain the grids overall function. Services vary in functional nature and timescale and service definitions and format vary between different RTOs and ISOs. We discuss commonly used electricity services relevant to commercial buildings. First and foremost, the primary electricity service the grid seeks to provide is that of energy, or the amount of electricity generated or used over time (kWh). For end-users such as commercial buildings, energy has indeed been the service of primary concern. In restructured and deregulated wholesale markets, electricity price is competitively determined in wholesale markets based on the supply and demand, congestion and losses using transmission-level locational marginal pricing (LMP). Few end-users such as buildings pay the wholesale LMP; typically, buildings pay pre-determined flat rates outlined in utilities contracts. Another primary service is capacity (kW), which refers to the maximum instantaneous

Figure 2-1: Map of U.S. RTOs and ISOs [30]



electricity generated or consumed. Electricity grids are interested in securing both firm and adequate capacity, where 'firm' refers to the short-term ability of the grid to meet existing peak demand adequately and adequate refers to the ensuring that the long-term supply is able to meet peak demand in the future.

Outside of energy and capacity, RTOs/ISOs also typically administer an ancillary services market. FERC defines ancillary services as those "necessary to support the transmission of electric power from seller to purchaser given the obligations of control areas and transmitting utilities within those control areas to maintain reliable operations of the interconnected transmission system" [2]. By FERCs definition, ancillary services can be divided into six categories: reactive power and voltage control, loss compensation, scheduling and dispatch, load following, system protection, and energy imbalance [81].

Energy imbalance refers to the need to manage the difference between actual demand and generation in order to keep system frequency in a tight band around 60Hz in the U.S. Within the ancillary services markets, the North American Electric Reliability Corporation (NERC) defines frequency control on different response time scales as different services. Primary frequency control or frequency response is provided in the first few seconds following frequency excursions; primary frequency control is provided through automatic responses to balance supply and demand on the grid. Secondary frequency control is defined on the timescale of minutes to hours but is typically deployed minutes after a frequency excursion to return frequency back to the preferred band. Secondary frequency control includes regulation, spinning and non-spinning reserves. Secondary frequency control does not necessarily need to be automatic but is dispatchable. Providers may respond manually or automatically to signals from the operator. Spinning reserves are required to respond more quickly than non-spinning reserves. Tertiary frequency control includes resources on the timescale of minutes to hours that respond for system readiness for future contingencies.

Demand response is not an electricity service; it refers to the change in consumption behavior to a signal or incentive (financial or not). The advantages of demand response are generally agreed upon. Managing consumption can result in avoided costs from construction of new generation to manage peak demand, reduce peak electricity costs, provide grid benefits and also manage the use of fossil fuel-based generation plants. Demand response programs or tariffs are established by individual RTOs/ISOs. There are two general types of demand response programs: price-based demand response programs where end users receive time-varying rates such as real-time pricing and critical peak pricing or time-of-use tariffs and incentive-based programs where end-users are paid to reduce their consumption at specific times requested by the program administrator, typically due to high prices or grid stability concerns.

2.2 Buildings Providing Traditional Demand Response

Demand response in various forms has been used to address grid stability issues for decades. Industrial customers have agreed to reduce load at requested moments from utilities in exchange for lower rates in reliability and emergency programs. Likewise, commercial buildings have participated in traditional demand response programs. Traditional demand response falls into two categories: the forward capacity market and the energy market. Buildings, especially commercial buildings, have traditionally provided demand response for peak demand (load shaving, shifting and shaping) purposes and for demand side participation in forward capacity markets.

System operators use forward capacity markets to procure necessary amounts of future capacity to satisfy resource adequacy requirements. After estimating the amount of future resources needed, the operator allows resources to bid in commitments to provide future resources in a competitive forward capacity market. In the capacity market, demand-side resources take on a very similar form as supply-side resources. Demand-side participants bid future reductions in capacity just as generation bid future generation capacity. The capacity market views guaranteed future capacity and guaranteed reduction in demand as equivalent entities, so demand response participants are paid for future reductions in energy use. Frequently, participants received both a capacity payment if their reductions are accepted as well as a payment if dispatched in real-time.

Four of the U.S. ISOs allow demand-side resources to participate in capacity markets: MISO, ISO-NE, PJM and NYISO. Of the four, all but NYISO allow energy efficiency to be considered in capacity markets. ISO-NE, PJM, and most recently MISO forward capacity markets (FCA) are on annual and multi-year planning periods. Within these markets, demand response (DR) and energy efficiency (EE) bids and cleared offers have gradually increased, though the absolute magnitude of their involvement is still minor. Offered MW from DR and EE resources in the capacity market in the recent decade are listed in Table 2.1. From 2007/8, when demand response was eligible, to 2013/14, when energy efficiency was eligible for participation in PJM capacity auctions, these resources have submitted market bids and a portion have been cleared as shown below in Table 2.1. In the 2014/2015 FCA, demand response accounted for 9.3% of cleared capacity. ISO-NEs most recent FCA for 2017/18 cleared 2,803 MW of demand-side resources out of 34,695 MW of total cleared resources, a value consistent with historical FCA results. In MISO, cleared capacity for demand resources in the Planning Resource Auctions increased by nearly 500 MW from the first allowed year in 2014/2015 to the 2015/16 planning auction, though DR still remains just 2.9% of total cleared capacity [69].

-	'07/08	'08/09	'09/10	'10/11	'11/12	'12/13	'13/14	'14/15
Cleared DR (MW)	128	536	893	939	1365	7047	8888	13108
Cleared EE (MW)	-	-	-	-	-	569	676	819
Cleared Total (GW)	129	130	132	132	132	136	142	141
Uncleared DR (MW)	-	180	44	29	290	2800	2700	1300
Uncleared EE (MW)	-	-	-	-	-	84	77	1
Uncleared Total (GW)	1.4	2.3	1.3	0.9	4.8	9.2	5.5	6.8
Offered EE (MW)	-	-				650	750	830
Offered DR (MW)	130	720	940	970	1700	9800	12000	130
Offered Total (GW)	131	132	134	133	137	145	148	148

Table 2.1: PJM Base Residual Auctions

Demand response in various forms has been used prior to market restructuring to address peak demand, manage electricity prices and increase system reliability. Programs utilizing mostly large industrial loads use "interruptible tariffs" to manage emergency grid situations. Peak demand management programs call on customers to reduce use during peak demand times to reduce prices and manage peak load through either explicit compensation programs or implicit programs where customers reap cost savings. Emergency or reliability programs ask customers to be dispatchable at fixed emergency time periods for reliability management and to avoid rolling blackouts. Program formats can vary: dynamic pricing and price responsive programs offer customers different prices at peak periods to incentivize behavior changes; direct load control programs allow controllers to access customer equipment such as residential air conditioning for emergency periods and temporal pricing designates specific prices for high load periods of time [63].

2.3 Commercial Buildings Providing Ancillary Services

Simulation, demonstration of and increasing participation in existing ancillary services markets from commercial buildings have generated excitement about their resource potential. Demand response for ancillary services occurs at time scales that are shorter than those used for traditional demand response for energy and capacity. Ancillary services needed all year round and throughout each day are utilized more frequently than the emergency load relief, peak load management and capacity market programs in which demand response has historically participated. At the same time, technical requirements are more restrictive for ancillary services. Often, telemetry and second-by-second signal tracking are necessary. There is low tolerance for delayed responses due to control or mechanical issues. Commercial buildings' thermal mass can supplement their energy storage capacity and flexibility potential. Already, the presence of large amounts of thermal mass can help smooth out a building's demand profile with both cooling and heating peaks. Optimal control strategies can exploit thermal mass to reduce energy consumption or costs since the inertia of thermal mass can enable regulation-following variations in conditioned airflow without substantially affecting thermal comfort.

Ancillary services of interest for commercial buildings are primarily frequency control on different time scales: regulation, spinning reserves and non-spinning reserves. Traditionally, frequency regulation has been provided by ramp-limited generation resources. Buildings, especially larger buildings with a sizeable amount of thermal mass, can provide regulation at small second-by-second time scales since variations in demand at small time scales are considered to have little impact on indoor air temperature. On average, regulation prices exceed spinning and non-spinning reserve prices in many markets [55].

Studies have simulated provision of ancillary response for regulation, non-spinning and spinning reserves with modifications in supply fan duct pressure, zonal temperature setpoint amongst other pre-existing demand response strategies. Direct load control (DLC) enabled variable speed heat pumps (VSHP) are modeled providing frequency regulation in [49]. When linked to a room thermal response model, [49] found little difference in DLC VSHP and non-DLC VSHP enabled room temperature trajectories. In [35], simulated supply fan power consumption flexibility provided regulation and found that 15% of total fan power could be used for regulation without impacting occupants thermal comfort. Two methods of control through the supply fan setpoint and temperature setpoint with various control parameters successfully provided frequency regulation in a $150m^2$ zone in [85]. Frequency regulation performance ability in a commercial building was summarized and a MPC algorithm that improves system performance from using buildings frequency regulation in addition to traditional AGC was developed in [53]. In [11], a dynamic VAV systems ability to provide regulation with four common demand response strategies under a range of intensities and cooling load conditions was simulated. Authors used both direct and indirect control of the HVAC system, noting the effects and constraints of either equipment dynamics or cascading control loops on service provision, depending on the strategy in question. In [10], the same model and set of demand response strategies were used to simulate provision of spinning reserves.

In addition to simulations of buildings potential, demonstrations have shown the use of HVAC to provide ancillary services, albeit with noted challenges from the complex mechanical and control systems involved. The ability of a University of Florida buildings air handling unit and building automation system (BAS) to provide regulation service that could qualify for PJMs markets was demonstrated in [51]. Motivated by [35]'s simulation results, [53] verified that a large commercial building with a BAS and controller software could use two 67 kW supply fans to provide 24 kW of regulation. Experimental work has also been done with commercial chillers, with estimates of +/− rated power for frequency regulation. In [48], three building types (retail store, government office building and bakery) successfully participated in bidding and supplying non-spinning reserves to a California participating load program using existing DR control strategies, while [54] demonstrated use of a large retailers HVAC system to provide spinning reserves and a VFD enabled fan to provide regulation. The resource potential for ancillary services in demand response across larger regions such as the entirety of the U.S. is not clearly known. In [52], a methodology of assessing potential ancillary services from demand resources by applying a flexibility weight to assumed demand profiles was developed. In multiplicative estimates from simulation through [35] and through demonstrations from [53] estimate high levels of potential. [53] estimated that scaling the same fan power consumption flexibility per unit floor area over all commercial space would provide an estimated 4 GW of regulation service. This is in comparison to the simulated 6.6 GW of regulation from 5 million commercial buildings in [35]. From chillers providing regulation through excess capacity, [71] estimates a potential of 41% of required, noting that the most potential in chiller provided regulation is in the south, due to the increased level and temporal use of chillers throughout the year.

2.4 Building Thermal Response Model and Model Predictive Control Literature Review

Much of the literature discussed thus far has focused on potential in provision of ancillary services from commercial buildings operated under standard control and not in an optimal manner. This is consistent with the operation of many commercial buildings in reality for a variety of factors. However, should operators be empowered with increased HVAC system controllability through enabling technology, software and building knowledge, optimal cooling and heating strategies could be calculated and implemented. In this work we focus on optimal cooling strategies in commercial buildings given provision of ancillary services in addition to energy consumption. Though heating can also be electric, nearly all of cooling in commercial buildings is electric while heating in commercial buildings where the primary building activity is 'office' is reported as 49% from gas and 42% electric [79]. Here, we focus on electric-only cooling strategies.

In buildings, optimal cooling strategies are affected not just by the amount of thermal mass available but also by design properties affecting its distribution internally and throughout the building. Building envelope, material building properties, climate, cooling system operation, and internal load patterns also affect the optimal cooling strategies [13]. In order to determine optimal cooling strategies for any building, a thermal response model is needed to characterize how loads and temperatures will change in a building. Thermal response models can be used to predict thermal loads on a building or the building's thermal and temperature response to different loads and cooling on a transient basis. Buildings with similar floor area may exhibit different thermal responses depending on these factors. The temperature trajectories of and influencing factors are also not necessarily well monitored at small time scales. Sensor accuracy, installation and the use of a building energy management system and/or controllers for HVAC equipment might be necessary to accurately characterize a buildings thermal response. Though detailed optimal control programs are not widely used in practice beyond optimal start-stop algorithms used at the beginning and end of work-days, building thermal response models could be implemented to help determine optimal building control for a variety of purposes. Using thermal response models and predictive control based on those models is necessary for determination of optimal building operation strategies. Thermal response models are frequently used to plan for daily scheduling and operation. For instance, transfer function models have been used to enable load shifting, pre-cooling and optimal cooling strategies to various degrees for decades [31].

The primary purpose of thermal response models is to characterize transient thermal responses to changing conditions, typically for short term operation, scheduling and optimal strategies for different objectives. When considering the short-term objectives, thermal response models can still be diverse in approach. Models can range from detailed, physically based representations of systems in forward models to purely data-driven models, to name the two extremes.

Forward models (or white box models) explicitly model a building's thermal response through detailed physics equations based on the construction of the specific building systems and equipment components. Forward models use specified building materials and constructions, , building equipment and schedules to explicitly simulate detailed building behavior during certain environmental conditions. Popular simulation programs such as eQUEST, EnergyPlus, TRNSYS are used to estimate load and temperature responses and electricity consumption. Forward models can be effective and accurate due to very detailed specification of the building. However, such specific information is not always available, computational times of simulations may be infeasible for use in more complex simulation and optimization programs, and pre-made simulation programs may not provide all the initialization parameters that users may need. Information may be expensive and time intensive to acquire if it is even available.

On the other hand, purely data-driven models use simulation or measured data to train a numerical model that sufficiently captures the primary dynamics of buildings' thermal response. Both experimental data from specific buildings or simulation data can be used to train models. Examples of data-driven models are black-box models that fit parameters that do not necessarily have physical significance or gray-box models from parameters with physical significance. In black-box models, statistical methods are used to fit parameters for thermal response prediction such as autoregressive exogenous models (ARX). [52] uses a ARX model to predict zone temperature and power and [82] uses an ARX time and temperature indexed model to predict hour ahead thermal loads and compares predictions to DOE Reference Commercial Building simulated loads. Though black-box models may be computationally efficient, they may not ensure physically realistic behavior unless explicit constraints that mandate such behavior are used. For instance, describing transient thermal responses in inverted comprehensive room transfer functions requires active enforcement of certain constraints to ensure that solutions obey a steady state heat transfer solution [6]. Gray-box models are also data-driven, but use model parameters that are based on some simplified representation of building physics. Gray-box modeling steps generally require development of a simplified physics building model, determining model physical parameter bounds from building design, and estimating optimal model parameters through appropriate methods to finally simulate building responses [12]. In the described gray-box model, [12] use a resistance and capacitance network model to representing building cooling load, where capacitors and resistances represent thermal capacitance and regression.

Because temperature response in buildings can be mostly described by heat transfer/heat balance equations, discrete-time transfer function models can be used to represent thermodynamically appropriate and plausible models through measured or simulated data [60] [46]. Heat balance transfer functions for multiple surfaces in one zone were combined into comprehensive room transfer function (CRTF) to represent overall zonal cooling load with fewer equations in [46]. [6] presents a transient thermal response model where a CRTF model describes heat flux response and proposes inverted comprehensive room transfer functions (inverse CRTF) to describe temperature response. Armstrong finds in a lab-controlled room and a Russian apartment building that these models reliably predict thermal response, with temperature with a five percent RMSE for temperature prediction and ten percent RMSE for cooling rate. In the companion paper, [7] fits an inverse CRTF model for a Los Angeles office building. Importantly, Armstrong uses constraints to ensure thermodynamically appropriate behavior. CRTF and inverse CRTF models do not require major assumptions about building properties or design since coefficients are fit from simulated or measured data. The model order number can be adjusted as appropriate;

more thermal mass and lag corresponds to a higher model order.

In [31], an inverse CRTF model was fitted to measured data from a test facility consisting of a climate chamber and single zone room to predict thermal response. Four modes of excitation (heat input through ceiling electric radiant heating panels, heat input through electric radiant heating underneath concrete paver layers, heat input through convective electrical heaters inside the test chamber, ambient temperature variation in climate chamber) were used for model fitting from 20 days of training data [31]. Inverse CRTF coefficients were then fit for zonal temperature, mean radiant temperature and operative temperature. The model was used to predict hour-ahead temperatures, validated with test data sets and used in an MPC optimization to find optimal cooling strategies. The inverse CRTF model performs much better when predicting hour-ahead temperatures as opposed to 24-hour-ahead predictions; [31] notes that selection of model order requires balancing complexity and accuracy and computational time required for simulation.

A single zone inverse CRTF model is trained and validated on TRNSYS building simulation data as part of a modeling environment developed for simulating building operation under MPC in [83] and [84]. The coefficients for the inverse model of a single zone with a VAV system and cooling from Thermally Activated Building Systems (TABS) is fitted. The author also extends the model to account for the dynamics of water vapor concentration within the building; inverse CRTF cofficients were fit to TRNSYS simulation data for zonal temperature, operative temperature, floor temperature and water return temperature for models of order two to eight, concluding that for the particular use case, an order of three offered a good balance between accuracy and computational speed. In their work with inverse models, both [31] and [83] note that higher model order was not necessarily better for temperature prediction when using inverse CRTF models. In [83]'s inverse models, convective and radiative loads are separated for better model performance. The inverse model is validated against TRNSYS simulation data and demonstrated good predictive power with significant reductions in computation time. [83] cites the benefits of variable initialization and significantly reduced computational time for using an inverse CRTF thermal response model since the model is subsequently implemented in a MPC optimization of a TABS and VAV system minimizing daily electricity consumption.

Both [31] and [83] apply inverse CRTF models for MPC purposes to single zones and are trained on measured data in [31] s case and TRNSYS simulation data in [83]s case. [7] fits a single zone inverse CRTF model for a five-story apartment building in [6] and a large municipal office building.. However, most buildings contain multiple thermal zones. Within each zone, transient thermal responses change based on exogenous factors as well as adjacent zone thermal responses. A multi-zonal thermal model requires consideration of thermal interactions between zones as well. [32] extends the inverse CRTF thermal model from a single zone to multiple zones in order to model a low-lift cooling system in a multi-zonal building with TABS. Authors write that thermal response model coefficients can be fit from training data in the building from sensors installed to measure each variable or a surrogate; coupled with a model of power consumption in the low-lift chiller, a procedure is developed for model predictive building control. Thermal response models in different forms can be combined with a model predictive framework to find optimal operational strategies, whether for heating or cooling. In [7], the use of inverse CRTF models for estimating the benefits of different peak-shifting and night-cooling strategies for cooling load reduction is explored. [84] describes an MPC framework that uses a thermal response model to optimize a variety of possible HVAC objectives, including minimization of total electricity consumption. In [66], a gray-box resistance-capacitance thermal response model in a MPC framework is used to determine optimal operating strategies for minimization of total electricity cost when a building can provide regulation and can provide peak demand response. To address the problem of optimal operation of multiple buildings, [67] optimizes multiple buildings operational strategies as a portfolio, noting that some synergistic savings effects which are dependent on portfolio construction, market design and building conditions can be observed.

Chapter 3

Small Commercial Building Thermal Response Model

3.1 Inverse CRTF Model

As noted in the previous chapter, inverse CRTF describe building temperature responses as functions of previous temperatures and heat fluxes. Using inverse models, we wish to capture the thermal response of the building to changes in exogenous conditions and changes in overall sensible heating or cooling rates. Inverse CRTF models can be formulated and trained on a dataset; model coefficients can be applied to test data to predict 24-hour ahead temperature responses. The careful selection of training data is important and affects model prediction errors. Here, a inverse thermal response model that is the multi-zonal extension of a single zone inverse CRTF model is fit to EnergyPlus simulation data. We review the single zone inverse CRTF formulation and the specific multi-zonal inverse CRTF formulation used in this thesis in this section.

3.1.1 Single Zone

The single zone inverse CRTF was successfully implemented in [6] and [7] for a test chamber, Russian apartment building, and Los Angeles office building; in [31] for an experimental test chamber; and in [83] for the same test chamber. In the single zone inverse CRTF model, transient changes for zonal temperature, operative temperature and other variable temperatures of interest are expressed as a weighted sum of past relevant temperatures, exogenous conditions and heat fluxes. Below, the mean zonal air temperature T_z is expressed as a weighted sum of T_x, the outdoor dry bulb temperature or ambient temperature, Q_{rad}, the radiative heat flux, Q_{conv}, the convective heat flux, and Q_{solar}, the representation for incident solar.

$$T_z^k = \sum_{t=k-n-1}^{k-1} a_z^t T_z^t + \sum_{t=k-n-1}^{k} b_z^t T_x^t + \sum_{t=k-n-1}^{k} c_z^t Q_{rad}^t + \sum_{t=k-n-1}^{k} d_z^t Q_{conv}^t + \sum_{t=k-n-1}^{k} e_z^t Q_{solar}^t \tag{3.1}$$

In [6], zonal temperatures are expressed as a weighted sum of past zonal temperatures, weather effects as described by ambient temperature, solar gains on the opaque and window building envelope surfaces, and total heat flux from internal loads and/or heating and cooling effects. Internal loads typically consist of lighting, plug-in loads and people. Heating and cooling effects can be from active changes from the HVAC system or from natural ventilation. Throughout the day, heat gain or loss occurs due to heat flows through building boundaries from the external environment and from solar gains on incident surfaces. At steady state conditions of constant temperatures, the total heat flux is zero; in order to ensure that the thermal response model obeys steady-state heat transfer equations; this yields an additional set of constraints must be applied to the coefficients. Below, a_z^t is the model coefficient for zonal temperature in zone z at time step t and b_z^t is the model coefficient for outdoor dry-bulb temperature in zone z at time step t.

$$1 - \sum_{t=k-n-1}^{k-1} a_z^t = \sum_{t=k-n-1}^{k} b_z^t \tag{3.2}$$

As noted, the number of lag terms for each variable is the order of the model. Buildings with higher thermal mass and thermal lag can be reflected in higher model order. This inverse CRTF model only applies well to sensible heating and cooling loads. When applying the inverse CRTF model to a test room in the above formulation, [6] uses the laboratory (test chamber exterior) temperature, adjacent room temperature, total zone heat flux. When applied to a Russian apartment building, [6] uses solar on the horizontal, outdoor dry-bulb temperature, and the product of wind speed and outdoor-indoor temperature difference to account for climate conditions. [31] uses the same generic formulation with the removal of the exogenous solar radiation term due to the lack of a solar excitation source in the test chamber used. Similarly, [83] excludes an exogenous solar radiation term due to use of the same test chamber.

3.1.2 Multi-Zonal

Inverse CRTF models fit to test chambers or buildings for MPC referenced in the previous section explored application of the models either to single zone rooms or multi-zonal buildings that were reduced to a single zone for analysis. Buildings typically have multiple thermal zones. Different building spaces may have dissimilar internal and external loads and experience variable climate conditions throughout the day. Residential buildings have a conditioned zone along with unconditioned zones; when discussing commercial, industrial, retail buildings and multi-family residences, multiple thermal zones should be considered.

Within a multi-zonal building, each zone is a component of the larger building thermal system and heat exchange between adjacent zones occurs throughout the day. An east-facing zone may absorb solar radiation in the morning and slowly release heat to adjacent thermal zones throughout the day through conduction and convection. These complex dynamic interactions vary on spatial and temporal scales and are affected by underlying building envelope properties, climate conditions and internal loads. At walls separating zones, there is conductive heat flow. There may be convective heat flow as well, though the location of convection boundaries between zones is less straightforward to identify [34]. Using data-driven inverse model simplifies the accommodation of multi-zonal interactions between adjacent zones by allowing weights on current adjacent zonal temperatures to encompass the information of effects of adjacent zones on each other. Coefficients in the multi-zonal model should reflect the relative effects of sensible heat transfer that different zones have on each other.

The multi-zonal inverse CRTF model discussed in [32] is specifically formulated for the Department of Energy's small office reference commercial building. The model formulation includes dependencies on past zonal temperatures, outdoor dry-bulb temperatures, radiative heat flux, convective heat flux, window-transmitted solar radiation, total incident opaque surface solar radiation, and ground temperature. Known temperature and heat rate data is used to fit an inverse multi-zonal CRTF model; an adjacency matrix details which zone adjacency relationships. The number of non-zero interzonal coefficients increases as the number of zones increases although specific adjacency properties depend on the specific building in question; the specific interzonal relationships in the small office building are detailed in Figure 3-1. Model coefficients are applied to validation data to predict zonal temperatures. Predicted and original simulated EnergyPlus zonal temperatures are compared to calculate measures of model error.

Below, T_z^t is the temperature in zone z at time step t, T_x^t and T_g^t are the outdoor dry-bulb temperature and ground temperature at time t respectively, $Q_{z,rad}^t$, $Q_{z,conv}^t$, $Q_{z,WS}^t$ and $Q_{z,SS}^t$ are the radative heat flux, convective heat flux, window-transmitted solar radiation, and total solar radiation incident on surfaces for zone z at time step t in that order. The model coefficient a_{ij}^t describes the effect of zone j on zone i at time step t, and b_z^t, c_z^t, d_z^t, e_z^t, f_z^t, and g_z^t are the coefficients for outdoor dry-bulb temperature, radiative heat flux, convective heat flux, window-transmitted solar radiation, and total solar radiation incident on surfaces for zone z at time step t in that order.

$$\begin{bmatrix} 1 & a_{12}^k & \cdots & a_{1z}^k \\ a_{21}^k & 1 & \cdots & a_{2z}^k \\ \vdots & & \vdots & \vdots \\ a_{z1}^k & a_{z2}^k & \cdots & 1 \end{bmatrix} \cdot \begin{bmatrix} T_1^k \\ T_2^k \\ \vdots \\ T_z^k \end{bmatrix} =$$

$$\begin{bmatrix} \sum\limits_{z=1}^{Z} \sum\limits_{t=k-n-1}^{k-1} a_{1z}^t T_z^t + \sum\limits_{t=k-n-1}^{k} b_1^t T_x^t + c_1^t Q_{1,rad}^t + d_1^t Q_{1,conv}^t + e_1^t Q_{1,WS}^t + f_1^t Q_{1,SS}^t + g_1^t T_g^t \\ \sum\limits_{z=1}^{Z} \sum\limits_{t=k-n-1}^{k-1} a_{1z}^t T_z^t + \sum\limits_{t=k-n-1}^{k} b_2^t T_x^t + c_2^t Q_{2,rad}^t + d_2^t Q_{2,conv}^t + e_1^t Q_{2,WS}^t + f_2^t Q_{2,SS}^t + g_2^t T_g^t \\ \vdots \\ \sum\limits_{z=1}^{Z} \sum\limits_{t=k-n-1}^{k-1} a_{1z}^t T_z^t + \sum\limits_{t=k-n-1}^{k} b_z^t T_x^t + c_z^t Q_{z,rad}^t + d_z^t Q_{z,conv}^t + e_z^t Q_{z,WS}^t + f_z^t Q_{z,SS}^t + g_z^t T_g^t \end{bmatrix} \tag{3.3}$$

subject to the constraint

$$\sum_{j=1}^{Z} \sum_{t=k-n}^{k} a_{ij}^t + \sum_{t=k-n}^{k} b_i^t = 0 \tag{3.4}$$

for all zones i and j in Z total zones where $a_{ii}^t = -1$ to enforce steady-state heat transfer.

Generally, the thermal response in each zone is affected by the following factors. Past zonal temperatures indicate the starting points and temperature trajectories that the zone is moving forward from. The outside environment provides variable heat flux from ambient temperature and solar radiation depending on the day and the season. In accounting for incident solar radiation, two separate terms are used to account for short-wave solar radiation transmitted through exterior windows and absorbed by zone surfaces and for long-wave radiation absorbed by opaque surfaces. Load variations occur due to changes in the building operation and schedule; internal loads from equipment such as lighting and operation are changed to accommodate occupants. Occupants schedules change depending on the location and day of interest. Thus, internal load variations can change greatly between weekends, weekdays and holidays. Heat fluxes are separated into convective and radiative categories. In this work, an active cooling system is not used and thus only use total convective heat flux and total radiative heat flux terms are used. We do not assume that the building surface touching the ground is adiabatic and must account for heat flows between the building surface and ground by including ground temperature as an additional exogenous factor. Ground temperature used is the constant value given by the reference building file that changes with different months. Weather file ground temperatures are not used because they describe undisturbed ground temperature and the ground temperature beneath buildings is affected by the building itself. However, the reference building approximates this temperature as a constant that varies throughout the year.

3.1.3 EnergyPlus and DOE Reference Building

Data used to fit an inverse CRTF model can be experimentally gathered through installed sensors, or acquired from simulation programs. Because we are ultimately interested in the ability of commercial buildings to provide a range of electricity services, we utilized the DOE's set of commercial reference buildings built using the EnergyPlus building simulation program.

EnergyPlus simulates building energy use including heating, cooling, lighting and ventilation through simultaneous simulation of the HVAC system and building heat balance system. In EnergyPlus, inputs and outputs are easily selected and modified. The program uses a heat balance model that accounts for building surface conduction, air convection, short wave radiation absorption and reflectance and long wave radiant exchange [20]. Zones are assumed to have well-mixed air, so a single temperature for each zone is outputted.

We use EnergyPlus to run reference-building models at one hour time-steps, a reasonable planning horizon for HVAC systems. The run period of each model is adjusted for the time period of interest. HVAC systems are turned off in order to observe the simulated thermal response behavior of the building envelope and system without active heating or cooling. Zonal temperature, outdoor-dry bulb temperature, short-wave windows-transmitted solar radiation, total surface incident solar radiation and radiative and convective heat fluxes for each zone are selected as outputs. Radiative and convective heat fluxes include contributions from internal loads including people, lighting, electric equipment, hot water equipment and steam equipment.

Window-transmitted solar radiation heat gain captures the heat gain from short wave solar radiation directly through windows, while the outside-face solar radiation heat gain term represents the relative strength of heat from absorption of solar radiation at outside surfaces.

The DOEs commercial reference buildings provide complete descriptions of different types of commercial buildings, including detailed construction and HVAC system information. The set contains 16 building types that cover 70% of all U.S. commercial buildings, including small, medium and large commercial buildings with specifications described in Table 3.1 [75].

Building Type	Floor Area	Number of Floors
Large Office	498,588	12
Medium Office	53,628	3
Small Office	5,500	1
Warehouse	52,045	1

Table 3.1: DOE Office-type Reference Commercial Building Models [79]

Ultimately, a comprehensive set of inverse CRTF models for all reference building types could be developed and used to determine optimal control strategy and investigate electricity service provision. This work begins with the small office commercial building model in order to demonstrate the efficacy of using inverse CRTF models to describe thermal response models for optimal control. The small office building contains one floor and six zones: a core zone and four perimeter zones along with an attic above the other five zones as shown in Figure 3-1. Internal walls are ASHRAE 90.1 above-grade, wood-frame non-residential with an overall heat transfer coefficient of $41W/m^2$. This u-factor describes the overall rate of heat transfer through one square feet given standard conditions. There are punch windows (5' by 6') in each of the four perimeter zones, and none on the attic. As noted previously, we consider both windows-transmitted solar and solar absorbed by surfaces through the perimeter zones and solar absorbed in the attic. All zones on the first floor are assumed to be adjacent to the ground.

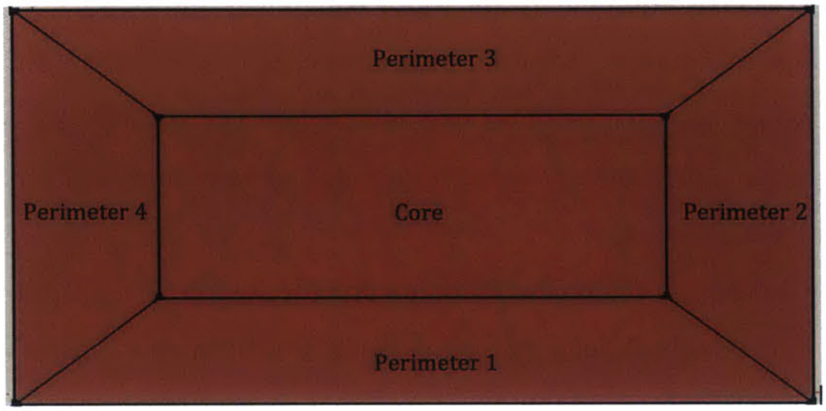


Figure 3-1: DOE Small Office Reference Building Floor Layout

Zone	Area (sq. ft)	Conditioned	Volume (cu. ft)	Gross Wall Area (sq. ft)	Window Glass Area (sq. ft)
Core	1611	Yes	16122	0	0
Perim 1	1221	Yes	12221	909	222
Perim 2	724	Yes	7250	606	120
Perim 3	1221	Yes	12221	909	222
Perim 4	724	Yes	7250	606	120
Attic	6114	No	25437	0	0
Total	5503	-	80502	5030	643

Table 3.2: DOE Small Office Reference Building Parameters [79]

3.2 Multi-Zonal Small Office Inverse CRTF Model

The final EnergyPlus-driven multi-zonal inverse CRTF model formulated for a small office reference building was described in Equation 3.3. Given full knownledge of EnergyPlus simulation data from a training set, model coefficients are identified using a constrained linear regression. Subsequently, the model performance is validated by predicting temperatures from a training set and examining model prediction errors and relative mean square errors.

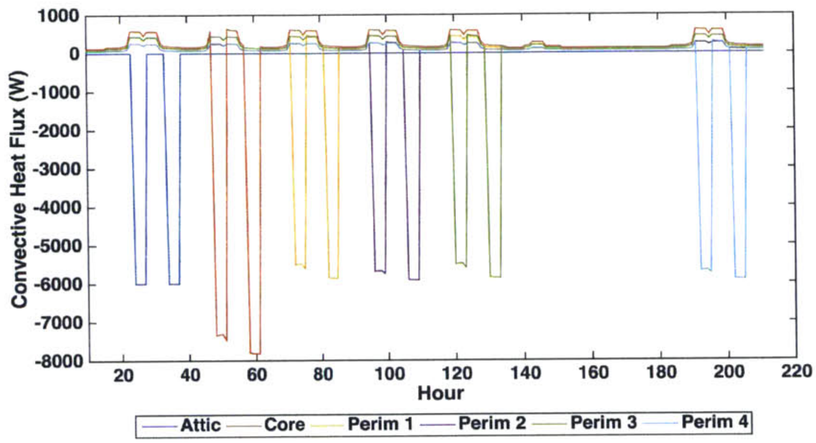
The selection of an appropriate training set is important; if trained on a set that is too dissimilar from the conditions of the day that will be predicted, the thermal response model may not perform well. The amount of training data required to fit inverse model coefficients for a well-performing model depends on the model and building. Other black-box models may require months of training data and gray-box RC models may require only a week or two of training data [12]. If trained upon the wrong set of data, the model may be unstable in predicting the thermal response for conditions that are too dissimilar from the training data.

[6] and [7] fit an inverse model to data where there are variations in climate and internal gains. The inverse model was first fit to a test chamber built within a larger laboratory room. The laboratory room temperature represented an 'outdoor' temperature while the test chamber temperature was the variable of interest. The inverse model was trained on average expected internal loads and climate for both training and test sets by allowing factors to vary within some small ranges. 'Climate' variations were produced by letting the laboratory temperature vary naturally, internal gains variations were produced by turning lights on and off within the test chamber. Similar temperature trajectories were observed in both training and test sets. Similar to our EnergyPlus set-up, the test chamber HVAC system is turned off before recording training and testing data.

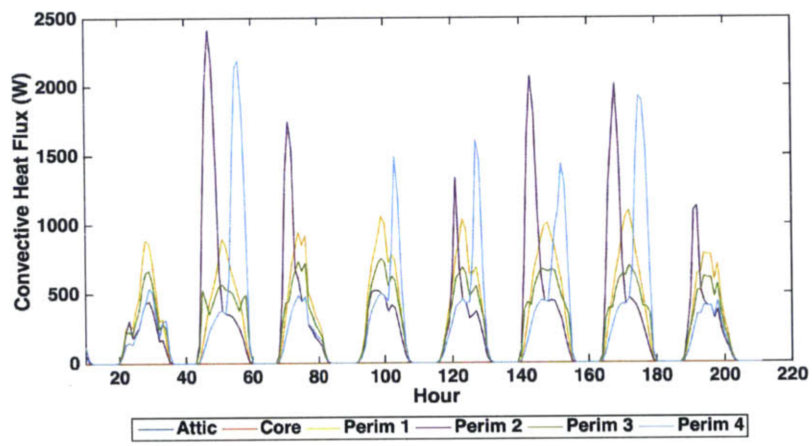
On the other hand, [31] used thermal excitations to observe resulting temperature trajectories in the training and test sets. [31] used around 20 days of training data to fit the inverse CRTF model since the test chamber used four different and separate methods of heat input. If all forms of heat input were used simultaneously, fewer days could be used in a training set. [31] uses pulses of heating input from the four methods to observe the resulting thermal response from the room.

Instead of specific pulses or a similar set of temperature variations to what is in the test set, [83] uses various ratios of internal loads to heat gain from a thermally active building systems (TABS). Two training sets were used, one of which had similar magnitudes of internal loads and cooling heat flux and one which had dissimilar ratios; when tested on data where ratios were significantly different from the first training set, the model did not perform well. This suggests that training on data that experiences a range of anticipated climate conditions and internal loads is necessary for a well-performing model. However, given that inverse CRTF models are trained for specific periods of time, locations and conditions, there is a trade off between a model that performs relatively well the majority of the time when conditions in climate or scheduling senses are not extreme and the ability of a model to predict more reasonable temperature responses when there happen to be extreme conditions.

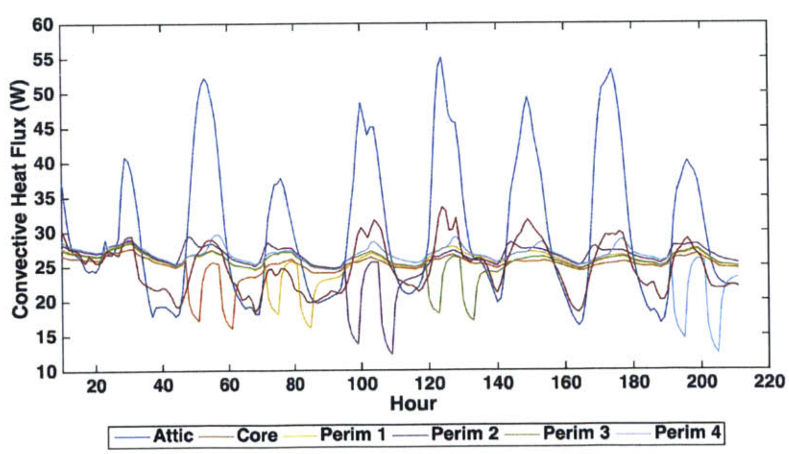
In this work, we use a training set that assumes typical internal gain scheduling from an office building along with pulses of cooling. The natural variations in ambient temperatures and solar radiation produce a range of excitations that could be typically expected in the period of time of interest. Additionally, we are interested in capturing the buildings thermal response to cooling inputs. In the subsequent optimization, convective cooling is added; in this model-fitting stage, it is important to expose the training set to pulses of cooling as well in order to best capture the building's thermal response. In this case, the training and testing sets are similar in terms of scheduling and climate conditions. The training data produces a model that performs well when climate conditions and internal load conditions are similar to training set data range. As shown in Figure 3-2a, the training set contains a typical internal gains schedule that includes arrival of people and use of lighting and electric equipment starting in the weekday mornings and departure and discontinuation of those same internal gains in the evening. Reduced schedules are assumed on Saturdays and Sundays. For each zone, a cooling pulse is added at an on-peak time period where overall building internal gains are at a peak and at an off-peak time. Cooling pulses are applied to each zone separately to observe effects on adjacent zones. We would need at minimum six days of data to apply cooling pulses to all zones. In Figure 3-2b, plots of incident solar radiation show that heat flux from solar peaks at different time periods for different zones; the east-facing perimeter 2 zone observes peak solar in the morning and the west-facing perimeter 4 zone experiences peak solar in the afternoon. Other zones observe peak solar in the middle of the day. Incident solar varies throughout the month. Similarly, there are natural variations observed



(a) Training Schedule Convective Heat Flux Rates (W)



(b) Training Schedule Total Window-Transmitted Solar (W)



(c) Training Schedule Zonal and Outdoor Dry-Bulb Temperatures (degrees Celsius)

Figure 3-2: Training Schedule Heat Fluxes and Temperatures in ambient temperature depicted in Figure 3-2c. Core and perimeter temperatures fluctuate generally between 18-33 degrees Celsius while the attic experiences a much larger range of temperatures. Temperature responses during each pulse of cooling can be observed. The range of temperatures in the attic is much greater than in the other zones; the attic temperature increases greatly during the day from absorbed solar radiation and drops at night as it the attic loses radiative heat.

The selection of an appropriate length of time is important due to the variation in climate conditions included in the training set. Here, the training set uses representative typical meterological year 3 (TMY3)-formatted weather data from the calendar month to train the model. The training set period length needed to train a well-performing model directly varies with the amount of variation experienced during the period. For instance, when predicting the thermal response on an average day in June, a thermal response model trained on similar days in June performs the best. However, a model trained on data from early June likely is trained on temperatures that are cooler than those experienced in a test day from late June. Similarly, if a model is trained on a time period with little solar radiation, the model may not perform well when used to predict thermal response on a day with high levels of solar radiation. In transition months between seasons, this effect may be especially important since there is more climate variability. Selection of a training set purely based on calendar month may not result in the best prediction performance. However, climate conditions can change rapidly, so using the a rolling training set consisting of previous weeks data does not necessarily produce a model that is more appropriate for any given test day. Here, the calendar month training set is employed for simplicity and ease of use.

Prediction errors decrease as model order increases. Decreases in the 1st, 25th, 50th, 75th and 99th percentiles of prediction error with increasing model order for a model fitted to the June training set and tested on the June testing set are shown in Figure 3-3. As model order increases from two to five, the lower percentiles of prediction errors drop by substantial fractions. However, increase in model order also can result in over-fitting of the inverse model to the training data. As noted by

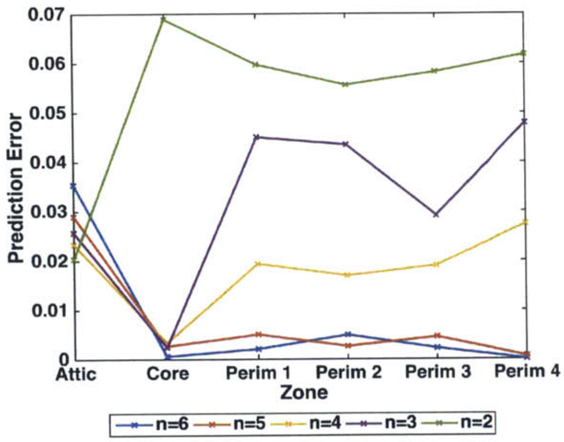
[31], there is a trade-off between lowering prediction error and over-fitting to training data. Generally, we observe that at a model order of four, we gain the benefits of lower prediction errors with less computation time and chance of over-fitting. Especially when looking at higher percentiles of prediction error, we recognize that continual increase in model order does not necessarily yield dramatic decreases in prediction error. In [83], authors report that a model order of three offered a good balance between accuracy and computation speed for the single zone inverse CRTF model.

Prediction errors are lower for the non-attic zones. Since we do not condition the attic in the optimization described in Chapter 4, it is less important to perfectly predict attic temperature trajectories. In addition, attic temperature fluctuations are much greater than those in the non-attic zones as well, so the attic relative error does not differ dramatically.

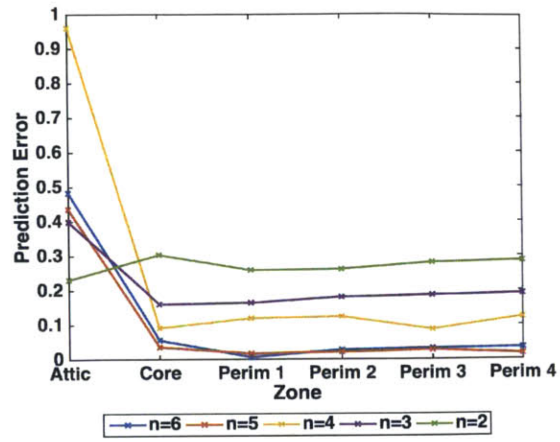
3.3 Inverse Model Validation

Fitted multi-zonal inverse CRTF model coefficients for a small office building for the months of June, July and August are included in Appendix D. After inverse CRTF model coefficients were fit to the training set, 24-hour ahead predictions were made using the inverse model given past zonal temperatures and present and past ambient temperatures, solar heat fluxes on windows and absorbed surfaces and convective and radiant heat fluxes. We predict 24-hour ahead zonal temperatures because MPC is used for planning purposes; typically, the optimization would be initially run for 24-hour ahead predictions for the following day with forecasted load and climate data. The resulting schedule could be implemented, but the optimization could be run again in real-time every consecutive hour with updated thermal response data. Accordingly, this work considers a 24-hour ahead prediction horizon. It is useful to note that at this step in the process, if the optimization returned a cooling strategy that departed greatly from typical operation, the operator would likely return to a default operation schedule.

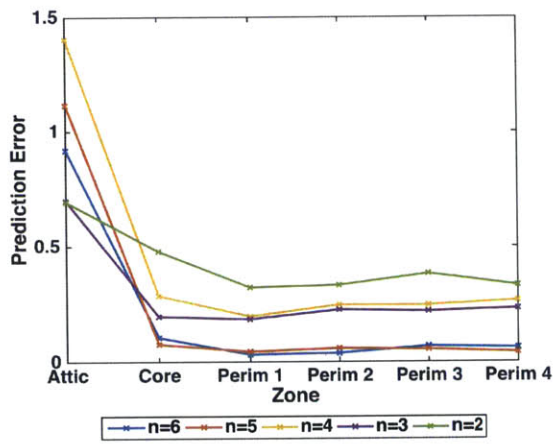
Because 24-hour ahead predictions assume no knowledge of exogenous and build-



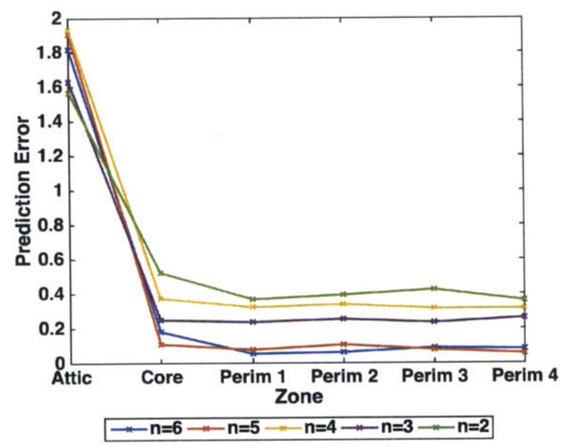
(a) 1^{st} Percentile of Prediction Error



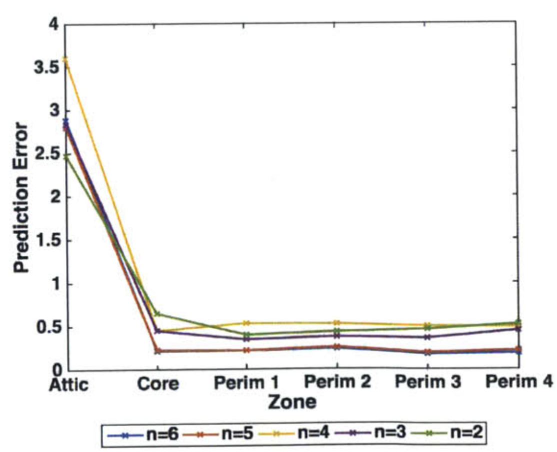
(b) 25^{th} Percentile of Prediction Error



(c) 50^{th} Percentile of Prediction Error



(d) 75^{th} Percentile of Prediction Error



(e) 99^{th} Percentile of Prediction Error

Figure 3-3: Prediction Errors with Increasing Model Order ing data for the 24 hours of interest, in order to predict the zonal temperatures in the first hour, the first n number of terms from the previous day are assumed to be known. Subsequently, $n-1$ known terms and the first hour of predicted temperatures are used to predict the thermal response in the second hour. Each successive hour follows the same procedure, where predictions after the nth hour use only predicted thermal response data to model future thermal responses.

We can validate the inverse CRTF model with the EnergyPlus simulation results where there is no active cooling or heating. We calculate errors for analysis in two methods by looking at absolute prediction errors (PE) and relative mean square error (RMSE) as defined below. For each 24-hour set of predictions, we have 24 PE values per zone. Then, the RMSE takes the mean of the normalized absolute PE values over the width of the range of zonal temperatures experienced in that zone during the day. Thus, each zone's RMSE rolls up the error distribution over the course of the day into one average measure of error. The RMSE is affected by the zonal temperature range experienced; for instance, in the unconditioned attic zone that has strong direct incident solar heat gain and more exposed surfaces, the range of temperatures experienced is greater than that of the core zone which is surrounded on all four sides by perimeter zones.

$$\text{Prediction Error (PE)} = |T_{EnergyPlus} - T_{inverseCRTF}| \tag{3.5}$$

$$\text{Relative Error (RE)} = \frac{T_{EnergyPlus} - T_{inverseCRTF}}{max(T_{EnergyPlus}) - min(T_{EnergyPlus})} \tag{3.6}$$

$$\text{RMSE} = \sqrt{mean\left(\left(\frac{T_{EnergyPlus} - T_{inverseCRTF}}{max(T_{EnergyPlus}) - min(T_{EnergyPlus})}\right)^2\right)} \tag{3.7}$$

The inverse CRTF model performs fairly well at predicting temperature trajectories and capturing the effects of different zones on each other. In this example July day, the inverse CRTF model fit to the corresponding calendar months data predicts temperature trajectories in the six different zones successfully. We may expect to see an upward trend in error throughout the day since predicted thermal responses are used to predict future responses, leading to a potential magnification in PE values. However, this trend is not evident in Figure 3-5. When validated against different days test data, the inverse CRTF models performance varies. For some days, PE and RMSE are both very low. Generally, the model performs well in predicting thermal response. However, there are specific days where conditions deviate from those that were trained for the inverse model and predictions depart from simulated zonal temperatures.

When observing absolute prediction errors, the inverse CRTF multi-zonal model performs well at predicting thermal response and temperature trajectories. Prediction errors for the month of July are shown in Table 3.3 and the distribution of PE for test days from the entire month are shown in Figure 3-6a. Results for the months of June and August are in Appendices A and B. The PE distribution of the attic is much larger than those for non-attic zones. To discuss the largest PE observed within a month, we look at the distribution of the 99th percentile of PE for each day in Figure 3-6c. This distribution describes the largest prediction errors observed for each test day; it remains far below 1 degrees C for non-attic zones and ranges between 1-3 degrees C for the attic. For the core and perimeter zones, the 99^{th} percentile of prediction error remains at or below 0.15 degrees Celsius for the training set. The 99^{th} percentile of PE is 2.35 degrees Celsius for the attic. Within the reference building, the attic is unconditioned, experiences a far greater range of temperatures through the day and can reach much higher temperatures. The median of PE remains below 0.06 degrees C for the core and perimeter zones and 0.86 degrees C for the attic. Consistently, the model performs well, especially on weekdays. Different internal loads schedules are experienced on weekends; the cooling pulses for the training set are also not applied to weekends. We would expect weaker model accuracy on weekend days or holidays.

Model-predicted RMSE are shown in Table 3.4 and boxplots of RMSE distributions from each day in the test month are displayed in Figure 3-6b. Median RMSEs are 1.41% for the core zone, 1.33% for the first perimeter zone and under 1% for the rest of the perimeter zones. When using RMSE to assess model error, much higher

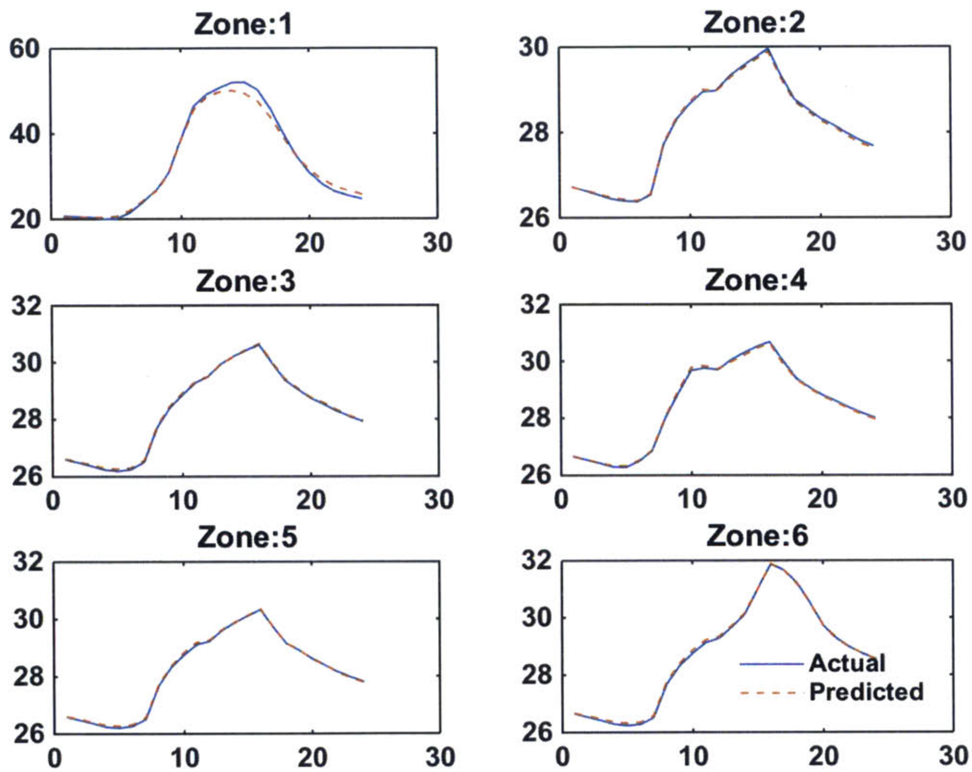


Figure 3-4: July 6th Predicted and Actual Zonal Temperatures (degrees Celsius)

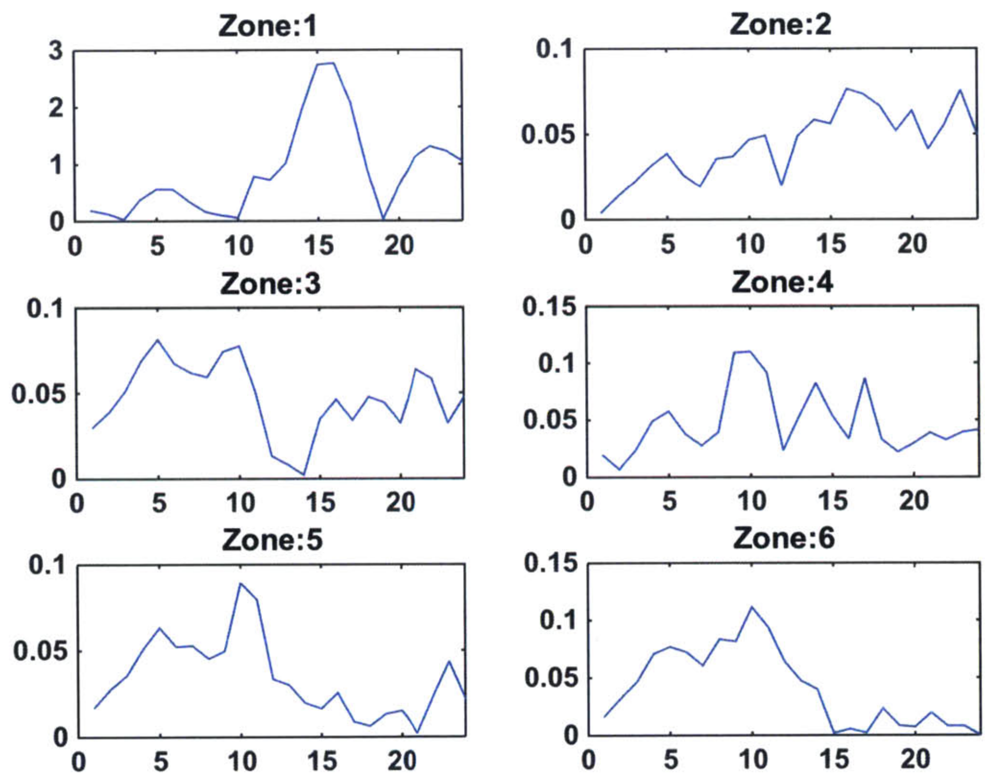


Figure 3-5: July 6th Zonal PE (degrees Celsius)

Quantile	Attic	Core	Perim1	Perim2	Perim3	Perim4
1	0.0028	0.0016	0.0021	0.0032	0.0016	0.0007
25	0.23	0.024	0.037	0.015	0.017	0.018
50	0.86	0.054	0.061	0.022	0.027	0.046
75	1.72	0.079	0.078	0.050	0.033	0.061
99	2.35	0.10	0.11	0.07	0.07	0.15

Table 3.3: PE of July Test Set (degrees C)

Quantile	Attic	Core	Perim1	Perim2	Perim3	Perim4
1	0	0	0.1	0.3	0.1	0
25	0.6	2.2	1.1	1.3	0.9	1.2
50	3.0	5.5	4.7	6.9	5.4	4.6
75	7.4	7.2	6.4	8.1	6.9	5.4
99	8.8	8.3	8.0	9.3	8.5	6.2

Table 3.4: Quantiles of July Test Set's RMSE (%)

error terms can be observed due to the tight temperature ranges experienced by different zones. When small PEs are divided by small max-min bands, the relative errors are large. Thus, RMSE distributions are more similar between the different zones despite the fact that absolute PEs of the attic are greater than those of non-attic zones. The median attic RMSE is still greater than those of the non-attic zones, although the upper tails of RMSE distributions are similar. Additionally, the RMSEs roll all 24 PE errors within one day into one error term and give all error terms equal weights. This allows higher errors to affect the day's RMSE. In practice, should extremely irregular temperature trajectories or control strategies be recommended using the thermal model, it is likely that the building operator would dismiss them.

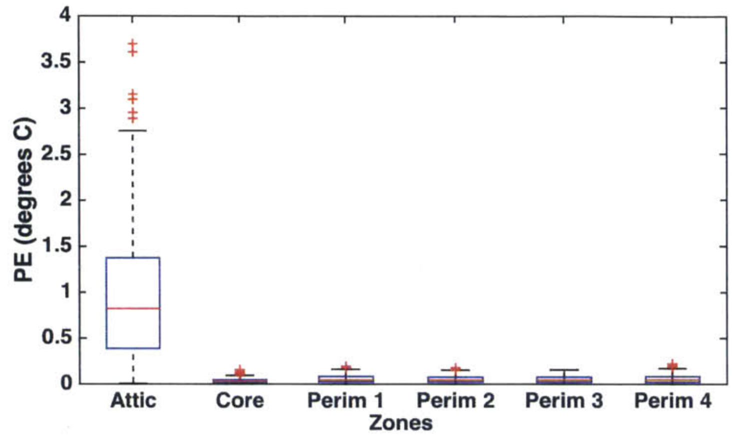
The training set-fitted inverse model performs well when validated against test data for the months of June, July and August. Median RMSEs are at or under 1% for non-attic zones and median PE fall under 0.06 degrees C for non-attic zones and 1 degrees C for the attic. PE and RMSEs are both acceptable; additionally, all physically measured quantities, such as temperature, are subject to some uncertainty in measurements. The accuracy and precision of HVAC sensors such as thermistors and RTDs depend on sensor type and manufacturer. Thermistors are precise usually to $+/-0.1$ or 0.2 degrees C and RTDs to $+/-0.15$ to 0.3 degrees C [8]. Thus, our inverse model PE fall well within those ranges and will likely not greatly affect the operation of building HVAC systems. Inverse model validation error ranges are acceptable for implementable building control. In practice, a building is predicting thermal responses for internal gains schedules similar to those previously experienced by the building. This is especially true for commercial office buildings without highly variable industrial loads or equipment, where internal gains result primarily from occupants, lighting, and plug loads.

Quantile	Attic	Core	Perim1	Perim2	Perim3	Perim4
50^{th} percentile	2.0	0.07	0.10	0.10	0.10	0.12

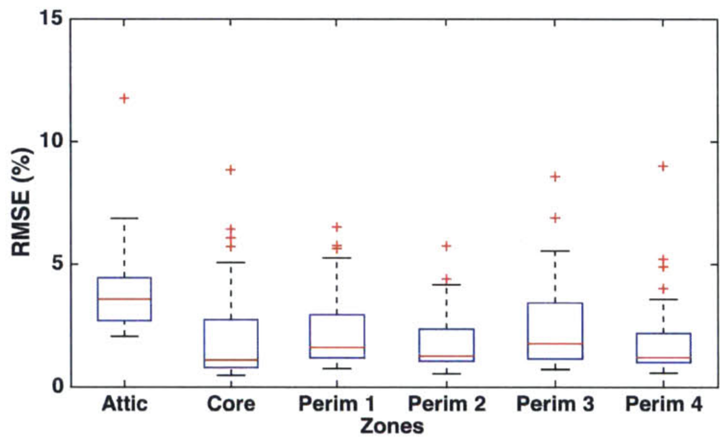
Table 3.5: 99^{th} Percentile of Prediction Error (degrees C)

3.4 Conclusion

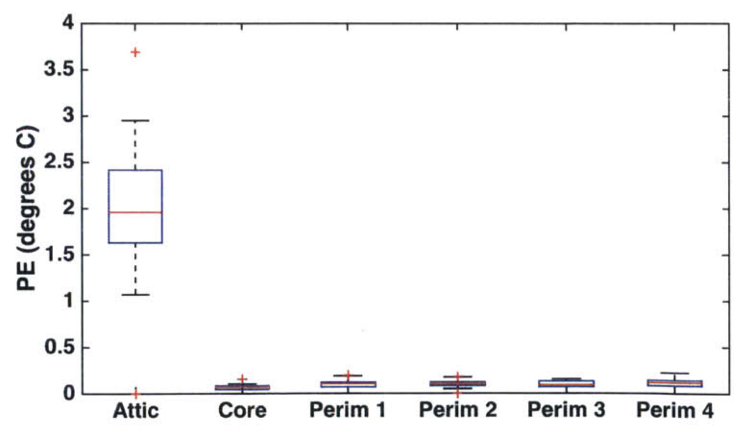
Single zone inverse CRTF building models have been successfully used to capture the thermal response of a building to changes in exogenous conditions and overall heating and cooling rates. In this work, an EnergyPlus-driven multi-zonal inverse CRTF model from [32] formulated specifically for a small office reference building with Boston, MA TMY3 weather data is fit to training data, validated and used to predict temperature response. Prediction error and relative mean square error are used to assess model performance. The inverse CRTF model performs well in predicting building thermal response with median prediction errors for the month of July of 0.9 degrees C in the attic zone and under 0.06 degrees C in non-attic zones; in comparison, commercial HVAC sensors are precise to within 0.1-0.3 degrees Celsius. A model order of 4 is selected to balance reduction in prediction error with increase in computational load and over-fitting to training data. The multi-zonal inverse CRTF will be used to describe thermal response in the subsequent optimization in Chapter 5.



(a) Month of July PE Distributions by Zone (degrees Celsius)



(b) Month of July RMSE Distributions by Zone (%)



(c) Month of July 99^{th} Percentile of PE

Figure 3-6: Distributions of PE and RMSE for July

Chapter 4

Model Predictive Control Building Optimization

4.1 Regulation and Spinning Reserves in U.S. ISO Markets

The ability of demand-side loads such as those in a commercial building to participate in ancillary services markets is different in each U.S. ISO. In addition, the actual market products themselves may differ in name, function and participation requirements in different markets. Generally, in accordance with NERC definitions, regulation products are on the order of 4 seconds-5 minutes and spinning and non-spinning reserves on the order of 10 to 105 minutes [62, 61]. A thorough review of demand response's potential to enter U.S. ancillary services markets was conducted by [55], but since 2012 ISOs have continued to publish papers and plans regarding demand response's ability to participate in future ancillary service markets. Below, we summarize current and future regulation and reserve products in each ISO and corresponding participation requirements.

4.1.1 ERCOT

ERCOT is the only ISO completely within one state and represents 85% of Texas' load [26]. Notably, ERCOT has high levels of installed wind capacity and is a summer peaking system due to the frequent use of air conditioning systems. Load can be highly variable throughout the year. ERCOT has noted its concern that increasing penetration of renewables leads to more non-synchronous resources that reduce overall system inertia. In order to participate in ERCOT ancillary services markets, loads need to be registered as a Resource Entity and represented by a Qualified Scheduling Entity. The minimum amount per resource for each product offered is 0.1 MW. Resources can offer more than one AS. Offers must be submitted by a Qualified Scheduling Entity.

ERCOT's current ancillary services are regulation up, regulation down, responsive reserve and non-spinning reserve [26]. Regulation Service consists of resources that can be deployed by ERCOT in response to changes in ERCOT system frequency to maintain the target frequency within predetermined limits according to the Operating Guides [27] [26]. Regulation up and down are two different products and ERCOT does not require that participants provide symmetric up and down regulation. In order to participate in regulation up and/or down service provision, load resources must be able to respond to ERCOT signals every 4 seconds, satisfy performance criteria and have real-time telemetry installed [27]. If loads are qualified for regulation, they are also qualified for responsive reserves and non-spinning reserves. In the responsive reserve service, ERCOT requires that the load respond to frequency changes and provide committed capacity within 10 minutes after an official notice. Unlike other markets, providing operating reserves in ERCOT requires that resources need to be autonomously frequency responsive and able to provide primary frequency response as well [23].

ERCOT released a concept paper in 2014 addressing adaptation of the ancillary services market to a system with higher penetration of renewable energy and new pay-for-performance mechanisms [25]. The study proposed changes in products that would open competition opportunities to both generation and new resources for ancillary services provision. The three existing products would be changed to:

1. Synchronous Inertial Response Service (SIR),
2. Fast Frequency Response Service (FFR),
3. Primary Frequency Response Service (PFR),
4. Up and Down Regulating Reserve Service (RR), and
5. Contingency Reserve Service (CR).
6. Supplemental Reserve Service (SR) (during transition period)

[25]

Generally, the role of regulation up and down would be acquired with up and down regulating reserve service (RR). The new proposed framework of ancillary services also allows for resource specific deployment signals from ERCOT to considered and pay-for-performance metrics will be implemented.

4.1.2 ISO-NE

ISO-NE procures resources to meet reserve requirements through a competitive forward reserve market and regulation and reserves markets. The regulation market is used to balance supply levels with second to second demand variations for frequency maintenance. In day-ahead (DA) markets, real time operating reserves are split into three products: 10 minute spinning reserves, 10 minute non-spinning reserves and 30 minute operating reserves.

Currently, demand resources are not fully integrated into ISO-NE markets and cannot provide regulation. ISO-NE plans to allow demand response resources to be fully integrated into the reserves market beginning June 1, 2017 [40] [42]. In order to participate, demand response resources must provide at least 0.1 MW of demand reduction and will comply with testing and telemetry requirements. When integrated, demand response resources (DRRs) will be able to participate in regulation, spinning and operating reserves and forward reserves markets [40].

Though demand response cannot currently provide all ancillary services, ISO-NE has modified its regulation market beginning March 31, 2015 such that Alternative Technology Regulation Resource (ATRR) with minimum of 1 MW of capacity can qualify for the regulation market. The modified regulation market has two different energy-neutral regulation signals. Aggregation is allowed for resources to reach the minimum resource size. The resource receives a single AGC SetPoint from ISO-NE and is required to respond accurately. Resources are required to have metering and telemetry such that real time performance can be measured and recorded. Bids must be submitted symmetrically such that up and down regulation are both possible. ISO-NE has already initiated use of pay-for-performance mechanisms where both a capacity and a service payment are used.

4.1.3 NYISO

Demand resources have been able to participate in the Demand Side Ancillary Services Program (DSASP) and provide operating reserves and regulation since 2013 [64]. Resources enroll as DSASP resources, but participate in the DSASP through registered DSASP Providers. DSASP Providers are responsible for maintaining metering infrastructure and communication with NYISO. For instance, Demansys Energy has been aggregating demand-side resources for participation in DSASP in regulation and reserves. In late 2014, Demansys reported bidding over 75 MW of aggregated load into DSASP [45].

Demand resources can bid into the DA and real-time (RT) markets for these two products. Demand resources must bid in symmetrically for regulation and are eligible for participation in spinning reserves and 30 minute reserves markets. The NYISO Ancillary Services manual describes regulation as the continuous balancing of resources with load to maintain frequency at 60Hz to follow rapid changes with load and maintain frequency at 60 Hz [65]. Full telemetry is required for DSASP resources and resources must have a minimum of 1 MW in order to participate and a maximum of 200 MW in order to participate [65].

4.1.4 CAISO

CAISO's ancillary services markets contain regulation up, regulation down and operating reserves (spinning and non-spinning reserves) products. Like ERCOT, regulation products are separate and symmetric regulation is not required. In 2010, CAISO modified the ancillary services market requirements by reducing minimum rated capacity from 1 MW to 0.5 MW and reducing the minimum continuous energy requirements to 60 minutes for DA regulation, 30 minutes for RT regulation and 30 minutes for operating reserves [17]. The majority of ancillary services in CAISO are provided by hydropower and gas resources [15]. Regulation, continuous balnacing resources to meet deviations between actual and scheduled demand, resources must meet a minimum performance threshold of 25%. In June 2013, CAISO added a pay-for-performance component to the compensation of regulation markets by including a performance payment in addition to the capacity payment [15].

Resources can participate in ancillary services markets as Participating Loads (PL). However, PL can only provide non-spinning reserves markets in the ancillary services markets and DRP are not yet eligible to provide ancillary service products [16]. PL provide curtailable demand that must be curtailable from CAISO direction in real-time; the majority of PL are pumping loads. DRPs such as the Proxy Demand Resource (PDR) and Reliability Demand Response Resource (RDRR) allow demand to participate in other DA markets. However, CAISO allows on-generation resources (NGR), introduced in 2012, that operate as generation or load and can dispatch any level within their capacity range and include energy storage devices such as flywheels and batteries to bid into ancillary services markets [17][14]. The NGR inclusion plan has two phases which include energy storage devices in phase 1 and will allow dispatchable demand response to bid into ancillary services markets in phase 2 [14]. All DR providers or resources and loads must be represented by a Scheduling Coordinator (SC) to participate and submit bids in CAISO DA markets; the SC may be the same as the DRP[17].

4.1.5 MISO

MISO has an ancillary services market that includes regulating reserves and contingency reserves. Payments for regulation products are divided into a capacity component and a regulation mileage component to account for pay-for-performance initiatives. Regulating reserves must be provided by symmetric up and down bids [59].

MISO divides demand-related resources into two categories: one set of capacity resources and a set of load-modifying resources. Capacity resources include Demand Response Resources Type I and Type II [57] [58]. DRR-I are direct load control resources and DRR-II are changes in consumption in a controlled manner. DRR-I are capable of supplying specific quantities of energy, reserves or capacity through a controllable load or behind-the-meter generation. DRR-II must be able to supply a range of energy instead of a specific quantity. Capacity resources are considered able to provide their capacity towards longer-term resource adequacy goals. Load-modifying resources might be behind-the-meter generation or demand resources that are interruptible. DRR-II resources are treated like generation resources and can be qualified to provide regulating, spinning and supplemental reserves in the ancillary services market. However, DRR-II resources also have a must-offer requirement which means they must make their capacity available in the DA or RT markets [57]. DRR-II resources must be at least 1 MW [57][58].

4.1.6 PJM

As [55] noted, PJM has one of the most favorable ancillary services markets for demand response participation. PJM's ancillary services markets include regulation through two different signals, synchronized and non-synchronized reserves. Regulation providers need to be able to follow the ISO's regulation signal in real time and must score a 75% or better on three consecutive tests to participate. Synchronized reserves providers must respond within 10 minutes and scheduling reserves providers provide supplemental reserves within 30 minutes.Providers must also meet a minimum resource size of 0.1 MW, the lowest minimum required size of the U.S. ISOs. Regulation can follow the RegA or RegD signal. Generally, PJM's non-synchronized reserves market is composed of pumped hydro, combined cycle and diesel plants [70].

Demand-side resources are able to participate in providing DA scheduling reserves, synchronized reserves and regulation. PJM has at least two demand-side resources participating in the regulation market since December of 2012, active participation in synchronized reserve provision from more than 120 resources and minimal demand-side participation in DA scheduling reserves [18]. In 2015, PJM reported an average 363 MW per month of synchronized reserves from 140 unique participating locations and 12 average MW per month of regulation were from demand-side resources [44].

4.2 Co-optimization of Energy and Ancillary Services

4.2.1 Objective function and constraints

An unpublished MPC optimization model from [9] is used to consider optimal cooling strategies from a small office building co-optimizing energy consumption and ancillary services provision. The general optimization can be specified in two components: the thermal response model (function (f) in Equation 4.1 below) and the HVAC system (function (g) in Equation 4.1 below). The data-driven thermal response model is fit to training data from a specific building-type with an assumed load schedule and a geographic location. In this work, the building-type used is the DOE's small office reference building and a multi-zonal inverse CRTF model described in Chapter 3 is used as the thermal response model. A VAV system with a centralized chiller provides cooling to all conditioned zones. Regulation service is provided by changes in chiller power consumption and spinning reserves are provided by changes in total system cooling consumption. Inputs of appropriate forecasted convective and radiative loads from people, lighting and equipment for the building type and location-specific weather data of outdoor dry-bulb temperature, solar radiation and ground temperature are taken from the DOE's small office reference building model. To validate optimization thermal response results, optimal cooling decisions were simulated in the same small office building in EnergyPlus; the difference in resulting temperature trajectories from optimal cooling decisions was within an acceptable range. Price inputs of wholesale LMPs, regulation and ten-minute spinning reserves prices are taken from ISO-NE's published DA market data. The optimization assumes the building is a price-taker and cannot affect the regulation, spinning reserves or wholesale electricity prices. This assumption is reasonable given the optimization results and will be discussed in the results section.

Given the inputs of prices, building data, weather conditions, multi-zonal inverse CRTF building thermal response model and VAV system, the optimization solves for a 24-hour set of optimal cooling strategies. For instance, a building operator may use a similar set-up to determine an initial set of building cooling strategies for the following day; once this day commences, the optimization could be re-run with updated information at each hour to determine that hour's cooling strategies. Different objective functions such as total daily energy cost or net daily operating energy cost can be selected. In this work, the objective function depicted in Equation 4.1 describes the total net daily operating cost and does not include any investment costs. The objective function contains the total daily electricity cost less revenues from provision of regulation and spinning reserves. The objective function also includes penalty terms for violation of thermal comfort constraints in all zones. Constraints fall into the categories of the building thermal response model, HVAC system constraints and regulation and reserve limits.

$$\underset{T^z,q^z,T'^z,q'^z}{\text{minimize}} \sum_{i=1}^{n} p_i^E x_i^E - p_i^R x_i^r - p_i^L x_L^E + \rho_T \sum_{z=1}^{Z} \left(max(T_i^z - T_i^{ul,z}, 0) + max(T_i^{ll,z} - T_i^z) \right) +$$

$$\rho_{T'} \sum_{z=1}^{Z} \left(max(T_i'^z - T_i'^{ul,z}, 0) + max(T_i'^{ll,z} - T_i'^z, 0) \right)$$

subject to

Building Thermal Model Constraints

$T_i^z = f(q_{i-N:i}^z, B_{i-N:i}^z)$

Energy Quantity

$x_i^E = g(q_i^z, S_i)$

Cooling Limits

$q_i^{ll,z} \leq q_i^z \leq q_i^{ul,z}$

Regulation Quantity and Limits

$x_i^L = min(x_i^{ul} - x_i^E, x_i^E - x_i^{ll})$

$x_i^{ll} = g(q_i^{ll,z}, S_i)$

$x_i^{ul} = g(q_i^{ul,z}, S_i)$

Spinning Reserve Quantity and Limits

$x_i^R = x_i^E - x_i'^E$

$x_i'^E = g(q_i'^z, S_i')$

$T_i' = f(q_i'^z, q_{i-N:i-1}^z, B_{i-N:i})$

$q_i^{ll,z} \leq q_i'^z \leq q_i^z$

(4.1)

The objective function net operating cost with the inclusion of a penalty term for thermal comfort limit violations in the primary minimization problem and the secondary problem solving for maximum spinning reserves capacity as described below from time step $i = 1$ to $i = n$. B^z and S represent the sets of all variables other than cooling rate that contribute to the thermal response model and system efficiency respectively. The variables T^z, q^z are zonal temperature and zonal cooling power for zone z in the primary optimization problem. Similarly, T'^z and q'^z are the same variables for zone z in the secondary problem solving for maximum spinning reserve capacity as described below. Variables $T_i^{ll,z}$ and $T_i^{ul,z}$ describe lower and upper thermal comfort temperature limits in zone z at time i respectively. The variables x_i describe the energy quantity of interest at time step i where x_i^E, x_i^L and x_i^R, describe hourly quantities of energy, regulation and reserves provided respectively.

The optimization determines two state variables of cooling provided and corresponding zone temperature. There are two sets of state variables: one set (T^z, q^z) for the primary problem of minimizing total net operating cost and one set (T'^z, q'^z) for the secondary problem of determining hourly spinning reserve capacities. Using total cooling power as a decision variable allows the optimization to be set up in a HVAC-system-agnostic framework; the relationship between cooling power for each ancillary service and total cooling power is determined by the selected HVAC system and described in function g in Equation 4.1. Different types of systems can be implemented in the optimization framework and corresponding system limits will affect regulation and reserve capacity.

The optimization uses MATLAB's $fmincon$ function utilizing an interior point algorithm. Minimization of the objective function is subject to system constraints. The use of a multi-zonal inverse CRTF model is implemented to constrain zone temperatures trajectories in a physically feasible manner in function (f). Minimum outdoor air constraints are enforced in order to provide ventilation to satisfy air quality standards.

Cooling limits are due to HVAC system limits. The implemented optimization assumes a VAV system in function (g) where constant temperature cooling air is delivered at different airflow rates to provide cooling and control indoor air quality. VAV systems have been popular, especially in newer commercial buildings. The VAV system uses an EnergyPlus reference ElectricEIRChiller York YCAL0033EE 100.6kW/3.1COP and VSD Fan regressed from [73]. Appropriate fan and chiller sizes are determined through an iterative trial and error process. All conditioned non-attic zones in the small reference commercial building are served by the same chiller and supply fan. In reality, a small commercial building of 5500 sq. ft will likely not have a centralized chiller or a VAV system. However, we assume such a system with the small office building model used in this work.

Regulation provision is treated as an approximately energy-neutral service that does not appreciably affect zonal air temperature, fan airflow or chilled water temperature [9, 71]. This problem assumes symmetric regulation is needed as is required in MISO, PJM, NYISO and ISO-NE. In the HVAC set-up, the chiller provides regulation capacity. Regulation capacity is limited by the maximum and minimum chiller electricity consumption given cooling power limits. A secondary optimization problem is included that determines temperature trajectories assuming that the system provides q' spinning reserves in addition to system cooling needs. The secondary optimization results in the optimal hourly set of spinning reserve capacity that the system can provide. All secondary problem variables are denoted by a tick after the same variable notations as the primary problem.

4.2.2 Prices and Conditions

The optimization is run with weather and price inputs associated with Boston, Massachusetts. ISO-NE is divided into eight load zones for market settlements; Boston sits within the Northeastern Massachusetts (NEMA) zone. Zone definitions are frequently important when assessing future capacity requirements and the role of transmission constraints and upgrades in allowing service. Wholesale electricity and ancillary services prices were taken from published ISO-NE DA wholesale market prices. It is assumed that the building pays the DA NEMA zonal LMP for electricity use. In practice, many buildings pay a fixed rate to the utility for electricity consumption, but the use of location-based electricity pricing is more reflective of actual costs of serving load at that point.

ISO-NE also uses competitive market-based mechanisms to procure regulation and operating reserves in the ancillary services markets and publishes DA clearing prices for both products. ISO-NE zonal regulation and spinning prices are used for NEMA to calculate revenue from provision of those ancillary services. ISO-NE publishes two regulation clearing prices: one for regulation capacity ($/MW committed) and one for regulation mileage ($/change in MW). The total regulation revenue is the sum of the regulation capacity and regulation mileage portions. However, ISO-NE does not publish daily mileage clearing values. It is stated that the long-term mileage component is calculated and intended to be similar in magnitude to the capacity component; the average mileage to capacity ratio in 2014 was 88% [22], so we use a multiplier of 1.88 on the regulation capacity clearing prices to approximate total regulation price.

Since we are focused on investigating the effects of cooling on provision of ancillary services, we look at optimal cooling strategies for three summer months during which cooling load is the highest: June, July and August. Model coefficients are trained on the calendar month training set as described in Chapter 3. We use one 24-hour set of LMP and ancillary services prices for each month averaged over all weekdays to represent an 'average' day. Representative average prices for each month are shown in Figure 4-1. Note that because LMPs are published hourly, the units displayed of $/MW for regulation and spinning reserves capacity are consistent with $/MW for the hourly LMP. Median weather conditions are used for as an input. Additionally, specific days with higher ancillary services prices relative to LMPs are selected in order to highlight the effects of higher ancillary service prices on optimal cooling strategies, service provision and building revenue. The following price cases were modeled:

1. June 2015 average price case

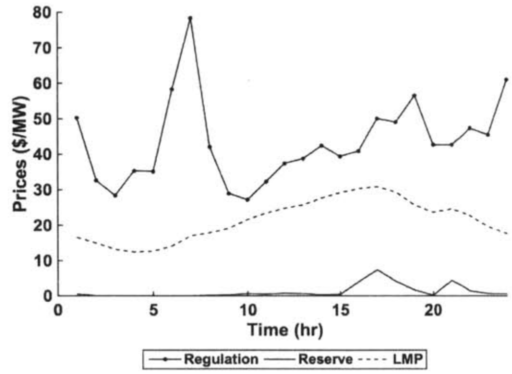
2. July 2015 average price case

3. August 2014 average price case

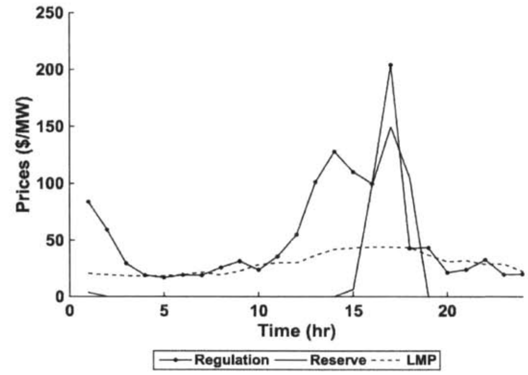
4. June 19th, 2015 example high ancillary services price case

5. July 20th, 2015 example high ancillary services price case

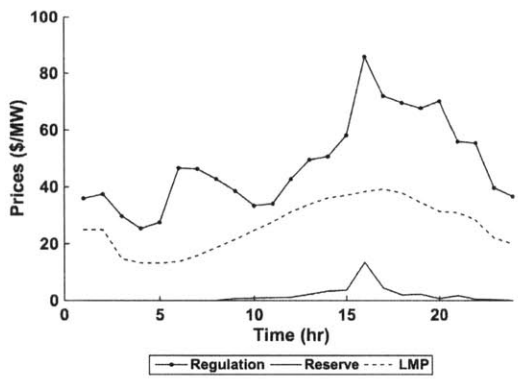
6. August 5th, 2014 example high ancillary services price case



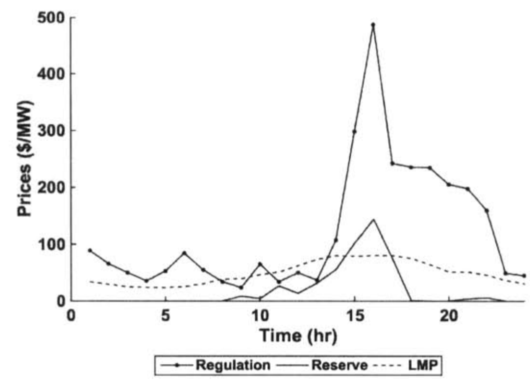
(a) Daily average June Price Case



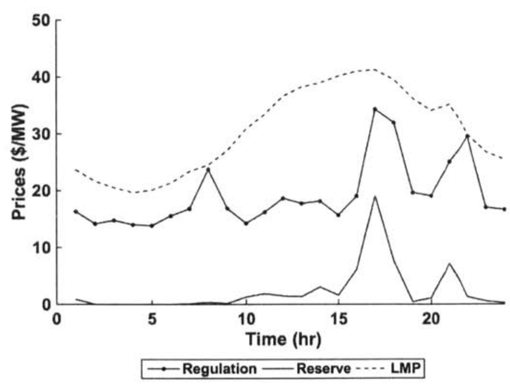
(b) June 19th, 2015 Price Case



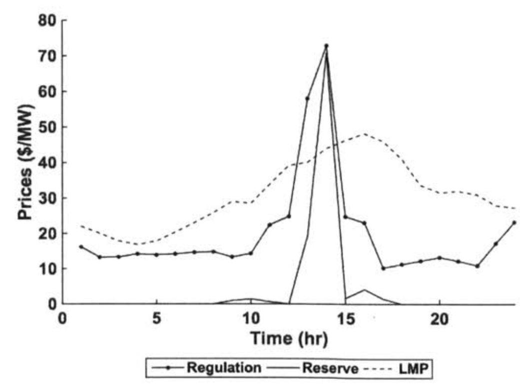
(c) Daily Average July Price Case



(d) July 20th, 2015 Price Case



(e) Daily Average August Price Case



(f) August 1st, 2014 Price Case

Figure 4-1: Price Inputs

Each month's scenarios use the same weather data, which includes typical solar radiation and outdoor dry-bulb temperature profiles in order to illustrate the effects of prices on optimal cooling and ancillary services' provision. In all three months, a gradual increase in LMPs is observed throughout the day. LMPs are lowest in the early morning and peak in the late afternoon; often, the hour ending 18 is considered to be the peak hour. Generally, regulation prices increase throughout the day as well for all three months; an early morning peak is observed in the average June price case. Regulation prices are higher than LMPs and generally range between \$20-\$80/MW for June and July and are lower than LMPs and range between \$10-\$30/MW for August. Thus, we would expect that the building will wish to provide regulation service when able for June and July representative days. Reserve prices are consistently low in the average month cases and present minor opportunities relative to regulation prices. A slight peak in reserve prices is observed in the late afternoon at the same time that daily LMPs are reaching an afternoon peak for all three months. In June and August, an increase in reserve prices is also observed at night after hour 21. On July 20th, LMPs, regulation and reserve prices are higher than the average price case. A large peak in regulation prices to nearly \$500/MW is observed in the late afternoon along with a peak in reserve prices. Regulation prices remain high throughout the night while reserve prices drop back down to low values. On June 19th, regulation and reserve prices spike in the afternoon on-peak hours. On August 1st, a hour 14 peak in regulation and reserve prices is observed where ancillary services prices exceed the LMP.

4.3 Results

Optimal cooling decisions were investigated for a 24-hour decision period where the objective function included energy costs, regulation revenue and spinning reserves revenue calculated using hourly-varying electricity LMPs, regulation prices and reserve prices. Optimal energy cost, regulation capacity provided, regulation revenue, spinning reserves provided and spinning reserves revenue for a 24-hour period under six different sets of 24-hour price conditions for LMPs and ancillary services are shown in 4.1 for one representative 'average' day and selected days where high ancillary services prices occur. A scaled up 20-weekday version of those values are shown in 5.1. The maximum hourly HVAC power used is the highest in the hottest month of July. Maximum hourly regulation capacity ranges from 2.4 to 3.2 kW and total daily regulation provided for one building ranges from 27 to 50 kW. Maximum hourly SR provided ranges from 1 to 6.8kW, where the highest hourly SR provision occured on June 19th where a few hours of high SR prices were observed. Less total SR was provided overall, with daily SR provided ranging from 7.6 to 45 kW. Because each individual building considered is able to provide at maximum 3.2 kW of regulation capacity, these small office buildings would not be eligible to individually participate in any of the ancillary services markets. PJM has the lowest minimum resource requirement of 0.1 MW which still far exceeds the maximum hourly regulation capability of a small office building as reported here. It will be necessary for small commercial buildings to use an aggregator whether through a third party or the utility in order to participate in ancillary services markets.

Total HVAC cooling power, and the optimal capacity used for regulation and reserve provision are shown for the three pricing cases in Figure 4-2. Provision of both ancillary services is fundamentally constrained by maximum HVAC cooling power. If no cooling is occurring, then ancillary services' provision cannot occur. Total HVAC power consumption is lower in June than in July and August. In all average monthly cases, pre-cooling of the building occurs before occupancy starts at 9AM. Cooling increases throughout the day, peaking in the mid-afternoon to avoid the highest electricity costs in the late afternoon and dropping at night when there are no more internal loads. In the average July, June 19th, June 20th and August 1st cases, the midday peak is likely also in anticipation of anticipating high regulation prices in the late afternoon. Ancillary services provision hourly patterns are different in the average June, July and August cases. In June, regulation and spinning reserves are consistently provided at 1-2 kW levels throughout the day. in July, regulation capacity is provided in the early morning and decreases until the late afternoon when

-	June Average	June 19	July Average	July 20	Aug. Average	Aug. 1
Max Hourly HVAC Power (kW)	3.57	8.17	7.74	9.08	5.63	4.84
Max Hourly Reg capacity (kW)	2.36	2.44	3.21	3.22	3.09	3.10
Max Hourly SR capacity (kW)	3.42	6.77	3.82	4.36	1.19	1.69
Total Daily Reg 1 building (kW)	39.65	26.67	50.90	49.02	38.90	43.20
Total daily SR 1 building (kW)	40.60	26.90	29.70	45.55	7.57	13.30
Optimal Energy Cost ($)	1.42	1.68	3.03	5.85	2.23	2.13
Optimal Regulation Revenue ($)	1.78	2.15	2.60	7.54	0.73	1.00
Optimal Spinning Reserve Revenue ($)	0.06	1.27	0.02	0.49	0.01	0.04
Reduction in Energy cost ($)	1.85	3.42	2.63	8.03	0.74	1.04
Optimal Operating Cost ($)	-0.43	-1.74	0.40	-2.18	1.50	1.09

Table 4.1: New England Daily Small Office Buildings' Ancillary Services Resource Potential

regulation prices are higher and reserves are only provided at midday when pre-cooling leaves flexibility for reserves to be offered despite the low reserves prices and when there is flexibility for reserves in the late evening due to cooling for regulation provision. In August, most regulation and spinning reserves provision only occurs until hour 19 and is in general lower compared to the other two summer months.

Total HVAC cooling power, and the optimal capacity used for regulation and reserve provision for three example days from June, July and August where high ancillary services prices are experienced during the day are also shown in Figure 4-2. Relative to the average July price case, overall HVAC power is higher in the July 20th case. Maximum HVAC power consumption exceeds 9 kW in early afternoon; in the average July prices case, HVAC power consumption reaches 7 kW. Levels of regulation and spinning reserves provided are generally higher in the July 20th case, with a noticeable peak in reserves at midday in hour 13. Despite the lack of occupancy after hour 19, it is optimal to consume power for cooling in order to provide both regulation and spinning reserves. In contrast, there is no ancillary services provision or HVAC cooling for that purpose observed on June 19th or August 1st price cases. However, in the June 19th price case, cooling and spinning reserves provision increase in hour 18 in response to a spike in spinning reserves price.

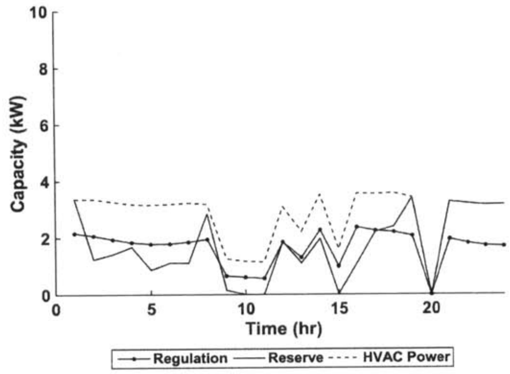
A few specific system responses of interest are described. In Figure 4-2b, a sharp increase in total cooling capacity and spinning receives occurs in response to a sharp peak in spinning reserves' price in hour 19 where building is cooled down to the lower thermal comfort limit as shown in Figure 4-3b . Cooling in hour 9 of July 20th to allow the building to move away from the upper thermal comfort limit so that regulation can be provided in hour 10 when regulation prices spike; while cooling is occurring in hour 9, reserves can be provided due to the movement of zone temperatures away from the upper thermal comfort limit. Simultaneous commitment of regulation and spinning reserves are possible such as after hour 18 of both July cases. Regulation prices greatly exceed LMPs starting at hour 15 and after occupancy ends, the building still provides cooling in order to provide regulation and spinning reserves after hour 18. As expected, when ancillary services prices are lower than LMPs as in the average August case, less regulation and reserves provision is observed in Figures 4-2e and 4-2f. A spike in reserves provision in Aug 1st price case is observed in response to a spike in spinning reserves price at hour 13.

Zonal temperature trajectories are depicted in Figure 4-3. In the average July and August price cases, after pre-cooling before occupancy, zonal temperatures hover at the upper thermal comfort limit in order to minimize the objective function for the majority of the occupied hours. Temperature trajectories climb after unoccupied hours terminate in the August price case. In June, because average evening ancillary services prices are higher compared to other months, cooling still occurs even after occupancy ends in the afternoon and temperature trajectories reflect those changes. In contrast, in the higher ancillary service prices cases (with the exception of August 1st), more cooling occurs throughout occupied hours so that ancillary services can be provided. Temperatures drop to the lower thermal comfort limits in the June 19th case so that ancillary service provision can occur at hour 18 and correspondingly, lower temperatures are observed.

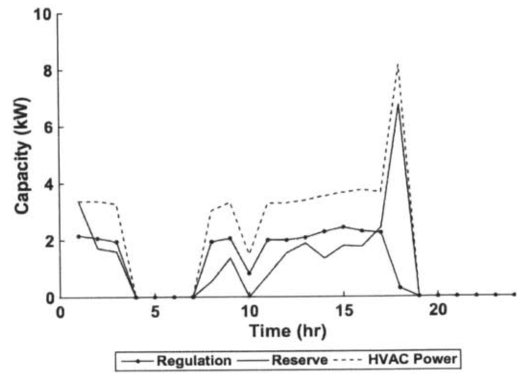
4.4 Conclusion

Though not currently allowed to participate in all U.S. ancillary services markets, all U.S. ISOs not allowing demand response participation have published plans on incorporation of demand-side resources into those markets in the near future and the use of pay-for-performance metrics. The market participation barriers to building entry are minimum resource sizes, telemetry and metering requirements and minimum performance requirements. It is likely that small and medium commercial buildings will need to participate through an aggregator, whether that is through the utility or a third-party since they will not meet the minimum resource requirement.

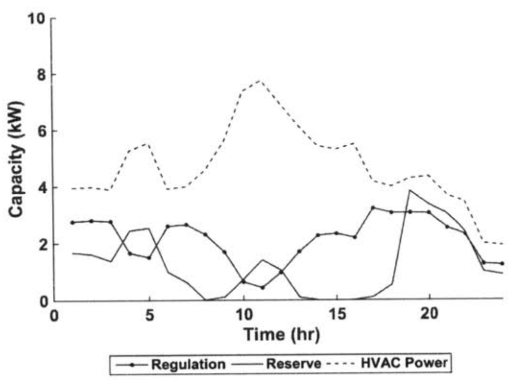
An co-optimization of energy consumption and ancillary services provision for a small office building is used where a building minimizes net operating cost subject to the building thermal response model presented in Chapter 3, system cooling limits, regulation provision and spinning reserves provision [9] . A VAV system and centralized chiller providing symmetric regulation are used. ISO-NE average monthly LMPs and ancillary service prices for the NEMA zone are used for June 2015, July 2015 and August 2014 and specific days are also used to investigate change in building behavior with peaks in ancillary service prices. 4.1 shows that the building chooses to provide ancillary services in each case, reduces overall operating cost and generates a positive net operating cost in the June average, June 19th and July 20th cases. The



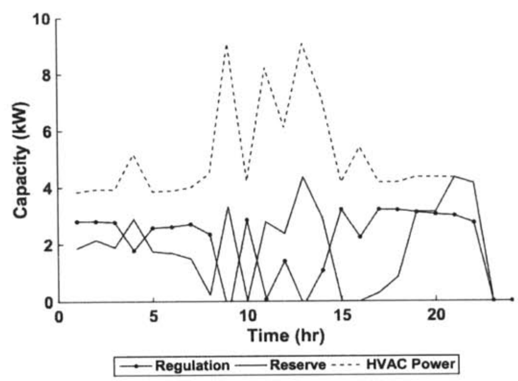
(a) Daily Average June Price Case



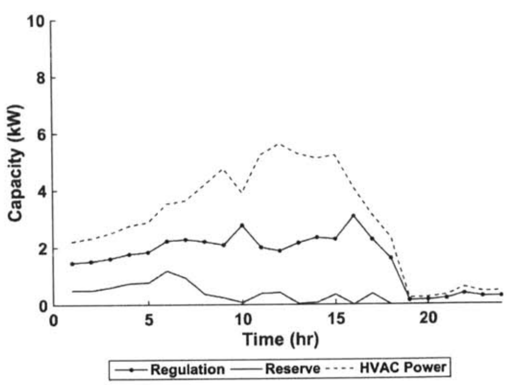
(b) June 23rd, 2015 Price Case



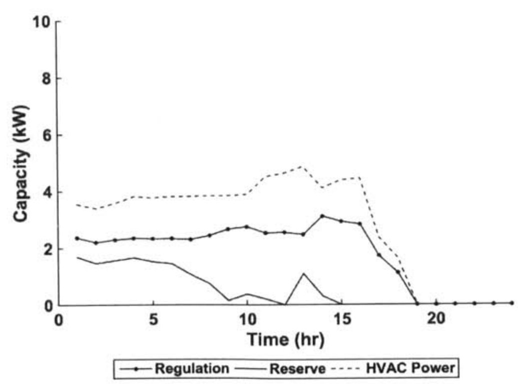
(c) Daily Average July Price Case



(d) July 20th, 2015 Price Case

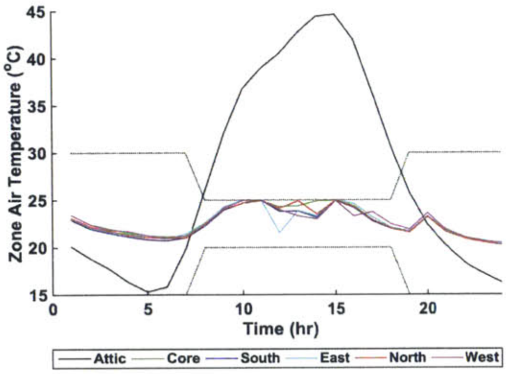


(e) Daily Average August Price Case

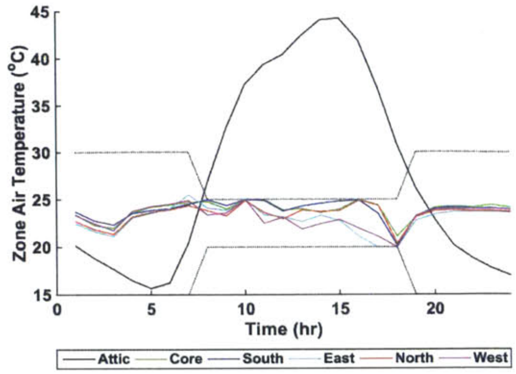


(f) August 1st, 2014 Price Case

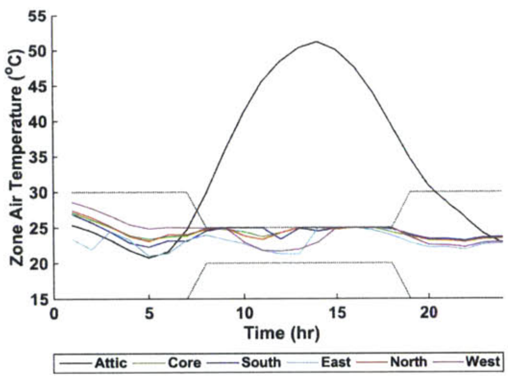
Figure 4-2: HVAC Power, Regulation Capacity and SR Capacity average June, July and August cases provided 40 kW, 51 kW and 39 kW of total daily regulation respectively and 41 kW, 30 kW and 7.6 kW of total daily spinning reserves respectively. When spikes in regulation or spinning reserves prices are observed, the building will consume electricity to cool during unoccupied hours for the purpose of providing ancillary services.



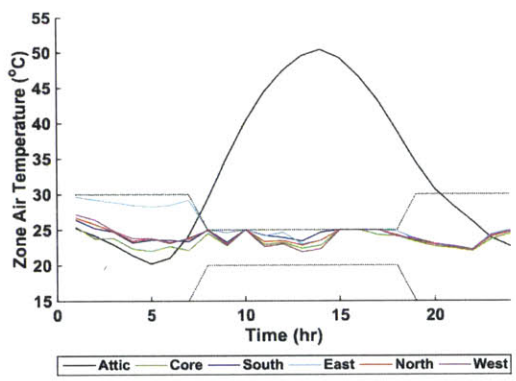
(a) Daily Average June Price Case



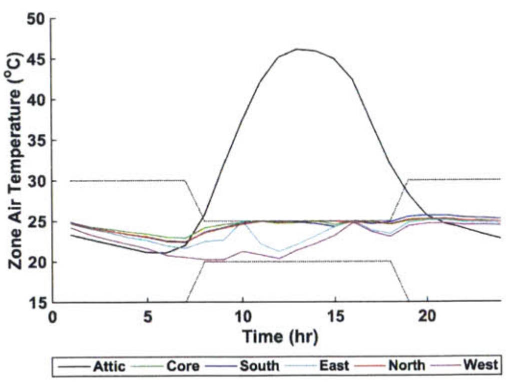
(b) June 23rd, 2015 Price Case



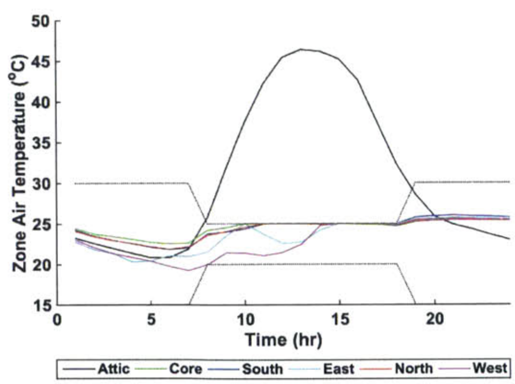
(c) Daily Average July Price Case



(d) July 20th, 2015 Price Case



(e) Daily Average August Price Case



(f) August 1st, 2014 Price Case

Figure 4-3: Zonal Temperature Trajectories

Chapter 5

Scaled Small Office Building Resource Potential in New England

5.1 Methodology

Previously, Chapter 4 described the optimal cooling strategies and resulting ancillary services provided by an individual small commercial building assuming average environmental conditions and different sets of wholesale electricity and ancillary services prices. The goal of this section is to estimate the scale of ancillary services provision and total energy costs' savings by a larger set of similarly sized commercial buildings within a geographic region using the Department of Energy's 2012 Commercial Buildings Energy Consumption Survey (CBECS). The methodology uses a straightforward scaling approach from CBECS weighting on similarly sized commercial office buildings.

In the previous chapter, individual buildings were able to provide daily totals of 20-50 kW of regulation, 7-45 kW of spinning reserves through average and example June, July and August prices and average environmental conditions. The individual buildings considered were small, commercial office reference buildings typically sized at 5,500 square feet.

In CBECS 2012, we scale individual building results up by regional, size and use data described in Table 5.1. CBECS is a national sample survey that seeks to describe the U.S. commercial building stock and includes all buildings where the majority of floorspace is used for commercial purposes [79]. CBECS includes office buildings in addition to schools, hospitals, stores, warehouses and other types of commercial property. The 2012 CBECS data was preliminarily released in 2014 and public-use microdata, which was used for the scaling, was released in June 2015. The key factors used in realizing the final weight by which to scale up optimal ancillary services provision on a typical day were the census division, principal building activity (PBA) and square footage. A map of CBECS census regions is depicted in Figure 5-1. The CBECS New England census division is well matched to the ISO-NE footprint including the majority of Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island and Vermont shown in Figure 5-2. Thus, individual building optimization performed using ISO-NE prices can be reasonably scaled by the New England census division region.

The CBECS database was filtered for buildings with a footprint at or below 5,500 square feet to match for building size. Further filtering by PBA ensures that the assumed office occupancy, lighting and overall internal gains schedule is a reasonable assumption. At the regional, PBA and square footage filter level, the buildings remaining in the CBECS database do not have central air handling units with VAV systems, like that modeled in the individual building in Chapter 4. Instead, the buildings have a packaged air conditioning unit, central air handling units with constant air volume systems or an unknown HVAC system. Furthermore, the actual building stock does not have a centralized chiller; this is not surprising since 5,500 sq. ft. buildings likely use packaged air conditioning units for cooling. In this case, the assumption that such buildings have a VAV system and are able to optimally control the cooling strategy as they would do with a building energy management system and necessary equipment is made. Because we wish to investigate the resource potential of the building type and stock, this is a necessary assumption. Note that the resulting resource potential estimates for ancillary services provision and operating cost reduction are then upper-bound estimates of maximum resource potential given the assumption that all buildings will have HVAC systems capable of ancillary services

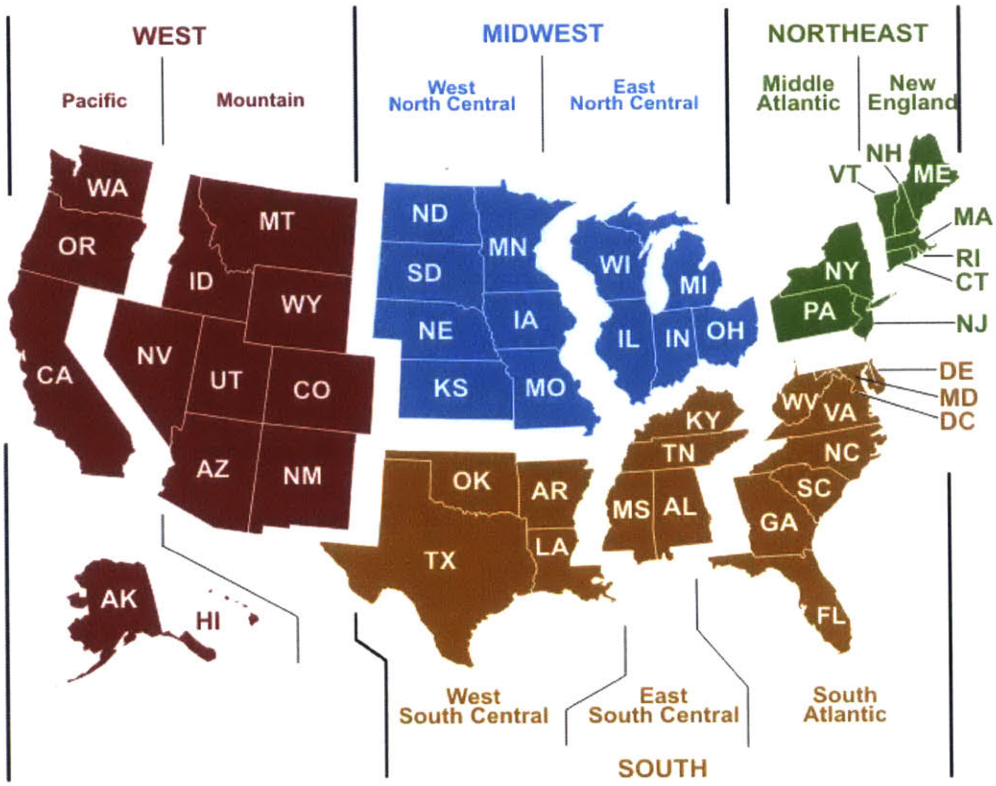


Figure 5-1: CBECS Census Divisions [24]

provision.

Nevertheless, after noting these differences, the resulting total New England small commercial office-type stock is 28,558 buildings. We reach the total building estimate by summing the final sampling weight for each sample building where the CBECS final sampling weight accounts for different probabilities of selection and survey participation rates and the final weight describes the number of buildings that the observed building represents in the actual population [78]. Individual daily or weekly/monthly optimal cooling and ancillary services provision are scaled by 28,558 to estimate the total provision of services by similar buildings in the New England building stock; total estimated daily ancillary services provision are in Table 5.1. The value of ancillary services is context dependent. It is necessary to compare ancillary services provided by buildings relative to regulation and reserve requirements in the ISO; requirements

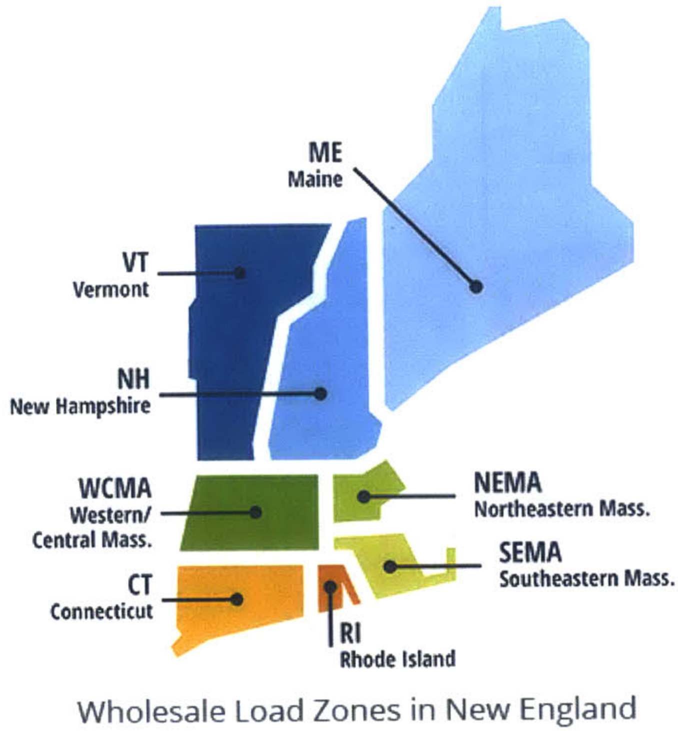


Figure 5-2: ISO-NE Load Zones [39]

are not constant throughout the day and needs may differ throughout seasons as well.

Regulation requirements in capacity and service MW are calculated based on historical control performance to meet ISO-NE, NERC and NPCC control standards and posted on the ISO-NE website [43]. The regulation market is then cleared for the required amounts. In March, 2015, ISO-NE changed the regulation market format to meet FERC 755 and the requirements changed accordingly. Bidders now bid both a capacity and service mileage price. Requirements are posted in capacity and service for each hour and day combination. Capacity represents capacity committed, and service describes MWs of regulation movement. For example, resources such as an energy storage device might bid in 1 MW of capacity but result in a much higher mileage or service movement of 10 MW to follow regulation signals; the fast-responding device is then compensated for both the capacity and the mileage movement. In our case, because hourly time steps are used, it is impossible to account for mileage movements within each hour. However, service and capacity components were both included in total regulation price to determine optimal cooling behavior. We provide a capacity estimate of building regulation provision without addressing an estimate of mileage.

The ten-minute total spinning reserve requirement (TMSR) differs daily; real-time 5 minute and finalized hourly reserve requirements are posted by ISO-NE. The TMSR requirement currently equals 50% of the largest first contingency or largest possible loss in the system [41]. In terms of general magnitude, ISO-NE reserve requirements do not vary greatly over the season or through the year since the first and second contingencies rarely change. However, there is some daily variation in TMSR requirements so we take the monthly average of TMSR requirements for an 24-hour profile for each month [19].

5.2 Results

Because neither the regionally-scaled estimates of regulation or TMSR provided by small office buildings exceeds hourly requirements, the total percentage of daily requirements provided by small office buildings can be calculated in Table 5.1. When scaled up over the same size, principal building activity and regional building stock, small commercial office buildings in the New England region are estimated to provide 7.4%, 9.5% and 7.3% of regulation required assuming average LMP and AS prices in the months of June, July and August respectively.The amount of regulation required that can be provided by the small commercial office buildings does not change dramatically between the summer months, but is highest in July and comparable in June and August. The other three price cases for those months estimate provision of between 5 to 8.1% of required regulation. In none of the individual hours does the capability of the small office buildings to provide regulation exceed the regulation required in Figure 5-3 below, and when aggregated over the day and month, the overall percentage of regulation that can be provided does not exceed 10%. More regulation is able to be provided in July compared to June and August because more cooling power is also used on an average July day. When more cooling is throughout the day, more flexibility to provide regulation is also available. As noted in [71], warmer climates show greater frequency regulation potential from chiller use due to the more frequent and higher utilization rates of chillers in those climates. Though not insignificant, we note that the ability of buildings to contribute to regulation requirements by up to 10% likely precludes the small office buildings from being price-makers in the regulation market. Furthermore, in this optimization, we are also assuming that the buildings are paying LMP in order to consume extra electricity to be able to provide it for regulation or spinning reserves; when buildings are providing ancillary services, the buildings are assumed to be have cleared their ancillary services bids.

-	June Average	June 19	July Average	July 20	Aug. Average	Aug. 1
Total daily regulation all buildings (MW)	1132	762	1450	1400	1111	1230
Total daily SR all buildings (MW)	1160	768	849	1301	216	381
% Daily Regulation Required	7.4	5.0	9.5	9.2	7.3	8.1
% Daily SR Required	8.0	5.3	4.8	7.3	1.1	1.9

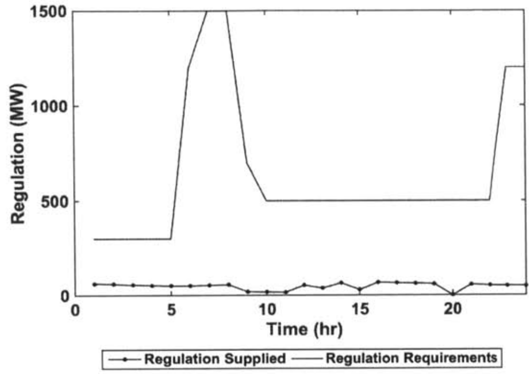
Table 5.1: New England region daily ancillary services resource potential from small office buildings by representative month

Spinning reserve requirements differ between months in ISO-NE as shown in Figure 5-4. Hourly reserves provided by small office buildings do not exceed requirements and small office buildings can provide between 1.1 to 8% of spinning reserve daily requirements. Low reserve prices in August contribute to little reserve provision by the building under those price cases. The largest amount of reserve provision occurs in the June average price case at 8%. In none of the cases does reserve provision exceed 8% of daily requirements and overall, buildings are satisfying less of the reserve requirements than the regulation requirements. This result is consistent with the appeal of higher regulation prices and less restrictive thermal interactions between regulation provision and the building.

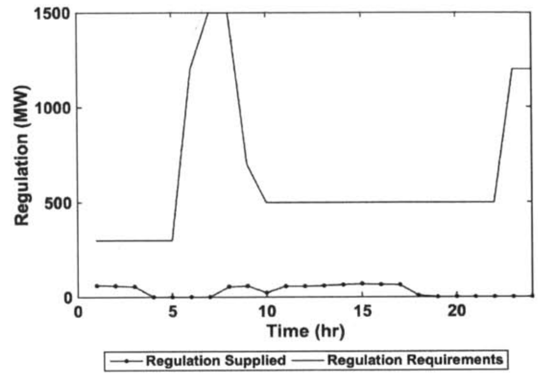
These estimates for regional small office building ancillary services provision provide an upper bound to what optimally cooled buildings might do when co-optimizing provision of ancillary services with electricity consumption. These estimates make assumptions about average LMPs and ancillary service prices as well as exposure to average environmental conditions. When scaling individual building cooling and service provision, the estimates assume a surveyed stock of similar buildings. Two assumptions dictate that these estimated ancillary services provision values are upper bounds: one is the 100% participation rate from the building stock, and the other is that all buildings within the stock contain necessary HVAC equipment to participate in service provision. In reality, participation rates are expected to be vastly lower when first starting and a variety of issues might be observed as further discussed in Chapter 6 and not all buildings within the stock will be technically capable of providing ancillary services.

5.3 Conclusion

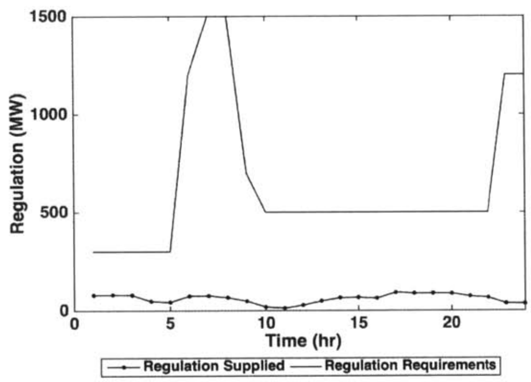
Assuming 100% participation rates from all small office buildings and assuming a day of average LMPs and ancillary services prices, the small office building stock can contribute up to ancillary services requirements New England. Ancillary services provision of 7.4%, 9.5% and 7.3% for daily regulation requirements and 8%, 4.8% and 1.1% for daily spinning reserve requirements are satisfied for the months of June, July and August respectively by the small office building stock. Despite the use of a range of ancillary service prices through the three summer months, the percentage of regulation requirements that can be satisfied by small office buildings in the New England region within each month does not vary greatly. Regulation provision is highest in July, followed by August and June, due to the increased use of HVAC systems for cooling during the hotter weather experienced in July. Spinning reserve is provided most frequently by small office buildings in June and least frequently in August due to high reserves prices in June and low reserves prices in August.



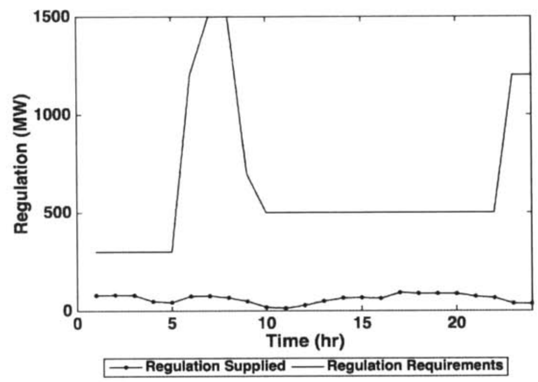
(a) Average June



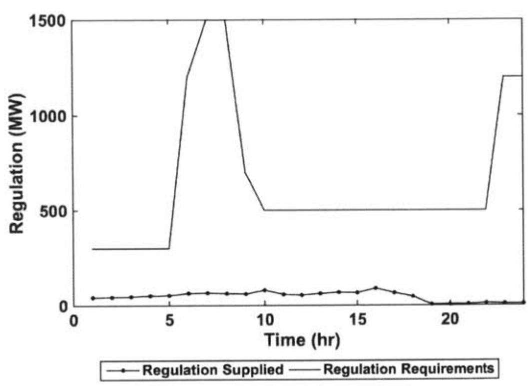
(b) June 19th, 2015



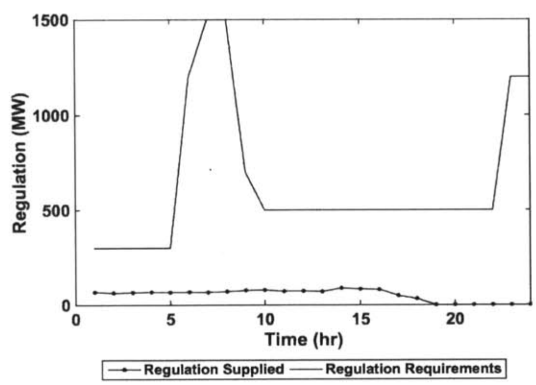
(c) Average July



(d) July 20th, 2015

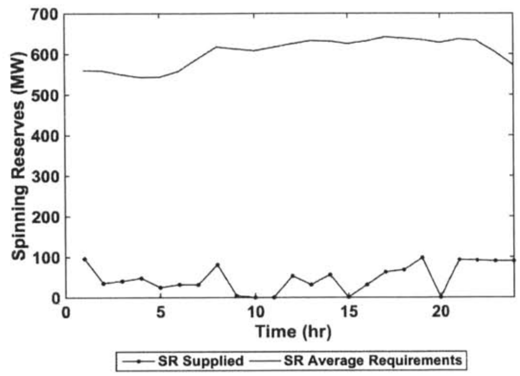


(e) Average August

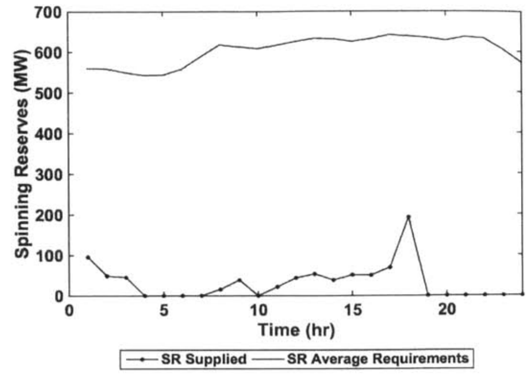


(f) August 1st, 2014

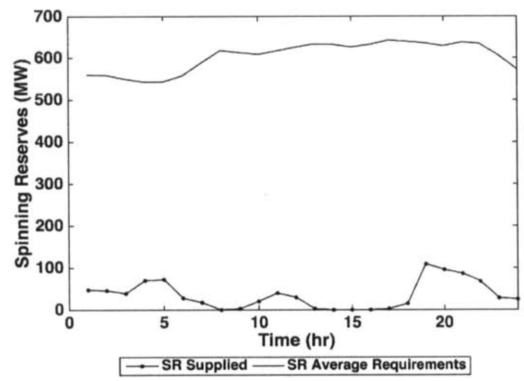
Figure 5-3: Daily Regulation Provided by New England Small Office Building Stock and ISO-NE Requirements



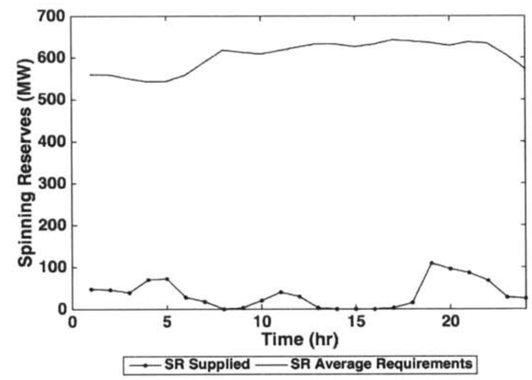
(a) Average June



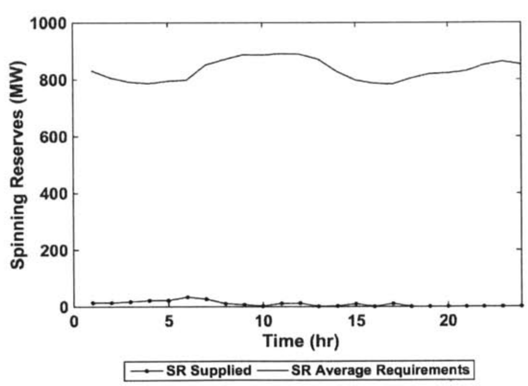
(b) June 19th, 2015



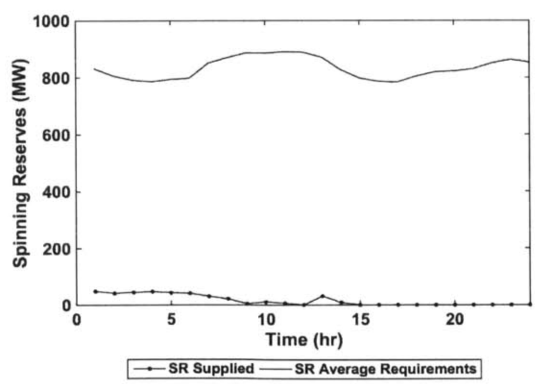
(c) Average July



(d) July 20th, 2015



(e) Average August



(f) August 1st, 2014

Figure 5-4: Daily Spinning Reserves Provided by New England Small Office Building Stock and ISO-NE Requirements

Chapter 6

Policy Implications

In this chapter, we discuss the economic implications of optimal cooling strategies and resulting ancillary services provision and energy costs in small office buildings and the attractiveness of participating in ancillary services markets for individual buildings. In Chapter 5, we saw that small office buildings may be able to provide a useful portion of regulation and spinning reserve needs in June, July and August. Assuming average LMPs and ancillary services prices and total participation, optimal cooling strategies result in the entire small office building stock in the New England region providing 7.4%, 9.5%, and 7.3% of regulation and 8%, 4.8% and 1.1% of spinning reserve requirements for the months of June, July and August respectively. Thus, ISO-NE and the electricity grid may view commercial buildings as a useful resource and method to satisfy ancillary services requirements without construction of new generation. However, individual buildings owners and operators may not find the proposition attractive under current ISO policies, ancillary service prices and electricity costs. In those cases, should the prioritization of demand-side resources be demanded, it is likely that policy instruments would need to be used to encourage building participation in ancillary services markets.

6.1 Individual Building Economic Perspective

Energy cost, revenue from provision of regulation and spinning reserves and net operating cost for an individual building for different sets of daily prices and environmental conditions were reported in Table 4.1. Assuming 20 on-peak weekdays in a month, an individual small office building's energy costs and ancillary services revenues are scaled up over the New England region in Table 6.1 below. Before discussing the economic implications of ancillary services provision on a building's energy costs, we note that the energy costs here account only for electricity consumed at the wholesale LMP. Unlike the retail rate, the LMP reflects the wholesale market clearing price of electricity at a location but does not include any additional network or regulated costs. Accordingly, though the optimal small office building energy costs in this work and CBECS reported monthly electricity expenditures are considered in parallel, a direct comparison cannot be made between the two sets of electricity costs.

Electricity costs under optimal operation and consideration of only the wholesale LMP will be lower than the retail rate that buildings experience in the current ISO-NE. Under optimized cooling conditions and actions, estimates energy costs for a scaled 20-weekday month of average June, July and August days energy costs are \$28.40, \$60.50 and \$44.70 respectively as shown in Table 6.1. The maximum month-scaled cost under any price case is \$117. Note that these values do not include weekend electricity costs; in commercial buildings, monthly weekend electricity costs are expected to be minor compared to monthly weekday electricity costs.

In comparison, the 2003 CBECS reports that office buildings in the Northeast region, totalling 14 billion square feet, spent \$16.9 billion for electricity. This yields an average of \$1.22 per square foot which is consistent with both the New England and Middle Atlantic sub-regions. For an assumed 5500 sq. foot building, electricity expenditures are expected to be in the range of \$6100 per year or on average \$510 per month. Since New England experiences experiences annual load peaks in the summer, the average summer month's electricity costs might be even greater than this average monthly cost.

The optimal monthly electricity cost estimates in Table 6.1 fall short of actual reported monthly electricity expenditures - there exists a difference by more than a factor of four up to over a factor of ten. This difference is largely due to the difference between wholesale LMPs and current electricity retail rates. When assuming that the cost of electricity is the wholesale LMP, electricity costs are 1-3 ¢/kWh. The EIA reports that the average retail price of electricity in New England in May 2015 was 15.06 ¢/kWh [80]. The retail rates of electricity are five to 15 times the wholesale cost of electricity; this difference is similar to the magnitude of differences between optimal monthly electricity costs and CBECS-reported monthly electricity costs. In addition, CBECS reported electricity expenditures likely do not result from a building stock that is operating under optimal control.

-	June Average	June 19	July Average	July 20	Aug. Average	Aug. 1
Optimal Energy Cost ($)	28.4	33.5	60.5	117.0	44.7	42.6
Optimal Regulation Revenue ($)	35.7	42.9	52.1	150.8	14.5	20.0
Optimal Spinning Reserve Revenue($)	1.3	25.4	0.4	9.8	0.2	0.9
Reduction in Energy Cost ($)	36.96	68.38	52.51	160.60	14.73	20.84
Optimal Operating Cost ($)	-8.6	-34.9	8.0	-43.6	29.9	21.7

Table 6.1: New England Estimated Monthly Weekday Energy Costs and Ancillary Services Revenue

Being able to provide ancillary services allows small office buildings to recoup the entirety of their energy costs under certain pricing and environmental conditions and if electricity cost does not include network costs and other regulated charges. Small buildings would be able to erase their electricity costs entirely under advantageous pricing conditions. In all cases, individual buildings choose to provide regulation and reserves; assuming a summer consisting of average June, July and August days, the building would see ancillary services revenue of $104 for the three summer months.

-	Floorspace (mil. sq. ft)	Electricity Costs (mil. $)	$/sq. ft	Annual costs for a 5500 sq. ft. building	Monthly costs for a 5500 sq. ft. building
Northeast	13899	16907	1.22	6082	507
New England	3430	4157	1.21	6060	505
Middle Atlantic	10469	12750	1.22	6089	507

Table 6.2: CBECS' New England Estimated Electricity Costs

Assuming an extreme case where monthly prices were all like those seen on July 20th, 2015, the building would earn $160 in ancillary services revenue in one month. Of course, it is unrealistic to expect either exact scenario; rather, we focus on the magnitude of the ancillary services revenue for the small office building which is the range of the low hundreds of dollars for three summer months. The summer describes the highest ancillary services provision potential from building cooling equipment time period. As noted, estimated revenue is lowest in August due to low regulation prices, and then lower in June compared to July despite similar magnitudes of ancillary services prices due to July's hotter weather and greater capacity for ancillary services provision. Though cooling may be occasionally necessary in the building in unseasonably warm months of April, May or September and October, it is reasonable to assume that the majority of revenue would be from June to August.

In general, the building will provide ancillary services when excess capacity is available or when the value of ancillary services exceeds the cost of electricity. Average revenue from ancillary services provision may be low, but there exists the potential for higher revenue when ancillary services prices peak. However, it is necessary to note that as electricity costs climb, the attractiveness of providing ancillary services wanes. Once again, this work assumes that the building pays the wholesale LMP instead of the retail rate for electricity consumption. In practice, retail rates can be in the range of five to 15 times the average LMP. Therefore, unlike the results depicted in Figures 5-3 and 5-4 where buildings provide ancillary services throughout much of the day, a building paying retail rates for electricity may find that provision of ancillary services is not attractive for the majority of the day, but only price spikes occur.

In order to provide ancillary services such as regulation and spinning reserves, buildings will necessarily incur costs. These may include installation of a VAV system and building automation system (BAS). In this optimization, we assume that the office building has a VAV HVAC system where the chiller or fan can be used to provide regulation service. Should the building not have a VAV system to begin with, the full installation of a VAV system is estimated to cost 4.25-5.25 $/square feet for an estimated upfront cost of $\$23-29,000$ for a $5,500$ square foot building [21]. In contrast, a 10 ton commercial packaged rooftop heat pump costs costs $5,000-$6,000 and a CAV system is estimated to cost 3.50 $/square feet for an estimated $\$19,000$ upfront cost[3, 21]. Frequently, a BAS is used to implement and control cooling strategy. At the minimum, a system needs a variable frequency drive for the chiller and controller software in order to be able to provide regulation through a chiller as demonstrated in [71]. Just the BAS is estimated to commonly cost between $50-$300 [1] and [71] cites a similar range of $500 for the chiller controller. Additionally, installation of power meter and engineering work could cost approximately $2,000 and $2,500 respectively for chiller use in regulation provision [71].

Assuming installation of a BAS, VAV system, power meter and any additional engineering work, the total upfront installation costs for a small office building total $\$28,000-34,000$. Assuming that the building already has a VAV system which accounts for the majority of the previously mentioned cost, the upfront cost for acquiring and installing telemetry and metering equipment and a BAS still totals $\$4,800$ or greater. Summer ancillary services revenues in the range of the low hundreds of dollars would suggest a very unrealistic payback period of multiple decades. In New England, the revenue from ancillary services provision is not enough by itself to make a strong economic case for small office buildings to invest in HVAC system and associated technology and control systems solely for the purpose of providing ancillary services.

Though we conclude that there is not an economic argument for small office buildings in New England to invest in metering, a BAS, or a VAV system solely purpose of providing ancillary services, there are other persuasive reasons to invest in the aforementioned systems. After all, VAV systems are already commonly used in commercial buildings due to energy cost savings from higher system energy-efficiency. CBECS 2012 reports that 24% of small (5,000 ft^2), 26% of medium (5,000-54,000 ft^2) and 63% of large commercial buildings contain VAV HVAC systems [75]. New buildings would likely already seriously consider the advantages of a VAV system in HVAC system selection even if they were not considering ancillary services provision. Metering and BAS installation costs are necessary to incur in order to participate in other demand response programs as well. Building operators may be interested in using a BAS to minimize total electricity costs even if ancillary services are not initially provided.

Furthermore, even when specifically discussing the provision of ancillary services, there can be great variance in potential revenue depending on the building type, size and location. Just as the equipment needed and system costs for each building are somewhat unique; ancillary services potential changes with building size, type and market location. In [71], a jump from \$1,850 to \$11,470 in potential frequency regulation annual revenue using chillers' extra capacity occurs when considering a large office building in PJM compared to a small office building in PJM assuming a constant estimated regulation price of \$77/MWh. Our projected annual regulation revenue in the low hundreds of dollars for a small commercial is not shocking in this context. Furthermore, [71] reports estimated potential frequency regulation annual revenue of \$770 and \$4,540 for a medium and large ERCOT office building respectively. Market potential can also vary greatly with geographic location. Future work should fit a thermal response model and run a similar optimization for different geographic locations and ISO market prices.

6.2 Encouraging Individual Building Participation

The economic perspective of a small office building considering co-optimizing energy consumption and ancillary services provision is presented in the section above. When prices are favorable, buildings are incentivized to consume additional electricity at strategic times in order to be able to provide ancillary services at later periods. In this work, when paying wholesale electricity costs and not including network or other regulated charges, buildings would be able to reduce their energy costs and even generate a net positive daily total operating cost in certain summer price scenarios and environmental conditions. The presence of a positive economic argument is necessary and a minimum qualification for buildings to consider participating in ancillary services markets.

Other policies and initiatives can increase the appeal of participation in ancillary services markets. The decrease in cost of enabling technologies facilitates greater building participation. A variety of financial instruments aimed at reducing the upfront costs of entering ancillary services markets such as subsidies or credits on enabling equipment or upon participation can be used. Utility programs, ISO-programs and federal or state-level incentives to lower the upfront costs of telemetry and metering installation costs increase program attractiveness. Increased ease of use, cost-effectiveness and popularity of BAS systems and a trend towards increased controllability of HVAC systems enables buildings to operate their systems with more flexibility.

There remains a tension associated with where the burden of service provision lies. More controllability on the building-end allows customization of building optimal behavior; however, decreased controllability often occurs with increased ease of use. When the burden of determining when and how much to participate is left on the end-user, it adds an additional barrier to participation. Greater participation rates may occur if the program appears as a less user-involved and more automated process; as long as no thermal comfort constraints are violated, the building operator and tenants will likely have little opposition to participation in providing electricity services. However, building operators may value the option to revert to a well-understood method of system operation if uncertain environmental or building system conditions are encountered. The trade-off between controllability and accessibility is not entirely clear but may evolve into the the divide between more user-driven demand response programs and more automatic demand response programs [47].

6.3 The Principal-Agent Problem

As noted before, the estimates discussed thus far are optimistic given the assumption of 100% participation rate from buildings within the stock. In reality, lower participation rates are expected due to a variety of factors. One can note a possible parallel in the winding road that adoption of energy efficiency measures has taken since the 1970s. Despite the strong economic case for energy efficiency investments, there have been slower rates of energy efficiency adoption than initially anticipated. Economists have attributed the energy efficiency gap, or under-utilization of energy efficiency, to both energy-related externalities and imperfect information [56, 50].

Another large contributing factor responsible for a lower than ideal participation rate in energy efficiency and also in the potential future participation of buildings in provision of ancillary services is the principal-agent problem. The principal-agent problem (also known as the landlord-tenant problem) describes a situation where the principal (or tenant) pays the agent (or landlord) for a service, such as use of a property. However, the principal and agent have divergent goals and asymmetric information, resulting in a suboptimal situation. In the case of optimal HVAC operation of the building, we can note that if the HVAC operator has incentives in line with the entity paying energy costs, then there is no principal-agent problem. This is the case assumed in the optimization. However, if the tenant is not responsible for the energy costs, the tenant is not encouraged to provide ancillary services when beneficial; rather, the tenant may favor a consistent, reliable and less profitable cooling schedule such as the use of cooling power during occupied hours without pre-cooling. From CBECS 2012, 47% of small office buildings are tenant-occupied, 41% are owner occupied and the remaining 12% are mixed occupancy. Thus, a significant portion of small commercial buildings may experience the principal-agent problem in which tenants have little interest in allowing participation in ancillary services markets. One would argue that in theory, enforcing comfort constraints would alleviate tenants' and owners' concerns, but this is not always the case. When rental revenue accounts for the majority of the building's income stream, owners may not always be so amenable to risking discomfort or loss of tenancy. This concern increases the importance of a flexible contract; should owners feel that tenants are uncomfortable with operating conditions or that specific days' operating conditions are too uncertain, they can opt out of service provision for a reliable control strategy.

6.4 Ancillary Services Market Barriers to Participation

As noted in Chapter 5, individual small office buildings are able to provide at maximum 3.2 kW of regulation capacity in an hour. These office buildings are far too small to be eligible for participation in ancillary services markets in all the ISOs where the lowest minimum resource requirement of 0.1 MW is currently in PJM. It would be necessary for small commercial buildings to use an aggregator through a third party or the utility in order to participate in ancillary services markets. Larger commercial buildings may meet the minimum resource requirements and be able to bid as an individual participant. Should other ISOs adopt smaller minimum resource sizes, it may encourage more commercial buildings, small or large, to participate in markets as individual participants or through aggregators. Additional ISO rules that impinge building operator flexibility (e.g. MISO's "must-offer" rules for DRR-Type II resources) are likely to discourage participation from buildings. Building operators and owners may prioritize consistency and ease of operation over optimal cooling routines; some buildings, especially smaller commercial buildings, may not have an operator to adjust and monitor different cooling strategies. There may be emergency cases where operators or the owner wishes to 'opt-out' of participation in any ancillary services markets; if operators are locked in, the appeal of participation is likely very low. Telemetry and revenue metering requirements are present in all ISOs for participation in ancillary services markets. As noted, there are upfront costs associated with installation of highly accurate meters that are able to communicate quickly with the ISO. Overall, when considering the magnitudes of costs and revenues associated with small office buildings, it is necessary to consider the integration of clear avenues for aggregator-enabled building participation.

6.5 Building Industry

Potential policy options that can be used to encourage participation from the building industry are the use of customer outreach and engagement programs, educational programs, development of labeling and certification programs, and standard setting. The building industry places an emphasis on the ability of individual owners to make independent decisions. Industry organizations such as the Building Owners and Managers Association (BOMA), a federation of 91 BOMA U.S. associations and other international affiliates promote the development of international building codes but place strong emphasis on the use of voluntary codes instead of mandatory standards. Thus, the integration of ancillary services' market participation into voluntary standards or certification programs can encourage greater participation from the building sector. BOMA consistently takes positions supporting voluntary actions; voluntary benchmarking using consistent energy management software is recommended and voluntary, incentive-based programs for carbon reduction are encouraged. This attitude is consistent with the fact that in the building industry, individual owners and operators may choose to act independently and without much oversight, leading to a wide range of potential interest.

However, the ownership of commercial buildings can be be quite concentrated. In [72], authors note that the top 50 retail property owners own 28% of enclosed retail spaces and the top 50 retail property managers manage 32% of enclosed retail spaces. If key players in optimal cooling decisions for a large swathe of commercial properties can be persuaded to participate in ancillary services markets, an increasing trend in building participation may be non-linear. Finally, information sharing and clear promotion of utility or ISO-level ancillary services demand response programs through building industry stakeholders such as BOMA, the US Green Building Council, ASHRAE, utility companies and local and state-level government contribute to an encouraging environment in which buildings can participate in providing a range of electricity services.

6.6 Conclusion

From the perspective of a small office building in New England, potential revenue in June to August from provision of ancillary services is not sufficiently large to motivate the building to invest in necessary control, metering, VAV systems and other necessary equipment. Potential ancillary services' revenues by themselves are not a sufficiently strong driver for small office building participation in ancillary services markets. However, minimization of energy costs, long-term efficiency investments and interest in participation in other demand response programs may drive deployment of the same enabling technology that would allow the building to also provide ancillary services. Additionally, individual buildings can be encouraged to participate in provision of electricity services with continuing decrease in costs of enabling technologies. The principal-agent problem in which non-owner building occupants and building owners face different incentives to participate must be addressed.

Finally, increasing rates of participation in ancillary services demand response programs from individual building owners and the building industry could be achieved if demand response programs address commercial buildings as a specific end-user. Ancillary services participation programs need to address building-specific concerns such as program controllability and convenience. An appropriate balance between controllability and accessibility in ancillary services' program design will suitably match the interests of a building owner who wishes to retain control over building operations but be able to conveniently participate in services provision. With the case of energy efficiency, analysts have noted that the gap is heterogeneous and targeted policies for energy efficiency adoption are more effective than general subsidies [5]. Similarly, targeted policies for demand response participants such as different types of commercial building owners may be useful in increasing participation rates. Compounded with the fact that in this work, individual small office buildings cannot reach the minimum resource sizes needed to participate in ISO-NE and other ISO ancillary services markets, targeted policies aimed at increasing availability of clear aggregator-enabled building participation avenues are essential.

Appendix A

Additional Tables

Quantile	Attic	Core	Perim1	Perim2	Perim3	Perim4
1	0.01	0	0	0.01	0	0.02
25	0.25	0.03	0.02	0.02	0.05	0.11
50	0.79	0.04	0.03	0.05	0.07	0.18
75	1.52	0.05	0.05	0.08	0.10	0.20
99	3.23	0.07	0.09	0.16	0.12	0.25

Table A.1: June Prediction Errors (degrees C)

Quantile	Attic	Core	Perim1	Perim2	Perim3	Perim4
1	0.0	0.7	0.2	0.4	0	0.7
25	0.8	4.7	1.8	0.6	6.7	3.9
50	2.6	6.9	3.5	1.8	9.8	6.6
75	5.0	9.2	5.2	2.7	13.4	7.5
99	10.7	11.8	10.0	5.6	15.6	9.4

Table A.2: June RMSE Quantiles (%)

Quantile	Attic	Core	Perim1	Perim2	Perim3	Perim4
1	0.07	0	0	0	0	0
25	0.57	0.08	0.07	0.08	0.03	0.10
50	1.19	0.14	0.23	0.21	0.11	0.29
75	2.45	0.26	0.41	0.31	0.28	0.34
99	3.85	0.33	0.47	0.37	0.35	0.50

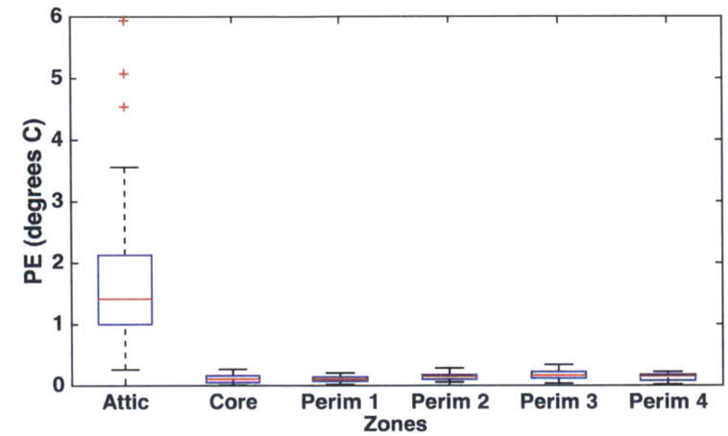
Table A.3: August Prediction Errors (degrees C)

Quantile	Attic	Core	Perim1	Perim2	Perim3	Perim4
1	0.3	0.1	0.0	0	0.1	0
25	2.3	1.8	1.2	1.5	0.7	1.5
50	4.7	3.3	4.1	4.1	2.4	4.4
75	9.8	6.0	7.2	6.1	6.1	5.1
99	15.4	7.7	8.2	7.3	7.5	7.6

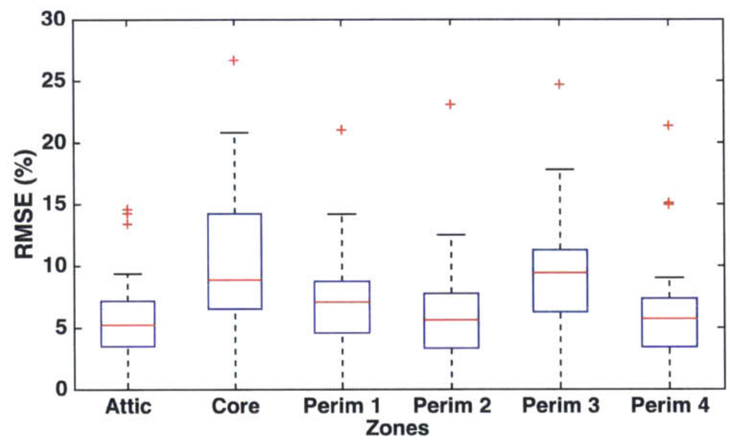
Table A.4: August RMSE Quantiles (%)

Appendix B

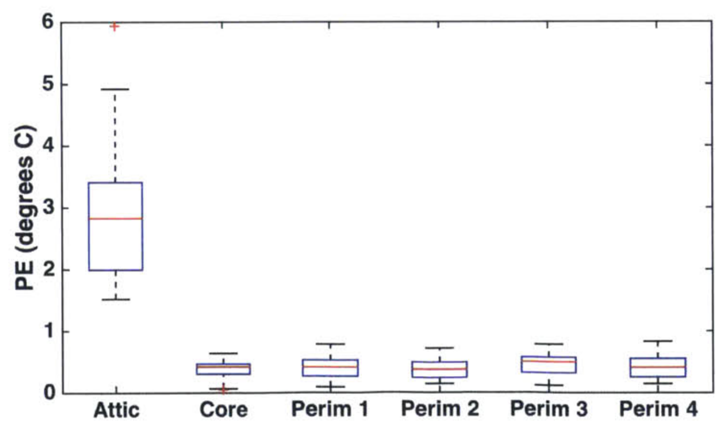
Additional Figures



(a) PE

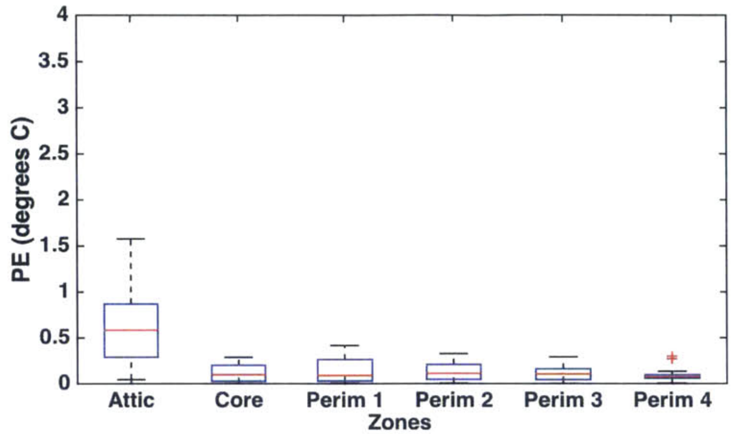


(b) RMSE

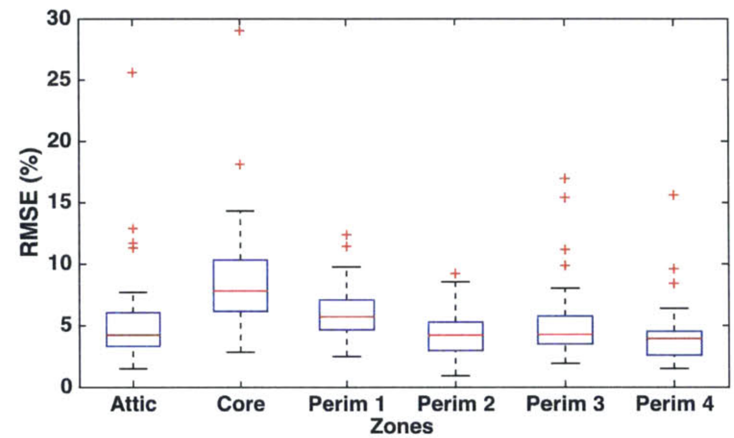


(c) 99^{th} Percentile of Prediction Error

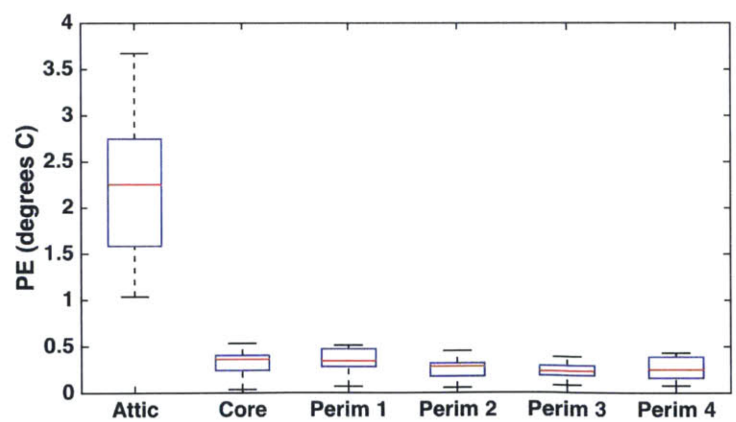
Figure B-1: Distributions of PE and RMSE for June



(a) PE



(b) RMSE



(c) 99^{th} Percentile of Prediction Error

Figure B-2: Distributions of PE and RMSE for August

Appendix C

Multi-zonal Inverse CRTF Model MATLAB Code

C.1 runiCRTFprocess.m

```
% Main file to run coefficient-fitting function 'findCoefficients.m' and
% prediction of temperatures function'predictTemps.m'

% Initialize variables
Tpredict=[];
Torig_predict=[];
Tx=[];
Qrad=[];
Qconv=[];
QWindowSolar=[];
QSurfaceSolar=[];
QGroundTemp=[];
all_PE=[];

for n=4 % n is the model order
    train_start= 744 % hour of most recent training set value
    train_length= 744-(n+1) % number of hours in training set

    % Fit inverse CRTF model coefficients for July
    [coefficients, coefficients_format, optimizationTime] = ...
        findCoefficients('8_12JulyP7',train_start, ...
        train_length,n,6,'6_16output.mat');
```

```
first=0; % for formatting of multi-day sets of data
for b = 10 % validation day in test month. e.g.  b = 10 is July 10th
    test_start= b*24; % hour of most recent test set value
    test_length=24;
    % Validate inverse CRTF model by predicting temperatures
    [Tpredict_s, Torig_predict_s, Tx_s, Qrad_s, Qconv_s, ...
        QWindowSolar_s, QSurfaceSolar_s, QGroundTemp_s,rel_RMSE, PE,...
        quant_PE, quant_RMSE] = predictTemps('8_12JulyNP',...
        coefficients, test_start,test_length,n,6);
    % Save output
    first=first+1;
    if first>1
        Tx=vertcat(Tx,Tx_s(n+1:end,:));
        Tpredict=vertcat(Tpredict,Tpredict_s);
        Torig_predict=vertcat(Torig_predict,Torig_predict_s(n+1:end,:));
        Qrad=vertcat(Qrad,Qrad_s(n+1:end,:));
        Qconv=vertcat(Qconv,Qconv_s(n+1:end,:));
        QWindowSolar=vertcat(QWindowSolar,QWindowSolar_s(n+1:end,:));
        QSurfaceSolar=vertcat(QSurfaceSolar,QSurfaceSolar_s(n+1:end,:));
        QGroundTemp=vertcat(QGroundTemp,QGroundTemp_s(n+1:end,:));
        all_PE=vertcat(all_PE,PE(n+1:end,:));
    end
    if first==1
        Tx=vertcat(Tx,Tx_s);
        Tpredict=vertcat(Tpredict,Tpredict_s);
        Torig_predict=vertcat(Torig_predict,Torig_predict_s);
        Qrad=vertcat(Qrad,Qrad_s);
        Qconv=vertcat(Qconv,Qconv_s);
        QWindowSolar=vertcat(QWindowSolar,QWindowSolar_s);
        QSurfaceSolar=vertcat(QSurfaceSolar,QSurfaceSolar_s);
        QGroundTemp=vertcat(QGroundTemp,QGroundTemp_s);
        all_PE=vertcat(all_PE,PE);
    end

    % Save error output
    all_rel_RMSE(b,:)=rel_RMSE;
    PE_99(b,:)=quant_PE(5,:);
    PE_75(b,:)=quant_PE(4,:);
    PE_50(b,:)=quant_PE(3,:);
    PE_25(b,:)=quant_PE(2,:);
    PE_1(b,:)=quant_PE(1,:);
    RMSE_99(b,:)=quant_RMSE(5,:);
    RMSE_75(b,:)=quant_RMSE(4,:);
    RMSE_50(b,:)=quant_RMSE(3,:);
```

```
        RMSE_25(b,:)=quant_RMSE(2,:);
        RMSE_1(b,:)=quant_RMSE(1,:);
    end
end
```

C.2 findCoefficients.m

```
function [coefficients, coefficients_format, opttime] = ...
    findCoefficients(inputData, k, d, n, m, outputData )

% Calculate multi-zonal inverse CRTF coefficients
%
% INPUTS
% inputData: EnergyPlus output file that has been imported into MATLAB and
% saved as a .mat file. Do not change original zone names.
% k: hour index of the most recent (last) hour we want. e.g. k=150 uses
% hour 150 as the most recent observation
% d: number of observations to include: e.g. d = 10 and k = 150 results in
% a data set of hours [140,150]
% n: model order, or number of lag terms
% m: number of non-zonal variables. e.g. m=6 includes Qconv, Qrad,
% Qwindow_solar, Qsurface_solar, Tground and Tx
% outputData: name to save output .mat file under
%
% OUTPUTS
% coefficients: coefficients in one vector
% coefficients_format: coefficients formatted for optimization code
% opttime: the time it takes to run the constrained linear regression


%% Load data
S=load(inputData);

%% Subset out variables of interest
ZoneTemps=subsetStructure(S,'MeanAirTemperature');
AmbientTemps=subsetStructure(S,'OutdoorDryBulb');
ConvHeatGain=subsetStructure(S,'TotalInternalConvectiveHeatGainRate');
TotHeatGain=subsetStructure(S,'TotalInternalTotalHeatGainRate');
RadHeatGain=subsetStructure(S,'TotalInternalRadiantHeatGainRate');
WindowSolar=subsetStructure(S,'TransmittedSolar');
SurfaceSolar=subsetStructure(S,'OutsideFaceSolar');
GroundTemp=subsetStructure(S,'GroundTemperature');
%% Define any parameters needed
```

```
numZones=length(fieldnames(ZoneTemps)); % number of zones
namesRad= fieldnames(RadHeatGain);
namesTemp=fieldnames(ZoneTemps);
namesAmb=fieldnames(AmbientTemps);
namesConv=fieldnames(ConvHeatGain);
namesTot=fieldnames(TotHeatGain);
namesWindSolar=fieldnames(WindowSolar);
namesSurfSolar=fieldnames(SurfaceSolar);

%% Format 'b' vector
% Dimensions: numZones*d by 1
% The format is multiple sets of d temperature values for each zone
% stacked up in a column
tempTime=zeros(numZones*d,1);
for i=1:numZones %for each zone
    tempTime((i-1)*d+1:i*d) = ...
        ZoneTemps.(namesTemp{i})(k-d+1:k); % Get historical temperatures
end
b=tempTime;

%% Format 'A' matrix
% For every matrix "row"  of A, we iterate through a zone. Each row
% in Atotal = [ Zeros_Bef A11 A12 Zeros_Aft A13]
% c = current zone
% Atotal dimensions: z*d by ((z*n) + (m*(n+1))*z + (z-1)*z
% # columns in A = (#A11 cols + #A12 cols)*z + #A13 cols

Atotal= zeros(numZones*d,((numZones*n) + (m*(n+1)))*numZones + (numZones-1)*numZones);

for c = 1:numZones

    % Matrix of zeros for number of zones before current zone
    Zeros_Bef=zeros(d,((numZones*n) + (m*(n+1)))*(c-1));
    % Matrix of zeros for number of zones after current zone
    Zeros_Aft=zeros(d,((numZones*n) + (m*(n+1)))*(numZones-c)); %0 colums for c=z

    % Submatrix A11
    % Contents: past zonal temperatures for all zones
    % Dimensions: d by n*z
    listNames=fieldnames(ZoneTemps);
    A11=zeros(d,numZones*n);
    tempA11=zeros(d,n); % Placeholder for each zone

    for i=1:numZones % For each zone's column within submatrix
        for j=1:n % each of 'n' lag terms
```

```
        tempA11(1:d,j) = ZoneTemps.(listNames{i})(k-d-(j-1):k-1-(j-1));
    end
    A11(1:d,(i-1)*n+1:i*n)=tempA11;
end


% Submatrix A12
% Contents: ambient temperatures, heat fluxes, solar fluxes, ground
% temperatures
% Dimensions: d by (n+1)*m
tempNonZonal=zeros(d,m*(n+1));
tempA12=zeros(d,n+1); % Placeholder for each variable
nonZonal=struct('nonzonal',{AmbientTemps,RadHeatGain, ConvHeatGain, ...
    WindowSolar,SurfaceSolar,GroundTemp});

for i=1:m  % For each of 'm' factors
    for j=1:n+1
        tempstruct=nonZonal(i).nonzonal;
        % relevant structure fieldnames
        listNames=fieldnames(tempstruct);
        tempA12(1:d,j) = tempstruct.(listNames{c})(k-d-(j-2):k-(j-1));
    end
    tempNonZonal(1:d,(i-1)*(n+1)+1:i*(n+1))=tempA12;
end
A12=tempNonZonal;

% Submatrix A13
% Contents: current zonal temperatures at t=k
% Dimensions: d by (z-1) * z
% Note: for each zone, you need a coefficient for all other (z-1) zones
A13=zeros(d,(numZones-1)*numZones);
tempCurrent=zeros(d,numZones-1);
tempA13=zeros(d,1);
listNames=fieldnames(ZoneTemps);
counter=1;
    for j=1:numZones % each of the other zones
        if j~=c % if not the current zone
            tempA13 = ZoneTemps.(listNames{j})(k-d+1:k);
            tempCurrent(1:d,counter)= tempA13;
            counter=counter+1;
        end
    end
A13(1:d,1+(c-1)*(numZones-1):c*(numZones-1) ) =tempCurrent;
A13=-1*A13;
AtotalTemp=[Zeros_Bef A11 A12 Zeros_Aft A13];
```

```
    Atotal(d*(c-1)+1:c*d,:)=AtotalTemp;
end


%% Set up constraint matrices
% Adjacency matrix describes relationships between adjacent zones.
% -1 = 'self' zone
% 1 = adjacent
% 0 = not adjacent
adjacencyMatrix=[-1 1 1 1 1 1;
                 1 -1 1 1 1 1;
                 1 1 -1 1 0 1;
                 1 1 1 -1 1 0;
                 1 1 0 1 -1 1;
                 1 1 1 0 1 -1 ];
widthZonal=n*numZones+(n+1)*m; % for easier notation later
dim=(widthZonal)*numZones+(numZones-1)*numZones; % number of columns


% Enforces the steady state temperature constraint
constraintMatrix=zeros(numZones,(widthZonal)*numZones+(numZones-1)*numZones);

for i=1:numZones % for each zone/row
    tempConstraint=ones(1,widthZonal); % needs to be inside loop to reset
    tempConstraint(n*numZones+n+2:n*numZones+(n+1)*m)=0; %Qrad, Qconv
        % Don't include non-adjacent zones
    for j=1:numZones
        if adjacencyMatrix(i,j)==0
            tempConstraint((j-1)*n+1:j*n)=0;
        end
    end
    constraintMatrix(i,(i-1)*widthZonal+1:i*widthZonal)=tempConstraint;
    tempConstraintCurr=ones(1,(numZones-1));
    for l=1:numZones
        if adjacencyMatrix(i,l)==0
            if i>l
                tempConstraintCurr(l)=0;
            end
            if i<l
                tempConstraintCurr(l-1)=0;
            end
        end
    end
    constraintMatrix(i, widthZonal*numZones + (i-1)*(numZones-1)+1 :...
        widthZonal*numZones + i*(numZones-1) )=tempConstraintCurr;
```

```
end
constraintMatrix((widthZonal)*numZones+1:(widthZonal)*numZones+...
    (numZones-1)*numZones)=1;


% Enforces adjacency relationships
% adjacencyMatrix row order: 1 = attic, 2= core, 3=perim 1, 4= perim 2,
% 5=perim 3, 6=perim 4
% Each row is 1 zone, columns are corresponding zones
% e.g. row 1 (zone 1) is adjacent to all other zones (since the attic is
% above and touching all zones). Row 3 (zone 3) is adjacent to zone 1, 2,
% 4, and 6, etc.
% Note: the numbered order here matches up with the listNames order of
% zones
[E_add g_add]=nonAdjacencyConstraints(adjacencyMatrix,widthZonal,n,dim ,m);
[E_curr_add, g_curr_add] = nonAdjacencyConstraintsCurr(adjacencyMatrix, ...
    widthZonal,n,dim ,m, numZones);

%[E_rmZI_add, g_rmZI_add] = rmZonalInteraction(widthZonal,n,dim,m,numZones);


% Set up final constraint matrices
E=vertcat(constraintMatrix,E_add, E_curr_add);
E_cm=ones(numZones,1);
g=vertcat(E_cm, g_add, g_curr_add);

%% Solve for coefficients
tic
coefficients=lsqlin(Atotal,b,[],[],E,g);
opttime=toc;

%% Formatting/post-processing
% Formatting coefficients
all=length(coefficients); % All coefficients
%time=k coefficients
current=coefficients(all-((numZones-1)*numZones)+1 : all);
% coefficients for time = k-d-1 to k-1
nonCurrent=coefficients(1:all-((numZones-1)*numZones));
widthZonal=(numZones*n)+m*(n+1);
for i=1:numZones
    coefficients_format(1:widthZonal,i)=nonCurrent( widthZonal*(i-1)+1: ...
        widthZonal*i ); %chunks of 21
    coefficients_format(widthZonal+1: widthZonal+(numZones-1),i)= ...
```

```
        -1*current( (i-1)*(numZones-1)+1:(i)*(numZones-1));
    %negative bc sign switching for time t=k
end
% Re-ordering zonal coefficients
for i= 1:numZones
    coefficients_format((i-1)*n+1: i*n,:) = flipud(...
        coefficients_format((i-1)*n+1: i*n,:));
end
% re-ordering non-zonal coefficients (Tx, Qrad, Qconv, Qws, Qss, Tground)
for i= 1:m
    coefficients_format((i-1)*(n+1)+(numZones*n+1): ...
       i*(n+1)+(numZones*n),:) = flipud( ...
       coefficients_format((i-1)*(n+1)+(numZones*n+1): ...
       i*(n+1)+(numZones*n),:) );
end
clear m n k d
save(outputData)
end
```

C.3 predictTemps.m

```
function [Tpredict, Torig_predict, Tx, QRad, QConv, QWindowSolar, ...
    QSurfaceSolar,TGround, rel_RMSE, error, quant_PE, quant_RMSE]...
    = predictTemps(inputData,coefficients, k, d, n, m)

% Predict 24 hour ahead temperatures (1 day)
% INPUTS
% inputData: EnergyPlus output file that has been imported into MATLAB and
% saved as a .mat file. Do not change original zone names.
% k: hour index of the most recent (last) hour we want. e.g. k=150 uses
% hour 150 as the most recent observation
% d: number of observations to include: e.g. d = 10 and k = 150 results in
% a data set of hours [140,150]
% n: model order, or number of lag terms
% m: number of non-zonal variables. e.g. m=6 includes Qconv, Qrad,
% Note: same model order must be used for training and testing sets
%
% OUTPUTS
% Tpredict: temperatures predicted using inverse coefficients
% Torig_predict: EnergyPlus simulation temperature values (deg C)
% Tx: Outdoor dry-bulb temperature (deg C)
% QRad: Radiative heat flux (W)
% QConv: Convective heat flux (W)
```

```
% QWindowSolar: Solar flux absorbed through the window (W)
% QSurfaceSolar: Solar radiation incident on opaque surfaces (W)
% Tground: Ground temperature (deg C)
% rel_RMSE: the averaged relative RMSE by zone for all hours
% error: Prediction error (deg C)
% quant_PE: Prediction error quantiles
% quant_RMSE: RMSE quantiles

%% Load in data
S=load(inputData);
ZoneTemps=subsetStructure(S,'MeanAirTemperature');
AmbientTemps=subsetStructure(S,'OutdoorDryBulb');
ConvHeatGain=subsetStructure(S,'TotalInternalConvectiveHeatGainRate');
ConvHeatGainOrig=ConvHeatGain;
TotHeatGain=subsetStructure(S,'TotalInternalTotalHeatGainRate');
RadHeatGain=subsetStructure(S,'TotalInternalRadiantHeatGainRate');
InfilVol= subsetStructure(S,'InfiltrationVolumeFlowRateStandardDensity');
ACH=subsetStructure(S,'AirChange'); %added on for single zone
WindowSolar=subsetStructure(S,'TransmittedSolar');
SurfaceSolar=subsetStructure(S,'OutsideFaceSolar');
GroundTemp=subsetStructure(S,'GroundTemperature');

namesRad= fieldnames(RadHeatGain);
namesTemp=fieldnames(ZoneTemps); %get fieldnames of temperatures
namesAmb=fieldnames(AmbientTemps);
namesConv=fieldnames(ConvHeatGain);
namesTot=fieldnames(TotHeatGain);
namesInfil=fieldnames(InfilVol);
namesACH=fieldnames(ACH);
namesWindSolar=fieldnames(WindowSolar);
namesSurfSolar=fieldnames(SurfaceSolar);
namesGround=fieldnames(GroundTemp);

str=date;

%% Define any parameters needed
numZones=length(fieldnames(ZoneTemps)); % total number of zones
all=length(coefficients); %total number of coefficients

V_room      = [720.19 456.46 346.02 205.26 346.02 205.26]; % m3
rho_air     = 1.2; %kg/m3
cp_air      = 1005; % J/kgK

for i=1:numZones
    initializeTemps(:,i) = ZoneTemps.(namesTemp{i})(k-d-n+1:k-d);
```

```
end
% Formatting coefficients
current=coefficients(all-((numZones-1)*numZones)+1 : all); %time =k coefficients
nonCurrent=coefficients(1:all-((numZones-1)*numZones));



%% For the first case, where you need at least 1 value from known previous
% data instead of using all predicted values in the lagged terms
% Predicted temp is deteremined from all E+ or a combo of E+ and previously
% predicted values
zonalTemps=zeros(n,numZones);
p=1;
%the  number of previous temps we have, equal to 'n' model order
numInitialObs=length(initializeTemps(:,1));
storedPred=[];

for t = k-d +1 : k-d+n % first 'n' terms
    t;
    prevInd= t-(k-d); %previous index , so n or n+1 or etc.
    numPrevNeeded= n+1-prevInd; %number of previous observations you need
    numPredNeeded = n- numPrevNeeded; %number of predicted observations needed

    for i=1:numZones
        Qconvective_orig(i)= ConvHeatGain.(namesConv{i})(t);
    end
    % Call iterative function to predict temperature, has option to include
    % infiltration calculations
    if t==k-d+1
        y0=initializeTemps(end,:);
    end
    if t>k-d+1
        y0=zonalTemps(p-1,:);
    end

    y=findTemps1(y0)'; % final predicted temperatures for each zone

    % Format predicted temperatures and data
    zonalTemps(p,:)=y;
    storedPred=zonalTemps;
    p=p+1;
end

%% For the second case, where previously predicted zonal temperatures are
% used for all 'lagged' terms
```

```
for t= k-d +n +1  : k
t;
    for i=1:numZones
        Qconvective_orig(i)= ConvHeatGain.(namesConv{i})(t);
    end
    y0=zonalTemps(p-1,:); %lagged terms needed
    y=findTemps2(y0)'; %iterative function call
    %format output data
    zonalTemps(p,:)=y;
    p=p+1;
end

%% Format output data
Tpredict = zonalTemps; % Dimensions are d x numZones
for i=1:numZones
    % Dimensions are d + lag terms x numZones
    Torig_predict(:,i)=ZoneTemps.(namesTemp{i})((k-(d+n)+1):k);
    % Dimensions: d + n x numZones
    Tx(:,i)=AmbientTemps.(namesAmb{i})((k-(d+n)+1):k);
    QConv(:,i)=ConvHeatGain.(namesConv{i})((k-(d+n)+1):k);
    QRad(:,i)=RadHeatGain.(namesRad{i})((k-(d+n)+1):k);
    QWindowSolar(:,i)=WindowSolar.(namesWindSolar{i})((k-(d+n)+1):k);
    QSurfaceSolar(:,i)=SurfaceSolar.(namesSurfSolar{i})((k-(d+n)+1):k);
    TGround(:,i)=GroundTemp.(namesGround{i})((k-(d+n)+1):k);
end
% Format coefficients
 widthZonal=(numZones*n)+m*(n+1);
for i=1:numZones
    coefficients_format(1:widthZonal,i)=nonCurrent( widthZonal*(i-1)+1:...
        widthZonal*i ); %chunks of 21
    coefficients_format(widthZonal+1: widthZonal+(numZones-1),i)= ...
        -1*current( (i-1)*(numZones-1)+1:(i)*(numZones-1));
end
for i= 1:numZones
    coefficients_format((i-1)*n+1: i*n,:) = flipud(...
        coefficients_format((i-1)*n+1: i*n,:));
end
for i= 1:m
    coefficients_format((i-1)*(n+1)+(numZones*n+1): ...
        i*(n+1)+(numZones*n),:) = flipud( coefficients_format((i-1)*...
        (n+1)+(numZones*n+1): i*(n+1)+(numZones*n),:) );
end
%% Error calculation
%E+ simulated values
simul_orig=zeros(d,numZones);
```

```
for i=1:numZones
    simul_orig(:,i)=ZoneTemps.(namesTemp{i})(k-d+1:k);
end

% ymax-ymin, for each zone
diff=repmat(max(simul_orig)-min(simul_orig), d,1);
% errors
orig_error=simul_orig-zonalTemps;
error=abs(simul_orig-zonalTemps);
rel_e= sqrt((error./diff).^2);
rel_RMSE=sqrt(mean((error./diff).^2));
quant_PE=quantile(error, [0.01 0.25 0.5 0.75 0.99]);
quant_RMSE=quantile(rel_e, [0.01 0.25 0.5 0.75 0.99]);
%% Plots
figure
for i=1:6 %each zone
    subplot(3,2,i)
    plot(ZoneTemps.(namesTemp{i})(k-d+1:k))
    hold on
    plot(zonalTemps(:,i),'--')
    title(strcat('actual and predicted train and n=',num2str(n),'zone: ',num2str(i)))
    set(gca,'FontSize',14,'FontWeight','bold')
    title(strcat('Zone: ',num2str(i)))
end
legend('Actual','Predicted','Location','SouthEast');
legend boxoff
str=date;
set(gcf, 'Units', 'Inches', 'Position', [0, 0, 8, 6.125], 'PaperUnits', ...
'Inches', 'PaperSize', [8, 6.125])
saveas(gcf,strcat('zone',num2str(i),'lag',num2str(n),str,'.png'))

%% Iterative functions that can include infiltration (commented out)

% First function for first case of using at least some E+ historical values
% in lagged terms
function result = findTemps1(y)
    zonalTempAs=y;
    for i=1:numZones
        oneZoneTemp = y(i) ;   % initializing data (lagged terms)
        ConvHeatGainCalc(i) = ConvHeatGainOrig.(namesConv{i})(t);%+ ...
%                   InfilVol.(namesInfil{i})(t)*rho_air*cp_air*...
%                   (AmbientTemps.(namesAmb{i})(t)-oneZoneTemp);
%               ConvHeatGain.(namesConv{i})(t) = ConvHeatGainCalc(i);
    end
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Format C
% C dimensions: z by z
tempZoneCurrent=zeros(numZones,numZones);
for i=1:numZones % for each row
    for j=1:numZones %each column
        tempZoneCurrent(i,j)=1; %current zone position gets a 1
        if j<i % before current zone
            tempZoneCurrent(i,j)=current( (i-1)*(numZones-1)+1+(j-1));
        end
        if j>i  % after current zone
            tempZoneCurrent(i,j)=current( (i-1)*(numZones-1)+1+j-2 ) ;
        end
    end
end
C=tempZoneCurrent;


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Format D for current time step

% second dimension matches up with noncurrent
D=zeros(numZones,(numZones*n+(n+1)*m)*numZones);
    for c=1:numZones %each row is a zone
        Zeros_Bef=zeros(1,((numZones*n) + (m*(n+1)))*(c-1));
        Zeros_Aft=zeros(1,((numZones*n) + (m*(n+1)))*(numZones-c));
        %submatrix A11
        % dimensions: 1 by n*z
        listNames=fieldnames(ZoneTemps); %names
        A11=zeros(1,numZones*n);
            for b=1:numZones %each n column chunk per zone
                nonPredObs=initializeTemps( numInitialObs - ...
                    numPrevNeeded +1 :numInitialObs,b);
                if length(storedPred) > 0
                    predObs= storedPred(1:1+(numPredNeeded-1), b);
                end
                if length(storedPred)==0
                    predObs=[];
                end
                tempA11=vertcat( nonPredObs, predObs);
                A11(1,(b-1)*n+1:b*n)= fliplr( tempA11' );
            end

        % Submatrix A12, non zonal temperatures
        % Dimensions: 1 by (n+1)*m
```

```
        A12=zeros(1,m*(n+1));
        nonZonal=struct('nonzonal',{AmbientTemps,RadHeatGain, ...
            ConvHeatGain, WindowSolar, SurfaceSolar, GroundTemp});
        for i=1:m  %submatrix for each non-zonal variable
            tempstruct=nonZonal(i).nonzonal;
            listNames=fieldnames(tempstruct);%relevant structure
            A12(1,(i-1)*(n+1)+1:i*(n+1)) = flipud(tempstruct.(listNames{c})(t-n : t));
        end
        D(c,:) =[Zeros_Bef A11 A12 Zeros_Aft];
    end
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Predict Temperatures
predictInitialTemps=C\(D*nonCurrent); %1 value per zone calculated here
result=predictInitialTemps;
end


% Second function for second case of using all previously predicted
% temperatures in lagged terms
function result = findTemps2(y)
    zonalTempAs=y;
    for i=1:numZones
        oneZoneTemp = y(i) ;
        ConvHeatGainCalc(i) = ConvHeatGainOrig.(namesConv{i})(t); %+ ...
%                 InfilVol.(namesInfil{i})(t)*rho_air*cp_air*...
%                 (AmbientTemps.(namesAmb{i})(t)-oneZoneTemp);
%             ConvHeatGain.(namesConv{i})(t) = ConvHeatGainCalc(i);
    end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    % Format C
    % C dimensions: z by z
    tempZoneCurrent=zeros(numZones,numZones);
    for i=1:numZones % for each row
        for j=1:numZones %each column
            tempZoneCurrent(i,j)=1; %current zone position gets a 1
            if j<i % before current zone
                tempZoneCurrent(i,j)=current( (i-1)*(numZones-1)+1+(j-1)) ;
            end
            if j>i  % after current zone
                tempZoneCurrent(i,j)=current( (i-1)*(numZones-1)+1+j-2 ) ;
            end
        end
    end
    C=tempZoneCurrent;
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    % Format D for current time step
    D=zeros(numZones,(numZones*n+(n+1)*m)*numZones);
    for c=1:numZones
        Zeros_Bef=zeros(1,((numZones*n) + (m*(n+1)))*(c-1));
        Zeros_Aft=zeros(1,((numZones*n) + (m*(n+1)))*(numZones-c));
        %submatrix A11
        % dimensions: 1 by n*z
        listNames=fieldnames(ZoneTemps); %names
        A11=zeros(1,numZones*n);
        for i=1:numZones
            A11(1,(i-1)*n+1:i*n)= fliplr( zonalTemps( t -(k-d+n): ...
                t -(k-d+n) + n-1,i)' );
        end
        % Submatrix A12, non zonal temperatures
        % Dimensions: 1 by (n+1)*m
        A12=zeros(1,m*(n+1));
        nonZonal=struct('nonzonal',{AmbientTemps,RadHeatGain,...
            ConvHeatGain, WindowSolar, SurfaceSolar,GroundTemp});
        for i=1:m
            tempstruct=nonZonal(i).nonzonal;
            listNames=fieldnames(tempstruct);%relevant structure
            A12(1,(i-1)*(n+1)+1:i*(n+1)) = flipud(...
                tempstruct.(listNames{c})(t-n : t));
        end
        D(c,:) =[Zeros_Bef A11 A12 Zeros_Aft];
    end
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    %predict Temperatures
    predictInitialTemps=C\(D*nonCurrent);
    result=predictInitialTemps;
    end

end
```

C.4 Other Functions

C.4.1 subsetStructure.m

```
function [outputStruct] = subsetStructure(inputStruct,inputString)
% Function takes out the desired sections of a structure that contain the
```

```
% 'inputString' phrase. To subset out all Zonal Temperatures for instance
    inputStringSet=strcat('\w+',inputString,'\w+');
    inputStringSetFinal = char(inputStringSet);
    %the fieldnames that match the inputString we received
    matchStr=regexp(strjoin(fieldnames(inputStruct),', '),inputStringSetFinal,'match');
    f= fieldnames(inputStruct);
    %list of fieldnames to remove and not include
    toRemove=f(~ismember(f,matchStr));
    %remove the fieldnames
    outputStruct=rmfield(inputStruct,[toRemove]);
end
```

C.4.2 nonAdjacencyConstraints.m

```
function [constraint_add, value_add] = nonAdjacencyConstraints(adjacencyMatrix,widthZonal,...
n, dim,m)
% Generates constraint matrices (E,G) in E x =g accounting for adjacency
% relationships in previous (t=k-d-1 to k-1) time steps
% Inputs: adjacency matrix
% Outputs: matrix to add vertically onto constraints matrix, matrix to add
% vertically onto constraints equal matrix (E, g) addends
totalNumNonAdj= sum(sum(adjacencyMatrix(:,:)==0));
sizeAdj=size(adjacencyMatrix);
length=sizeAdj(1);
width=sizeAdj(2);
constraint_add=zeros(totalNumNonAdj,dim);
counter=1;
for i=1:length  %focused zone
    numNonAdjacent=sum(adjacencyMatrix(i,:)==0); %number of non adjacent zones
        for j=1:width
            if adjacencyMatrix(i,j)==0  %if not adjacent
                for m=1:n
                    constraint_add(counter, (i-1)*widthZonal + n*(j-1) + m)=1;
                    counter=counter+1;
                end
            end
        end
end
value_add=zeros(totalNumNonAdj*n,1);
end
```

C.4.3 nonAdjacencyConstraintsCurr.m

```
function [constraint_add, value_add] = nonAdjacencyConstraintsCurr(adjacencyMatrix,...
widthZonal,n, dim,~, numZones)
% Generates constraint matrices (E,G) in E x =g accounting for adjacency
% relationships for t=k current time step
% Inputs: adjacency matrix
% Outputs: matrix to add vertically onto constraints matrix, matrix to add
% vertically onto constraints equal matrix (E, g) addends
totalNumNonAdj= sum(sum(adjacencyMatrix(:,:)==0));
sizeAdj=size(adjacencyMatrix);
length=sizeAdj(1);
width=sizeAdj(2);
constraint_add=zeros(totalNumNonAdj,dim);
counter=1;
for i=1:length
    numNonAdjacent=sum(adjacencyMatrix(i,:)==0); % number of non adjacent zones
    nonAdjZoneCounter=0; % counts which of the nonadjacent zones you are in
    adjZoneCounter=0;
        for j=1:width %adjacent zones
            if j<i
                if adjacencyMatrix(i,j)~=0
                    nonAdjZoneCounter=nonAdjZoneCounter+1;
                end
                if adjacencyMatrix(i,j)==0  %if not adjacent
                adjZoneCounter=adjZoneCounter+1;
                constraint_add(counter, (widthZonal)*numZones + ((i-1)*(numZones-1) ) +...
                adjZoneCounter+nonAdjZoneCounter)=1;
                counter=counter+1;
                end
            end
            if j>i
                if adjacencyMatrix(i,j)~=0
                    nonAdjZoneCounter=nonAdjZoneCounter+1;
                end
                if adjacencyMatrix(i,j)==0  % not adjacent
                adjZoneCounter=adjZoneCounter+1;
                constraint_add(counter, (widthZonal)*numZones + ((i-1)*(numZones-1) ) +...
                adjZoneCounter+nonAdjZoneCounter)=1;
                    counter=counter+1;
                end
            end
        end
end
value_add=zeros(totalNumNonAdj,1);
end
```

Appendix D

Small Office Multi-Zonal Inverse CRTF Model Coefficients

D.1 June Monthly Coefficients

-	Attic	Core	Perim 1	Perim 2	Perim 3	Perim 4
T_1^{k-1}	-0.00054	0.00246	0.0103	0.00886	0.01025	0.01176
T_1^{k-2}	0.15734	-0.00051	-0.00714	-0.01215	-0.00863	-0.01078
T_1^{k-3}	-0.67456	-0.00257	-0.00164	0.0118	0.00273	0.00301
T_1^{k-4}	1.41345	0.0042	-0.01038	-0.01182	-0.00856	-0.00418
T_2^{k-1}	0.01443	-0.25492	-0.00834	-0.00766	-0.01148	-0.00562
T_2^{k-2}	-0.00414	0.44254	-0.01377	-0.01114	-0.00978	-0.01037
T_2^{k-3}	0.0005	0.57942	-0.00419	-0.00187	-0.00398	-0.00613
T_2^{k-4}	-0.0277	0.1232	0.02388	0.01891	0.02328	0.01973
T_3^{k-1}	-0.18185	-0.0159	-0.22015	-0.0043	0	-0.00065
T_3^{k-2}	0.22272	-0.00956	0.24837	-0.00532	0	-0.00546
T_3^{k-3}	0.02946	-0.0021	0.41203	-0.00512	0	-0.01007
T_3^{k-4}	-0.12439	0.05328	0.48507	0.00829	0	0.01133
T_4^{k-1}	0.00874	-0.00373	-0.00003	-0.21147	0.00022	0
T_4^{k-2}	-0.02517	-0.00764	-0.00765	0.26367	-0.00892	0
T_4^{k-3}	0.00295	-0.00197	-0.00242	0.40656	-0.0025	0

T_4^{k-4}	0.0003	0.02665	0.01064	0.46012	0.01161	0
T_5^{k-1}	0.00188	-0.01111	0	-0.00505	-0.20809	-0.00178
T_5^{k-2}	-0.02563	-0.01436	0	-0.0099	0.25868	-0.01257
T_5^{k-3}	-0.02489	-0.0016	0	0.00119	0.40981	-0.00218
T_5^{k-4}	0.05668	0.05338	0	0.01903	0.4609	0.01913
T_6^{k-1}	-0.0056	-0.0066	-0.00361	0	-0.00379	-0.22248
T_6^{k-2}	0.01601	-0.00785	-0.00636	0	-0.00603	0.25917
T_6^{k-3}	-0.03188	-0.00118	-0.00289	0	-0.00307	0.4056
T_6^{k-4}	0.03806	0.02548	0.01082	0	0.01015	0.47726
T_x^{k}	-0.01056	0.00324	0.00646	0.01097	0.00704	0.0079
T_x^{k-1}	0.08002	-0.0099	-0.01776	-0.02148	-0.01963	-0.02501
T_x^{k-2}	-0.18621	0.00692	-0.01401	-0.00944	-0.0046	0.00651
T_x^{k-3}	-0.20204	-0.00184	0.01263	0.00734	0.00857	-0.00059
T_x^{k-4}	0.41335	0.00637	0.02199	0.02156	0.01688	0.01955
Q_{rad}^{k}	0	0	0.00004	0.00003	0.00002	0.00004
Q_{rad}^{k-1}	0.00001	-0.0003	-0.00024	-0.00049	-0.00029	-0.00049
Q_{rad}^{k-2}	0	-0.00005	-0.00014	-0.00023	-0.00018	-0.00015
$Q_{rad}d^{k-3}$	0	0.00001	-0.00007	-0.00005	0.00005	-0.00023
Q_{rad}^{k-4}	-0.00005	0.00053	0.00057	0.00095	0.00054	0.00104
Q_{conv}^{k}	0.00001	0.00009	0.00013	0.00017	0.00012	0.00019
Q_{conv}^{k-1}	-0.00004	-0.00043	-0.00034	-0.00051	-0.00034	-0.00051
Q_{conv}^{k-2}	0.00017	-0.00038	-0.00042	-0.00058	-0.0004	-0.00059
Q_{conv}^{k-3}	-0.00045	0.00015	-0.00017	-0.00021	-0.00015	-0.00023
Q_{conv}^{k-4}	0.00044	0.00078	0.00096	0.00142	0.00096	0.00142
Q_{ws}^{k}	0	0	-0.00014	0.00008	0.00015	0.00016
Q_{ws}^{k-1}	0	0	-0.00029	-0.00046	-0.00004	-0.00043
Q_{ws}^{k-2}	-0.00001	0	-0.00007	-0.00031	-0.00026	-0.00012
Q_{ws}^{k-3}	0.00003	0	0.00003	-0.00004	0.00011	0.00046
Q_{ws}^{k-4}	0	0	0.0007	0.00105	0.0003	0.00107
Q_{ss}^{k}	0	0	0.00001	0	-0.00001	-0.00001

Q_{ss}^{k-1}	0.00001	0	0.00002	0.00001	-0.00001	0.00001
Q_{ss}^{k-2}	-0.00001	0	0	0	0.00001	-0.00002
Q_{ss}^{k-3}	-0.00001	0	0.00001	0.00002	0.00001	-0.00002
Q_{ss}^{k-4}	0.00003	0	-0.00004	-0.00003	0	-0.00004
T_{gnd}^{k}	0	0.01075	0.00596	0.0061	0.00627	0.0057
T_{gnd}^{k-1}	0	0.01075	0.00596	0.0061	0.00627	0.0057
T_{gnd}^{k-2}	0	0.01075	0.00596	0.0061	0.00627	0.0057
T_{gnd}^{k-3}	0	0.01075	0.00596	0.0061	0.00627	0.0057
T_{gnd}^{k-4}	0	0.01075	0.00596	0.0061	0.00627	0.0057
T_z	0.03107	-0.00365	0.01369	0.00841	0.00839	0.00609
T_z	0.06214	-0.01428	0.01776	0.01173	0.01837	0.01199
T_z	0.00137	0.00031	0.00819	0.01854	0	0.01625
T_z	-0.00699	-0.00797	0	0.00968	0.01063	0
T_z	-0.03008	-0.00057	0.00899	0	0.01043	0.01551

Table D.1: June Monthly Inverse Multi-zonal CRTF Model Fitted Coefficients

D.2 July Monthly Coefficients

-	Attic	Core	Perim 1	Perim 2	Perim 3	Perim 4
T_1^{k-1}	0.03202	-0.00002	0.00684	0.00541	0.00765	0.00514
T_1^{k-2}	0.10857	0.00434	-0.00721	-0.00941	-0.0016	-0.01094
T_1^{k-3}	-0.77303	-0.00711	0.00604	0.014	-0.00109	0.01452
T_1^{k-4}	1.5395	0.0037	-0.02209	-0.01274	-0.01353	-0.01635
T_2^{k-1}	-0.04816	-0.23051	-0.00554	-0.00649	-0.00951	-0.0036
T_2^{k-2}	0.03385	0.42506	-0.01537	-0.00997	-0.01441	-0.01411
T_2^{k-3}	-0.00359	0.5475	-0.00329	-0.00169	-0.00061	-0.00172
T_2^{k-4}	0.01656	0.14402	0.02326	0.01873	0.02185	0.02077
T_3^{k-1}	-0.04916	-0.01146	-0.19512	-0.00106	0	0.00359
T_3^{k-2}	0.01428	-0.01155	0.26343	-0.01097	0	-0.01397
T_3^{k-3}	-0.01724	-0.0018	0.397	0.00089	0	-0.00337

T_3^{k-4}	0.05085	0.05775	0.44886	0.00295	0	0.01037
T_4^{k-1}	-0.00515	-0.00623	-0.00471	-0.20552	-0.00501	0
T_4^{k-2}	-0.04105	-0.00685	-0.00543	0.2681	-0.00618	0
T_4^{k-3}	0.03749	-0.00075	-0.00179	0.39745	-0.00146	0
T_4^{k-4}	-0.00408	0.02412	0.01053	0.45106	0.01024	0
T_5^{k-1}	-0.01037	-0.0107	0	-0.00158	-0.19266	0.00117
T_5^{k-2}	-0.01837	-0.01396	0	-0.01083	0.26446	-0.01535
T_5^{k-3}	0.03128	0.00206	0	0.00208	0.3955	-0.00464
T_5^{k-4}	-0.03301	0.04783	0	0.0086	0.44204	0.02018
T_6^{k-1}	0.03297	-0.00801	-0.00449	0	-0.00415	-0.20988
T_6^{k-2}	-0.0681	-0.00767	-0.00842	0	-0.0079	0.27326
T_6^{k-3}	0.0162	0.00123	0.00073	0	-0.00146	0.39741
T_6^{k-4}	0.01262	0.02375	0.01349	0	0.01243	0.44462
T_x^{k}	-0.14009	0.00728	0.01242	0.0002	0.0082	0.0205
T_x^{k-1}	0.34837	-0.00916	-0.02024	-0.00033	-0.0167	-0.03059
T_x^{k-2}	-0.42258	0.00115	-0.00928	-0.01583	-0.00831	-0.00097
T_x^{k-3}	0.01224	0.00188	0.0038	0.00563	0.01263	0.00484
T_x^{k-4}	0.26936	0.00579	0.02511	0.0242	0.01607	0.02134
Q_{rad}^{k}	-0.00061	-0.00001	0	0	0.00002	-0.00003
Q_{rad}^{k-1}	-0.00006	-0.00027	-0.00021	-0.00044	-0.00024	-0.00034
Q_{rad}^{k-2}	-0.00002	-0.00005	-0.00015	-0.00017	-0.00015	-0.00011
$Q_{rad}d^{k-3}$	-0.00007	0.00002	0	-0.00007	0.00002	-0.00018
Q_{rad}^{k-4}	-0.00011	0.00051	0.00053	0.00092	0.00052	0.00092
Q_{conv}^{k}	-0.00001	0.00008	0.00011	0.00016	0.0001	0.00017
Q_{conv}^{k-1}	-0.00002	-0.00041	-0.00035	-0.00051	-0.00035	-0.00052
Q_{conv}^{k-2}	0.00019	-0.00036	-0.0004	-0.00057	-0.00039	-0.00056
Q_{conv}^{k-3}	-0.00052	0.00014	-0.00013	-0.0002	-0.00012	-0.00018
Q_{conv}^{k-4}	0.00041	0.00078	0.00097	0.00143	0.00097	0.00142
Q_{ws}^{k}	0	0	-0.0002	0.00003	-0.00016	-0.00004
Q_{ws}^{k-1}	0	0	-0.0002	-0.0005	-0.00011	-0.00053

Q_{ws}^{k-2}	0.00001	0	-0.00014	-0.00034	-0.00011	-0.00024
Q_{ws}^{k-3}	0	0	0.00017	-0.0001	0.0002	0.00038
Q_{ws}^{k-4}	-0.00001	0	0.00061	0.00101	0.00027	0.00114
Q_{ss}^{k}	0	0	0.00001	0	0	0.00001
Q_{ss}^{k-1}	0.00001	0	0.00001	0.00001	0	0.00002
Q_{ss}^{k-2}	-0.00001	0	0	0	0	-0.00001
Q_{ss}^{k-3}	-0.00002	0	0	0.00002	0	-0.00001
Q_{ss}^{k-4}	0.00003	0	-0.00004	-0.00003	0	-0.00004
T_{gnd}^{k}	0	0.01174	0.00793	0.00601	0.00877	0.00652
T_{gnd}^{k-1}	0	0.01174	0.00793	0.00601	0.00877	0.00652
T_{gnd}^{k-2}	0	0.01174	0.00793	0.00601	0.00877	0.00652
T_{gnd}^{k-3}	0	0.01174	0.00793	0.00601	0.00877	0.00652
T_{gnd}^{k-4}	0	0.01174	0.00793	0.00601	0.00877	0.00652
T_z	-0.01056	-0.00134	0.02061	0.00442	0.01143	0.00884
T_z	0.02568	-0.0181	0.01819	0.0146	0.01996	0.0133
T_z	-0.00765	-0.00118	0.00786	0.02432	0	0.02085
T_z	0.03668	-0.00669	0	0.01448	0.00952	0
T_z	0.02297	-0.001	0.00682	0	0.01051	0.01413

Table D.2: July Monthly Inverse Multi-zonal CRTF Model Fitted Coefficients

D.3 August Monthly Coefficients

-	Attic	Core	Perim 1	Perim 2	Perim 3	Perim 4
T_1^{k-1}	-0.00363	-0.00081	0.00438	0.00455	0.00574	0.00794
T_1^{k-2}	0.17708	0.00273	0.00689	-0.00702	-0.00182	-0.008
T_1^{k-3}	-0.79941	-0.00551	-0.02812	0.00637	0.00434	-0.00445
T_1^{k-4}	1.55614	0.00862	0.00715	-0.00514	-0.00619	0.00613
T_2^{k-1}	0.01653	-0.25092	-0.00928	-0.00753	-0.00995	-0.00223
T_2^{k-2}	-0.06859	0.45904	-0.01487	-0.01263	-0.01287	-0.01034
T_2^{k-3}	0.07104	0.59201	-0.00901	-0.00081	-0.00808	-0.01088

T_2^{k-4}	-0.03019	0.08337	0.04109	0.02135	0.03297	0.02566
T_3^{k-1}	-0.01063	-0.01083	-0.20436	-0.00457	0	0.00047
T_3^{k-2}	-0.03151	-0.01278	0.26538	-0.00946	0	-0.01125
T_3^{k-3}	0.03894	0.00192	0.40785	-0.00188	0	-0.00681
T_3^{k-4}	-0.01316	0.04975	0.45856	0.02047	0	0.02223
T_4^{k-1}	0.00483	-0.00556	-0.00315	-0.21574	-0.00352	0
T_4^{k-2}	0.00589	-0.00763	-0.00558	0.27124	-0.00758	0
T_4^{k-3}	-0.04405	-0.00107	-0.00652	0.40444	-0.00481	0
T_4^{k-4}	0.0216	0.0258	0.01815	0.45694	0.01575	0
T_5^{k-1}	0.00207	-0.01161	0	-0.0045	-0.21497	0.00006
T_5^{k-2}	0.00838	-0.01388	0	-0.01258	0.26281	-0.01305
T_5^{k-3}	-0.0578	0.00265	0	0.00281	0.40718	-0.00409
T_5^{k-4}	0.03531	0.05043	0	0.01749	0.46701	0.02186
T_6^{k-1}	-0.02647	-0.00706	-0.00288	0	-0.00347	-0.14669
T_6^{k-2}	0.03849	-0.00813	-0.00685	0	-0.00823	0.11594
T_6^{k-3}	-0.00683	0.00098	-0.00636	0	-0.00444	0.37116
T_6^{k-4}	-0.00305	0.02412	0.01662	0	0.01713	0.57495
T_x^{k}	-0.08804	0.00963	0.01067	0.01233	0.0137	0.01115
T_x^{k-1}	0.22688	-0.00903	-0.01395	-0.01132	-0.01926	-0.00782
T_x^{k-2}	-0.32519	0.00495	-0.01665	-0.01462	-0.02241	-0.01601
T_x^{k-3}	-0.04919	-0.01303	-0.00013	-0.00071	0.009	-0.0023
T_x^{k-4}	0.30817	0.01292	0.03023	0.0276	0.02991	0.0254
Q_{rad}^{k}	-0.00004	-0.00005	0.00003	-0.00007	-0.00001	-0.00001
Q_{rad}^{k-1}	-0.00006	-0.00028	-0.00028	-0.00041	-0.00025	-0.00029
Q_{rad}^{k-2}	-0.00004	-0.00004	-0.00016	-0.00011	-0.00009	-0.00014
$Q_{rad}d^{k-3}$	0.00003	0.00004	-0.00009	-0.00017	-0.00004	-0.00036
Q_{rad}^{k-4}	-0.00009	0.00052	0.00065	0.00101	0.00053	0.00101
Q_{conv}^{k}	0	0.00009	0.00011	0.00018	0.00012	0.00013
Q_{conv}^{k-1}	-0.00007	-0.00045	-0.00035	-0.00052	-0.00035	-0.00031
Q_{conv}^{k-2}	0.00021	-0.00038	-0.00041	-0.00058	-0.00041	-0.00059

Q_{conv}^{k-3}	-0.00056	0.00018	-0.00014	-0.00021	-0.00015	-0.00037
Q_{conv}^{k-4}	0.00045	0.00078	0.00097	0.00143	0.00097	0.00143
Q_{ws}^{k}	0	0	0.00012	0.00005	0.00043	-0.00003
Q_{ws}^{k-1}	-0.00002	0	-0.00048	-0.00049	-0.00067	-0.00046
Q_{ws}^{k-2}	0	0	-0.00021	-0.0004	-0.0001	-0.00014
Q_{ws}^{k-3}	0	0	0.00018	0.00003	0.00007	0.00029
Q_{ws}^{k-4}	0	0	0.00069	0.00108	0.00056	0.00123
Q_{ss}^{k}	0	0	-0.00002	0	-0.00004	0.00001
Q_{ss}^{k-1}	0.00001	0	0.00004	0.00001	0.00003	0.00001
Q_{ss}^{k-2}	-0.00001	0	0.00002	0.00001	0	-0.00001
Q_{ss}^{k-3}	-0.00002	0	-0.00002	0.00002	0.00001	-0.00002
Q_{ss}^{k-4}	0.00003	0	-0.00004	-0.00003	-0.00002	-0.00005
T_{gnd}^{k}	0	0.01194	0.00684	0.00781	0.00743	0.00716
T_{gnd}^{k-1}	0	0.01194	0.00684	0.00781	0.00743	0.00716
T_{gnd}^{k-2}	0	0.01194	0.00684	0.00781	0.00743	0.00716
T_{gnd}^{k-3}	0	0.01194	0.00684	0.00781	0.00743	0.00716
T_{gnd}^{k-4}	0	0.01194	0.00684	0.00781	0.00743	0.00716
T_z	0.01054	-0.00489	0.01465	0.00368	0.00189	0.00246
T_z	-0.00476	-0.01176	0.00481	0.00913	0.01101	0.0088
T_z	0.01086	-0.00137	0.00259	0.00687	0	0.00803
T_z	0.01181	-0.00945	0	0.00577	0.0073	0
T_z	0.01355	-0.00147	0.00563	0	0.00613	0.00815

Table D.3: August Monthly Inverse Multi-zonal CRTF Model Fitted Coefficients

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