CONTROL FOR PERFORMANCE AND ENERGY EFFICIENCY WITH APPLICATIONS IN SMART BUILDINGS AND COMMUNITIES

by

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ABSTRACT OF THE DISSERTATION

“Control for Performance and Energy Efficiency with Applications in Smart Buildings and Communities”

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The emergence of Building Internet of Things (BIoT) technology as backbone for intra- and inter-building collaborations, and the recent advances in building technologies are expected to act as transformative enablers for energy smart connected communities. Architects are already moving toward connected buildings and commercial industry is advocating open space allocation practices using real-time data. Moreover, many cities have already started setting forth more stringent policies and regulations for clean air and protection of environment. For instance, some cities are already establishing guidelines and will soon be mandating Zero Net Energy (ZNE) building codes. Despite many challenges and barriers, these changes and advances are all good news for the power grid and the society as a whole; by the virtue of advanced data mining tools and control techniques the
power grid will take advantage of lower quantity risks, and communities will be able to cut costs and engage in new business opportunities. The current building energy automation systems work in silos and are incapable of taking advantage of these advances and opportunities, community-based cooperation schemes and controls are not in existence. This work will fill some of the gaps in building and community controls and data mining tools and create a real-time information exchange loop between building communities.

The overarching goal of this dissertation is to develop novel advanced soft controls, collaboration schemes and forecasting and data mining tools that allow for buildings to connect and collectively plan and manage their energy loads. A simulation platform is developed to model different levels of energy systems such as buildings, building clusters, and DER. Building thermal behavior is captured via data-driven approaches and incorporated into optimization models to develop optimal setpoint controls that can also pre-heats or pre-cools for given zone(s) taking into account dynamic energy pricing, weather conditions, occupancy patterns, human comfort and business functions. This control strategy is extended to building community operation to achieve peak demand and energy consumption reduction at network level via load synchronization. Load synchronization and balancing between buildings in a community and between communities in a region will result in smoother aggregate load and load shifting to off-peak times, hence the average unit cost of electricity will go down. The proposed planning and control scheme will reduce energy and environmental footprints of communities and cities, create a better living and working environment for residents and occupants.
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Table of Contents

Abstract ........................................................................................................................................ ii

acknowledgement .................................................................................................................. iv

Table Of Contents .................................................................................................................... v

List Of Figures .......................................................................................................................... x

list Of Tables............................................................................................................................... xv

CHAPTER I: INTRODUCTION AND BACKGROUND ............................................................ 1

1.1 OVERVIEW ....................................................................................................................... 1

1.2 MOTIVATION ..................................................................................................................... 1

1.3 SYNOPSIS OF CONTRIBUTIONS .................................................................................. 4

1.3.1 Cyber-Physical testbed for energy smart communities .............................................. 4

1.3.2 Machine learning approaches to predict building indoor temperature in VAV systems ................................................................................................................................. 6

1.3.3 HVAC Distributed Control based on Physical Statistical Modeling .................. 7

1.3.4 Connected Building Operation Scheduling ......................................................... 8

CHAPTER II A CYBER-PHYSICAL TESTBED FOR SMART CONNECTED
ENERGY COMMUNITIES ...................................................................................................... 10

2.1 INTRODUCTION ............................................................................................................. 10

2.1.1 Motivation ................................................................................................................ 10

2.1.2 Net-zero community cyber-physical preliminaries and literature review ..... 11

2.2 TESTBED DESCRIPTION OVERVIEW ....................................................................... 14
2.2.1 Overview ......................................................................................................................... 14

2.3 CASE STUDY I: ENERGY COMMUNITY SIMULATION ................................................. 18

2.4 CASE STUDY II: REAL BUILDING SIMULATION AND IMPACT OF RETROFITTING .... 24

2.4.1 Simulation....................................................................................................................... 24

2.4.2 Model Description ......................................................................................................... 25

2.4.3 Model Development and EEM implementation ............................................................. 26

2.4.4 Applying a VAV system ................................................................................................. 27

2.4.5 Demand controlled ventilation ....................................................................................... 30

2.4.6 Building infiltration reduction ....................................................................................... 31

2.4.7 Building envelope improvement ..................................................................................... 32

2.4.8 Lighting load reduction .................................................................................................. 35

2.4.9 Daylighting control ........................................................................................................ 36

2.4.10 Vacancy sensors ........................................................................................................... 36

2.5 DATA GENERATION FOR TRAINING AND TESTING ..................................................... 37

2.6 METHODOLOGY FOR DESIGNING GENERATION SYSTEM METHOD ....................... 40

2.6.1 Constants ...................................................................................................................... 41

2.6.2 Sizing ............................................................................................................................. 43

2.7 CONCLUSION .................................................................................................................... 46

CHAPTER III: MACHINE LEARNING APPROACHES TO PREDICT BUILDING

INDOOR TEMPERATURE IN VAV SYSTEMS ........................................................................ 47

3.1 INTRODUCTION ............................................................................................................... 47

3.2 HEAT TRANSFER ANALYSIS IN A BUILT ENVIRONMENT ............................................. 53

3.2.1 Conservation of Energy ................................................................................................. 53
3.2.2 Indoor temperature prediction models ................................................................. 55
3.2.3 Unrolled time series for zone temperature values .............................................. 57
3.2.4 Predictive modeling .............................................................................................. 58
  3.2.4.1 Multivariate Regression Model ........................................................................ 58
  3.2.4.2 Application of neural networks in thermal modeling ..................................... 60
3.3 Simulation and data generation ................................................................................ 63
3.4 Results ..................................................................................................................... 64
  3.4.1 Multivariate regression model results ................................................................. 64
    3.4.1.1 Impact of independent variables on indoor temperature .............................. 64
  3.4.2 Prediction of indoor temperature over time ......................................................... 70
  3.4.3 Zone temperature response to damper position and impact of degradation ....... 71
  3.4.4 Damper position as a categorical variable ......................................................... 74
3.5 Model performance and error evaluation .................................................................. 75
3.6 Conclusion and applications .................................................................................... 80

CHAPTER IV DISTRIBUTED AIR CONDITIONING CONTROL IN COMMERCIAL BUILDINGS BASED ON A PHYSICAL-STATISTICAL APPROACH ...................................................... 83

  4.1 Introduction ............................................................................................................. 83
  4.2 Problem statement and preliminaries ..................................................................... 88
    4.2.1 Zonal thermal response ...................................................................................... 88
    4.2.2 External signals .................................................................................................. 89
    4.2.3 Pre/post occupy HVAC operation ...................................................................... 89
    4.2.4 Human comfort ................................................................................................. 90
    4.2.5 Human comfort ................................................................................................. 90
4.2.6 Human productivity ........................................................................................................ 91

4.3 BUILDING THERMAL CHARACTERISTIC IDENTIFICATION ......................................... 92

4.3.1 Heat transfer problem for room thermal response ...................................................... 92

4.3.2 Statistical approach to predict room thermal response .............................................. 94

4.3.3 Statistical approach to predict and find cooling demand .......................................... 97

4.4 SIMULATIONS, PREDICTIVE MODEL RESULTS AND VALIDATION .............................. 98

4.4.1 Building control and thermal simulation ................................................................. 98

4.4.2 Thermal response model results .............................................................................. 99

4.4.3 Damper position and airflow effect ....................................................................... 100

4.4.4 Cooling demand prediction results ....................................................................... 102

4.5 SOLUTION APPROACH AND CONTROL ALGORITHM ............................................... 103

4.5.1 Operation control based on occupancy ................................................................. 103

4.5.2 Pre/post occupy HVAC operation control .............................................................. 105

4.5.3 Operation optimization and demand side management ........................................ 107

4.5.4 Building air conditioning control algorithm description ...................................... 110

4.6 ILLUSTRATIVE RESULTS .......................................................................................... 111

4.7 CONCLUSION .............................................................................................................. 114

CHAPTER V: CONNECTED BUILDINGS AND SMART COMMUNITIES:

SYNCHRONIZING HVAC OPERATION IN BUILDING COMMUNITIES ..................... 116

5.1 INTRODUCTION ........................................................................................................... 116

5.2 PROBLEM STATEMENT ............................................................................................. 122

5.3 BUILDING THERMAL INERTIA AND TEMPERATURE SETPOINT SCHEDULING ...... 127

5.3.1 Building thermal inertia ......................................................................................... 127
5.3.2 Periodic temperature setpoint ................................................................. 128

5.4 HVAC OPERATION AND COORDINATION IN CONNECTED BUILDINGS .......... 134

5.5 OPTIMIZATION OF COOPERATION OF BUILDINGS ........................................... 139

5.5.1 Thermal inertia and cooperation of buildings ........................................... 140

5.5.2 Optimization model .................................................................................. 143

5.5.3 Load clustering ......................................................................................... 145

5.5.4 Asset degradation ..................................................................................... 147

5.5.5 Control tuning ......................................................................................... 148

5.6 CASE SCENARIO: LARGE SCALE BUILDING COORDINATION AND GRID

INTERCONNECTION ............................................................................................. 149

5.7 PERIODIC ELECTRICITY DEMAND FORECAST ......................................... 152

5.8 CONCLUSION .............................................................................................. 157

REFERENCES ..................................................................................................... 159
List of Figures

Figure 1: A smart community composed of residential and commercial buildings along with renewable sources and grid. ........................................................................................................................................ 15

Figure 2: Hierarchy of the components, and data exchange in the community. .............................. 16

Figure 3: Testbed framework. .................................................................................................................. 16

Figure 4: Schematic of the community. ..................................................................................................... 20

Figure 5: Community consumption and generation in December for three different climate zones. ........................................................................................................................................ 21

Figure 6: Purchased energy ratio. ............................................................................................................. 22

Figure 7: Storage pattern difference under different climate zones. ....................................................... 22

Figure 8: Geometry of the model. ............................................................................................................ 24

Figure 9: A comparison between the simulation results and real data.................................................... 26

Figure 10: A comparison between CAV and VAV fans electricity consumption. .............................. 28

Figure 11: A comparison between CAV and VAV pumps electricity consumption. .......................... 28

Figure 12: A comparison between CAV and VAV total electricity consumption................................ 29

Figure 13: A comparison between CAV and VAV total natural gas consumption. ............................ 29

Figure 14: Total electricity saved in kWh .................................................................................................. 30

Figure 15: Total electricity saved in percent ............................................................................................. 30

Figure 16: Monthly electricity saved by ventilation control ................................................................. 31

Figure 17: Monthly natural gas saved by ventilation control ............................................................... 31

Figure 18: Monthly natural gas saved by infiltration reduction ............................................................ 32

Figure 19: Monthly electricity saved by infiltration reduction .............................................................. 32

Figure 20: Monthly electricity saved using exterior wall insulation ...................................................... 33

Figure 21: Monthly gas saved using exterior wall insulation ............................................................... 33

Figure 22: Monthly gas saved using roof insulation ............................................................................... 33
Figure 44: Comparison of different prediction methods and simulation data for 6 representative zones in the small and medium office.................................................................71
Figure 45: Temperature response to different damper positions in the small office in a central zone (a) and east zone (b), and medium office in a central zone (c) and east zone (d)..............73
Figure 46: Impact of degradation on zone thermal response for two case scenarios with different motor efficiencies of AHU fans.................................................................73
Figure 47: A comparison between predictions resulting from equations 3.12 (Interaction categorical model) and 3.18 (weighted sum model)..................................................75
Figure 48: A comparison between performance of different neural network methods in the medium office (top) and small office (bottom).................................................................77
Figure 49: Impact of timestep on model performance.........................................................78
Figure 50: Impact of assuming airflow as a categorical variable and interaction models on model performance.................................................................79
Figure 51: ASHRAE 55 recommended thermal comfort level..............................................91
Figure 52: Human performance and dry bulb temperature relationship developed by Seppanen et al.................................................................92
Figure 53: Room average temperature prediction over time by assigning different inlet airflows. ......................................................................................................................95
Figure 54: Zone thermal behavior comparison between predictive model and real data in Small Office (top row), Medium Office (middle row), and large office (bottom row)..................101
Figure 55: Room thermal response under different imposed airflows.................................101
Figure 56: Air system cooling electricity consumption vs prediction in every two minutes for (a) Large Office. (b) Medium Office (C) Small Office.................................................................102
Figure 57: Different cases based on zone occupancy over two hours .................................104
Figure 58: Finding optimal pre-occupy operation using zone thermal response .................106
Figure 59: Finding optimal post-occupy operation using zone thermal response................................. 107
Figure 60: Control process flowchart.................................................................................................. 111
Figure 61: Optimal setpoint assignment and zone thermal response.................................................. 112
Figure 62: Impact of optimal setpoint scheduling and setback control on facility total electricity consumption and in three different days................................................................. 114
Figure 63: A comparison of response of building electricity demand to variable temperature setpoints and a constant temperature setpoint.................................................................................. 124
Figure 64: (a) A comparison of response of building electricity demand to variable temperature setpoints and a constant temperature setpoint for a large space (supermarket). (b) A comparison between operation of two buildings (office and small hotel) via variable.............................................. 124
Figure 65: Noticeable building total peak demand change in a building cluster for a periodic control policy. ....................................................................................................................................... 126
Figure 66: Representation of temperature setpoint schedules and their parameters presented in equation 5.6 (a) and equation 5.7 (b) with B=24 °C,Δ=1 °C,and τ=60 min ..................................................... 130
Figure 67: Incremental temperature setpoint scheduling on a sinusoid shape........................................... 131
Figure 68: Building total demand response to sinusoid and constant temperature setpoint variations in office (a) and supermarket (b).................................................................................................. 131
Figure 69: Impact of sinusoid profile parameters variations on building electric demand. (a) shows the impact of variation in period (τ) in the medium office, (b) shows the impact of variation in amplitude (Δ) in the medium office, (c) shows the impact of variation in period (τ) in the restaurant (c) shows the impact of variation in amplitude (Δ) in the restaurant. ................. 132
Figure 70: Variation of building HVAC electric demand with temperature setpoint for the office (a) and restaurant (b)....................................................................................................................................... 133
Figure 71: Setpoint scheduling for connected buildings based on equations 5.10 and 5.11.............. 135
Figure 72: Setpoint scheduling for three buildings with δ=5 minutes and ΔT=0.5 °C............... 136
Figure 73: Impact of periodic temperature setpoint scheduling on electric demand of different building clusters (Δ=1°C, τ=1 hour, and B=24°C, and δ=1 minute) ................................................................. 136

Figure 74: Precooling planning for three office buildings when the price of electricity increases at 5 PM for (a) when φ=0 and (b) φ=2π/3. ............................................................................................................. 139

Figure 75: Room temperature response as a result of sinusoid temperature setpoint scheduling. .............................................................................................................................................................................. 141

Figure 76: Impact of cooling design factor on room temperature response to sinusoid setpoint schedules ............................................................................................................................................................................ 142

Figure 77: Room temperature response as a result of constant periodic setpoint scheduling..... 142

Figure 78: Identifying the impact of λ in room comfort deviation. .............................................. 144

Figure 79: Simulation of building community configuration in BCVTB........................................... 150

Figure 80: Net HVAC electric demand of the building community over a 12-hour period. ...... 152

Figure 81: Predicting maximum/minimum demand values to construct a demand profile. ........ 153

Figure 82: Comparison of predicted and simulation values for maximum and minimum demand test dataset........................................................................................................................................................................ 156

Figure 83: Estimated demand profile by forecasting maximum/minimum points and constructing sinusoid segments. ........................................................................................................................................................................... 157
List of Tables

Table 1: Building simulation description........................................................................................................... 19
Table 2: Average beta coefficient for temperature change prediction in 15-minute time intervals. ........................................... 67
Table 3: $R^2$ Values for temperature prediction over a timestep ............................................................................. 80
Table 4: Building models characteristics. ............................................................................................................. 98
Table 5: Error analysis for long-term temperature absolute value prediction................................................. 100
Table 6: Error analysis for long-term cooling electricity value prediction ...................................................... 103
Table 7: Saved HVAC energy and cost comparison in three different buildings ............................................. 113
Table 8: Saved consumption and peak demand change in three presented scenarios................................. 125
Table 9: Saved consumption and peak demand change in three presented scenarios from June to August ........................................................................................................................................... 132
Table 10: Comparison of saving opportunities in the scenarios presented in Figure 73. ......................... 137
Table 11: Configuration of the existing buildings in the community simulation. .............................................. 149
Chapter I: Introduction and Background

1.1 Overview

This thesis intends to deliver control scheme solutions for built environments and building communities to achieve a responsive and energy efficient system. The focus is on understanding building and zone level thermal behavior via data-driven approaches and incorporate them into a distributed decision-making framework. A simulation platform is developed in Chapter 2 to model buildings and communities to generate credible data and evaluate the impact of the proposed methodologies in this work. In Chapter 3, a data-driven methodology is constructed to identify significant physics-based factors to model and understand building thermal behavior under different circumstances. In Chapter 4, building thermal behavior along with other factors such as human factors (e.g. occupancy patterns and human productivity) are used to develop a real-time distributed optimization framework that responds to electricity price signals for bill management. The framework is based on a zonal performance mapping system, where individual zones aim to achieve an aggregate optimal operational state. In Chapter 5, a periodical strategy is proposed for the operation of building communities to create opportunities for peak demand reduction, energy consumption reduction and load leveling.

1.2 Motivation

Residential and commercial buildings account for almost 42% of total energy consumption in the U.S while a large portion of energy consumption in this sector is dedicated to HVAC (35% in residential and 32% in commercial buildings) [1]. Consequently, energy efficiency
improvement via smart operation strategies has a considerable potential to obtain significant economic and social benefits in built environments and building communities. The future of building automation systems becomes more promising with the advancement of new communication and control technologies along with incorporation of novel data-driven approaches in building decision making platforms [2]. The building automation sector is steadily growing and will be generating 45 billion dollars annually by 2021 [3]. Besides local operation control, at a larger scale, building/community decision making platforms can lead into effective solutions for sustainable and smart cities and communities and create numerous benefits such as power grid reliability/responsiveness, deferring upgrades to transmission and distribution (T&D) infrastructure, and emission reduction.

For decades, electricity utilities distributed electricity through power networks to end-users while their main concerns were mostly about power generation efficiency, generation technologies, market expansion, market competition, etc. However, incidents such as 1965 blackout crisis, oil embargo, and natural disasters had a message for power companies to change their stand and be more aware and well-prepared for unexpected situations [4], [5]. To this end, smart energy communities and micro-grids participation initiated, and demand-side management programs were increasingly promoted across the United States [6]. Utility companies employ day-ahead and real-time electricity pricing schemes to control grid dynamics for more efficiency, interconnection, risk management, and reliability [7]. End-users, including communities and large facilities, are able to participate, through bidirectional communications and contractual arrangement, in day ahead or real time markets based on their functionality to reduce their electricity bills, make revenue, and, alleviate uncertainties in the network and differences between commitments and
network demand by load scheduling or optimal dispatch of distributed energy resources [8].

Aside from grid connected communities and energy market participation, building local control by itself is highly effective that can result in up to 20% energy savings. Since 30% to 40% of building load is dedicated to heating, cooling and ventilation, and HVAC operation has more control flexibility, building HVAC optimal operation would be an appropriate subject of study for energy efficiency. However, a comprehensive study of building HVAC operation planning and scheduling is in need of fully understating and quantifying physical/thermal attributes of buildings.

The aforementioned building/community local operation control and bidirectional communication with the utilities needs to incorporate multi-source sensor data and other externalities to construct an effective and responsive decision-making framework. Besides this input, physical behavior of each participating component and uncertainties that are mostly originated from human behavior and weather condition should be comprehensively quantified [9].

To this end, instead of predetermined or rule-based models, a thorough understanding of building thermal characteristic, human behavior, and other externalities, results in more effective, reliable, and accurate optimization methodologies. This is also true for distributed energy resources as the other important elements in energy communities and power grids. Consequently, reliable control methodologies in energy systems are in need of valid physical evaluations along with complex statistical analysis of the whole energy system which results in hybrid physical statistical modeling approaches [10].
At last, in energy systems, one of the barriers of research studies are lack of data and experimental testbeds for objectives such as training predictive models and evaluation of proposed methodologies. This indicates that if we want to fully understand the dynamics in an energy system, e.g. a building, connected buildings or a micro-grid, a flexible simulation testbed is necessary to reflect physical behavior of such systems. This testbed should be composed of actors such as buildings, photovoltaic systems, wind turbines, energy storage systems, fuel cells, CHPs, shared assets and EV simulators that are widely used in modern energy communities. All components in this framework should be integrated and interconnected; that is, the system should have the capability of data exchange (this data can be control signals, weather data, sensor data, asset state information, etc.) across the network nodes. This integrated network can be employed for case scenario generation, sensitivity analysis for different control logics, generation of training datasets for predictive models, and model validation.

1.3Synopsis of Contributions

1.3.1Cyber-Physical testbed for energy smart communities

In this chapter, a cyber-physical testbed is constructed, which is capable of simulating several levels of energy systems. These layers are described as below:

- Level 1- Building Zone Level: All the thermal attributes and energy behavior are simulated for individual thermal zones in a single building through Energy Plus software. At this level, variables such as internal gain power consumption, average temperature, CO2 level, humidity, lighting, occupancy, equipment, cooling demand, heating demand, infiltration, inlet airflow, etc., are measured and tracked in different
time resolutions. On the other hand, controlled variables such as temperature setpoint, lighting schedule, equipment schedule, damper minimum airflow, zone-level equipment (unit heaters, fan units, exhaust fans, etc.) operation are capable of being controlled in the system framework.

- **Level 2- Building Level:** At this level, facility electricity demand, natural gas demand, plant (e.g. boilers, chillers, cooling towers, etc.) electricity demand, plant natural gas demand, air distribution system, etc. are trackable and analyzed for building supervisory control level.

- **Level 3- Building Community Level:** This level is composed of clusters of buildings that are aware of state of the whole network. These buildings are capable of having data exchange at different time resolutions for any trackable variable in individual buildings. This flow of information is implemented for real-time decision making or model predictive control for future timesteps. Individual building attributes are composed of load profiles, base load, peak demands, time of peak demand, and load shifting potential.

- **Level 4- Community Asset Level:** At this level, physical attributes of shared assets in the SCEC are taken into account for supplying community load and balancing services in the power system. Distributed energy resource variables are monitored in real time and evaluated via forecast models for decision making processes. Impact of weather condition variation is an important factor at this level. Asset design, asset degradation, district equipment (e.g. district chillers and boilers) behavior are other important elements that should be taken into account.
Level 5- Grid Level: Aggregate behavior of SCECs are important at power grid level. The interaction with the grid, net-metering, and balancing services decision-making processes are made at this level, which results in a more reliable and stable system benefitting communities and power grids simultaneously.

The framework introduced in Chapter 2 is a flexible and reliable testbed that simulates real-time building control systems, building cluster interactions, and DER operation. These simulations are necessary due to the lack of data for building operation, building control response, and DER operation under preferred conditions. The simulation output datasets are fed into predictive models for learning processes while the impact of different control policies can be evaluated through aforementioned simulations. This testbed is also connected to real-world entities through data communication ports, sensors, microcontrollers, and internet practices, which upgrades the cyber system to a cyber-physical system. Real buildings are modelled to be integrated in the system and connected through physical sensors for real-time simulation. These real-building simulations are validated through meter data and implemented to study the impact of retrofitting and system operation improvement on facility energy consumption and energy efficiency indices as well. Furthermore, design procedures are developed in Chapter 2 for distributed energy resources based on different climate zones and functionalities.

### 1.3.2 Machine learning approaches to predict building indoor temperature in VAV systems

In this chapter, hybrid physical-data-driven approaches are developed to predict building zone level average temperature response to cooling in Variable Air Volume Systems under different circumstances. The proposed methodologies are based on heat transfer analysis
of a zone and via neural network and multivariate regression. Damper position is introduced as a categorical variable to alleviate the nonlinearity in predictive indoor temperature models. Factors that contribute to zone temperature models including internal gains, environment dry-bulb and wet-bulb temperature, zone location, solar irradiation, wind speed, sky clearness, and time-of-day are identified in VAV air conditioning systems. The room temperature response to different damper positions from minimum airflow to maximum airflow is elaborated. The impact of data resolution/timestep and the interaction between the independent variables are investigated. Complex and numerical methods for building simulation can be replaced by the proposed methodology for building temperature evaluation. Model performance analysis is performed and results are presented for different case scenarios. Also, the impact of asset degradation on the response model is presented. The proposed model can enhance control and optimization of building space cooling, and, be used to optimize building’s participation in demand response, load shifting or other control applications in smart energy systems. This methodology is used later in Chapter 4 to be incorporated in a building control optimization framework.

1.3.3 HVAC Distributed Control based on Physical Statistical Modeling

If the thermal behavior of a building under different conditions is fully understood, this knowledge can be extremely useful in many building control applications. If thermal response can be quantified through hybrid modeling, it would save a considerable amount of time and cost for processing, especially in optimization frameworks. The determination of building thermal response can be employed in many frameworks such as precooling preheating processes, demand response, and setpoint scheduling under different conditions such as weather variation and occupancy patterns. Finding the relationship between
temperature setpoint and HVAC electricity consumption, and, zonal thermal response can lead into more reliable and accurate HVAC operation optimization frameworks. In chapter III, we quantify thermal characteristics of individual zones through statistical approaches based on fundamental laws of heat transfer and numerical/statistical methods. This determination defines HVAC electricity consumption as a function of room average dry-bulb temperature, which is plugged into building HVAC operation control framework. Also, the physical-statistical approach can be implemented for pre/post-occupy HVAC operation planning to maintain thermal zones in human comfort zone by the time the zone is occupied, which is in turn, used in operation optimization constraints. In the proposed control optimization system, thermal comfort is always satisfied, human productivity is taken into account, and price of electricity is also considered to construct one-hour ahead HVAC operation planning. In all stages, simulations, validation, predictive model learning, and output evaluation are all conducted in the testbed introduced in Chapter 2.

1.3.4 Connected Building Operation Scheduling

Operation of individual buildings as a cluster with DERs and community assets might be totally different from single building operation. These connected buildings receive input signal associated with electricity price, energy availability, and state of other buildings at different time spans to conduct their operation planning. The objective here is to fully understand the relationship with accurate HVAC load profiles and responses to control signals in cooling/heating, finding individual buildings base loads and ways to do load shifting, and role of individual building operation in the system and their contribution in the system hierarchy. In this study, a methodology is proposed to assign HVAC operation planning schemes for connected buildings with the objective of energy saving and load
leveling. The idea is to use building thermal inertia in a periodic pattern by relaxing the temperature setpoints to an upper bound and setting back to a lower bound to avoid air conditioning while the room is still within human comfort zone. This periodic operation planning in turn facilitates the collaboration across a building community to reduce the aggregate demand. The objective is to assign periodic temperature setpoints for a building cluster so that the aggregate cooling electric demand reduces with the minimum cost and steady aggregate load shape. Ideal operation schedule forms are identified and elaborated in detail. Human comfort level and demand-side management applications are evaluated and incorporated into an optimization framework. The impact of peak demand reduction on the grid and power generation costs and the impact on the society is also investigated. The results demonstrate up to 12.5% savings in electricity consumption and 10% peak demand reduction for a community of 26 buildings.
Chapter II A Cyber-Physical Testbed for Smart Connected Energy Communities

2.1 INTRODUCTION

2.1.1 Motivation

As explained in Chapter 1, some elements in the energy systems, which will be introduced in Chapters 3 to 5, should be thoroughly investigated. These components are as follows:

- Building thermal dynamics
- Building HVAC control
- Building appliance control
- Distributed energy resources dynamics
- Data exchange
- Electric vehicles dynamics
- Zero-net energy community dynamics
- Smart connected buildings
- Local operation controller
- Energy community operation coordinator

The simulation of these elements will be implemented in many applications such as data generation, model validation, model effectiveness evaluation, and constructing case scenarios. On the other hand, connecting these cyber simulations to real physical world objects can lead into more applicative results. These implementations, model simulations, and physical integration can be realized through a cyber-physical energy testbed for zero net communities. This testbed should be capable of simulating from detailed building zone
level thermal dynamics to high level control across an energy community and integrating all data from lowest information layers to the highest levels of information layer.

Advanced operational controls and maintenance plans supported by data and technology are essential for ensuring sustained Net-Zero energy over the lifetime of a building or a community. In this chapter we describe a cyber-physical testbed that is capable of a combined virtual and physical simulation of a community in real-time. The community includes user-defined buildings of different types, renewable generation facilities, charging stations for electric vehicles, energy storage facilities, thermal storage, and an infrastructure that supports power grid connection whenever necessary. Each building is equipped with advanced controls at zonal and whole building levels. There is also inter-building communication for the purpose of ensuring community level energy efficiency measures. Other factors that are included in this testbed are:

- Simulation of real buildings to study of impact of retrofitting and different control policies and comparison with real data and load trends.
- Sizing methods for renewable resources
- Imposing different weather conditions and climate zones
- Data generation for training predictive models

### 2.1.2 Net-zero community cyber-physical testbed preliminaries and literature review

A net-zero community is one that uses energy efficiently and switches over to renewable energy to meet the demands or remaining demands. [11] clearly defines the major categories within the broad subject of net-zero energy and includes design goals and
priorities when designing systems to achieve net-zero energy. It is estimated that by 2025 nearly 62% of all commercial buildings will be net-zero [12]. Such a realization cannot be possible by physically monitoring only a few parameters in the community. Complex analysis and controls are needed to optimize building energy usage, maintain occupant comfort, and use renewable energy efficiently. These features can be efficiently realized using Cyber-Physical aspects [13]. A cyber-physical system integrates sensors, network components, and controllers to gather data from the environment and perform operations to control the environment. It is believed that cyber-physical systems will change the way we interact with the physical world, just as the advent of the Internet has changed the way we communicate with people [14]. The process of incorporating physical world information autonomously in a cyberworld is what differentiates cyber-physical systems from traditional industrial control systems [15], [16]. [17] presents the role of cyber-physical systems in developing net-zero energy buildings and optimally harvesting wind and solar power. The ultimate goal of a smart community is to provide better comfort while maintaining sustainability and energy efficiency. A smart community replaces the existing traditional grids with smart grids. The traditional grid falls short when it comes to communication capabilities. The smart grid, however, is a powerful system of sensing and computing components that facilitates communications between different parts the grid [18]. In fact, processing and analyzing large amounts of data is the real power of smart grids, which can result in making smarter decisions by both energy consumers and suppliers [19]. Integrating different types of communication networks in smart grids and simulating their impact on electric power systems is a challenging topic in smart energy community studies [20]. Experimental studies of smart grids in large scales cannot be
justified economically at this time. However, development of cyber-physical simulation of a smart energy community using real time data is an effective and economically feasible way to improve the efficiency and reliability of communications in these power systems [21], [22].

Recent work on this testbed has particular focus on designing the wind farm component of the renewable energy generation system. It is first important to understand the theoretical process of analyzing wind turbine geometry and power output, including blade design, tip speed ratio, cutin and cutout speeds, power curves, and wind distribution concepts [23]–[25]. Through this investigation, it is found that the wind turbines should be spaced between 5 and 9 rotor diameters apart in the prevailing wind directions, and between 3 and 5 rotor diameters apart in the perpendicular wind direction. This spacing causes near-wake effects to be negligible and thus wind speed attenuation due to turbulence can be neglected. The land is also assumed to be flat at the same elevation and it is assumed that the wind distribution is constant throughout the site [26].

Commercially available wind turbine models range from 50kW to several MW and companies like GE, Vestas, and PowerWind have several well-documented models that can be used for analysis [27]. When deciding what turbine capacity to use, one must consider the size of the load and type of community that will use the energy. Utility-scale turbines sell energy directly to power markets, whereas residential turbines can power a single or a few homes. When choosing a location, one must also consider government regulations and subsidies that factor into the cost and array layout of the generation system.

A cost-benefit analysis report can be generated for each turbine model that weighs installation, operation, permitting, and other costs against energy revenue.
In this work a cyber-physical testbed is presented that is able to analyze and optimize the energy usage in a given community. Section II describes the community as a whole, while Section II focuses on the design methodology for designing the renewable generation aspect of the testbed. Embedded controls for buildings and other assets will allow for experimentation with different controls at various levels. This testbed will also be instrumental in the assessment and evaluation of energy policies and regulations at community levels, and will also be used for valuation of major investments in a community.

2.2 TESTBED DESCRIPTION OVERVIEW

2.2.1 Overview

This community is composed of multiple commercial and residential building types, onsite generation, energy storage, geothermal, combined heat and power (CHP), district cooling and heating systems, electric vehicles, data servers, central and distributed control, energy storage, and access to making energy transactions with the grid. Sixteen reference buildings from the Department of Energy (DOE) database, along with real building models enables the testbed to evaluate the interaction between any combination of buildings. The testbed has the capability of modeling numerous types of wind turbines and solar panels to design the renewable energy system, monitor its behavior, conduct cost and benefit analysis, and achieve net-zero energy for the community. This testbed can not only be simulated for the whole community but can also be simulated on the building and zonal levels.

Some of the tools used in the testbed are EnergyPlus, TRNSYS, Matlab, Google Sketchup, and BCVTB (Building Control Virtual Testbed). After 3D models of the buildings are
designed in Google Sketchup, the models are imported into EnergyPlus to run the building simulation and implement control. Renewable energy and storage systems are modelled in TRNSYS, whose models are built and modifiable in Fortran. The simulation of each component across the testbed is synced by the Building Controls Virtual testbed (BCVTB) developed by the Lawrence Berkeley National Laboratory. BCVTB allows the coupling of different simulation programs for co-simulation in real-time. The framework of the testbed and architecture of the work can be seen in Figure 2 and Figure 3.

Figure 1: A smart community composed of residential and commercial buildings along with renewable sources and grid.
The system is initially set up when initial design parameters are given. These parameters define the community, including the geometry of buildings, their average loads, and any
land or budget constraints. These parameters are used to choose the best generation system design (see Section III) as well as define the configuration of the buildings.

Initially the system uses deterministic building and generation models based on both historical data and initial parameters. For every iteration of the testbed simulation that follows, the processor repeatedly receives real-time data to improve optimize the community’s operation and improve the forecast models for the next simulation. The optimization process incorporates constraints defined by the required comfort of the building occupants, energy demand, and external utility energy prices. The processor will generate optimal lighting and temperature setpoint schedules for the building simulation, as well as optimal storage and external energy purchase setpoint schedules for the renewable generation simulation. This Optimization Iteration Process (OIP), comprised of simulating, analyzing, and sending control signals back, enables the system to approach its optimal settings. The lighting and temperature control will decrease the building’s energy usage, thus decreasing the energy that needs to be purchased from the grid at peak demand. Simultaneously, the storage control will balance the generation and maximize it when it is needed the most, resulting in less excess energy can only be sold back to the grid because it is not needed. The resulting community approaches optimal behavior, in which the amount of energy bought or sold from the grid is not only minimized, but is also net-zero, where the total energy bought from the grid is equal to the total energy sold. This minimizes interaction with the group coupled with net-zero energy is the ultimate objective of the smart community.

One innovation of this work is that the testbed will include simulations of both virtual, or cyber, components as well as real-world, or physical, components. In earlier phases of the
work the cyber aspect is the focus. This allows more flexibility when establishing the testbed itself and quickly collecting data. One challenge in the cyber part is choosing parameters and specification of the buildings and generation system that are realistic and scale up well. It may be easy to determine the behavior of a few solar panels, but doing so for a virtual farm of thousands of solar panels is a necessary challenge. Addressing these scaling, realistic, and complexity concerns is essential for creating a robust system that can be applied to any real-world community.

The work will include a physical aspect, where Rutgers University will be the first testbed location. Physical sensors and meters are available throughout several buildings at the university to collect data. This data, once analyzed and converted, will contribute greatly to increasing the accuracy of the processor’s forecast models that result in more realistic and applicative models. This machine learning capability enables the forecast models to adjust quickly to actual data received, thus increasing the accuracy of the system. In addition, the incorporation of real-time physical data can help obtain a good estimation of demand side behaviors and microgrid participation. Finally, generated control signals in the processor will be sent not only to the virtual building simulation but also has the capability to be applied on physical controllers that will assign the building operation schedules.

2.3 Case Study I: Energy community simulation

A community of 8 cyber buildings is built that utilizes onsite generation along with a battery storage system. The buildings are US DOE reference buildings described in Table 1.
Table 1: Building simulation description.

<table>
<thead>
<tr>
<th>Building type</th>
<th>Number of buildings</th>
<th>Area</th>
<th>Number of Thermal Zones</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medium Office</td>
<td>2</td>
<td>4,982 m²</td>
<td>15</td>
</tr>
<tr>
<td>Midrise Apartment</td>
<td>4</td>
<td>3,135 m²</td>
<td>27</td>
</tr>
<tr>
<td>Primary School</td>
<td>1</td>
<td>6,871 m²</td>
<td>25</td>
</tr>
<tr>
<td>Service Restaurant</td>
<td>1</td>
<td>511 m²</td>
<td>3</td>
</tr>
</tbody>
</table>

A schematic of the full community is shown in Figure 4. Weather data is inputted to the solar and wind generation, and the storage control chooses whether to direct the generated energy to the building load or to store the energy. Communities are modelled in three different climate zones in Illinois, New Jersey, and Texas to evaluate the impact of climate on the combined onsite generation and storage behavior. It is assumed that the elevation and design of the renewable energy site and storage remains constant in the three scenarios. Also, the buildings have a controller that can adjust their operating conditions depending on the peak demand and availability of onsite generation. The timestep for the simulation is 15 minutes.
Throughout the simulation, because the human occupancy patterns and plug loads are variable, perturbation and stochasticity are applied to the behavior of the community. Figure 5 compares three communities in different climate zones. Figure 6 shows the impact of climate zone on the amount of energy that should be purchased from the grid due to unavailability of onsite generation. Figure 7 presents different storage patterns given that storage is available in the community.
Figure 5: Community consumption and generation in December for three different climate zones.
Figure 6: Purchased energy ratio.

Figure 7: Storage pattern difference under different climate zones.

In data analysis for energy systems, demand response programs evaluation, energy community controls, etc., lack of data and a reliable assessment is one of the most important
challenges. As shown in this case study, the current testbed has this ability to produce any scenario to develop data and make a highly reliable assessment. On the other hand, utilization of real sensor data and communication with physical world, dramatically decreases the evaluation costs and design risks for energy communities.
2.4 Case study II: Real building simulation and impact of retrofitting

For the evaluation of different control policies, retrofitting, and other energy efficiency measure, real building simulations are constructed in this study to provide the physical aspects of the aforementioned cyber-physical testbed. The testbed can be integrated with acquisition of real data through sensors in the physical building. In the next section, a real building simulation and impact of retrofitting is investigated. The description of real building model simulation and evaluation of energy efficiency measures and retrofitting are explained in this section.

2.4.1 Simulation

All the energy interactions, energy consumptions, and EEM implementation were developed by EnergyPlus. The base model was developed according to the plans of a real building. The geometry of the building is shown in Figure 8.

![Figure 8: Geometry of the model.](image_url)
2.4.2 Model Description

All the specifications of the building are according to an on-campus building located in New Brunswick, New Jersey, Climate Zone 4 in ASHRAE. This model is a three story building composed of multiple thermal zones. There are multiple functionalities in the building such as offices, classrooms, laboratories, libraries, study rooms, mechanical rooms, corridors, etc. The schedule of each thermal zone and building equipment were assigned as close as the real schedule of the building.

The HVAC system of the base model is a constant air volume system. There are three AHU unites supplying the conditioned air of the building. One of the AHUs is mainly implemented for the laboratories, in which chemical experiments are carried out, meaning that this unit does not have any return fan to the building. The hot water is supplied by two boilers located in the building. On the other hand, the chilled water is supplied by the main district chiller of the campus. As discussed, the system is constant, and all the pumps and fans in the VAC system are constant. The building does not have a smart control system neither for HVAC nor lighting.

The simulation run period was 8760 hours over a year. The net area of the building is 7158 m², and the net conditioned area is 6826 m². A comparison between the electricity energy consumption of the model simulation and the average real building over 15 years shows a good agreement between the model and the real building. Figure 9 presents a comparison between the simulation results and the real data collected over 15 years. The difference in summer period is due to the fact that EnergyPlus default operation/occupancy schedules were used in the absence of real building schedules.
2.4.3 Model Development and EEM implementation

In building energy consumption efficiency, there are many suggested measures. It is obvious that a controllable system has a considerable potential to save energy by applying effective strategies. The base model is not capable of being effectively controlled. Consequently, the first step to enhance the energy consumption in the building is to assign a variable and controllable system. It can be predicted that using a variable HVAC system would lead to a noticeable drop in the net energy consumption.

One of the main purposes of HVAC system design is to provide a comfortable environment for the occupants of the building. Aside from energy consumption of the building, it can be inferred that improving the HVAC control system would also increase the total occupied hours that the set point is met and the occupants are in the comfort zone.

Besides, lighting serves an important role in the electricity consumption. As a result, controlling internal lighting according to occupancy schedules, and also, reducing the lighting loads would bring about a decrease in the electricity consumption in the building. Also, control strategies would be another way to save energy in the building. Another way
to obtain more energy saving in the building is building envelope enhancement, which was also applied to the base model to examine its effect.

The energy efficiency measures applied to the model are as follows:

- Switching the CAV system to a VAV system
- Ventilation control.
- Building infiltration reduction.
- Building envelope improvement.
- Lighting load reduction.
- Daylighting control
- Vacancy sensors.

2.4.4 Applying a VAV system

The base model operates with a constant air volume system (CAV). Mainly, in constant air volume systems, there is no energy saving opportunity due to the fact that the system is not capable of being controlled. Consequently, the first step to enhance the energy consumption of the building would be improving the CAV system to a controllable VAV system. As can be predicted, there is a huge energy consumption enhancement in this retrofit. As shown, in Figure 10 and Figure 11, the monthly energy consumption of fans and pumps in the base model is almost constant over a year, whereas the variation is much more noticeable in the VAV system, specially over July and August, during which the occupancy is lower.
The same results can be inferred from Figure 12 and Figure 13, in which the total electricity and natural gas consumption is plotted. According to Figure 14 and Figure 15, almost 41380 kW which is 45% of the total energy can be saved by switching to a VAV system. It should be mentioned that this retrofit decreases the peak demand of the building to a large extent. This is an indication of a considerable opportunity to decrease energy expenditure.

It should be pointed out that all the results in the rest of the article are compared to the improved VAV system.
Figure 12: A comparison between CAV and VAV total electricity consumption.

Figure 13: A comparison between CAV and VAV total natural gas consumption.
2.4.5 Demand controlled ventilation

Another suggested method to save energy in the base model is to control the building ventilation according to the occupancy of the building. As shown in Figure 16 and Figure 17, this building retrofit can save both electricity and natural gas, however, the important
role of this building retrofit is air quality enhancement in the building as the amount of CO\textsubscript{2}
can be regulated in this method.

![Figure 16: Monthly electricity saved by ventilation control.](image-url)

![Figure 17: Monthly natural gas saved by ventilation control.](image-url)

### 2.4.6 Building infiltration reduction

Another method to save energy in the base model is to reduce building infiltration, as one of the most important factors affecting energy dissipation in buildings is air infiltration. As can be seen in Figure 18, this building retrofit has a noticeable effect during the heating period of the building. The effect of energy consumption during summer is almost zero.
2.4.7 Building envelope improvement

One of the factors impacting heat transfer interaction between building and outside air is the building envelope. The heat transfer resistance of the walls and roofs directly affects this process. To enhance the energy consumption of the building, this resistance should increase. In order to increase the R-value of the roofs and the exterior walls, wall and roof insulations should be applied to the building. As can be compared in Figure 20 to Figure 25, the impact of insulation is more noticeable over heating period. The amount of saved energy by applying roof insulation is twice as much as exterior wall insulation. Figure 24 and Figure 25 present the saving opportunities by using both exterior wall and roof insulation.
Figure 20: Monthly electricity saved using exterior wall insulation.

Figure 21: Monthly gas saved using exterior wall insulation.

Figure 22: Monthly gas saved using roof insulation.
Figure 23: Monthly electricity saved using roof insulation.

Figure 24: Monthly electricity saved using roof and exterior wall insulation.

Figure 25: Monthly natural gas saved using roof and exterior wall insulation.
2.4.8 Lighting load reduction

Almost one third of building electricity consumption is used for lighting of the building. This indicates that by reducing or controlling the lighting load in the building, there would be plenty of opportunities to save energy. Figure 26 shows the important role of lighting loads in the building energy consumption. As shown in Figure 26, more than 10000 kWh can be save by lighting load reduction, which is a considerable portion of electricity consumption in the building.

![Figure 26: Monthly electricity saved by lighting load reduction.](image)

On the other hand, only by controlling the lighting load of the corridors for a specific period of time over a day, up to 1200 kWh can be saved.
2.4.9 Daylighting control

One of the most popular ways toward energy consumption reduction is to apply daylighting control in the lighting system. As the base model does not have any lighting control, the implementation of this method shows a considerable amount of electricity, up to 5575 kWh, to be saved over a year. The result is shown in Figure 28.

2.4.10 Vacancy sensors

The last measure studied is to use vacancy sensor in the zones. This implementation also led into a considerable amount of saved energy, which is shown in Figure 29.
As expressed previously, the evaluation of retrofitting and different control policies is costly to be carried out on real physical buildings. To this end, an accurate model of the building would result in a reliable source of information for decision making and cost and benefit analysis for possible investments and improvements. The presented model in this section can be implemented by building owners for these objectives. Also, this building simulation, is added to the cyber-physical energy testbed as a physical component of the energy community. All the meter data and thermal variables are trackable, and building operation can be controlled in real-time via the cyber-physical testbed.

### 2.5 Data Generation for Training and Testing

Lack of data is one of the major challenges in research studies when statistical approaches are implemented. Due to the fact that a considerable part of this work is based on statistical methods, a solution was needed to answer this problem. This data is necessary for training and testing predictive models. The testbed described earlier, is a strong means to generate any sort of data for different levels of an energy community. There are sets of hybrid models, which will be described in later chapters, to fully capture thermal behavior of zones in a building. These predictive models are implemented in a model predictive control
scheme to control building HVAC operation. The data generation system is illustrated in Figure 30.

![Figure 30: Data generation network in the testbed](image)

In this system, desired variables, e.g. temperature setpoint, lighting schedule, occupancy, asset operation, etc., are controlled real-time for individual timesteps based on the logic defined in the controller, which is a Matlab code. These sets of controlled variables are used for different applications. For instance, a regression model predicts room average temperature in future time steps based on lagged values of previous temperatures and some other independent variables. Since, the objective is to construct a flexible predictive model that is effective at different conditions, an algorithm generates random setpoints in an acceptable operative range ($22{}^\circ C$ to $27{}^\circ C$) to create training data sets to be fed into the predictive model. To generate random temperature setpoint values, the algorithm (Figure 31) is based on a scalar random walk with different lengths obtained from a preferred
interval which results in a set of random setpoints for desired variables (This is similar to the algorithm described in [28]).

Figure 31: Algorithm introduced by Farzan et. al [28], employed for data generation in the testbed.

The resulting setpoints are collected along with thermal zone average temperature and other variables generated by EnergPlus simulation engine. Figure 32 illustrates resulted room average temperature response to induced random setpoints for 9 zones for a timestep of 10 minute.
In order to begin the simulation of the community, a set of buildings and generation system must be defined. Once the generation system is chosen, it cannot be modified, just as after building a certain number of wind turbines it is inconvenient and costly to demolish or add another. Therefore, a methodology is created to heuristically design the generation system that when combined with the rest of the system would be capable of achieving net zero energy for the community. This methodology, outlined in Figure 33, begins by isolating the generation components and designing each individually, followed by designing the combined system. Major factors for designing the generation system were defined: model type, quantity, cost, land, time period, component generation goal, and site location. The design method is chosen to be heuristic, in that most variables are held constant with default or estimated settings and then the system is designed for one a single variable. As each
variable is added onto the result of the previous, the design accounts for more considerations, ultimately resulting in a close-to-optimal design.

![Diagram of Generation System Design Template](image)

**Figure 33: Generation System Design Template.**

### 2.6.1 Constants

A case study illustrating this design methodology was conducted with specific focus on designing the wind farm. First, major factors were set. For location, interactive maps and data from NREL, SWERA, and Open EI are used to determine that Los Angeles would be a feasible location for the wind design case study. TMY3 weather data is available, solar irradiance is high, and the wind power class of 4 is high enough to be a viable location for a combined generation system according to [16]. Next, the percentage of total energy generation that should be met by wind was set at 25%, according to the solar vs. wind guideline for California in [20].

Next, the time period to design over was chosen. Choosing a worst-case time period in which loads are high and generation is low would result in designing the system to be too large; it would be a net-positive energy community that suffers the steep upfront cost of a large generation system receives relatively less revenue when selling the excess energy
back to the grid. Conversely, choosing a best-case time period would yield a generation system that is sized too small, resulting in the need to constantly purchase external energy for a high price. Hence, according to net-zero energy guidelines in [12], it is best to size the generation system according to an average-case time period. Data was obtained from running the standard simulation settings of our testbed in order to plot the relative trends of wind power, solar power, and load. Figure 34 shows that the average power generation and consumption across a month becomes equal to the average load across the year during the mild season months, making these months representative of the whole year as the average-case scenario. The mild August 15 to September 14 time period was chosen.

![Figure 34: Determination of representative time period to use in designing generation system.](image)

Finally, the turbine models were chosen. [17] was used to help select four different commercially common distribution class wind turbine models from [wind turbine database] with different rated capacities. For this study, it was found that choosing models with rated capacity between one times and five times the wind generation goal illustrates the different sizing options well.
2.6.2 Sizing

MATLAB is used to determine the quantity for each turbine to achieve the energy generation goal. The wind distribution and power curves are first plotted. It is noted from these plots that majority of the time, at least in this location, the wind speed is not high enough for the turbine to produce the rated power. Hence quantities cannot be found by simply dividing the energy generation goal by each turbine model’s rated capacity. Two different sizing methods are used to determine the quantities (see equations below). The Average Velocity Method divides the energy generation goal by the power output that corresponds to the average wind velocity across the time period. The Direct Power Method divides the energy finds the power output for every wind speed across the time period.

Average Velocities Method: \[ N = \frac{P_G}{P_{avg} v_{avg}} \text{ where } v_{avg} = \sum v_i \]  \hspace{1cm} (1.1)

Direct Power Method: \[ N = \frac{P_G}{P_{avg}} \text{ where } P_{avg} = \sum P(v_i) \]  \hspace{1cm} (1.2)

\( P_G \) is wind power generation goal in kW. The power generation of the four wind turbines were simulated in TRNSYS twice, once for each sizing recommendation from the two methods. MATLAB was used to analyze the power output results from TRNSYS and show in Figure 35 that the Direct Power Method was more accurate in sizing the turbines. In addition, the PowerWind56 model with rated power of 900 kW was chosen to best meet the 185 kW wind power generation goal. Finally, the load and generation data are plotted together in Figure 36, along with the net power that is separated into surplus power than can be sold to the grid and shortage of power that warrants the purchase of energy from the grid.
The theory and methodology for designing the generation has been established, but the illustrative example to establish and confirm the theory is in progress. There is capability to design the wind farm component but several factors, such as cost and land constraints
have not been accounted for. The next phase will include a thorough cost-benefit analysis to help choose between turbine models, and after the design methodology is applied to solar PV and battery components this cost-benefit analysis will be conducted when varying other factors such as the distribution of energy generation between solar and PV and varying the representative time period to worst or best case scenarios. This sensitivity analysis will make the testbed more dynamic and accommodating of a wide range of communities. Another improvement to the testbed will be to use real-time weather data such as that from Meteonorm rather than historical. The power grid components of the community will be evaluated to ensure the testbed is accurately modeling those aspects of real distribution systems. Once the generation system design is fully established, the testbed will be expanded to incorporate electric vehicle charging stations in the simulation and design processes.

On the building development side of this work, physical sensors will be established at Rutgers University. Some of the external inputs, such as weather, occupancy, and utility energy prices will be real and obtained through these physical sensors and/or from publically available sources. Building occupancy and use of transportation assets will be physically obtained real time through sensors and real time mobility data. In addition, energy-saving synergies between certain combinations of buildings in a community will be investigated, as well as the ability to prioritize energy demand of some buildings over others.
2.7 CONCLUSION

There is a clear need to establish net-zero communities in the real world. This can only be done if analysis is conducted and recommendations are produced for how best to design and optimize the given community. The data analysis for energy systems, demand response programs evaluation, energy community controls, etc., lack of data and a reliable assessment are some of the most important challenges for implementing these testbeds. This testbed that has this ability to use initial parameters about the climate and buildings to create any scenario, develop data, and make a highly reliable assessment. The energy forecast, building, and generation models will continue to develop with a focus on designing the generation system for a new community that will allow for the achievement of net-zero energy when the testbed simulation begins. In addition, the utilization of real sensor data and communications from the physical world will dramatically decreases the evaluation costs and design risks for the energy communities of interest. Also, this can be implemented in decision making systems in grids to obtain a good estimation of the demand side behavior and micro grid participation.
Chapter III: Machine learning approaches to predict building indoor temperature in VAV systems

3.1 Introduction

In building engineering applications such as HVAC system design and modeling, most of the fundamental thermodynamics and heat transfer relationships are considered linear and simplified. However, the mathematical description for predicting building hydrothermal dynamics is complex, due to non-linearities and interdependence among several variables [29]. Advanced controls that take into account thermal behavior of built environment can significantly improve energy efficiency and reduce load uncertainty. This, in turn, can help improve building’s response to demand response, load shifting and peak shaving specifically in smart grids and power grids. Thermal response analysis can be achieved by transient state or quasi steady state solutions through numerical methods such as CFD [30] or finite difference methods [31]. There are also simulation tools (e.g. TRNSYS [32] and EnergyPlus [33]) with capability of solving the aforementioned equations with an acceptable accuracy. These tools, while very useful for offline analysis and design stage, are generally slow and computational expensive for control applications. However, a data-driven approach would be a practical alternative to estimate building thermal response reasonably accurately and generically [34].
## Nomenclature

<table>
<thead>
<tr>
<th>Index</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(t)</td>
<td>Time</td>
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<tr>
<td>(z)</td>
<td>Zone index</td>
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<tr>
<td>(j)</td>
<td>Damper position index</td>
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<tr>
<td>(p)</td>
<td>Input unit index in neural network system</td>
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<td>(q)</td>
<td>Hidden unit index in neural network system</td>
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<td>(k)</td>
<td>Output unit index in neural network system</td>
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<td>(m)</td>
<td>Input batch size</td>
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### Parameters

<table>
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<th>Symbol</th>
<th>Description</th>
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</thead>
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<td>(A_i)</td>
<td>(i)th wall surface area (m(^2))</td>
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<tr>
<td>(C_p)</td>
<td>Air specific heat (J/kg.K)</td>
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<td>Rate of change of outlet energy to a zone (W)</td>
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</tr>
<tr>
<td>$T^t_z$</td>
<td>Zone z average temperature at time t (°C)</td>
</tr>
<tr>
<td>$T^t_{_z}$</td>
<td>Temperature of zones excluding zone z (°C)</td>
</tr>
<tr>
<td>$T_{x,i}$</td>
<td>ith wall surface temperature (°C)</td>
</tr>
<tr>
<td>$T_\infty$</td>
<td>Dry-bulb external temperature (°C)</td>
</tr>
<tr>
<td>$T_w$</td>
<td>Wet-bulb external temperature (°C)</td>
</tr>
<tr>
<td>$T_{sup}$</td>
<td>Supply air temperature (°C)</td>
</tr>
<tr>
<td>$u$</td>
<td>Input unit in neural network system</td>
</tr>
<tr>
<td>$V_\infty$</td>
<td>Outside air velocity (m/s)</td>
</tr>
<tr>
<td>$X$</td>
<td>Regression model independent variable</td>
</tr>
<tr>
<td>$Y$</td>
<td>Regression model response variable</td>
</tr>
<tr>
<td>$\eta$</td>
<td>Regression model categorical variable</td>
</tr>
<tr>
<td>$\Delta T$</td>
<td>Zone average temperature variation (°C)</td>
</tr>
<tr>
<td>$\tau$</td>
<td>Time of day categorical variables</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>Regression error</td>
</tr>
<tr>
<td>$\phi$</td>
<td>The activation function for the hidden layers in neural network system</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>The activation function for the output layer in neural network system</td>
</tr>
<tr>
<td>$\eta$</td>
<td>Learning rate</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Regularization parameter</td>
</tr>
<tr>
<td>$\Gamma$</td>
<td>Cost function with respect to model parameters</td>
</tr>
<tr>
<td>$\delta t$</td>
<td>Timestep (minutes)</td>
</tr>
</tbody>
</table>
There are several approaches developed for building thermal modeling. Early attempts for simplified building models were based on response factor methods, conduction transfer functions, finite difference methods, and Lumped capacitance methods [35]. Today, there are new approaches that we can categorize into grey-box (RC networks), white-box (thermal balance equations), and black-box (data-driven approaches) models [34]. Resistance-Capacitance (RC) models are among the methods that are fully investigated and implemented in building thermal modeling. In this method, building thermal zones are considered as thermal storage and heat transfer actors, e.g. conduction, convection, radiation, are modeled as a resistance in a network, and coupled differential equations are formulated as state-state systems. Goyal et al. [36] developed balanced truncation methodologies for model reduction in building thermal modeling to predict room humidity and temperature and address nonlinearity in building thermal behavior. Deng et al. reduced coupled differential equations of a building thermal model, based on a large RC network, using aggregation of states. There are research studies using lumped capacitance, subspace methods, and complex RC models [37]–[39].

Besides grey-box methods, data driven methods are widely used for building thermal modeling and physical behavior prediction. Zhao et al. [40] developed a building thermal modeling method based on non-linear state recurrent neural network architectures and Elman recurrent neural network architecture. In addition, they generated data via EnergyPlus models and evaluated their model performance via cross validation methods. Ya et al. [41] used genetic algorithm and feed forward neural network methods to develop algorithms to model building internal temperature behavior. Martinez et al. [42] utilized
Artificial Neural Networks (ANNs) to predict short-term temperature changes in a building. This ANN was composed of two hidden layers for time series forecasting and a back-propagation algorithm was applied to find ANN weights. Moon et al. also used an ANN model to develop a temperature control algorithm to apply a setback temperature predictively for the cooling system of a residential building during occupied periods by residents [43]. In addition, Multiple Linear Regression (MLR), Extreme Learning Machines (ELM), Non-linear Autoregressive Exogenous (NARX), Neural Network Autoregressive Exogenous (NNARX), and Autoregressive Exogenous (ARX) methods are investigated for such applications [44], [45]. There are also some other studies employing statistical methods to predict room temperature in the literature with same approaches and model performance comparisons [46]–[48]. With the advancements in Building Energy Management Systems and new energy efficiency indices, numerous smart energy saving opportunities are emerging [2]. Taking into account physical characteristics of buildings, facility operators are able to implement optimal planning for operation of buildings assets to satisfy comfort level of the occupants and achieve essential criteria for sustainability and energy saving indices [49]–[53]. For instance, Vaghefi et. al [10] used building thermal behavior models to construct model predictive control systems based on physical/statistical hybrid modeling to optimize building HVAC operation under dynamic pricing.

There are research studies investigating different aspects of building indoor environment via inverse modeling for thermal response [54]–[56]. These studies indicate that zone temperature is weighted sum of past zone temperature and heat rates. In this work, we show that in VAV systems, this relationship is not linear and not a weighted sum of independent
variables. To the best of our knowledge, there is a lack in the literature with respect to identifying the impact of inlet airflow and other independent factors on indoor temperature response. Identifying these elements such as the impact of external temperature, solar radiation, wind speed, sky clearness, and inlet air volume in VAV systems would result in a better decision making in control applications such as model predictive control approaches and optimization of building HVAC operation planning. In this work, we focus more on damper positions in VAV systems and zone thermal response to different damper position (ranges between minimum airflow to maximum airflow in a room). Our studies show that assuming damper position as a categorical variable would dramatically improve predictive model performance, which has not been addressed in the literature. We define a systematic approach to construct statistical models via neural network and multivariate regression models. We also impose interaction between damper position and other independent variables in the regression models to reduce non-linearity effects. In this work, we study the impact of different internal gains (lighting, equipment, and occupancy) along with time-of-day impacts and external weather conditions for two different climate zones. The impact of other factors such as asset degradation is also investigated. Model performance evaluations and error analysis are also conducted and compared to evaluate the proposed models. The application of the proposed models in control systems is investigated and examples are presented. These response models can be used in model predictive control applications, pre-heating/cooling, demand response, and pre-occupy and post-occupy controls (see [10], [57]–[59]). To this end, we address the following problems:

- Identifying independent variables influencing building indoor temperature through heat transfer equations and discretizing these equations to construct predictive models.
• Introducing impact of variable inlet airflows on building indoor temperature by damper position as a categorical variable to address the nonlinearity in the equations.

• Adding interaction between damper position and other independent variables to improve the model accuracy.

• Introducing another categorical variable representing time of day to reflect the impact of complex or unknown factors (such as adjacent objects and shadings) affecting indoor temperature over time.

• Development of methodologies to predict indoor temperature variation over time by multivariate regression and neural network models.

• Identifying the influence of the proposed independent variables on indoor temperature variation

• Investigating the capability of the predictive models to capture asset degradation.

• Comparison of different machine learning approaches and data resolution in terms of model performance.

3.2 Heat transfer analysis in a built environment

3.2.1 Conservation of Energy

Heat transfer phenomenon in a building thermal zone is composed of non-linear complex physical interactions. Mainly, conduction, convection, and radiation heat transfer models along with internal gains, inlet and outlet mass flows constitute a system that can be described via energy conservation and partial differential equations [60].

\[
\frac{dE_{\text{system}}}{dt} = \dot{E}_{\text{system}} = \dot{E}_{\text{in}} - \dot{E}_{\text{out}} + \dot{E}_g \quad (3.1)
\]
For a specific thermal zone, if the objective is to find temperature at time $t$, Equation 3.1 can be demonstrated as a simplified relationship (equation 3.2) [61].

$$
\dot{E}_{\text{system}} = C_v \frac{dT_z}{dt} = \sum \dot{E}_g + \sum_{i=1}^{N_{\text{Surfaces}}} hA_i(T_{z,i} - T_z) + \sum_{i=1}^{N_z} \dot{m}_iC_p(T_{z,i} - T_z) + \dot{m}_{\text{inf}}C_p(T_{\infty} - T_z) + \dot{m}_{\text{sys}}C_p(T_{\text{sup}} - T_z) \quad (3.2)
$$

In equation 3.2, $\sum \dot{E}_g$ represents room internal gains arising from multiple sources such as human, appliances, and lighting. The term $\sum_{i=1}^{N_{\text{Surfaces}}} hA_i(T_{z,i} - T_z)$ is the convective heat transfer because of building external/internal conditions such as external wind speed, air density, internal air temperature, wall surface temperature, and due to temperature differences. In this term, $h$ is the convective heat transfer coefficient associated with internal surfaces. Some elements such as solar irradiance and impact of opaque surfaces are captured in wall temperature surface ($T_{s,i}$) which will be elaborated later in this work.

On the other hand, $\sum_{i=1}^{N_{\text{zones}}} \dot{m}_iC_p(T_{z,i} - T_z)$ represents inter-zone air mixing, which is dependent on other thermal zones conditions. $\dot{m}_{\text{inf}}C_p(T_{\infty} - T_z)$ is the infiltration effect and a function of external temperature, internal and external pressure difference, building envelope, air leakage, etc. Lastly, $\dot{m}_{\text{sys}}C_p(T_{\text{sup}} - T_z)$ is the inlet airflow supplied by the air distribution system, which is a function of air system design, system condition, etc.

There is no closed-form solution to equation 3.2; therefore, we have to solve this equation by discretization methods. Implementing finite difference methods [31], we can find an explicit relationship between temperature and other factors in addition to average temperatures at previous time-steps as follows:
\[
\frac{dT_z}{dt}\big|_t \approx (\delta t)^{-1} \left( \frac{11}{6} T_z^t - 3 T_z^{t-\delta t} + \frac{3}{2} T_z^{t-2\delta t} - \frac{1}{3} T_z^{t-3\delta t} \right) + O(\delta t^3) \quad (3.3)
\]

\[
T_z^t = \frac{1}{\left( \frac{11}{6} \right)} \frac{C_z}{\delta t} + \sum h_i A_i + \sum \dot{m}_i C_p + \dot{m}_{sys} C_p + \dot{m}_{inf} C_p \left( \sum \dot{E}_g + \sum h_i A_i T_{s,i} \right)
+ \sum \dot{m}_i C_p T_i + \dot{m}_{inf} C_p T_{\infty} + \dot{m}_{sys} C_p T_{supply}
- \left( \frac{C_z}{\delta t} \right) \left( -3 T_z^{t-\delta t} + \frac{3}{2} T_z^{t-2\delta t} - \frac{1}{3} T_z^{t-3\delta t} \right) \quad (3.4)
\]

### 3.2.2 Indoor temperature prediction models

To solve equation 3.4 in a real case scenario, all the introduced elements should be quantified. However, it is difficult, even with sensor data, to accurately measure or define some of the coefficients in equation 3.4 (such as surface temperature, internal gains, specific heat, and convective heat transfer coefficients). On the other hand, impact of solar radiation transferred through windows, longwave/shortwave radiation effects, wet-bulb temperature, wind speed, and sky clearness are neglected or hidden in equation 3.4. One solution can be data-driven approaches (such as supervised learning methods) to identify and solve equation 3.4, and also, add other complex factors. This can be described as follows:

\[
T_z^t = f(\dot{E}_g, T_z^{t-\delta t}, T_z^{t-2\delta t}, T_z^{t-3\delta t}, A_i, h_i, T_{\infty}, T_s, T_{-z}, R_{\infty}, \dot{m}_i, \dot{m}_{sys}, \dot{m}_{inf}, T_{supply}) \quad (3.5)
\]
equation 3.5 indicates that room average temperature is also a function of past temperature values \((T_z^{t-\delta t}, T_z^{t-2\delta t}, T_z^{t-3\delta t})\). We only included three past timestep according to equation 3.3, according to [31], while it should be noticed that these terms might be different for buildings with different thermal capacitance (buildings with large thermal capacitance might need more past terms and vice versa for small thermal capacitance). In equation 3.5,
\( T_s \) (zone wind/sun exposed wall temperature) is not a tangible element to be simply calculated through mathematical modeling or measured by surface temperature sensors in engineering applications. Note that heat flux absorption, reflection, and diffusion can be modeled by Stefan-Boltzmann laws, heat flux exchange in the boundary, and view factors, which are complex models. This value is a complex function of shortwave/longwave radiation, wall conduction, surface convective heat transfer with internal/external airflows (including wind velocity), and ambient temperature [61].

\[
T_s = \Psi(R_\infty, k_{\text{wall}}, h, h_\infty, T_\infty, V_\infty) \quad (3.6)
\]

Considering the impact of external wet-bulb temperature \( (T_w) \) and sky clearness (I is a measure based on ASHRAE measures and is defined as the ratio of direct incident solar radiation to the extra-terrestrial solar atmosphere \((\text{MJ} \cdot \text{m}^{-2} \cdot \text{day}^{-1})\)) and equations 3.5 and 3.6, equation 3.7 can describe zone average indoor temperature value as below:

\[
T_z^t = f(\dot{E}_g, T_{z}^{t-\delta t}, T_{z}^{t-2\delta t}, T_{z}^{t-3\delta t}, A_i, h_i, T_\infty, T_{z})
\]

\[\text{, } \dot{m}_{\text{inf}}, \dot{m}_{\text{sys}}, T_{\text{supply}}, R_\infty, k_{\text{wall}}, h, h_\infty, T_\infty, V_\infty, T_w, I) \quad (3.7)\]

In this equation, the impact of some terms such as wall area, convective/conductive heat transfer coefficients, infiltration rate, and air specific heat are variables that can be captured via machine learning approaches. In general, monitoring sensor data for these elements is difficult to obtain via measurement; however, the predictive models can be trained to capture these phenomena. Internal mass, which greatly affects the zone temperature dynamics, is often not modeled/estimated in RC models and the previous equations; however, these impacts can be captured in the regression weight vector under different circumstances. There are other external factors (specially in urban areas) such as impact of
adjacent buildings and temperature of surrounding objects that cannot be simply represented mathematically or measured. These factors can also be addressed via aforementioned approaches. All other variables ($\dot{E}_g, T_{zt}^{t-\delta t}, T_{zt}^{t-2\delta t}, T_{zt}^{t-3\delta t}, T_{zt}, T_{\infty}, R_{\infty}, V_{\infty}, T_w, I$) in equation 3.7 are independent variables that directly interact with room average temperature and can be measured at different timesteps.

### 3.2.3 Unrolled time series for zone temperature values

We propose two methods to unroll zone indoor temperature variation over time. The first method is to directly find zone temperature values at time $t$ ($T_{zt}^t$). As mentioned in equation 3.7, zone temperature value is a function of previous temperature values and current values of independent variables at time $t$. Here, we first read temperature values from previous timesteps and current values associated with other independent variables at time $t$. Then we predict the temperature response over the next timestep based on the inlet airflow $\dot{m}$. This procedure continues over time as the past temperature values ($T_{zt}^{t-\delta t}, T_{zt}^{t-2\delta t}, T_{zt}^{t-3\delta t}$) will be updated and replaced for the future timesteps. This methodology is demonstrated in Figure 37. The second approach is to continue thermal modeling by predicting temperature change ($T_{zt}^{t-\delta t} - T_{zt}^{t-\delta t}$ or $\Delta T_{zt}^t$) rather than temperature values ($T_{zt}^t$). Since the relationship between $T_{zt}^t$ and $T_{zt}^{t-\delta t}$ is linear, equation 3.7 is also valid for temperature change over a timestep ($\Delta T_{zt}^t$). As a result, for temperature values at time $t$, we can calculate it by:

$$T_{zt}^t = T_{zt}^{t-\delta t} + \Delta T_{zt}^t \quad (3.8)$$

where $\Delta T_{zt}^t$ can be found by a function similar to equation 3.7. The predition can continue based on a similar approach presented in Figure 37. $\Delta T_{zt}^t$ is an important factor to evaluate
the impact of change of independent variables on indoor temperature. This impact will be presented later in this study.

Figure 37: Unrolled temperature response modeling for future timesteps based on previous temperature values and independent variables (X) for zone z and time t.

3.2.4 Predictive modeling

In order to continue thermal modeling over a period, we need to predict $T_z^t$ or $\Delta T_z^t$ values (Figure 37). In this section, the objective is to utilize machine learning approaches to predict the aforementioned values based on equation 3.7. Multivariate linear regression models and different neural network methods are utilized to achieve this goal. The neural network approaches that are investigated are: Levenberg-Marquardt, Bayesian Regularization, BFGS Quasi-Newton, and Gradient Descent. In what follows in this section, we first demonstrate how to linearize equation 3.4 to be able to develop multivariate linear regression models and how to implement neural network models to predict building indoor temperature.

3.2.4.1 Multivariate Regression Model

In this section, we demonstrate how to construct a multivariate linear regression model to predict indoor temperature, and how to define and add categorical variables to address non-linearity demonstrated in equation 3.4. As seen in equation 3.4, even in the simplified model of room average temperature, inlet airflow appears in the denominator, which results
in more nonlinearity and interaction between supply inlet airflow and other parameters. Zone average temperature can be represented as the response variable of an interaction model based on the relationship demonstrated in equation 3.7. Since inlet airflow has interaction with other independent variables, we consider it as a categorical variable. This categorical variable is an ordinal variable based on zone damper position, and can represent zone temperature response under different damper positions from fully closed to fully open. Thus, zone inlet airflow can be represented by this categorical variable. Equation 3.9 shows the multivariate regression prediction model in which model’s parameters can be found by minimizing the cost function with MSE (Mean Square Error) and a regularization term (to avoid overfitting) presented in equation 3.10. Model parameters are found via a mini-batch (with size m) gradient descent optimization method to construct a learning framework based on equation 3.11.

\[
\bar{y} = h(X, \beta) = \beta^T.x \quad (3.9)
\]

\[
\Gamma(\beta) = \frac{1}{m} \sum_{k=1}^{m} \left( y^{(k)} - h(X, \beta) \right)^2 + \frac{\alpha}{2} \sum_{k=1}^{m} \beta_k^2 = \frac{1}{m} \sum_{k=1}^{m} \left( y^{(k)} - \beta^T.x^{(k)} \right)^2 + \frac{\alpha}{2} \sum_{k=1}^{m} \beta_k^2 \quad (3.10)
\]

\[
\beta^{n+1} = \beta^n - \eta \Gamma_{\beta}(\beta) \quad (3.11)
\]

Since we assume that damper position is a categorical variable with J (and j=1,...,J-1), we consider this variable as a dummy vector. Consequently, this categorical variable updates beta coefficients to \( \beta_{i,j} \) where \( i \) is the independent variable index (\( x_i \)), and \( j \) is damper position index. Damper position categories are calculated via K-Means clustering methods. The near-optimal number of damper position clusters is iteratively found to achieve a better
model performance. Equation 3.12 presents the regression model as a function of 12 independent variables as:

\[
T^t_z = \beta_{j,0} + \beta_{j,1}\dot{E}_g^t + \beta_{j,2}T_Z^{t-\delta t} + \beta_{j,3}T_Z^{t-2\delta t} + \beta_{j,4}T_Z^{t-3\delta t} + \beta_{j,5}T_{-z}^t + \beta_{j,6}T_\infty^t + \beta_{j,7}R_{\infty}^t + \beta_{j,8}V_\infty^t + \beta_{j,9}\tau + \beta_{j,10}T_W^t + \beta_{j,11}I^t + \epsilon^t \tag{3.12}
\]

where \(\tau\), as another categorical variable, is introduced to reflect impact of unknown factors (such as adjacent building shadows, radiation reflection of adjacent buildings, adjacent objects temperatures, etc.) that vary over time. \(\tau\) is a 1x24 vector representing 24 hours in a day and directly impacts regression model intersect \((\beta_{j,0})\) based on time of day. In equation 3.12, beta coefficients represent the effect of unit change in independent variables on temperature response and \(T_{-z}^t\) is average temperature of all zones excluding zone \(z\). Also, \(\dot{E}_g^t\) is redefined with three new variables of lighting schedule, equipment schedule, and occupancy schedule \((S_{lg}^t, S_{eq}^t, S_{oc}^t\) respectively) and their own beta coefficients. These schedule values are ratios between zero to one. To predict temperature change over a timestep \(\Delta T^t_z\) we use exactly the same formulation in equation 3.13:

\[
\Delta T^t_z = T^t_z - T_{-z}^{t-\delta t} = \beta_{j,0} + \beta_{j,1}\dot{E}_g^t + \beta_{j,2}T_Z^{t-\delta t} + \beta_{j,3}T_Z^{t-2\delta t} + \beta_{j,4}T_Z^{t-3\delta t} + \beta_{j,5}T_{-z}^t + \beta_{j,6}T_\infty^t + \beta_{j,7}R_{\infty}^t + \beta_{j,8}V_\infty^t + \beta_{j,9}\tau + \beta_{j,10}T_W^t + \beta_{j,11}I^t + \epsilon^t \tag{3.13}
\]

### 3.2.4.2 Application of neural networks in thermal modeling

When there is no clear relationship between the inputs and outputs, Artificial Neural Networks (ANNs) are able to tackle problems without prior assumptions [62] and knowing clear relationship between the neurons. Consequently, these approaches can be utilized for non-linear relationships introduced in equation 3.4. There are some important factors in the
performance evaluation of an ANN model. These factors are categorized into NN model construction and NN model training. NN model construction includes type of connection, activation functions, and number of nodes and hidden layers. NN model training represents pre-processing data and number of training examples [63]. In this paper, since a temperature prediction problem is studied, a feed-forward Multilayer Perceptron (MLP) neural network has been developed to learn and generalize the network.

A neural network consists of three main parts: the input layer, the hidden layer(s) and the output layer. The hidden layers connect the inputs to the output and help to solve non-linear problems. In an MLP network, more than one hidden layer can exist. Some researchers believe that more hidden layers can be added to obtain a quite powerful multilayer network [64], [65]. On the other hand, based on the Kolmogorov’s theorem [66], some others argue that just one or two hidden layers are sufficient since more hidden layers could cause the overfitting problem. For this paper, we consider different cases with one or two hidden layers to achieve accurate results in our NN model. Figure 38 illustrates the structure of a feed-forward MLP structure.

![Figure 38: Multilayer feed-forward structure of the neural network](image-url)
The MLP activation functions are one of the most crucial parts in designing neural network architecture. We chose two activation functions in this study, one for the hidden layers and another for the output layer. Sigmoid activation is a common activation function with output intervals varying between zero to one. Another activation function is the hyperbolic tangent function with an output interval of -1 to 1 which is used in back-propagation networks. In this paper, the activation function $\phi(x)$ for the hidden layer is hyperbolic tangent function as follows:

$$\phi(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$  \hspace{1cm} (3.14)

where $x$ represents the model parameter. In addition, $\gamma(x)$ is the linear activation function for the output layer. Hence, the final mathematical equation of our ANN is as follows:

$$\bar{y}_t = \gamma(\sum_{q=1}^{n} u_{kq}\phi(\sum_{p=1}^{m} w_{qp}u_p + b_q) + b_k)$$  \hspace{1cm} (3.15)

where $\bar{y}_t$ is the prediction using NN, $u_{kq}$ and $w_{qp}$ are weights, $b_q$ and $b_k$ are bias values, and $m$ and $n$ are the number of input variables and the number of hidden units, respectively.

Each ANN can include $m$ neurons in input layer and neurons in hidden layers should not exceed $2m + 1$ neurons [62]. Based on equation 3.16, we have 14 inputs which means we should have 14 input neurons. In this paper, we assume the number of hidden neurons are equal to the number of input units. So, we also have 14 neurons in the hidden layers, and one output which can be seen in Figure 38.

One approach to evaluate the performance of ANNs is using walk-forward testing routine, also known as either sliding or moving window testing. In this method, input data are
divided into three groups: training, validation and testing sets [67]. The training or learning set is the largest one and chosen to learn the behavior and patterns of input data. The testing set is used to evaluate the neural network model prediction. Validation set is also used to minimize the overfitting and it is a final check on the performance of the trained network. In this paper, the neural network is trained using 85% of the data set, 10% of the data set is used for testing the performance of NN, and 5% of the data is utilized for validating the network. A validation set is used for early stopping in order to prevent the network from over-training. The criterion for this set is met when the validation accuracy stays the same or decreases while the accuracy of learning datasets increases. In addition, testing datasets are used to check whether or not the network error will reduce. If the network error resulting from the testing datasets differs substantially from the training datasets error, then the network is not well-trained [68]. Different training algorithms are available for learning process in neural networks with different characteristics and performance. In this paper, we use Bayesian Regularization, Levenberg-Marquardt, Gradient Descent, and Quasi-Newton’s method. The last two need much more time for the convergence, and the first two algorithms converge better and faster; however, the results show that Bayesian Regularization algorithm gives better results and minimizes the errors more than Levenberg-Marquardt algorithm.

3.3 Simulation and data generation

We use EnergyPlus building simulation models to generate data for training and test datasets. Building Control Virtual Testbed (BCVTB) [69] is also utilized for room temperature setpoint control. We present two building simulations in this study and construct our models based on these models. The first model is a one-story office building
located in Newark, NJ with an electric chiller and an air handling unit, VAV fans, and VAV boxes. The building is composed of nine similar zones, each with a floor area of 100 m². The second building is DOE Medium Office Reference Building with 15 thermal zones and a VAV system located in Chicago, IL. The building envelopes for both models are based on ASHRAE Standard 90.1-2004, Climate Zones 5A and 4A. The geometry of the buildings and histogram of weather condition in the two climate zones in NJ and IL are illustrated in Figure 39. It should be mentioned that the simulations are performed for 1, 5, and 15 minute time intervals for 30 days.

![Figure 39: X-ray and original building geometry of the small office (bottom) and medium office (top).](image)

### 3.4 Results

#### 3.4.1 Multivariate regression model results

##### 3.4.1.1 Impact of independent variables on indoor temperature

In this section, we first evaluate multivariate regression models and the impact of independent variables on zone temperature variation ($\Delta T^I_z$) over 15-minute timesteps. We first train all the models with 80% of the data while 20% is used as test data to avoid from overfitting. Our results show that 15-minute time intervals results in better predictive
models compared to 1-minute and 5-minute timesteps (this will be presented in model performance analysis and due to model stability). Considering that the interactive model in equation 3.12 is composed of 80 beta coefficients, evaluation and presentation of the independent variables and their impact on response variable would become tedious. Hence, to evaluate the impact and importance of beta coefficients, we simplify the interaction model in equation 3.13 into a non-interaction model to identify, present, and compare major actors in room temperature response (equation 3.15). Our results also indicate that equation 3.16 has acceptable accuracy, which will be presented later in model performance section. Thus, we consider damper position as a new categorical variable (DP) that has no interaction with other variables as:

\[ \Delta T_Z^t = T_Z^t - T_Z^{t-\delta t} = \beta_0 + \beta_1 E^t_g + \beta_2 T_Z^{t-\delta t} + \beta_3 T_Z^{t-2\delta t} + \beta_4 T_Z^{t-3\delta t} + \beta_5 T_{-z}^t + \beta_6 T_\infty^t + \beta_7 R_\infty^t + \beta_8 V_\infty^t + \beta_9 \tau + \beta_{10} T_w^t + \beta_{11} I^t + \beta_{12} DP + \epsilon^t \] (3.16)

We also take an average value over the buildings zones for each coefficient as follow to be able to present the average beta coefficients for the whole building:

\[ \bar{X}_i = \frac{1}{N_z} \sum_{z=1}^{N_z} \beta_{i,z} \] (3.17)

where \( \bar{X}_i \) is the average beta coefficient of the equivalent variable over all zones, and \( \beta_{i,z} \) is the beta coefficient of the variable X in zone z. Table 2 presents average beta coefficients for each building based on equation 3.16. These beta coefficients are obtained based on multivariate linear regression models. As seen in Table 2, the level of significance of factors (evaluated via t-tests) are different based on climate zone, building envelope,
internal gains etc. The ordinal categorical variables that reflect the impact of damper position and time of day on indoor temperature are also presented in Table 2. Damper positions are clustered via K-means clustering method. In this regard, the value of k, which is the optimal number of clusters, should be found. The most common way to find the best number of clusters is using elbow method. The idea of this method is to run k-means method on the dataset for different values of k (here we use 1 to 20 for k), and for each value of k, we calculate the sum of square errors (SSE). Then we plot a chart of the SSE for each k. We try to have a small SSE, but it is obvious that the SSE tends to decrease toward 0 as we increase k. Hence, we need to choose the smallest possible value of k that still has a low SSE. Figure 40 shows SSE versus the number of clusters in 15-minute time interval for both small office and medium office.

Figure 40: Clustering SSE versus the number of clusters for both small and medium offices.

Figure 40 illustrates that taking 6 clusters in this problem is reasonable since the value of k is relatively small and it has a low SSE. By using this assumption that we have 6 clusters for damper positions, we use k-means clustering to find the near-optimal percentage range for each cluster. We take each percentage of damper position as one of our observations.
So, we have 100 observations and we want to group them into 6 clusters. The results show that damper positions could be optimally categorized into these 6 clusters: 0% to 5%, 5% to 20%, 20% to 30%, 30% to 60%, 60% to 80%, and 80% to 100%. The categorical variable that represent these values are presented as $D{P}_{a-b}$, where $a$ is the lower damper position and $b$ is the higher damper position value. Also, the models are developed for 7 AM to 7 PM, which is demonstrated as $\tau_{a-b}$, where $a$ and $b$ represent start and end time of the categorical variable.

**Table 2: Average beta coefficient for temperature change prediction in 15-minute time intervals.**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Beta</th>
<th>t-Stat</th>
<th>Beta</th>
<th>t-Stat</th>
<th>Variable</th>
<th>Beta</th>
<th>t-Stat</th>
<th>Beta</th>
<th>t-Stat</th>
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<tr>
<td>$\beta_0$</td>
<td>5.666</td>
<td>11.669</td>
<td>13.25114</td>
<td>16.35944</td>
<td>$D{P}_{5-20}$</td>
<td>-0.39117</td>
<td>-12.7569</td>
<td>-0.76648</td>
<td>-19.574</td>
</tr>
<tr>
<td>$S_{iy}$</td>
<td>0.302</td>
<td>5.179</td>
<td>0.063522</td>
<td>1.053899</td>
<td>$D{P}_{20-30}$</td>
<td>-0.89522</td>
<td>-24.2513</td>
<td>-1.46869</td>
<td>-30.4489</td>
</tr>
<tr>
<td>$S_{eq}$</td>
<td>0.694</td>
<td>12.318</td>
<td>0.248228</td>
<td>3.688298</td>
<td>$D{P}_{30-60}$</td>
<td>-1.52156</td>
<td>-47.2885</td>
<td>-2.14268</td>
<td>-43.6814</td>
</tr>
<tr>
<td>$S_{oc}$</td>
<td>0.034</td>
<td>0.549</td>
<td>0.003903</td>
<td>0.08017</td>
<td>$D{P}_{60-80}$</td>
<td>-2.16494</td>
<td>-48.6294</td>
<td>-2.82089</td>
<td>-39.1885</td>
</tr>
<tr>
<td>$\tau_{7-8}^{\delta t}$</td>
<td>-0.476</td>
<td>-31.321</td>
<td>-0.60705</td>
<td>-39.1952</td>
<td>$D{P}_{80-100}$</td>
<td>-2.54897</td>
<td>-53.9335</td>
<td>-3.27585</td>
<td>-37.5322</td>
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<tr>
<td>$\tau_{10-11}^{3\delta t}$</td>
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<td>-1.961</td>
<td>0.005272</td>
<td>0.328624</td>
<td>$\tau_7$</td>
<td>0.11584</td>
<td>2.692447</td>
<td>0.187047</td>
<td>3.664006</td>
</tr>
<tr>
<td>$\tau_{7-8}^{\delta t}$</td>
<td>0.065</td>
<td>4.789</td>
<td>0.07675</td>
<td>5.69238</td>
<td>$\tau_9$</td>
<td>0.18706</td>
<td>4.319366</td>
<td>0.171772</td>
<td>3.351384</td>
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<tr>
<td>$\tau_{11-12}^{3\delta t}$</td>
<td>0.186</td>
<td>9.529</td>
<td>0.074474</td>
<td>2.384834</td>
<td>$\tau_{10-11}$</td>
<td>0.146551</td>
<td>3.298587</td>
<td>0.10195</td>
<td>2.117457</td>
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<tr>
<td>$\tau_{11-12}^{3\delta t}$</td>
<td>0.049</td>
<td>11.369</td>
<td>0.006307</td>
<td>0.863857</td>
<td>$\tau_{11-12}$</td>
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<td>$\tau_{12-13}^{3\delta t}$</td>
<td>0.0002</td>
<td>1.29</td>
<td>2.34E-05</td>
<td>0.031149</td>
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<tr>
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<td>-0.005</td>
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<td>3.131164</td>
<td>0.201919</td>
<td>3.750085</td>
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<td>$\tau_{14-15}^{3\delta t}$</td>
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<td>1.522</td>
<td>0.06277</td>
<td>5.299514</td>
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<td>0.207456</td>
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<td>$\tau_{15-16}^{3\delta t}$</td>
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<td>1.86</td>
<td>0.011848</td>
<td>0.462726</td>
<td>$\tau_{15-16}$</td>
<td>0.202547</td>
<td>4.174907</td>
<td>0.194161</td>
<td>3.244087</td>
</tr>
<tr>
<td>$\tau_{16-17}^{3\delta t}$</td>
<td>0.197761</td>
<td>4.021051</td>
<td>-0.05045</td>
<td>-0.8581</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>$\tau_{17-18}^{3\delta t}$</td>
<td>0.194911</td>
<td>4.012628</td>
<td>-0.20495</td>
<td>-3.16678</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau_{18-19}^{3\delta t}$</td>
<td>0.190249</td>
<td>3.932377</td>
<td>-0.37124</td>
<td>-5.72309</td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>
Table 2 presents useful information. As seen in this table, DP is highly statistically significant in both cases while time of day values have lower impact on indoor temperature variation. Figure 41 illustrates how beta coefficients decrease when damper in the VAV box increases. This means that higher damper positions result in higher temperature drop, which can be intuitively deduced. To implement these categorical variables, one has to first specify the damper position $DP_{a-b}$ category. Afterwards, all other damper position coefficients are assigned as zero except the specified damper position coefficient, which is non-zero and summed up to $\beta_0$. If damper position is between 0% and 5%, $\beta_0$ remains the same. The same procedure is also valid for time-of-day categorical variables.

![Figure 41: Variation of beta coefficients by increasing damper position in the VAV box.](image)

On the other hand, significance of lighting and equipment internal gains are higher in the small office compared to the medium office while occupancy gains have small effect on indoor temperature. In addition, external dry-bulb temperature in small office has the highest impact on indoor temperature variation, indicating that the HVAC systems in these buildings can dominate the impact of external conditions. Fig. 7 illustrates a comparison of maximum, minimum, and average temperature change (15-minute intervals) caused by unit change in lighting internal gain, equipment internal gain, people internal gain, external
temperature, solar irradiance, wind velocity, sky clearness, external wet-bulb temperature considering all other variables remain constant. These values are all based on minimum, maximum, and mean values of datasets used in this analysis for the two weather conditions and building characteristics. As seen in Figure 42, different independent variables have different effects based on weather condition and building characteristics such as building construction material and internal gains features. However, it should be noticed that these results are based on building average data while individual zones have different response to changes in independent variables.

Figure 42: The impact of different categories interacting in temperature change over 15-minute intervals in the small (top) and medium (bottom) offices.

As an example, the maximum impact of external temperature on the small office is illustrated in Figure 43. As seen in this figure, western zones (W, SW, SE) are more
affected by external temperature variations while the central zone (C) that has no external walls has the lowest effect.

![Figure 43: Effect of external temperature on indoor temperature of different zones in the small office.](image)

As demonstrated in Table 2 and Fig. 7, statistical significance of independent variables, and in turn, t-test analysis is case sensitive and changes with respect to building envelope, air conditioning design, weather conditions, etc. Thus, t-test analysis cannot be generalized to identify statistically significant variables.

### 3.4.2 Prediction of indoor temperature over time

To demonstrate the performance of different linear regression and neural network that are proposed in this work, we compare EnergyPlus simulation results versus the predictive methods for different scenarios. Figure 44 demonstrates a comparison between simulation temperature values and predictive models based on equations 3.12, 3.13, 3.15 and the procedure illustrated previously in Figure 37. The predictive models used in these results are Multivariate Linear Regression based on equation 3.12 (we call it MLR) to predict indoor temperature absolute value, Multivariate Liner Regression based on equation 3.13 (we call it MLRT) to predict temperature variation during a time-step, Neural Network
trained by Bayesian Regularization algorithm to predict indoor temperature absolute value (we call it BR), and the same approach to predict temperature variation during a time-step (we call it BRT). Later in model performance section, we will show that for neural network models, Bayesian Regularization with two hidden layers method has the best performance among other introduced neural network methods. As seen in Figure 44 there is a good agreement between simulation data and response model considering the fact that these results are based on test data. Also, MLR and MLRT behavior are the same so we only use MLR from this point. It should be noted that large departures from normal operating conditions cannot always be predicted or fully studied due to the fact that large temperature deviations are very rare and cannot be artificially generated in the simulations (these large deviations are dependent on uncontrollable externalities such as weather conditions).

Figure 44: Comparison of different prediction methods and simulation data for 6 representative zones in the small and medium office.

3.4.3 Zone temperature response to damper position and impact of degradation

One application of the proposed predictive thermal modeling methods is to find the maximum/minimum temperature response of a variable air volume air conditioning system
for different damper positions over time. Figure 45 demonstrates predictive behavior of central and eastern zones in the small and medium offices under different damper positions based on multivariate regression models. These simulations occur at 10 AM for a one-hour period. We assume that the initial temperature for cases are 24 °C. Figure 45 gives different response patterns for different zones demonstrating that a zone facing to east have a higher rate of temperature increase when dampers are closed or partially open compared to internal zones. In addition, we can see that the response model is able to find maximum/minimum HVAC system capacity to change the temperature of a zone. Another comparison is demonstrated in Figure 46, where all conditions are maintained the same for the two case scenarios except impact of asset degradation. It is assumed that the variable fan in the AHU system of the first case has total efficiency of 60% while it decreases to 50% in the second scenario due to degradation or poor maintenance. If the initial temperature of the two cases are both 24 °C and all other independent variables are the same, the expected thermal response would dramatically change as a result of fan heat gains and inlet airflow reduction. One can compare the expected thermal response based on the proposed model and the real monitored thermal response for fault detection applications. This demonstrates that although fan efficiency is not an independent variable, the predictive models can learn the degradation effect without fan efficiency measurement.
Temperature response prediction in a zone is important since one can use these predictions in applications such as pre-cooling in demand side management. If the maximum and minimum temperature changes in a building with specific circumstances are identified accurately, operation scheduling (specifically in MPC and demand response applications) would become more reliable to make sure the system is maintained in human comfort zone.
3.4.4 Damper position as a categorical variable

Lastly, we demonstrate that assuming temperature variation as a weighted sum of independent variables [54]–[56] can be improved for systems with variable inlet flow. In general, airflow can be described in the form of a categorical variable (as different damper positions represented with j index) that has interaction with all other variables in equations 3.13 and 3.14. Another option is to consider it as a categorical variable (DP) that has not interaction with other independent variables (equation 3.16). The last option is to consider airflow as a regular independent variable ($\dot{m}$) in a weighted sum of independent variables:

$$T_z^t = \beta_0 + \beta_1 \dot{E}_g^t + \beta_2 T_z^{t-\delta t} + \beta_3 T_z^{t-2\delta t} + \beta_4 T_z^{t-3\delta t} + \beta_5 T_{-z}^t + \beta_7 T_{\infty}^t + \beta_9 R_{\infty}^t + \beta_9 V_{\infty}^t + \beta_{10} \tau + \beta_{11} T_w^t + \beta_{12} I^t + \beta_{12} \dot{m} + \epsilon^t$$  (3.18)

We already demonstrated through equation 3.4 that due to the fact that inlet airflow appears in the denominator of the equation, if inlet airflow is variable, the relationship between indoor temperature and other variables will no longer be linear. Consequently, a categorical variable that has interaction with all other independent variables to represent impact of variable inlet airflow can fulfill this condition. Figure 47 compares simulation results versus predicted values by interaction categorical model (equation 3.12) and simple weighted sum model (equation 3.18) under the same conditions. Our results indicate that prediction error for test data can improve up to 200% by the proposed methodology (this will be presented in model performance analysis section).
In this section, we first discuss model performance of the proposed neural network models. Afterwards, the neural network method with the highest accuracy will be selected and compared with multivariate linear regression models. The impact of timestep and interaction/non-interaction models on model performance will be discussed further. To evaluate the performance of the models, equations 3.19 and 3.20 were used for training and testing datasets to find mean square error (MSE) and mean absolute percentage deviation (MAPD).

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (\hat{T}_i - T_i)^2 \quad (3.19)
\]

\[
MAPD = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{T_i - \hat{T}_i}{T_i} \right| \quad (3.20)
\]
where $\hat{T}_i$ is the predicted value, $T_i$ is the simulation temperature value, and $n$ is the number of observations. Equations 3.19 and 3.20 are our criteria to evaluate the models with acceptable accuracy.

In this study, we designed a multilayer architecture for the neural networks with 14 input units, 14 hidden units, and one output. To find the least error in our model, we need to choose the best number for hidden layers. Based on the Kolmogorov’s theorem, using just one or two hidden layers could be sufficient. Consequently, we developed all the models with one or two hidden layers to avoid from overfitting. Moreover, we used four different training algorithms, Quasi-Newton (QN), Bayesian Regularization (BR), Gradient Descent (GD), and Levenberg-Marquardt (LM), to find the best algorithm for indoor temperature prediction. Our results illustrate that Bayesian Regularization algorithm with two hidden layers minimizes the errors more than the other algorithms. Figure 48 illustrates a comparison between MSE and MAPD values associated with the different neural network approaches averaged on all zones in the small and medium offices and for fifteen-minute time intervals. In this figure, the digits in front of the method’s short name indicates the number of hidden layers.
As seen in Figure 48, Bayesian Regularization with two hidden layers results in the best prediction performance while Gradient Descent has the lowest performance among the methodologies. Bayesian Regularization method has an average MAPD error of 0.709% for the medium building and 0.498% for the small building. Assuming an average indoor temperature of 23 °C, this would result in about 0.16 °C and 0.114 °C error on average.

We previously discussed that 15-minute time interval was chosen in this work as our main timestep. A comparison between three different timesteps of one, five, and fifteen minutes indicate that fifteen-minute time interval has the best results. This also dramatically reduces the process time of the predictive models. Larger timesteps may lose variation of independent variables over the time interval and create overfitting issues. Figure 49 demonstrate the impact of timestep on model performance associated with the small and
medium offices. These results are based on equations 3.15 (BR2) and 3.12 (MLR) for test datasets.

As seen in Figure 49, the model performance significantly improves from 2% and 1.08% to 0.71% and 0.49%.

Figure 15 demonstrate the impact of assuming inlet airflow as a categorical variable on the model performance versus a weighted sum model. In this figure, Multivariate Regression models and neural networks are constructed by assuming:

- Inlet airflow as a categorical variable with interaction with all other variables (we call it MLR-Interaction)
- Inlet airflow as a categorical variable with no interaction (we call it MLR-no-Interaction)
- Inlet airflow as regular independent variable and inlet temperature as a weighted sum of independent variables (we call it WSMLR)
As seen in Figure 50, assuming airflow as a categorical variable dramatically improves model performance. The improvement is more noticeable on the test data while it can also be observed for the training data. On the other hand, although interaction model improves the performance, the improvement is not a considerable amount. The best MAPD for the medium office test dataset is 0.709% through Bayesian Regularization method with two hidden layers while multivariate linear regression model gives rise to 0.733%. On the other hand, for the small office, multivariate linear regression models result in an MAPD of 0.467% while MAPD of Bayesian Regularization is 0.498%. However, selecting the method depends on the applications. Linear regression models can be represented in a much simpler form compared to Neural Network models. As a result, one can find the estimated coefficient of controlled variables and incorporate them in a linear optimization framework while this is not feasible for Neural Network estimations. Lastly, we present average $R^2$ values over all the zones for the multivariate linear regression and Bayesian Regularization models over a timestep ($\delta t$) based on equation 3.21. These values also
indicate that the proposed predictive models can be utilized for indoor temperature prediction.

Table 3: $R^2$ Values for temperature prediction over a timestep

<table>
<thead>
<tr>
<th></th>
<th>Small Office</th>
<th>Medium Office</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLR</td>
<td>0.958</td>
<td>0.945</td>
</tr>
<tr>
<td>BR2</td>
<td>0.925</td>
<td>0.913</td>
</tr>
</tbody>
</table>

3.6 Conclusion and applications

The proposed response model has the capability of predicting temperature behavior of building zones with an acceptable accuracy. The major variables were identified, which signifies monitoring of such variables in building control decision making. It was demonstrated that different independent variables have different effects on the estimation of indoor temperature through machine learning approaches. Also, it was shown that statistical significance of independent variables, and in turn, t-test analysis is case sensitive and changes with respect to building envelope, air conditioning design, weather conditions, etc. The positive impact of considering inlet airflow as a categorical variable in indoor temperature prediction was also demonstrated for variable air volume systems. Different thermal responses to dampers positions for individual zones in VAV systems can be estimated via the proposed model. This response predictor can be utilized in different applications for energy saving in buildings such as:

- Demand response programs
- Pre-post occupy control strategies
- HVAC distributed control
• Building operation control optimization frameworks
• Fault and failure detection

In many applications, such as building control in demand side management, we need to identify thermal behavior of individual zones. For instance, in precooling during off-peak hours in real time electricity markets, it is advantageous to know thermal inertia of a zone after decreasing the temperature to a low setpoint. The gradual temperature change of each zone can be estimated by the proposed methodology. This estimation can be used to check if zone comfort level will not be violated or to find the maximum possible cooling capacity of a zone for pre-cooling. On the other hand, the response model can be used for pre/post-occupy control strategies as well. That is, response model can estimate the optimal time to start cooling a zone before the zone is occupied. This would avoid from unnecessary electricity consumption specially in large spaces. As demonstrated, since thermal response of different zones in a building is different, response model would be applied for distributed zonal control methodologies. That is, each zone can have its specific HVAC control strategy based on its predicted thermal response. Furthermore, there are numerous control optimization frameworks in literature [10], [28], [70] that are applicable in demand side management and electricity markets. The proposed response model can be implemented in the constraints of such optimization models to achieve more accuracy in decision making for building operation optimization systems. If the response model is incorporated in a real time data acquisition system of a Building Management System, fault and failure can be detected via comparison between expected building thermal response and real building thermal behavior. This might be used for maintenance planning and asset condition
monitoring as well. The future studies can be the application of this response model in the aforementioned topics.
Chapter IV Distributed Air Conditioning Control in Commercial Buildings based on a Physical-Statistical Approach

4.1 Introduction

Conventional building air conditioning systems have long been implemented in building spaces to provide a pleasant environment for occupants. Over the years, Heating, Ventilation and Cooling (HVAC) designers endeavored to meet heating and cooling demands within the specifications defined by building standards, often designed on the principles of oversizing and conservative safety and reliability requirements [71], [72]. Control systems were based on real time sensor data and mostly PID controllers, and pre/post occupy operation scheduling was determined through trial and error procedures without considering human occupancy factor and building thermal characteristics [73]–[75]. However, research studies are all indicative that human factor and building thermal characteristics also play an important role in building energy management system (BEMS). With BEMS having information on building’s thermal-physical characteristics, and human occupancy and behavior, one would expect more energy efficient and higher performing HVAC system. To that end, BEMS technology has slowly but surely been making a quick turn toward context-aware advanced controls using data rich analytics and tools and taking advantage of near real time data [76], [77].

Optimal control of building HVAC systems can lead to energy saving potentials such as energy bill management, peak shaving, load shifting, etc. [78] which indicates the importance of such opportunities. Dobbs et. al [79] demonstrated a predictive HVAC
control method to lower energy consumption through Markov chain occupancy models, and compared discomfort levels and energy consumptions under predictive, triggered, and scheduled schemes. Beltran et. al [80] proposed a model predictive control to reduce cooling and heating energy consumption and to maintain comfort levels based on building occupancy patterns. In this work, they used simplified methods to evaluate temperature and power consumption behavior of thermal zones. Their results showed 15.5% and 9.4% in cooling and heating energy consumption, respectively. Veghefi et.al [10] introduced hybrid-physical based time series models to forecast HVAC electricity demand and develop an MPC for building cooling and heating control. Farzan et.al [28] developed an optimization framework for day-ahead and real-time operation planning of building clusters. In this study, using a hybrid physical-statistical model, they related the physics of the building to HVAC energy consumption for demand-side management participation based on price signals under uncertainty. Ma et. al [81] demonstrated a model predictive control scheme by taking into account the dynamics of building thermal zones. In this work, building operation optimization is solved to reduce energy consumption and peak power consumption while thermal dynamics is evaluated by a simplified resistance-capacitance circuit analogy. Using dynamic programming, Dong et. al [82] developed a real-time MPC approach based on occupancy patterns and building dynamics as a thermal resistant circuit. They applied this methodology in an experimental study, including a sensor network to retrieve building information, which resulted in a noticeable energy reduction compared to regular temperature set-point control systems. Considering room temperature dynamics, Oldewurtel et. al [83] proposed a methodology for integrated room automation control and compared rule-based control, deterministic MPC, and stochastic
MPC in multiple case scenarios to demonstrate energy saving potentials. Koehler et. al [84] proposed a distributed temperature MPC for networked buildings and an optimal solution via Lagrangian approach and KKT conditions based on governing physical laws. They also evaluated their approach on Trim and Respond controllers. There are several other research studies on building temperature control through physics-based predictive models [58], [59], [85].

In order to evaluate a HVAC predictive control decision, thermal response and load forecasts have to be taken into account under different operating conditions. Many predictive models have been proposed to predict room temperature under different independent variables. Mateo et. al [86] constructed a methodology to forecast room temperature using autoregressive, multiple linear regression, MLP, extreme learning machine, and NARX methods. Salque et. al [87] predicted room temperature with ARX and ANN methods, while Wu et. al [88] used ARMAX and pbARMAX based on conservation of heat in rooms. On the other hand, building load forecast has been addressed in research studies based on methods such as SVM and time series models [89]–[91]. With smart buildings being aware of their own thermal characteristics, power profiles, and human occupancy patterns, they will be able to participate in demand side programs more effectively, and play a crucial role in balancing power demand and supply [92]. Model predictive control systems have been demonstrated for building demand response in real-time and day-ahead pricing considering uncertainties such as weather, electricity price and occupancy [28], [93]–[95].

The above models and tools all employ simple thermal behavior of buildings and occupancy patterns, and assume no interactions between human comfort level and building
physics. Moreover, distributed zonal level controls have been largely ignored or over simplified, ignoring potentially major contributors such as zone orientation, construction material, internal gains, and number of occupants. Besides, no methodology has been proposed to address set-point scheduling and pre/post-occupy operation at the same time. In this work, we propose a methodology that provides an optimal short-term planning for operation of a commercial building based on occupancy, accurate thermal models of building zones, and external signals to fulfill environment comfort and lower electricity bills in cooling seasons. This work specifically concentrates on distributed zone level control and individual thermal zone attributes in terms of zone facet orientation, thermal capacity, inlet air flow impact on zone temperature over time, and individual zone occupancy patterns. The methodology employs adaptive algorithms to address changes in building HVAC equipment operation, which can be an effective way to evaluate building asset reliability and degradation. The methodology is composed of multiple control levels for individual zones in different conditions, and addresses pre/post-occupy occupied mode operation scheduling. A robust test-bed was built to perform real-time simulations to generate reliable and valid data for training datasets and evaluation purposes. This test-bed has also the capability of simulation of connected buildings to assess the effect of smart control systems in a building complex or a community [96]. All variables used in the proposed model are measureable and trackable through building management systems which make the framework applicable to real world buildings as well.
## Nomenclature

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<th>Description</th>
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<tr>
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<td>Index of timestep</td>
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<table>
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<th>Description</th>
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</tr>
<tr>
<td>E&lt;sub&gt;system&lt;/sub&gt;'</td>
<td>Thermal zone rate of change of energy (W)</td>
</tr>
<tr>
<td>E&lt;sub&gt;in&lt;/sub&gt;</td>
<td>Rate of heat added to the thermal zone (W)</td>
</tr>
<tr>
<td>E&lt;sub&gt;out&lt;/sub&gt;</td>
<td>Rate of heat removed from the thermal zone (W)</td>
</tr>
<tr>
<td>E&lt;sub&gt;g&lt;/sub&gt;</td>
<td>Rate of change of internal gains in the thermal zone (W)</td>
</tr>
<tr>
<td>m&lt;sub&gt;sys&lt;/sub&gt;</td>
<td>Air system inlet airflow (kg/s)</td>
</tr>
<tr>
<td>m&lt;i&gt;l&lt;/i&gt;</td>
<td>Infiltration airflow (kg/s)</td>
</tr>
<tr>
<td>C&lt;sub&gt;p&lt;/sub&gt;</td>
<td>Specific heat (J/kg·K)</td>
</tr>
<tr>
<td>t</td>
<td>Time (s)</td>
</tr>
<tr>
<td>h</td>
<td>Convective heat transfer coefficient (W/m²·K)</td>
</tr>
<tr>
<td>A</td>
<td>Surface area (m²)</td>
</tr>
<tr>
<td>HP</td>
<td>Human performance</td>
</tr>
<tr>
<td>RH</td>
<td>Relative humidity (%)</td>
</tr>
<tr>
<td>CL</td>
<td>Cooling load (kWh)</td>
</tr>
<tr>
<td>ASE</td>
<td>Air system electricity consumption (kWh)</td>
</tr>
<tr>
<td>EP</td>
<td>Expected profit ($)</td>
</tr>
<tr>
<td>HW</td>
<td>Hourly wage ($)</td>
</tr>
<tr>
<td>PEF</td>
<td>Profit expectation factor</td>
</tr>
<tr>
<td>TS</td>
<td>Timestep</td>
</tr>
</tbody>
</table>
4.2 Problem statement and preliminaries

Consider a commercial building with a given specific thermal characteristic and human occupancy patterns. Individual zones have different response patterns to the air conditioning system due to their orientation, size, internal gains, and other intrinsic factors and external conditions. The occupancy patterns are also different for individual zones. We are particularly interested in devising a distributed predictive control scheme that takes into account zone physical characteristics and occupancy patterns, and avoids unnecessary utilization of assets. The model must employ pre cooling and pre heating control schemes at zonal levels and on the basis of near real time occupancy data. We hypothesize that near real time control schemes would result in a major improvement over the conventional building controls in terms of human comfort and demand side management. Furthermore, such a control scheme would be able to take advantage of external energy price signals and avoid peak time price hikes.

In this research, the following main factors are considered:

- Zonal thermal response
- Pre/post occupy HVAC operation
- Demand side management programs
- Human comfort
- Human productivity

4.2.1 zonal thermal response

Thermal response prediction of zones is a challenge in pre/post operation control and building pre cooling/heating. The control system should be aware of an accurate thermal
response of each individual zone under different circumstances. For instance, we know that the heat generated by solar radiation during daytime is absorbed in building surface and different layers, such as gypsum and cement layers. The trapped heat is released at nighttime, which makes HVAC operation planning of the building more complex in the morning. The specific thermal response of each zone also becomes much more variant over different time intervals due to incident solar radiation energy, incident solar beam angles, and many other factors such as internal gains, number of occupants, and room size. The research question here is how to address all these complex interactions when planning for the operation and control of building HVAC system. It is evident that thermal characteristics and thermal response of a building play important roles on the pre-cooling and pre-heating, and pre/post occupy operation planning. For example, what happens if we start cooling up a zone with a fully opened damper, or, what is the temperature variation if we switch from a set-point to a setback control.

4.2.2 External signals
Utility rates and energy price could also be a major contributing factors to optimal HVAC controls, since HVAC constitute up to 40% of a given facility’s energy consumption. If the building is participating in a demand side management program, the HVAC operation control can be modified according to real-time price of energy or utility signals. This can be addressed by finding the relationship between HVAC operation and power demand.

4.2.3 Pre/post occupy HVAC operation
No or minimal air conditioning may be required in the absence of occupants at a given zone. Also, the transition or response time for a temperature change from an initial state to another at a zone is highly dependent on air distribution system and thermal characteristics
of that zone. Temperature changes in different thermal zones are highly variant due to
different thermal attributes and room sizes. Once the thermal response of a room to air
conditioning systems is identified and predicted, pre/post occupy operation control would
become more effective to avoid unnecessary air conditioning and find the best time for
starting cooling/warming up the zone to reach the desired set-point once thermal zone is
occupied. This illustrates that if the operation control is based on a smart pre/post occupy
operation, there are valuable opportunities to enhance building HVAC operation to save
energy and increase environment quality.

4.2.4 Human comfort

In general, human factor serves the most important role in commercial buildings air
conditioning, since the comfort level has a direct relationship with human performance and
profitability. In this work, thermal comfort is evaluated with average room temperature and
relative humidity. Thermal environmental conditions for human occupancy are defined by
ISO and ASHRAE standards. In this article, the criteria for human comfort level is based
on ASHRAE 55 which takes into account different factors such as dry-bulb temperature,
wet-bulb temperature, and relative humidity [97].

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on ASHRAE 55 which takes into account different factors such as dry-bulb temperature, wet-bulb temperature, and relative humidity [97].

![Figure 51: ASHRAE 55 recommended thermal comfort level.](image)

### 4.2.6 Human productivity

There is a relationship between human comfort zone and task performance especially in office buildings. An uncomfortable environment can reduce task performance of human up to 10%. Seppanen et al. [98] measured the relationship between human performance in tasks such as text processing, calculation, length of telephone customer service time, etc. defined in equation 4.1.

\[
HP(T) = 0.1647524T - 0.0058274T^2 + 0.0000623T^3 - 0.4685328 \tag{4.1}
\]

where HP is relative human performance ratio and T is dry-bulb temperature.
4.3 Building thermal characteristic identification

4.3.1 Heat transfer problem for room thermal response

There are several factors that contribute to heat transfer phenomenon in a thermal zone. Generally speaking, convective, conductive, radiation heat transfer, internal heat gains along with inlet and outlet flows caused by air distribution system, infiltration, and inter-zone air mixing constitute a thermal system. This can be explained by the fundamental heat transfer equations and conservation of energy as shown in equation 4.2 [60].

\[
\frac{dE_{system}}{dt} = \dot{E}_{system} = \dot{E}_{in} - \dot{E}_{out} + \dot{E}_g \quad (4.2)
\]

Equation 4.2 can be extended to an air conditioning system for a thermal zone [31], [61]. This is given by equation. 4.3.
\[ \dot{E}_{\text{system}} = C_p \frac{dT_z}{dt} \]

\[ = \sum E_g + \sum_{i=1}^{N_{\text{Surfaces}}} hA_i(T_{s,i} - T_z) \]

\[ + \sum_{i=1}^{N_{\text{zones}}} \dot{m}_i C_p (T_{z,i} - T_z) + \dot{m}_{\text{inf}} C_p (T_\infty - T_z) \]

\[ + \dot{m}_{\text{sys}} C_p (T_{\text{supply}} - T_z) \quad (4.3) \]

where \( C_p \frac{dT_z}{dt} \) is the stored energy in the zone, \( \sum E_g \) is the internal gains, \( \sum_{i=1}^{N_{\text{Surfaces}}} hA_i(T_{s,i} - T_z) \) is the heat transfer due to convection, \( \sum_{i=1}^{N_{\text{zones}}} \dot{m}_i C_p (T_{z,i} - T_z) \) is the heat transfer due to interzone air mixing, \( \dot{m}_{\text{inf}} C_p (T_\infty - T_z) \) heat transfer due to infiltration, and \( \dot{m}_{\text{sys}} C_p (T_{\text{supply}} - T_z) \) is the heat transfer due to inlet air flow from the air conditioning system to the zone. The objective is to find \( T_z \) at each time step, which is defined as temperature response of a zone to interactive heat transfer variables. However, there is no analytical solution to this equation. The best possible option here is to approximate the derivative part with finite difference methods, which results in a third order backward finite difference approximation given by equation 4.4.

\[ \frac{dT_z}{dt} \big|_t \approx (\delta t)^{-1} \left( \frac{11}{6} T_z^t - 3T_z^{t-\delta t} + \frac{3}{2} T_z^{t-2\delta t} - \frac{1}{3} T_z^{t-3\delta t} \right) + O(\delta t^3) \quad (4.4) \]

Thus, the solution of \( T_z \) follows:

\[ T_z^t = \frac{\sum E_g + \sum h_i A_i T_\infty + \sum \dot{m}_i C_p T_i + \dot{m}_{\text{inf}} C_p T_\infty + \dot{m}_{\text{sys}} C_p T_{\text{supply}} - (C_p/\delta t) \left( (-3T_z^{t-\delta t} + \frac{3}{2}T_z^{t-2\delta t} - \frac{1}{3}T_z^{t-3\delta t}) \right) \left( \frac{11}{6} \right) \sum h_i A_i + \sum \dot{m}_i C_p + \dot{m}_{\text{sys}} C}{\left( \frac{11}{6} \right) \sum h_i A_i + \sum \dot{m}_i C_p + \dot{m}_{\text{sys}} C} \quad (4.5) \]
Equation 5 indicates that temperature at time \( t \) is a function of temperature at three time steps before, internal gains, external temperature, average thermal zones temperature excluding the studied zone, and inlet airflow generated by HVAC system.

### 4.3.2 Statistical approach to predict room thermal response

We hypothesize that the average temperature at time \( t \) is predictable by a multivariate regression model as a hybrid physical-statistical model with lagged temperature values. Similar assumptions on hybrid physical-statistical models for electricity demand forecast were studied and explained in detail in earlier research studies from the same team [10], [28], but did not include zonal level behavior and temperature forecast. In equation 5, \( \dot{m}_{sys} \) is a key variable which appears in both nominator and denominator; hence, the model becomes non-linear. To linearize equation 5, we assume \( \dot{m}_{sys} \) as a categorical variable to achieve a linear model to forecast temperature at different timesteps. This categorical variable has interaction with all other decision variables to address the mentioned problem. Also, elements such as specific heat, convective heat transfer coefficient, surface areas, etc. can be assumed as constant values whose possible impacts would be included in the model’s white noise error term. To address variant of building thermal behavior at different hours of day, which is caused by several factors such as incident solar radiation and thermal zone orientation, another categorical variable is also included in the forecast model. It has been shown in the literature that relative humidity is also statistically significant independent variable that interacts with thermal zone average temperature. Average room temperature can be expressed by equation 4.6.
\[ T(t) = \beta_{j,0} + \beta_{j,1}\dot{E}_g(t) + \beta_{j,2}T_\infty(t) + \beta_{j,3}T(t-1) + \beta_{j,4}T(t-2) + \beta_{j,5}T(t-3) \]

\[ + \beta_{j,6}T(t) + \beta_{j,7}\sum_{i=1}^{N_\text{z}} T_i(t) + \beta_{j,8}RH(t) + \varepsilon(t) \quad (4.6) \]

where \( i \) is indicative of interaction between each decision variable and inlet airflow categorical variable. Also, \( T(t-1), T(t-2), \) and \( T(t-3) \) are lagged values of average temperature in previous timesteps. Average temperatures can be obtained from sensor data.

On the other hand, external temperature is also available through weather data in each time step with a high accuracy, due to short-term forecasting in one hour timespans. \( \dot{E}_g(t) \) can be obtained by operation schedule of each zone or sub-meter data for lighting, equipment, and occupancy. All these variables enable us to predict room average temperature for different time steps and different periods of time under various air conditioning operations.

That is, if average temperature for the last three time steps, lighting and equipment schedules, and external temperature are available for the next time step for a given inlet airflow ratio, average room temperature can be predicted with a high accuracy for the next timestep. This also allows us to continue the forecast ahead of time for given independent variables and inlet airflows as Figure 53.

**Figure 53:** Room average temperature prediction over time by assigning different inlet airflows.

The test-bed of section 4.1 will be used to generate training dataset for the thermal response model. At each time step, the portion of inlet airflow over maximum airflow, internal gain schedules, external temperature, and average room temperature are stored. In real
buildings, the training dataset can easily be obtained by sensor and weather data. To obtain a reasonably generic response model, random set-points and random minimum airflows are assigned to the building thermal simulation at each time step. Each thermal zone in a building has its own thermal response model according to its inlet flow designs, facing orientation, area, and internal gains.

Heat transfer problem for room sensible cooling load

Zone cooling demand can be calculated by equation 4.3. This demand should be provided by the air conditioning system to maintain thermal environment within human comfort zone. The cooling load demand can be expressed by:

\[
CL = m_{sys}C_p(T_{sup} - T_z) = C_p \frac{dT_z}{dt} - \sum E_g
- \sum_{i=1}^{N_{Surfaces}} hA_i(T_{s,i} - T_z)
- \sum_{i=1}^{N_{zones}} m_iC_p(T_{z,i} - T_z) - m_{inf}C_p(T_{\infty} - T_z) - \sum m_iC_p(T_i - T_z) \quad (4.7)
\]

The differential part can also be linearized similar to equation 4.4 which gives rise to:

\[
CL = m_{sys}C_p(T_{sup} - T_z)
= \left(\frac{11}{6} \frac{C_p}{\delta t} + \sum h_iA_i + \sum m_iC_p\right)T_z - \frac{C_p}{\delta t}(-3T_{t-\delta t} + \frac{3}{2}T_{t-2\delta t}
- \frac{1}{3}T_{t-3\delta t} + \sum E_g + \sum h_iA_iT_{s,i} + \sum m_iC_pT_i + m_{inf}C_pT_{\infty} \quad (4.8)
\]
As seen in equation 4.8, temperature coefficients at each time step, and also, external temperature coefficient have the same behavior explained in section 3.2.

4.3.3 Statistical approach to predict and find cooling demand

Due to the fact that HVAC air system electricity consumption and cooling demand are correlated, Equation 9 can be deployed as a multivariate linear regression model to estimate air system electricity energy consumption to meet thermal zones cooling demand at each timestep. Also, HVAC system should meet latent heat originated from humidity; thus, relative humidity is also statistically significant to estimate HVAC air system electricity consumption. Since cooling demand behavior alters over different times of day, a categorical variable \((\tau)\) is added to address this issue. \(\tau\) categorizes 24 hours of day as a variable that addresses thermal attribute alteration due to external factors such as solar radiation. The cooling load electricity consumption can be modeled as:

\[
ASE(t) = \beta_0 + \beta_1 \dot{E}_g(t) + \beta_2 T_\infty(t) + \beta_3 T(t) + \beta_4 T(t-1) + \beta_5 T(t-2) + \beta_6 T(t-2) + \beta_7 \tau(t) + \beta_8 \sum_{i=1}^{N_z} T_i(t) + \varepsilon(t) \quad (4.9)
\]

Eventually, equation 4.9 would be related to control scheme in later sections. In this equation, temperature coefficients represent the impact of a zone temperature variation on the air distribution system serving that zone. But prior to that we will briefly explain our simulation test bed and validation of predictions from the above response model.
4.4 Simulations, predictive model results and validation

4.4.1 Building control and thermal simulation

To evaluate the impact of different control plans, data generation, and data analysis, all building thermal simulation and control systems are modeled by Energy Plus and Matlab. Building thermal simulation are controlled by Matlab through LBNL’s BCVTB tool that establishes data exchange through the whole system. Each control signal, sensor data, or meter data is transferred by BSD socket connections on a simulation testbed described in [96]. This study is done in three different office spaces, two of which are DOE commercial reference buildings [99]. All building envelopes are according to ASHRAE Standard 90.1-2004. All the case scenarios are located in Austin, Texas. The building information is presented in Table 4.

Table 4: Building models characteristics.

<table>
<thead>
<tr>
<th>Building Type</th>
<th>Area</th>
<th>Number of Controlled Zones</th>
<th>Number of Stories</th>
<th>Cooling System</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>DOE Large Office</strong></td>
<td>46320 m²</td>
<td>61</td>
<td>12</td>
<td>Electric chiller/VAV</td>
</tr>
<tr>
<td><strong>DOE Medium Office</strong></td>
<td>4982 m²</td>
<td>15</td>
<td>3</td>
<td>DX Packaged unit/VAV</td>
</tr>
<tr>
<td><strong>Small Office</strong></td>
<td>910 m²</td>
<td>9</td>
<td>1</td>
<td>Electric chiller/VAV</td>
</tr>
</tbody>
</table>

Matlab receives all the necessary data and processes the information and generates operation control signals. These control signals assign building HVAC operation through optimal cooling setpoints, and also, assign preferred operation control for training datasets.
In this study the main signal input to the Matlab processor are zone occupancy forecast or schedule, external temperature, zone relative humidity, zone average temperature in previous time steps, real-time price of energy. In order to generate datasets to train models presented in equations 6 and 9, random temperature setpoints and random minimum inlet airflows were assigned to the building simulations to cover all possible combinations of independent variables in equations 6 and 9. Consequently, response models are capable of predicting zonal thermal behaviors under different conditions such as initial average temperature, external temperature, internal gains, etc.

4.4.2 Thermal response model results

Figure 54 presents different results comparing temperature forecasts and real temperature values over different timespans, building models, and thermal zones for different zone orientations. As can be seen in Figure 54, the thermal response follows the real data pattern based on different inlet airflows and at different time intervals. Since the control algorithm of Section 5 only needs short-term response forecasts in order of at most one-hour timespans, longer-term forecasts will not be of major concern for us in this article. The main application of the forecast models is to find thermal capacity of the zone. That is, only temperature change under different conditions over a time step is important, and absolute value of temperature would not be used in our evaluations. Nevertheless, our results show that the response model performs reasonably well (within average 0.7% to 1.9%) even for longer periods. The error evaluation results are indicative that zonal absolute temperature forecast accuracy is highly dependent on room facing orientation. The forecast models are more accurate for zones with no wind-exposed or sun-exposed walls. On the other hand, the forecast accuracy of zones with external walls in North or
South sides are more than Zone located in East or West of a building. Table 5 presents average of mean square error (MSE) and mean absolute percentage deviation (MAPD) based on zone orientation for a three-month period zone average predication.

Table 5: Error analysis for long-term temperature absolute value prediction.

<table>
<thead>
<tr>
<th>Orientation</th>
<th>MSE</th>
<th>MAPD</th>
</tr>
</thead>
<tbody>
<tr>
<td>East</td>
<td>0.369</td>
<td>1.54 %</td>
</tr>
<tr>
<td>West</td>
<td>0.221</td>
<td>1.40 %</td>
</tr>
<tr>
<td>South</td>
<td>0.110</td>
<td>1.98 %</td>
</tr>
<tr>
<td>North</td>
<td>0.120</td>
<td>1.07 %</td>
</tr>
<tr>
<td>Interior</td>
<td>0.061</td>
<td>0.72 %</td>
</tr>
</tbody>
</table>

4.4.3 Damper position and airflow effect

The thermal response model is capable of predicting the behavior of any thermal zone under different damper positions in VAV boxes. Starting from an average room temperature initial condition, the predicative model calculates average room temperature in future time steps under different airflows and damper positions. Figure 55 illustrates the thermal response of a zone starting from an initial average temperature and under different inlet airflows for 60 minutes, and also, thermal behavior under different imposed airflows. It should be noted that, for constant air volume systems, the response predictive model is also applicable with only one airflow mode.
Figure 54: Zone thermal behavior comparison between predictive model and real data in Small Office (top row), Medium Office (middle row), and large office (bottom row).

Figure 55: Room thermal response under different imposed airflows.
4.4.4 Cooling demand prediction results

Equation 4.9 presents estimated air system cooling electricity consumption to meet cooling demand. Figure 56 illustrates different comparisons between air system cooling electricity and real electricity consumption. Once again, since short-term predictions are preferable in this method, for demonstration purposes only 3 cases for each model are illustrated in Figure 56.

![Figure 56: Air system cooling electricity consumption vs prediction in every two minutes for (a) Large Office, (b) Medium Office (C) Small Office.](image)

Even though the air system electricity consumption prediction in long term is not applicable in the framework, the predictive model shows a good accuracy in long-term evaluation (in three months). The error evaluation for average air system cooling electricity (in kWh) MSE and MAPD is presented in Table 6. The accuracy of the models are dependent on employed building HVAC system.
Table 6: Error analysis for long-term cooling electricity value prediction.

<table>
<thead>
<tr>
<th>Building</th>
<th>MSE</th>
<th>MAPD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small Office</td>
<td>0.0122</td>
<td>18.55 %</td>
</tr>
<tr>
<td>Medium Office</td>
<td>0.0073</td>
<td>9.63 %</td>
</tr>
<tr>
<td>Large Office</td>
<td>0.0097</td>
<td>10.78 %</td>
</tr>
</tbody>
</table>

4.5 Solution approach and control algorithm

4.5.1 Operation control based on occupancy

In this research, control algorithm is broken down to different modes, categorized according to human occupancy pattern, which is assumed to be known two hours in advance. This can be according to building operation schedules (most common since commercial buildings follow a regular occupancy pattern) and also adaptive predictive models. Deterministic occupancy tracking can be realized by occupants’ individual time tables, deadlines, seasons, human tracking devices, etc. The advances in smart building technologies have made human presence detection easier, for example, a garage detection system can notify the smart system of the presence of a specific occupant at the building. On the other hand, spatial and temporal occupancy patterns can be recognized by adaptive predictive models such as Neural Networks, ARMA, Bayesian, SVM methods, etc. [80], [100]–[102]. In this work, control decisions are made every 10 minutes for the next coming hour. A zone is assumed occupied/unoccupied if it remains nonempty/empty more than an hour. Thus, two-hour-ahead occupancy pattern is necessary to evaluate whether a zone is occupied or unoccupied for short-term planning. Since decision making timestep is every 10 minutes, if a room is nonempty/empty for 70 minutes, it means that the room is
occupied/unoccupied. It should be noted that the time intervals are only assumptions and can be subjected to change based on building operation plans and objectives. There are several cases in which an optimal decision would remain the same over the next hour while these decisions might also be subjected to change based on different circumstances over time intervals ahead. Human occupancy data for the next two hours will yield the following modes:

- **Unoccupied mode**: The zone is unoccupied for the next 70 minutes.
- **Pre-occupied mode**: The zone is unoccupied for the next hour but it will be occupied afterwards.
- **Occupied mode**: The zone is occupied for the next 70 minutes.
- **Post-occupied mode**: The zone is occupied for the next 60 minutes but it is unoccupied afterwards for at least 60 minutes.

These scenarios are illustrated in Figure 57 with undetermined blocks being not applicable.

![Figure 57: Different cases based on zone occupancy over two hours](image)

Case I is mainly in setback mode while Cases II and III are applicable in pre-occupy and post-occupy operation control, respectively. Case I model indicates that if the zone is unoccupied over next 70 minutes, the operation is on setback mode with designed
minimum system airflow ratio. This lowers the load on chilled water loop and air loop system dramatically. This case is not only active over nighttime and weekends but also during lunchtime, in conference rooms, kitchens, etc. Case II occurs more in the morning before the zone is occupied, and also, if the occupants leave the space for a long time. Case III occurs more often in the evening and before a zone is unoccupied for a long time. Finally, case IV is the most occurred scenario in operation hours which can be more involved in demand response programs according to utility rates and signals though optimization or rule-based models.

4.5.2 Pre/post occupy HVAC operation control

**Pre-occupy control:** Assume that the HVAC operation plan is to make a commercial building environment prepared before it is occupied. Thus, room average temperature should be in human comfort zone right at the moment occupant(s) arrive. One way is to start air conditioning at a safe time before the arrival. However, there is a high possibility that the room temperature reaches the setpoint before the arrival. Finding the optimal starting time for air conditioning the zone can be realized through thermal response predictive model introduced in section 3.2. As mentioned in section 5.1, the proposed method scans the occupancy schedule for two-hours ahead and initiates pre-occupy operation one hour before arrival. Room thermal response is predicted with a combination of regular airflow and minimum air flow to find the optimal plan in an exhaustive search with a time frequency of 10 minutes.

There are 6 different combinations in pre-occupy air conditioning planning. The exhaustive search starts with regular airflow for 60 minutes. If the room temperature reaches the setpoint before the arrival, the next combination starts with 10 minutes minimum airflow
and 50 minutes with regular airflow. The exhaustive search continues until the next combination violates setpoint requirements; the last feasible solution is the optimal plan. This method is illustrated in Figure 58. In pre-occupy planning presented in Figure 58, the zone is planned to be occupied at 9 am. The system starts looking for the best combination starting from 8am. As seen in Figure 58, if the air conditioning starts at 8am, the average temperature reaches the setpoint around 8:35 am. If the system works with minimum airflow and starts air conditioning from 8:10 am, it reaches the set point at 8:40. This exhaustive search continue until optimal pre-occupy plan in which the system reaches the setpoint right before 9 am. In the optimal case, air conditioning starts at 8:30 am, and before that, the thermal zone is in setback mode with minimum inlet airflow. It can be seen if the operation starts at 8:40 am, the average room temperature reaches the setpoint after 9 am, which is not preferred.

![Finding Optimal Pre-Ocupy Operation](image)

**Figure 58: Finding optimal pre-occupy operation using zone thermal response.**

**Post-occupy mode:** Assume that the thermal zone is planned to be unoccupied in an hour for a considerable period of time. According to thermal capacity of the zone, if the air conditioning system switches to setback mode, there is a time during which the room
environment condition does not violate thermal comfort level. This period can be found by zone thermal response evaluation. Similar to pre-occupy operation planning, the optimal plan can be found by an exhaustive search. The model starts by evaluating the thermal response for the next hour if the system switches to setback mode with minimum airflow. If the thermal response forecast exceeds the comfort level, the next combination would be 10 minutes regular operation and 50 minutes setback mode. This evaluation continues, until longest period is found that meets the environment comfort level with the optimal operation plan. Figure 59 illustrates an example explaining the method. The room is planned to be unoccupied at 6:00 pm for the rest of the day.

![Finding Optimal Post-Occupy Operation](image)

Figure 59: Finding optimal post-occupy operation using zone thermal response.

### 4.5.3 Operation optimization and demand side management

The distributed air conditioning operation planning is based on short-term (1 hour ahead) room temperature scheduling for different times of day and time steps (10 minutes) according to occupancy patterns, building thermal behavior and utility rates. In section 3, the relationship between temperature change and cooling energy demand was defined by
equation 4.9. This sensible cooling energy load should be supplied by building air conditioning system. Besides sensible cooling energy to maintain room setpoint temperature, there are some other factors such as latent heat, sensible internal gains, heat loss, zone infiltration, inter-zone air mixing, etc. However, since the control variable in the optimization model is room dry-bulb temperature, only those elements that have relationship with dry-bulb temperature are effective in the operation optimization model.

A commercial building operator is able to implement all the physical relationships and business models to lower their cost given that the zone operation is always at its optimal point, and all the occupants are at their comfort level. The operation optimization model implements real time (RTP) locational marginal price of energy (Pricing structure and uncertainty are described in [28]) and building physics for setpoint scheduling purposes.

The objective function (equation 4.10) is to minimize price for cooling load electricity caused by zone temperature setpoint and human performance penalty cost for comfort level deviation explained in section 2.2 ¹. The decision variable is $T_i(\theta)$, which is temperature setpoint for zone i at time $\theta$.

$$\begin{align*}
\text{minimize} & \quad \sum_{i=1}^{N_z} \sum_{\theta=1}^{6} ASE_i(T_i(\theta)) \times P(\theta) + \left(1 - HP_i(T_i(\theta))\right) \times EP \quad (4.10) \\
\text{s.t} & \quad T_{\text{comfort,min}}(RH_i) < T_i(\theta) < T_{\text{comfort,max}}(RH_i) \\
& \quad T_i(\theta) - T_i(\theta - 1) \leq T_{\text{max,raise}}(\theta), \theta \neq 1 \\
& \quad T_{\text{max,drop}}(\theta) \leq T_i(\theta - 1) - T_i(\theta), \theta \neq 1
\end{align*}$$

¹ The control decision making can also be based on rule-based algorithms or other models such as Pareto optimality methods. It should be noticed that the rule-based models are compatible with this paper’s methodology; however, on the other hand, since the penalty cost for deviation from comfort level (which is mostly used in operation planning optimization models in the literature) is not tangible and applicable in real systems, it was decided to include human performance in the optimization model.
\[ T_i(\theta) > 0 \]

\[ ASE_i(T_i(\theta)) \geq 0 \]

where HP and \( ASE_i \) can be obtained by equations 1 and 9, respectively. P is the real time energy price at each time step in $/MWh. EP is the constant profit made by each occupant at each timestep (equation 4.11). If each occupant is assumed to work based on preferred business models, there is a profit expectation factor from 3 to 4 times occupant’s annual salary.

\[
EP = \frac{HW \times PEF}{60 (T_S)} \quad (4.11)
\]

\( T_{comfort,min} \) and \( T_{comfort,max} \) are suggested maximum and minimum dry-bulb temperatures for human comfort level as a function of room relative humidity, which can be found in psychometric chart presented in HVAC standards [97]. \( T_{max,drop} \) and \( T_{max,raise} \) are maximum temperature drop or temperature raise at each time step which can be found by equation 4.6. To find maximum temperature raise or drop, equation 4.6 will be solved twice for 6 timesteps assuming minimum airflow and maximum airflow at all time steps. This will give rise to vector sets as follows:

\[
\begin{bmatrix}
\Delta T_1 \\
\Delta T_2 \\
\Delta T_3 \\
\Delta T_4 \\
\Delta T_5_{max,flow}
\end{bmatrix}
\quad \begin{bmatrix}
\Delta T_1 \\
\Delta T_2 \\
\Delta T_3 \\
\Delta T_4 \\
\Delta T_5_{min,flow}
\end{bmatrix}
\]

\( ^2 \) This model is applicable on commercial buildings, and EP value can also be evaluated for non-permanent occupants such as visitors and customers.
\( \Delta T_i \) represents temperature change as a result of maximum or minimum air flow over a timestep. \( T_{\text{max,drop}} \) and \( T_{\text{max,raise}} \) are:

\[
T_{\text{max,drop}} = \frac{1}{5} \sum \Delta T_{i, \text{maximum airflow}} \tag{4.12}
\]

\[
T_{\text{max,raise}} = \frac{1}{5} \sum \Delta T_{i, \text{minimum airflow}} \tag{4.13}
\]

This temperature difference constraint has two main benefits in the model. First, it assigns optimal schedule changes that are feasible based on thermal capacity of the zone, and second, it schedules incremental setpoints in order to prevent sudden changes in the air conditioning system that avoids sudden changes and improves HVAC equipment operation in terms of asset degradation and short cycling prevention.

### 4.5.4 Building air conditioning control algorithm description

The control process starts with initial conditions before the initiation of building operation (Case I). At this stage, the zone is unoccupied, and there is no need for air conditioning except supplying minimum airflow. The process continues with pre-occupy HVAC operation planning (Case II). Pre-occupy operation planning starts based on each zone occupancy schedule to prepare zone comfort environment as the occupant arrives at the space. At this stage, input information is occupancy schedule (deterministic/stochastic), one-hour weather forecast (which is highly reliable in short periods), and zonal thermal characteristics. This guaranties the optimal time for the zone to start its air conditioning operation. After the zone is occupied (Case IV), thermostat schedule will be determined based on model presented in equation 4.10 based on signals received from utilities (in this study the signal is energy price). In this mode, zone thermal characteristics are also
implemented to find the best operation condition to preserve energy and provide thermal comfort. The final part is to find the best time to lower air conditioning system before an occupant leaves the zone (Case III). The input information at this stage is the same Case II. It should be noted that decision making is done every 10 minutes for each zone except Cases II and III, in which after finding the optimal starting or ending point, there is one-hour delay in decision making process. The whole control system is demonstrated as a flowchart in Figure 60.

![Flowchart](image)

**Figure 60: Control process flowchart.**

### 4.6 Illustrative results

The process presented in section 5.4 was applied on the building simulations described previously. The setpoint scheduling results is presented in Figure 61 for some representative days in randomly selected zones and buildings. As seen in Figure 61, the
zone thermal comfort is satisfied as the occupant arrives at the space. On the other hand, before the zone becomes unoccupied, the system uses thermal resistance of the zone and lowers the air conditioning system operation to save money while the thermal comfort is met. Besides, the variation of the temperature setpoint, which is an output of equation 4.12, is based on the utility signals (in this problem locational marginal energy price). Figure 61 presents optimal setpoint assignment on 4 random representative different zones. As can be seen, pre/post-occupy operations are assign accordingly based on human occupancy in the zones.

Figure 61: Optimal setpoint assignment and zone thermal response.

Figure 61 illustrates that the smart system assures the environment comfort level of the building occupants by learning the thermal response of each specific zone. This comfort
zone can be modified by the user as a constraint input in the model. On the other hand, the best pre-occupy operation start is also presented in Figure 61. The variation of setpoint schedule in occupied mode is based on electricity price signals that results in optimal schedules to lower the costs. Besides, since the setpoint schedule is based on zone thermal resistance, most of the time, the average temperature is the same as assigned setpoint. Incremental setpoint variation to avoid sudden changes in the air conditioning system is also shown in Figure 61. To evaluate the value of the proposed smart operation control, a regular operation control schedule was assigned to the building simulations. This control system starts 1 hour before the zone operation starts and ends by the time the zone is unoccupied. The results show a highly noticeable change in HVAC electricity consumption and HVAC electricity cost over building operation hours that is presented in Table 7.

**Table 7: Saved HVAC energy and cost comparison in three different buildings.**

<table>
<thead>
<tr>
<th>Building Type</th>
<th>Saved energy (%)</th>
<th>Saved electricity cost (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DOE Large Office</td>
<td>17.48</td>
<td>22.93</td>
</tr>
<tr>
<td>DOE Medium Office</td>
<td>14.66</td>
<td>18.97</td>
</tr>
<tr>
<td>Small Office</td>
<td>12.13</td>
<td>17.19</td>
</tr>
</tbody>
</table>

Figure 62 presents facility electricity consumption in 2 minute intervals comparing two described methods. The graph illustrates impact of smart setpoint control on building total electricity consumption.
Figure 62: Impact of optimal setpoint scheduling and setback control on facility total electricity consumption and in three different days.

4.7 Conclusion

The main objective in this work was to control air conditioning operation of a commercial building to save energy and cost and maintain comfort level by a robust and applicable method. This objective was achieved through combined physical and statistical models emphasizing on zone level thermal response and human occupancy patterns. The relationship between zone dry bulb temperature and building HVAC electricity consumption was found and zone thermal response under different conditions was accurately determined. The proposed procedure discovers best potential opportunities to save energy and lower cost. The final evaluation showed a remarkable change up to 12-18% in building HVAC energy consumption. One of the most important factors in the demand response optimization model is incentives for end users since there are many cases
in which the penalty cost for temperature deviation is so high that the end users might be reluctant to participate in such programs. Thus, utilities have to offer more incentives that motivate the end-user to collaborate.

The hybrid models described in this work can not only be used for operation planning, but also for other purposes such as load forecasting and building temperature forecasting. In all control algorithm stages, all the input measures are available through sensor and meter data in BAS systems, which make the method practical. This method can also be applied to residential and other commercial buildings as well. The method was based on RTP pricing; however, it can also be implemented for day ahead programs since the regression models are robust and highly reliable for forecasting purposes. Besides single building operation planning, this method can also be used in building communities and smart connected systems.
Chapter V: Connected buildings and smart communities: Synchronizing HVAC operation in building communities

5.1 Introduction

Residential and commercial buildings account for almost 42% of total energy consumption in the U.S while a large portion of energy consumption in this sector is dedicated to HVAC (35% in residential and 32% in commercial buildings) [1]. Consequently, control and optimization of HVAC systems can significantly reduce the energy consumption in buildings and communities [103]. Today, new communication and control technologies create substantial opportunities in building management systems and connected buildings to achieve sustainable systems [104]. At a larger scale, building smart control, in turn, can lead into effective solutions for sustainable and smart cities and communities. In this paper, we investigate a new building operation strategy for indoor temperature control that takes advantage of thermal inertia. By the way of periodical setpoint change control, we show that energy can be saved while ensuring appropriate levels of occupancy comfort. Based on the proposed strategy, we also develop a new cooperative operation strategy for connected buildings to achieve more sustainability at large scales.

Installation of an efficient temperature set-point control system in buildings is a practical and effective approach to manage and control building load. Basic scheduling techniques only involve the manipulation of ON/ OFF states of the HVAC system whereas contemporary advanced scheduling techniques use pre-cooling or pre-heating methodologies to reduce peak demand by temperature setpoint scheduling [105], [106]. There are several research studies investigating efficient ways to control heating and
cooling setpoints in residential and commercial buildings. Ghahramani et al. [107] introduced a systematic approach for quantifying the influence of building size, construction category, climate, occupancy schedule, and setpoint on HVAC energy consumption. They found that when the outdoor temperature is within -20 to 30 °C, the optimal setpoint depends on the building size, and for the other temperatures, setpoint selection would only slightly influence the energy consumption. Calculation of optimal setpoint is necessary in many applications to obtain minimum energy consumption in the buildings [10], [108]. In this regard, many researchers have introduced approaches for optimal setpoint scheduling, such as introducing an algorithm to solve the problem of the transition between two constant temperature setpoints in small buildings [109]. Saurav et al. [110] proposed a pre-cooling framework that uses a “gray box” thermal model of a building to compute the optimal set-point temperature schedules to minimize the operational cost of HVAC. Asad et al. [111] presented a degree of freedom (DOF) based set-point reset instead of the conventional step-change or rate-limited set-point reset for the real-time optimal control of air-conditioning systems. Besides single building control systems, there are other studies presenting energy management approaches for multiple energy consumers and producers aggregated in a coalition. They use building simulations to evaluate the impact of multiple set-point modulation strategies on the demand of a baseboard-heated cottage during grid peak periods [112]. Guo et al. [113] presented a new multi-objective optimal planning model for medium voltage stand-alone microgrids, considering conflicts between a power distribution company and a distributed generation owner.
There is a growing demand for improving the control strategies to minimize HVAC energy consumption by taking into account different factors such as building thermal behavior, available onsite power generation, and occupancy factors. Ghofrani and Jafari [114] developed a distributed control methodology for air conditioning operation in commercial buildings based on building thermal physics and human behavior/productivity. They also proposed pre/post occupy HVAC operation schemes to avoid unnecessary cooling based on zone thermal characteristics. Fratean and Dobra presented an extensive evaluation which analyzes the contribution of several control methods to decrease the energy consumption associated with heating and cooling of buildings. They proposed heating and cooling control methods combined with a set of cost-based optimum allocation of onsite energy production, variable indoor temperature setpoint for following the production curve and a battery storage system [115]. Another study by Ascione et al. presented an approach to support cost-optimal design of building envelope’s thermal characteristics and HVAC systems in presence of a simulation-based MPC method for heating and cooling operations [116]. Michailidis et al. proposed a methodology which can provide automated fine-tuning of the building optimization and control system. In their method, no human intervention or a simulation model are required for the initial deployment of the controller as well as for the continuously applied fine-tuning procedure [117]. Carreira et al. proposed a system that incorporates dynamic user feedback control loops to optimize the energy/comfort trade-off considering occupants’ votes [118]. In addition, Capozzoli et al. presented a methodology to implement an occupancy-based HVAC system operation schedule. The process is based on the convenience of displacing groups of occupants with similar occupancy patterns to
the same thermal zone [119]. There are other studies that incorporates grid interconnection into the control strategies.

Predictive control methodologies and building interconnection with the grid are crucial in design of energy smart buildings and communities to achieve a balance between consumption and production [120]. One of the most important practices to achieve this balance is optimal control of building HVAC systems for peak shaving, load shifting, and demand side management [121], [122]. It is well-known that large quantities of electrical energy cannot easily be stored, and the relation between the price and profile steering is too complex; as a result, demand side management by shifting electrical loads (and specifically HVAC load) is one of the feasible efforts to deal with this complications [123], [124]. Haidar et al. proposed a real time Consumer-Dependent Energy Management System (CD-EMS) in micro-grids for smart buildings [125]. They transformed the building manager to a Consume-Actor who participates directly on reducing greenhouse gas emission by fixing a consumer’s acceptability margin that allows buying renewable energy, even if it is slightly more expensive than non-renewable ones. Najafi et al. found that the operation cost of the interconnected multi-smart apartment buildings was significantly decreased by considering the effects of power exchange capability among smart apartment buildings under control and management of a home energy management system [126]. Chuang et al. proposed a design of robust intelligent control for stabilization of grid-connected microgrid system, consisting of photovoltaic, wind power, and fuel cell [127].

In recent years, some research studies have shifted their scope from single building scale to connected systems and communities. When buildings are assumed as a community, cooperation in building communities and connected buildings create even more energy
saving opportunities. A building community is made of residential or commercial buildings situated in a close proximity and share space for recreation, parks, parking lots, etc. Vigna et al. made a comprehensive overview of the theoretical approaches for the evaluation of Energy Flexibility of building clusters in order to create a framework for the performance assessment of the future generation of Energy Flexible buildings. In this study, they clarified the importance of designing at cluster scales and explained the meaning ‘clusters’ and the level of interaction among buildings [128]. Bonnet et al. [129] defined and implemented a tool allowing to address the diversity of activities and end-uses when analyzing energy demand and environmental impact on a building cluster. Li et al. [130] proposed to develop a Net-zero building cluster emulator that can simulate realistic energy behaviors of a cluster of buildings and their distributed energy device. Saghezchi et al. [131] considered a smart grid scenario with a single utility company and multiple users where the utility company adopts day-ahead pricing strategy. Hajj and Awad [132] proposed a game theoretic approach to the demand side management where several subscribers share one common energy supplier. Utility companies use time of use pricing policies to encourage their customers to shift their demand from peak hours to off-peak hours. Zhu et al. [133] proposed a cost for deviation pricing scheme to reduce day ahead planning uncertainties in building communities and facilitate the cooperation of building clusters.

In this work, we take advantage of thermal inertia as an opportunity to reduce energy consumption and propose a periodic HVAC operation planning approach that utilizes building thermal capacity. We also investigate the effect of temperature setpoint change on building electric demand. In addition, we address how to mitigate sudden peaks that follow
temperature setpoint changes with periodic temperature setpoint profiles. To the best of our knowledge, there is a lack in the literature with respect to periodic operation planning and its impact on building load demand. In addition, HVAC planning in building communities needs to be more investigated. Thus, we also focus on synchronizing the proposed periodic operation schedules for building clusters and devise optimization models for this community to cooperate. Moreover, we investigate human comfort levels, occupancy behavior, asset degradation, community constraints and incorporate them into the proposed control schemes. This methodology results in energy saving opportunities and a steady load profile for building communities. The results show a noticeable improvement in building energy consumption and peak demand. Finally, we present methodologies to predict electricity demand resulting from the proposed control strategies via Neural Networks for applications in MPC and day-ahead planning. In this work, all the building simulations are modeled by EnergyPlus [33] and building cluster operations are modeled by Building Virtual Testbed by LBNL [69].

**Nomenclature**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A$</td>
<td>Surface area ($m^2$)</td>
</tr>
<tr>
<td>$B$</td>
<td>Average periodic temperature ($^\circ$C)</td>
</tr>
<tr>
<td>$Bi$</td>
<td>Biot number</td>
</tr>
<tr>
<td>$C_p$</td>
<td>Specific heat ($J/kg/K$)</td>
</tr>
<tr>
<td>$D$</td>
<td>Electric demand (kW)</td>
</tr>
<tr>
<td>$E$</td>
<td>Energy consumption (kWh)</td>
</tr>
<tr>
<td>$\dot{E}_{system}$</td>
<td>Rate of change of internal energy (W)</td>
</tr>
<tr>
<td>$\dot{E}_{in}$</td>
<td>Rate of change of inlet energy (W)</td>
</tr>
<tr>
<td>$\dot{E}_{out}$</td>
<td>Rate of change of outlet energy (W)</td>
</tr>
<tr>
<td>$\dot{E}_g$</td>
<td>Rate of change of internal gains in a zone (W)</td>
</tr>
<tr>
<td>$E_{system}$</td>
<td>Internal energy (J)</td>
</tr>
<tr>
<td>$f$</td>
<td>Temperature periodic form ($^\circ$C)</td>
</tr>
<tr>
<td>$h$</td>
<td>Convective heat transfer coefficient ($W/m^2K$)</td>
</tr>
</tbody>
</table>
### 5.2 Problem statement

Building HVAC operation is a flexible and controllable load, and advanced controls can provide the means to utilize this potential for demand response, load leveling, energy saving, etc. This potential becomes even more profound for connected buildings, where cooperation between buildings can significantly enhance the resulting benefits. Here we will formulate a periodical temperature setpoint scheduling model and will characterize its
properties with respect to load profiles in single and clustered buildings. We will show that periodical patterns help smooth out load spikes due to setpoint changes and provide the means for multiple loads (e.g., buildings) to synchronize. Let us start with Figure 63 which illustrates the impact of periodic temperature setpoint versus energy consumption in a commercial building (DOE medium office reference building [61]). For both scenarios, internal loads, weather condition, and occupancy patterns are the same. In this example, we compare building total hourly demand if temperature setpoint periodically varies from 23 °C to 25 °C (controlled operation) versus a setback temperature policy with 23 °C for occupied and 25 °C for unoccupied (base demand). For the rest of this work, all reference scenarios operate under this setback policy and are compared with different scenarios. As seen in the figure, despite demand reduction for some periods, there are adverse effects due to the variable temperature setpoint control policy. Figure 63 demonstrates that there is a large increase in building peak demand while a residual consumption (compared to the base load) remains in the building electricity demand. This is due to the remaining internal gains and additional loads as a result of temperature setpoint variation. The adverse effects will multiply if we apply such control policies to large spaces and in building communities because of higher internal gains and aggregate peak demand of multiple buildings. Figure 63 (a) illustrates the same scenario presented in Figure 63 but for a supermarket with larger spaces compared to an office space. Figure 63 (b) demonstrates a scenario that an office and a small hotel are operating to reduce the demand.
Figure 63: A comparison of response of building electricity demand to variable temperature setpoints and a constant temperature setpoint.

Figure 64: (a) A comparison of response of building electricity demand to variable temperature setpoints and a constant temperature setpoint for a large space (supermarket). (b) A comparison between operation of two buildings (office and small hotel) via variable
Figure 64 (a) demonstrates that residual internal gain in a large space dramatically increases, hence a high peak demand follows when switching back from 25 °C to 23 °C. On the other hand, a collaboration between an office space and a hotel (Figure 64 (b)) is always effective because the occupancy and operation schedule patterns are complementary. As a result, we expect that a bidirectional interaction would result in effective energy reduction opportunities (e.g. load leveling and peak shaving). However, the energy consumption reduction in this scenario is not noticeable. Table 8 presents a comparison between the saved energy and peak demand for the three aforementioned scenarios.

Table 8: Saved consumption and peak demand change in three presented scenarios.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Saved Energy (%)</th>
<th>Peak Increase (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single Office</td>
<td>2.21</td>
<td>32</td>
</tr>
<tr>
<td>Single Supermarket</td>
<td>1.97</td>
<td>78.02</td>
</tr>
<tr>
<td>Small Office and Hotel</td>
<td>2.61</td>
<td>36.18</td>
</tr>
</tbody>
</table>

According to Table 8, temperature setpoint variation would result in high peak demands but roughly 2.5% in energy consumption reduction, which is against the expectations. On a larger scale, these random peaks with uncertain values can cause instability in the distribution network. Figure 65 illustrates an example of aggregate load behavior of three office buildings over 5 consecutive days. The unpredictable electricity consumption response of the building cluster is noticeable in this case scenario.
Figure 65: Noticeable building total peak demand change in a building cluster for a periodic control policy.

We now state the specific problems that we like to address in this paper as main objectives and by-products:

Main objectives:

- Find an effective method to use thermal inertia in buildings for energy and cost saving.
- Find a control strategy to synchronize the operation of a building cluster.

By-products:

- Avoid sudden peaks that result from temperature setpoint variations.
- Find feasible control policies for HVAC operation systems in building communities.
- Maintain human comfort level and operation constraints.
- Find factors influencing HVAC demand and their significance in such control schemes.
- Construct optimization frameworks for the operation of building clusters.
- Find a method to estimate HVAC demand for planning and optimization.
5.3 Building thermal inertia and periodic temperature setpoint scheduling

5.3.1 Building thermal inertia

Any physical object has volumetric heat capacity and thermal inertia. For example, for a hot object with a controlled volume around and immersed in a fluid (lumped capacitance), we can formulate the transient heat transfer phenomenon as [60]:

\[ \frac{dE_{\text{system}}}{dt} = \dot{E}_{\text{system}} = \dot{E}_{\text{in}} - \dot{E}_{\text{out}} + \dot{E}_{g} \]  \hspace{1cm} (5.1)

For derivation we refer the reader to [60]. The final solution is:

\[ \frac{d\theta}{dt} = \frac{\theta}{\theta_i} = \frac{T - T_{\infty}}{T_i - T_{\infty}} = \exp \left[ -\left( \frac{hA}{\rho Vc} \right) t \right] \]  \hspace{1cm} (5.2)

Although lumped capacitance method is over simplified and only effective for objects with a small Biot number \((Bi = \frac{hL}{k} \text{ and } Bi \ll 1 \text{ to be valid})\), equation 5.2 contains useful information about the heat capacity of objects. Equation 5.2 indicates that there is a relationship between the time that temperature variation occurs and its size, initial temperature, external temperature, density, heat capacity, and convective heat transfer coefficient. Solving energy equations for an environment as complex as a building is only possible via numerical methods. However, equation 5.2 implicit results can be utilized in building HVAC control methodologies. That is, HVAC system operation can decrease when there is enough cooling/heating capacity in a thermal zone. Precooling/heating are the most used methodologies using thermal inertia in buildings [105]. Here, we also use
room thermal inertia in a periodic pattern to avoid air conditioning while the room is still within human comfort zone.

5.3.2 Periodic temperature setpoint

In this paper, we propose a periodic temperature setpoint to save energy by using building thermal inertia. This methodology is specifically periodic and expanded for the application in connected buildings concept and how the operation of connected buildings can be synchronized (which will be discussed in later sections). An example of a periodic setpoint assignment was introduced previously. The mathematical form of temperature setpoint assignment is necessary to identify the effective factors in such functions. Since the schedule is periodic, the mathematical representation of any temperature setpoint profile can be formed by Fourier series:

\[
 f(t) = \frac{A_0}{2} + \sum_{n=1}^{\infty} A_n \cos(\omega_n t) + B_n \sin(\omega_n t) \quad (5.3)
\]

\[
 A_0 = \frac{2}{\tau} \int_{0}^{\tau} f(t) dt
\]

\[
 A_n = \frac{2}{\tau} \int_{0}^{\tau} f(t) \cos(n\omega_n t) \, dt
\]

\[
 B_n = \frac{2}{\tau} \int_{0}^{\tau} f(t) \sin(n\omega_n t) \, dt
\]

Since we use odd functions in this methodology, equation 5.3 takes the form:

\[
 f(t) = \sum_{n=1}^{\infty} B_n \sin(\omega_n t) \quad (5.4)
\]
\[ B_n = \frac{2}{\tau} \int_0^\tau f(t) \sin(n\omega_n t) \, dt \]

The constant periodic setpoint schedules presented in previous cases can be extended as:

\[ f(t) = \begin{cases} +\Delta, & 0 \leq t \leq \tau \\ -\Delta, & -\tau \leq t \leq 0 \end{cases} \quad (5.5) \]

\[ B_n = \frac{2\Delta}{n\pi} (1 - \cos(n\pi)) = \frac{4\Delta}{n\pi}, n = 2k - 1 \]

\[ f(t) = \frac{4\Delta}{n\pi} \sum_{n=1}^{\infty} \frac{\sin(\frac{\pi(2n-1)}{\tau} t)}{(2n-1)} \]

For this profile and assuming an average of B, the temperature setpoint as a function of time can be described as below. We call this form constant periodic setpoint.

\[ T(t) = B + f(t) = B + \frac{4\Delta}{n\pi} \sum_{n=1}^{\infty} \frac{\sin(\frac{\pi(2n-1)}{\tau} t)}{(2n-1)} \quad (5.6) \]

As depicted in Figure 63 to Figure 65, there are adverse effects of temperature setpoint changes in constant periodic form. A sinusoidal form with gradual temperature changes rather than sudden changes, however, can eliminate these problems and provide smooth transitions within comfort zones of occupants (this will be elaborated later in this work). This periodicity can also facilitate the synchronization and collaboration in connected buildings. The mathematical representation of such schedules can be obtained by equation 5.7. As long as sinusoid form is periodic, Fourier series would not change.

\[ T(t) = B + f(t) = B + \Delta \sin \left( \frac{\pi}{\tau} t \right) \quad (5.7) \]
Figure 66 illustrates temperature setpoints and the variables presented in equations 5.6 and 5.7.

![Figure 66: Representation of temperature setpoint schedules and their parameters presented in equation 5.6 (a) and equation 5.7 (b) with B=24 °C, Δ=1 °C, and τ=60 min.](image)

Since a continuous temperature setpoint assignment over a period is not feasible for current HVAC control systems, we assign incremental setpoint values over a timestep (δ). Also, we define a value (ΔT) which is determined based on the measurement and control accuracy of the thermostat and temperature resolution of the control system. It should be noted that these values should be assigned in the problem definition based on the capability of the control system. This temperature setpoint scheduling is demonstrated in Figure 67. Figure 68 compares medium office and supermarket demand response to the setpoints resulting from equation 5.7 in a representative day from 8 AM to 6 PM.
Figure 67: Incremental temperature setpoint scheduling on a sinusoid shape.

Figure 68: Building total demand response to sinusoid and constant temperature setpoint variations in office (a) and supermarket (b).

As demonstrated in Figure 68, peak demand dramatically decreases in sinusoid form with a smoother load profile. Table 9 indicates that while the peak demand decreases as a result of sinusoid form, more energy is also saved in such control policy compared to constant
periodic control policy. Table 9 results are based on building simulations over a three-month period from June to August.

Table 9: Saved consumption and peak demand change in three presented scenarios from June to August.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Constant Periodic</th>
<th>sinusoid</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Saved Energy (%)</td>
<td>Average Peak Increase (%)</td>
</tr>
<tr>
<td>Single Office</td>
<td>2.17</td>
<td>67.50</td>
</tr>
<tr>
<td>Single Super Market</td>
<td>1.68</td>
<td>83.02</td>
</tr>
</tbody>
</table>

Sinusoid temperature setpoints have two main characteristics of amplitude (Δ) and period (τ) that directly affects the demand. It is obvious that sinusoid average (B) also plays an important role; here we assume that temperature oscillates around 24°C. Figure 69 demonstrates impact of changing Δ and τ in the two case studies presented previously.

Figure 69: Impact of sinusoid profile parameters variations on building electric demand. (a) shows the impact of variation in period (τ) in the medium office, (b) shows the impact of variation in amplitude (Δ) in the medium office.
A close look at electricity demand profile in Figure 69 shows sinusoid patterns with amplitude varying over time. Our studies show that frequency of building electric demand is equal to temperature setpoint frequency. On the other hand, amplitude of building electric demand would not remain constant and would vary over time and at different times of day. However, there is always a phase difference between temperature and electric demand profiles (γ). Figure 70 illustrates how building HVAC electric demand follows temperature setpoint of the office and supermarket examples (with Δ=1, τ=60 min, and B=24 °C). This excludes electric demand associated with lighting, equipment, etc. It should be noted that in this paper, depending on the building air conditioning system, HVAC electric demand includes the total electricity associated with chillers, DX coils, exhaust/supply fans, pumps, packaged units, etc.

Figure 70: Variation of building HVAC electric demand with temperature setpoint for the office (a) and restaurant (b).

The values for γ are shown in Figure 70. In general, this value has a direct relationship to space size; the phase difference is larger in the restaurant compared to the office building.
that has smaller spaces. Figure 70 also demonstrates how we can reshape building electric demand by temperature setpoint variation. This load shaping is more controllable with less uncertainty. The hills and valleys and periodic form of such load profiles would suggest that there should be a way to achieve a stable load profile when multiple buildings are coordinating. We discuss this idea in the next section under the concept of connected buildings.

5.4 HVAC operation and coordination in connected buildings

Most of the existing studies on connected buildings are conceptual with no methodology supporting them. In general, these works focus on appliances and shiftable loads, and ignore HVAC operations. Here, our objective is to synchronize building loads using the periodic setpoint changes that we introduced above. Since building demand response to a periodic HVAC schedule becomes harmonic, synchronizing connected buildings would fill the gaps in individual load profiles to achieve a steady aggregate load profile for load leveling purposes. Meanwhile, the proposed methodologies would also implement thermal inertia for more energy efficiency in individual buildings. The aggregate behavior would result in lower energy consumption and more stable load profiles. Equations 5.8 and 5.9 present periodic temperature setpoint functions for a group of N buildings. The most important parameter in these equations is \( \varphi \), which synchronizes all the temperature setpoint profiles.

\[
T_i(t) = B_i + f_i(t) = B_i + \frac{4\Delta}{n\pi} \sum_{n=1}^{\infty} \frac{\sin\left(\frac{n(2n-1)}{n}\left(t + \frac{\tau \varphi_i + \gamma_i}{n}\right)\right)}{(2n-1)} \quad , i = 1, 2, ..., N \quad (5.9)
\]

\[
T_i(t) = B_i + f_i(t) = B_i + \Delta\sin\left(\frac{\pi}{\tau}(t + \varphi_i + \gamma_i)\right) \quad , i = 1, 2, ..., N
\]
where $q_i = \frac{2\pi}{N}(i-1)$, $i = 1,2, ..., N$. Consequently, equations 5.8 and 5.9 take form:

$$T_i(t) = B_i + f_i(t) = B_i + \frac{4\Delta}{n\pi} \sum_{n=1}^{\infty} \sin \left( \frac{n(2n-1)}{t} \left( t + \frac{2\pi}{N} (i-1) + \gamma_i \right) \right) \frac{\pi}{(2n-1)}$$  \hspace{1cm} , i = 1,2, ..., N \hspace{1cm} (5.10)$$

$$T_i(t) = B_i + f_i(t) = B_i + \Delta \sin \left( \frac{\pi}{t} (t + \frac{2\pi}{N} (i-1) + \gamma_i) \right) \hspace{1cm} , i = 1,2, ..., N \hspace{1cm} (5.11)$$

It should be noted that electric demand phase difference ($\gamma$) should be taken into account to guarantee that the demands are properly synchronized. Figure 9 illustrates how temperature setpoints vary over time for the proposed equations and different number of buildings.

![Figure 71: Setpoint scheduling for connected buildings based on equations 5.10 and 5.11.](image)

To see the impact of setpoint time intervals and temperature measurement/control resolution, Figure 72 demonstrates sinusoid temperature schedule for three buildings with $\delta=5$ minutes intervals and $\Delta T=0.5 \degree C$. 
Electric demand of building clusters as a consequence of the proposed policies show desired results. Figure 73 demonstrates the aggregate behavior of four scenarios from 8 AM to 8 PM in a representative day in July. In these scenarios, electric demand as a result of constant periodic and sinusoid setpoint scheduling for (a) office-hotel (b) 3 offices (c) 3 residential (mid-rise apartments) (d) 3 restaurants are presented.

As demonstrated in Figure 73, peak demand and electricity consumption dramatically decrease by implementing synchronized sinusoid temperature setpoints while saving
opportunities are also observed in this periodic form. The resulting load profiles based on sinusoid temperature scheduling are steady with large peak demand removed and the total demand shifted down. This automatically results in load leveling and peak shaving via HVAC control. Table 10 compares the savings based on proposed control policies. Peak demands are compared in peak hours from 4 PM to 7 PM.

Table 10: Comparison of saving opportunities in the scenarios presented in Figure 73.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Constant Periodic</th>
<th>sinusoid</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Saved Energy (%)</td>
<td>Peak Increase (%)</td>
</tr>
<tr>
<td>Office – Hotel</td>
<td>2.5</td>
<td>+9.78</td>
</tr>
<tr>
<td>Three Offices</td>
<td>5.83</td>
<td>+21.82</td>
</tr>
<tr>
<td>Three Supermarkets</td>
<td>2.49</td>
<td>+19.62</td>
</tr>
<tr>
<td>Three Residential Apartments</td>
<td>7.13</td>
<td>-1.65</td>
</tr>
</tbody>
</table>

Table 10 indicates that peak demand does not increase by applying sinusoid control policy while for most cases there is a peak demand increase by applying constant periodic control policy. As a conclusion to this section, we make the following observations:

- Selection of buildings that are synchronized together is important. It is recommended that buildings with same sizes and behavior cooperate by incorporating time lag between temperature (γ) and building demand size. In large communities, the cooperating buildings can be broken down into clusters. The clustering method will be later discussed in this article.
If time of use of electricity is not our priority, it is not necessary that periodic temperature setpoints be assigned continuously. Periodic control policies can be applied over peak hours or periods that the availability of electricity is limited (such as PV or wind generation limits). This also mitigates the risks associated with asset degradation and resulting maintenance costs.

This operation planning can also be integrated with shared assets and transportation systems (such as BEVs and PHEVs) across the community.

If the comfort level of the occupants is important, we should modify $\Delta$ and $B$ deviations from comfort zone according to rule-based or optimization models.

For precooling purposes before peak hours, temperature setpoints would obtain same phases ($\varphi_i = 0$) and $\tau$ becomes significant in decision making while the objective is to decrease the peak demand at a specific period. Figure 74 (a) illustrates a scenario for three cooperating offices, in which maximum electricity price occurs at 5 PM. As a result, if we assume $\tau$=1 hour, precooling process starts at $t = (3:30 PM - \frac{\gamma}{\pi} \tau)$ so the minimum demand occurs at 5 PM (in this scenario, is $\frac{\gamma}{\pi} \tau = 4 \text{ min}$). Also, a scenario with ($\varphi_i = \frac{2\pi}{3}$) is illustrated in Figure 74 (b) where load leveling and peak shaving are happening simultaneously.
Figure 74: Precooling planning for three office buildings when the price of electricity increases at 5 PM for (a) when φ=0 and (b) φ=2π/3.

Figure 74 demonstrates that only adopting periodic scheduling policy over peak hours reduces the peak demand from 185 kW to 130 kW if all buildings have the same phase, and, the peak demand reduces to 155 kW if they have phase difference. This demand reduction is noticeable, and in large scales, it will enhance grid stability. This peak demand reduction is more noticeable in larger scales such as microgrids and power distribution levels.

5.5 Optimization of cooperation of buildings

So far, we have discussed a number of rule-based strategies for the periodic operation planning of single buildings and building clusters. In this section, we present mathematical models to improve the cooperation within a building community according to some constraints such as occupancy and electricity price signals. We also include the cooperation between zones at building level. We first study the relationship between discomfort levels
and thermal inertia, and how it creates a way to reduce the aggregate demand of the community. Then, we present an optimization framework to interconnect the collaborative community to the grid based on the price of electricity and incorporate discomfort levels and different constraints to the models. Also, we identify those buildings that can have collaboration as a cluster. For instance, a single small residential building cannot impact the aggregate demand of a building cluster if a large hospital is included in the cluster. As a result, the buildings in a cluster should be identical in terms of demand size and shape. This also means that a building community can be broken down into multiple sub-clusters.

We use clustering methods as a similarity metrics to identify the buildings that are capable of cooperating. It should be noted that since the relationship between control strategies and electric demand needs to be incorporated in the optimization platform, this relationship has to be estimated or simulated (see [114]). We propose a data-driven approach in section 7 to estimate the relationship between periodic control planning and load behavior. Finally, we describe the possible impacts of asset degradation and auto-tuning control in the operation decision making and control system stability.

5.5.1 Thermal inertia and cooperation of buildings

As discussed previously, we assign periodic temperature setpoints to be able to use room thermal inertia and avoid air conditioning while the room is still within human comfort zone. On the other hand, this periodic setpoint scheduling enables us to facilitate a coordination between building clusters. Figure 75 shows how room average temperature (EnergyPlus DEO Medium Office Reference Building) follows the setpoint schedules based on sinusoid forms. This sinusoid temperature schedule follows a pattern with $\Delta=1 \, ^0\text{C}$, $\tau=60\,\text{minute}$, $B=24 \, ^0\text{C}$, $\delta=5\,\text{minute}$, and $\Delta T=0.5 \, ^0\text{C}$. As seen in this figure, room
temperature does not follow the setpoint and shows a behavior that stems from the room thermal inertia. This behavior depends on many factors such as internal gains and weather conditions. Besides, cooling design also plays an important role in this behavior. As an example, Figure 75 demonstrates different room temperature patterns based on different cooling sizing factors and under identical conditions. As seen in this picture, for higher sizing factors, room thermal inertia becomes more noticeable. In this work, we have used a cooling design factor of 1.2 in the EnergyPlus models.

![Room temperature response as a result of sinusoid temperature setpoint scheduling.](image)

We have also presented constant periodic setpoint scheduling as another alternative to use room thermal inertia. Figure 76 shows room temperature behavior under constant periodic temperature setpoints with a design factor of 1.2. As seen in this figure, thermal inertia is also noticeable in such systems.
If one wants to evaluate the deviation from a comfort level (discomfort level), the area under the room temperature curves can be a good evaluation.
5.5.2 Optimization model

A In general, for a specific time horizon, discomfort penalty can be incorporated in building HVAC operation optimization frameworks to minimize energy cost in a dynamic electricity market according to equation 5.12.

$$\begin{align*}
\min & \quad P_p(t) \times PD + P_t(t) \times E + \epsilon \times H(T, T_{\text{comfort}}) \\
\text{s.t} & \quad \text{operation constraints}
\end{align*} \quad (5.12)$$

where $P_p(t)$ is the peak demand charge ($$/kW$), $P_t(t)$ is the time of use price of electricity ($$/kWh$), PD is the peak demand (kW), and E is the energy consumption over time (kWh), $\epsilon$ is the penalty cost for deviation from temperature comfort level ($$/^\circ\text{C}$), and H is comfort deviation function. For constant periodic and sinusoid temperature schedules and over a period ($2\tau$), H is:

$$H = 2\tau \Delta T \quad (5.13)$$

This means that for sinusoid setpoint forms, the penalty function is only dependent on $\tau$ and $\Delta T$ factors. However, due to the thermal inertia of the room, H is less than the real value in equation 5.13 and varies over time while it depends on setpoint parameters, thermal characteristics of the zone, cooling design factor, latent/sensible heat fluxes interacting with the room, etc. As a result, the exact discomfort deviation of the room temperature can be identified and merged into the optimization frameworks for better decision makings. This can be addressed by a factor ($\lambda$), which improves equation 5.12 to:

$$\begin{align*}
\min & \quad P_p(t) \times PD + P_t(t) \times E + \lambda \times \epsilon \times H(T, T_{\text{comfort}}) \\
\text{s.t} & \quad \text{operation constraints}
\end{align*} \quad (5.14)$$

where $\lambda$ depends on room thermal inertia (this ratio depends on the highlighted area in Figure 78). H and $\epsilon$ can be defined as constant or variable functions based on user
preference. In addition, operation constraints depend on factors such as occupancy, weather conditions, and building schedules. We incorporate the same methodologies and constraints, proposed in [10], [28], [114] to equation 5.14 to enhance the optimization.

Equation 5.14 can be applied for periodic operation planning between controlled zones at building level and between multiple buildings at community level. Thus, as a more general model equation 5.14 can be rewritten as:

\[
\begin{align*}
\min & \sum_{i=1}^{N} \sum_{j=1}^{Z_i} P_P(t) \times P_D_i + P_i(t) \times E_i + \lambda_{i,j} \times \epsilon_{i,j} \times H_i(T_{l,j}, T_{i,j,\text{comfort}}) \\
\text{s.t} & \quad \text{community and building constraints}
\end{align*}
\]

(5.15)

where N is the number of buildings collaborating and \(Z_i\) is the number of controlled zones in building i. Equation 5.15 also indicates that penalty functions, setpoint temperatures, and physical characteristics for different buildings and different zones in buildings are different and subjected to the constraints associated with the single buildings and the community. These constraints can be factors such as occupancy, utility signals, unpredicted events, availability of onsite power generation resources, storage systems etc. for day ahead.
planning and longer time periods, equation 5.15 should be expanded for different timesteps and appropriate predictive models should be used accordingly.

In general, there is a tradeoff between deviation from preferred temperature setpoint and resulting electricity demand/consumption that should be computed via equation 5.15 to minimize human discomfort and costs. Also, the electricity peak demand and consumption response \((P_p \text{ and } P_t)\) to different periodic control strategies should be captured via estimation or simulation methods to be integrated in the above optimization framework, which is presented in section 7 (for more information, similar approaches are also used in [114]). As mentioned previously, buildings that are capable of collaboration together should be identified. This can be done by clustering methods to group suitable collaborative buildings (section 5.3).

5.5.3 Load clustering

Load profile clustering can be performed based on different methodologies. One of the most common methods is traditional load profiling. In this method, time-series load profiles are usually the input data of clustering techniques [134]. Also, different partition methods (e.g., Euclidean distance) between load profiles can be used to perform clustering more accurately. In this study, clustering methods such as K-Means and X-Means are used for load clustering. As the input load data are normalized according to its daily peak in the clustering process, the clustering process is entirely based on the similarity of load shapes. However, the traditional clustering method has some limitations in handling magnitude, volatility and uncertainty [135]. Although traditional clustering methods are sufficient for our purpose, wavelet-based clustering method is recently being studied and applied for load disaggregation, load forecasting, and load clustering [136], [137]. This method can
decompose load profiles into different levels, and each level has different scales and shifts over time [138], [139]. In this method, the load profile is broken down by high-pass and low-pass filters. The down-sampling process uses wavelet transform to decompose the load profiles into lower resolution components. After applying wavelet-based disaggregation method, time-series load profiles transform to frequency-domain profiles, and K-Means or X-Means clustering can be done more accurately. The advantage of wavelet-based multi resolution analysis (MRA) over traditional method, which uses time-series parameters, is the fact that daily load profiles can be used in the frequency-domain. Taking advantage of frequency-domain enables us to decompose a volatile and irregular load profile into a smooth large-scale component describing the underlying shape, and several small scale components describing volatilities [135]. Having applied MRA method, clustering can be done by selecting similar load profiles in terms of peaks demands, sudden fluctuations, amplitude, ups and downs, and steadiness. However, due to the non-complex behavior of the load profiles in this study, we use K-Means method. K-Means algorithm is a non-hierarchical method to cluster the load profiles into different groups considering the similarity of the data. The algorithm consists of the following steps:

1. Assign an initial number of load profile clusters (K) to dataset.

2. Assign load profiles to a cluster center based on a distance metric such as Euclidean Distance.

3. Find the mean of each cluster which would be the new center of that cluster.

4. Repeat steps 2 and 3 until there would be no change in the cluster patterns during some successive iterations.
One of the biggest disadvantages of this method is that the initial random choice of cluster centers can often cause very different clusters to form [140]. Xu and Wunsch suggested to run the algorithm several times and choose the solution with the lowest sum of squared distance between the data and cluster centroids [141]. Some features in daily load profiles, such as average load demand, peak demand, number of peaks and valleys, and the difference between the minimum and maximum daily load demand, have been used to cluster them in different groups. The load synchronization attempts to adjust profiles within a cluster to minimize the aggregate load profiles and this clustering method enables us to do improve the community operation. Although it is beyond the scope of work of this paper, in the next two sections we review two important factors in the control strategies.

5.5.4 Asset degradation

In general, new performance requirements and modern building control methods could result in more asset degradation and necessitates proper maintenance planning strategies. The proposed control strategy in this paper may also result in more maintenance costs over long periods of time. One can take into account the risk and costs associated with the operation of building asset maintenance and incorporate them into the decision-making platform. Key Performance Indicators (KPIs) attributed to operation, maintenance and repairing a building can be found in [142]. Also, evaluation methodologies to estimate the buildings’ degradation level based on the causes of the anomalies are investigated in [143]. As another example for maintenance planning, a climate conscious multi-period maintenance planning approach can be found in [144] to manage public buildings by prolonging service life while maintaining a target condition rating, and more importantly, incorporating the dynamic nature of the parameters. However, it should be noted that the
proposed strategy in this work is not necessarily employed 24 hours a day. One can evaluate the benefit arising from this strategy during peak hours, in case of emergency, etc. and deploy the periodic planning during these periods.

5.5.5 Control tuning

HVAC controller systems in the proposed optimization framework should be responsive to the inherent nonlinear characteristics, uncertain disturbance factors and thermal inertia. Besides, thermal dependency of adjacent zones may interfere the control system. To mitigate the above challenges, a proper auto-tuned control system should be considered. This system should guarantee a stable performance of the optimal HVAC operation plan and human comfort levels. Advanced tuning methods are currently utilized to regulate transient behavior of HVAC systems, monitor HVAC operation, and avoid high maintenance and degradation costs [117], [145]. In our work, after decision making for the periodic setpoint schedules, the model can then be adjusted based on online tuning methodologies to guarantee the stability of the system as a combined platform [146]. One can also analyze the impact of sinusoid variables on the system stability and adjust these parameters or define constraints based on the resulting thermal and control responses. It seems that gradual variations (such as low frequencies or slight temperature changes) in the temperature setpoint schedules might lead into a more stable control system; however, since these interactions cannot be captured via our simulations, it requires more investigation.
5.6 Case scenario: Large scale building coordination and grid interconnection

To demonstrate the impact of the proposed operation control in building communities, a community composed of 26 buildings and a maximum HVAC demand of 2.33 MW was modeled to represent a university campus. The details of this community are demonstrated in Table 11.

Table 11: Configuration of the existing buildings in the community simulation.

<table>
<thead>
<tr>
<th>Building Type</th>
<th>Number of Buildings</th>
<th>Area</th>
<th>Number of Controlled Zones</th>
<th>Number of Stories</th>
<th>Cooling System</th>
</tr>
</thead>
<tbody>
<tr>
<td>Housing Suits</td>
<td>3</td>
<td>3800 m²</td>
<td>74</td>
<td>4</td>
<td>PTAC/PSZ-AC</td>
</tr>
<tr>
<td>Department Buildings</td>
<td>7</td>
<td>5000 m²</td>
<td>15</td>
<td>3</td>
<td>DX Packaged unit/VAV</td>
</tr>
<tr>
<td>Health Center</td>
<td>1</td>
<td>3500 m²</td>
<td>118</td>
<td>3</td>
<td>DX Packaged unit/VAV</td>
</tr>
<tr>
<td>Housing Apartments</td>
<td>8</td>
<td>3100 m²</td>
<td>27</td>
<td>4</td>
<td>DX Split</td>
</tr>
<tr>
<td>Restaurants</td>
<td>1</td>
<td>511 m²</td>
<td>3</td>
<td>1</td>
<td>PSZ-AC</td>
</tr>
<tr>
<td>Retail Store</td>
<td>3</td>
<td>2300 m²</td>
<td>5</td>
<td>1</td>
<td>PSZ-AC</td>
</tr>
<tr>
<td>Classrooms</td>
<td>2</td>
<td>19600 m²</td>
<td>46</td>
<td>2</td>
<td>Electric chiller</td>
</tr>
<tr>
<td>Supermarket</td>
<td>1</td>
<td>4200 m²</td>
<td>6</td>
<td>1</td>
<td>PSZ-AC</td>
</tr>
</tbody>
</table>

The simulation is based on DOE EnergyPlus reference models and the communication and control systems are modeled via Building Virtual Testbed (BCVTB) by Lawrence Berkley.
Labs (Figure 79). In this study, we used different initial numbers of clusters and the results show that K=5 gives the most accurate clustering results, we identify five building clusters based on electric load behavior and according to what we presented in section 5.3.

![Figure 79: Simulation of building community configuration in BCVTB.](image)

We use equation 5.15 optimize HVAC operation planning. Different occupancy patterns and building schedules are used in the simulations. The electricity price is based on the locational marginal prices presented in [28] and the impact of occupancy constraints and building schedules are addressed according to [114]. The impact of peak demand and electric consumption in the optimization framework is predicted based on the procedure in
section 7 and [114]. In the reference scenario, temperature setpoint is assigned 23 °C in occupied mode and 25 °C in unoccupied mode (setback policy). For the periodic strategy, temperature setpoints vary between 23 °C and 25 °C, \( \delta \) is 5 minutes and \( \Delta T \) is 0.5 °C. For a representative day in July over a 14-hour period (7 AM to 9 PM), the HVAC electricity peak demand for the base scenario is 2.33 MW. This peak demand reduces by \%10.41 (about 253 kW) for operation planning resulting from periodic operation planning and electricity consumption reduces by \%12.55. To evaluate the impact on grid scale, we assume that marginal production costs for the operator follows a cost function as equation 5.16 [147].

\[
g(D) = \frac{D^2}{\beta} + \alpha D + \psi \quad (5.16)
\]

Where \( g \) is the cost function, \( D \) is electricity demand in kW, and \( \alpha, \beta, \psi \) are cost model parameters. Assuming that \( \alpha = 0.1 \) and \( \beta = 500 \), the consumption reduction can result in US$2350 in the slack bus, which is a considerable saving for a one-day period. This peak demand reduction can also result in less investment in infrastructure upgrade and T&D deferral at grid level. This load reduction is illustrated in Figure 80.
5.7 Periodic electricity demand forecast

For different applications in community and microgrid levels, a reliable forecast of electric demand would significantly improve operation planning and decision-making frameworks in such systems. Consequently, in this section, we describe a methodology that can forecast building electric demand resulting from the proposed periodic operation planning. There are several factors influencing building electric demand. These variables are environment dry bulb temperature, humidity, solar radiation, wind speed, and building operation schedules (e.g. occupancy, light, and equipment), and time of day [148]. As demonstrated previously, if we practice control policies based on presented periodic HVAC operation planning, building electric demand would take a periodic form. Consequently, main parameters presented in equations 5.10 and 5.11 become important in electric demand forecasting. As a result, building electric demand (D (kW)) can be presented as:

\[
D = \Gamma(T_\infty, J_\infty, R_\infty, W_\infty, SC_L, SC_O, SC_E, TD, \Delta, \tau, B) \quad (5.17)
\]
As shown in the previous sections, for periodic setpoint scheduling, electric demand will also become periodic with the same frequency as the schedule frequency. Thus, knowing setpint frequencies along with electric demand amplitude would result in a forecast for building HVAC electric demand. However, electric demand amplitude may vary over time based on the aforementioned independent variables in equation 5.17. As a result, the objective is to find maximum and minimum values for building electric demand sinusoid form. Some target points for prediction are shown in Figure 81 where maximum and minimum values should be predicted at time $t$, based on available information of independent variables in equation 5.17.

![Figure 81](image.png)

**Figure 81:** Predicting maximum/minimum demand values to construct a demand profile.

Maximum and minimum predicted values of electric demand can form electric demand time series as follows:

$$
\hat{D}(t) = \frac{\hat{D}_{\text{max}}(t) + \hat{D}_{\text{min}}(t)}{2} - \frac{\left(\hat{D}_{\text{max}}(t) - \hat{D}_{\text{min}}(t)\right)}{2} \sin \left(\frac{\pi}{\tau} (t) + \gamma\right)
$$  \hspace{1cm} (5.18)
To estimate $\hat{D}(t)$, we need to segment the time period into $\tau/2$ time intervals. Predicted values ($\hat{D}_{\text{max}}(t)$ and $\hat{D}_{\text{min}}(t)$) are the values that occur in the beginning and at the end of the interval (or vice versa). However, a method to predict maximum/minimum values is also a challenge. In this work, we predict maximum/minimum to generate a more stable aggregate load profile based values by Artificial Neural Network (ANN) method. ANN has two benefits that we can take advantage of: 1) it is not limited by the assumption of functional relationship (e.g. linear relationship) between the inputs and outputs, 2) the results obtained by ANN are not influenced by correlation among inputs. There are different classes of neural network models, two of which have received considerable attention in recent studies: multilayer neural networks and recurrent networks. Multilayer networks have proved extremely successful in pattern recognition problems while recurrent networks have been used in associative memories as well as for the solution of optimization problems [149]. In this paper, a feed-forward Multilayer Perceptron (MLP) neural network is used to learn and generalize the network.

A neural network consists of three main parts: the input layer, the hidden layer(s) and the output layer. The hidden layers connect the inputs to the output and help to solve non-linear problems. In an MLP network, more than one hidden layer can exist. Some researchers believe that more hidden layers can be added to obtain a quite powerful multilayer network [62]. On the other hand, based on the Kolmogorov’s theorem, some others argue that just one or two hidden layers are sufficient since more hidden layers could cause the overfitting problem. For this paper, we use one hidden layer to achieve accurate results and prevent overfitting in our ANN model.
The MLP activation functions are one of the most crucial parts in designing neural network architecture. We need to choose two activation functions, one for the hidden layer and another for the output layer. Sigmoid activation is a common activation function with output intervals varying between zero to one. Another activation function is the hyperbolic tangent function with an output interval of -1 to 1 which is used in back-propagation networks. In this paper, the activation function \( \phi(x) \) for the hidden layer is hyperbolic tangent function as follows:

\[
\phi(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}
\]  

(5.19)

where \( x \) represents the model parameter. In addition, \( f(x) \) is the linear activation function for the output layer. Hence, the final mathematical equation of our ANN is as follows:

\[
\hat{Y}_t = f\left( \sum_{q=1}^{n} u_{kq} \phi\left( \sum_{p=1}^{m} w_{qp} u_p + b_q \right) + b_k \right)
\]  

(5.20)

where \( \hat{Y}_t \) is the prediction using ANN, \( u_{kq} \) and \( w_{qp} \) are weights, \( b_q \) and \( b_k \) are bias values, and \( m \) and \( n \) are the number of input variables and the number of hidden units, respectively. Each ANN can include \( m \) neurons in input layer and the number of neurons in the hidden layer should not exceed \( 2m + 1 \) neurons. In this paper, we assume that the number of hidden neurons equals to the number of input units. In this study, we have 14 input neurons, 14 neurons in hidden layers, and one output. Moreover, different training algorithms are available for learning process in neural networks with different characteristics and performances. In this paper, we use Levenberg-Marquardt algorithm. This algorithm
combines the Gradient Descent method and Quasi-Newton method to ensure the locally fast convergence speed [150] and also decrease the total error more than other algorithms. As an example, the training and testing data were generated for DOE medium office reference building over a three-month period. The results for maximum/minimum show an MAPD of 6.4% and R-squared value of .86 for maximum values, and, MAPD of 1.94% and R-squared value of .97 for minimum values associated with the testing dataset. Figure 82 demonstrates how predicted values follow the testing data. If $\tau$ and $\Delta$ are constant, these values improve to 2.11 MAPD and R-squared value of .95, and 1.01 MAPD and R-squared value of 0.98 for maximum and minimum values respectively.

![Figure 82](image_url)  

Figure 82: Comparison of predicted and simulation values for maximum and minimum demand test dataset.

Consequently, for an operation schedule with $\tau = 1 \text{ hour}$, and available information about weather forecast and schedules, maximum/minimum values can be estimated based on the trained Neural Network. Electric demand for an 8-hour period can be estimated based on equation 5.18. A comparison between estimated values for electric demand and simulation results is demonstrated in Figure 83 for the medium office.
As seen in Figure 83, with less calculation and finding only 8 targets, we managed to estimate demand behavior for an 8 hour period. This indicates that, periodic operation planning makes demand forecast less complex. In addition, for specific periods that the maximum demand is only important, these values can be estimated properly via the described methods.

5.8 Conclusion

In this paper, the objective was to develop an algorithm to employ building thermal inertia to save energy and facilitate collaboration within building clusters. A periodic temperature setpoint schedule was proposed that creates saving opportunities, takes advantage of building thermal inertia, and avoids sudden peak demands. The proposed methodology can simultaneously use building thermal inertia and synchronize HVAC operation of building clusters. An optimization framework based on the thermal behavior of the buildings and periodic schedules were proposed and elaborated. The building cooperation based on this optimization framework reduces the aggregate electricity consumption and peak demand of a representative community with a smooth and steady load profile. The results
demonstrate up to 12.5% electricity consumption reduction and up to %10 improvement in peak demand for the representative building community. The results also indicate that at grid level, the proposed control policies can lead into transmission and distribution upgrade deferral, which in turn, benefits the society. While the methodology aims to synchronize temperature setpoints, it can also be implemented in energy communities to integrate other significant factors such as electric vehicles, DERs, and shared assets (district heating/cooling etc.). In future research studies, the operation collaboration of buildings and aforementioned factors should be evaluated. Also, risk factors and costs attributed to asset maintenance and degradation can improve the decision making process. Due to the fact that the behavior of such dynamic strategies might negate the control system performance, control tuning strategies should also be taken into account in the future studies to develop a multi-stage decision making system that avoids from possible transient behaviors. Lastly, the proposed strategies are suggested to be deployed in commercial building where users cannot override the scheduled operation. The proposed strategies for specific end-users might require incentive modeling.
References


S. Koehler and F. Borrelli, “Building Temperature Distributed Control via Explicit MPC


