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**NANYANG
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SINGAPORE

**BUILDING ENERGY MANAGEMENT AND
DEMAND RESPONSE**

ZHANG HANWEN

SCHOOL OF ELECTRICAL & ELECTRONIC ENGINEERING

2019

BUILDING ENERGY MANAGEMENT AND DEMAND RESPONSE

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School of Electrical & Electronic Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Master of Engineering

2019

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

23 Aug 2019
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Authorship Attribution Statement

This thesis contains material from one paper accepted at conference and one paper published in the following peer-reviewed journal in which I am listed as an author.

Chapter 3 is published as H. Zhang and A. Ukil, "Model Predictive Control of Induction Machine for Energy Efficient HVAC Operation," in 2018 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia), 22-25 May 2018 2018, pp. 1068-1073, doi: 10.1109/ISGT-Asia.2018.8467875.

The contributions of the co-authors are as follows:

- Dr. Abhisek Ukil provided the initial project direction and edited the manuscript drafts.
- I prepared the manuscript drafts. The manuscript was revised by Dr. Abhisek Ukil.
- Dr. Abhisek Ukil offered various expert guidance in the meetings which helped the research progress.
- Under Dr. Abhisek Ukil's kind guidance, continuous support, and timely suggestions in the research progress, I did all the simulations and constructed all mathematical models.

Chapter 4 is published as H. Zhang, P.L. So, and A. Ukil, "Smart Building Energy Management with Multi-storage Systems for Demand Response" IEEE Transactions on Sustainable Energy, 2019. (under revision).

The contributions of the co-authors are as follows:

- Assoc. Prof. So Ping Lam and Dr. Abhisek Ukil provided the initial project direction and edited the manuscript drafts.
- I prepared the manuscript drafts. The manuscript was revised together with Assoc. Prof. So Ping Lam and Dr. Abhisek Ukil.

- Assoc. Prof. So Ping Lam edited the manuscript drafts and provided guidance in addressing reviewer comments.
- Assoc. Prof. So Ping Lam offered various expert guidance in the meetings which helped the research progress.
- I presented my initial idea of the building energy management system model to Assoc. Prof. So Ping Lam who suggested including wind turbine as a second renewable energy available in the building.
- Under Assoc. Prof. So Ping Lam's kind guidance, continuous support, and timely suggestions in the research progress, I did all the simulations with various optimization approaches in the simulation models.

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Abstract

Recently, the energy efficiency of a building has been receiving much attention from the researchers. Many papers discuss the optimizations around the Heating, Ventilation, and Air-Conditioning (HVAC) system, such as sensors and model predictive control (MPC) based thermostats. However, most of them do not consider the energy usage on the drive devices where the fans and pumps are powered by the induction machines which consume about 50% to 75% of total energy consumption in the overall HVAC system. Various drive control strategies could render different energy savings by considering the losses in an induction machine under the different scenarios of a HVAC system. Hence, one of the research works in this thesis investigates the energy efficiency of an induction machine controlled by a MPC based approach for the central fan application in a HVAC system. The integrated HVAC and model predictive flux control (MPFC) drive model is constructed in Matlab/Simulink where a HVAC is formulated by a RC-network model. The simulations are carried out to study the drive performance under various scenarios in a HVAC system where the induction machine's torque ripple, speed ripple, torque loss, and power consumption are investigated.

Besides improving the energy efficiency of system components in a HVAC system, optimizing the Energy Management System (EMS) and Demand Response (DR) of a building is another essential way to reduce the building's electricity bill. Thus, the other research work is presented in this thesis to shed light on how the EMS with multi-storage systems can be optimally and coordinately controlled in a demand responsive building by providing a price-based integrated automation model for managing various building loads, renewable energy, and multi-storage systems. This work focuses on the optimizing an EMS framework for the Demand Side Management (DSM) instead of the utility side optimization discussed in the

literature. It also extends the previous works done by other researchers and addresses their presented issues for deploying the ice storage system. The proposed method is validated by the simulation environment conducted on EnergyPlus™ and CPLEX®. In the proposed EMS framework, the deterministic approach is adopted for the battery and renewable energy optimization that operate in a coordinated manner with the DR programs in a building. The smart price-priority strategy is designed in EnergyPlus™ using EnergyPlus runtime language (Erl) to make a smart decision for coordinated control of the thermal energy storage (TES) device, battery, HVAC-based DR, and the Demand Responses (DRs) of lighting and miscellaneous loads. The simulation results show that the proposed smart price-priority strategy for coordinated control of ice storage with other DR programs can make a proper trade-off between the peak-load reduction and energy consumption in the building with storage systems. In addition, a hybrid cooling-and-ventilation control algorithm is developed for a HVAC-based DR event, which shows a similar performance of the conventional global temperature adjustment of all zones in the building for a HVAC-based DR, in terms of the net operating cost and energy consumption.

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Acronyms and Symbols

Acronyms

AAPSO	Advanced adaptive particle swarm optimization
AI	Artificial intelligence
AMI	Advanced metering infrastructure
B2G	Buildings-to-Grid
BCVTB	Building Controls Virtual Test Bed
BEMS	Building Energy Management System
BES	Battery energy storage
CAV	Constant air volume
CHP	Combined heating and power
COP	Coefficient of performance
DCV	Demand controlled ventilation
DR	Demand Response
DRQAT	Demand response quick assessment tool
DRs	Demand Responses
DSM	Demand Side Management
DSP	Digital signal processor

DTC	Direct torque control
DX	Direct expansion
EMA	Exponential moving average
EMS	Energy Management System
Erl	EnergyPlus runtime language
ESS	Energy storage system
EV	Electric vehicle
EVs	Electric vehicles
FCU	Fan coil unit
FEL	Following electric load
FOC	Field oriented control
FTL	Following thermal load
HEMS	Home Energy Management System
HVAC	Heating, Ventilation, and Air-Conditioning
IM	Induction machine
IoT	Internet of things
ISOs	Independent system operators
LBNL	Lawrence Berkeley National Laboratory
MDP	Markov decision process
MILP	Mixed-integer linear programming
MPC	Model predictive control
MPFC	Model predictive flux control

MPTC	Model predictive torque control
NOCT	Nominal operating cell temperature
NREL	National Renewable Energy Laboratory
NTU	Nanyang Technological University
OA	Outdoor air
PEV	Plug-in electric vehicle
PI	Proportional-integral controller
PMV	Predicted mean vote
PSO	Particle swarm optimization
PV	Solar photovoltaic
PVs	Solar photovoltaics
RTOs	Regional transmission organizations
SAT	Supply air temperature
SBPI	Simulation-based policy improvement
SMA	Simple moving average
SOC	State of charge
TAC	Thesis advisory committee
TES	Thermal energy storage
THD	Total harmonic distortion
THIC	Temperature and humidity independent control of air-conditioning system
TOU	Time-of-use

VAV	Variable air volume
VFD	Variable frequency drive
VOC	Volatile organic compounds
VRF	Variable refrigerant flow
VSI	Voltage source inverter
WT	Wind turbine
WTs	Wind turbines

Symbols

C_{bat}	Operating cost of battery
α_{pv}	Module transmittance absorptance product
α_{wt}	Blade's angle of attack
$\bar{p}_{ema}$	Exponential moving average of electricity price
$\bar{p}_{sma}$	Simple moving average of electricity price
δ_{oc}	Temperature coefficient of open-circuit voltage
δ_{sc}	Temperature coefficient of short-circuit current
$\eta_{c,pv}$	Module conversion efficiency
η_s	Efficiencies of selected energy storage
$\Gamma_{e,ref}$	Radiation incident at reference conditions
Γ_e	Total radiation incident on PV array
λ_{hvac4}	HVAC4 operating status
λ_{nv}	Nature ventilation status in HVAC4

λ_{pv}	Empirical PV curve-fitting parameter
ω_r	Rotor speed and fan speed notation
ω_{wt}	Angular velocity of wind turbine
ρ_{rh}	Local air density at the rotor height
σ_p	Standard deviation from the exponential moving average of the real-time price
τ_2	Time constant for equation (3.2)
τ_m	Energy capacity of the battery
θ_r	Rotor angular position
θ_{wt}	Azimuth angle of a vertical axis wind turbine
Υ_{hl}	Rate of heat loss due to the performance of work
Υ_{mr}	Metabolic rate per unit area
Υ_{occ}	Internal heat production rate of an occupant per unit area
ε_b	Semiconductor bandgap
ξ_{rms}	Error between two RMS values in %
a_i	Required airflow rate ratio in HVAC system
$A_{wt,c}$	Blade chord area of wind turbine
B	Viscous friction coefficient
B_{U1}	1 st -boundary
B_{U2}	2 nd -boundary
c_1	Constant coefficient for fan power estimation in W
c_2	Constant coefficient of a fan

C_{grid}	Net power cost from grid
C_{ice}	Operating cost of ice
C_i	The i-th zone capacitance, J/K
C_{pv}	Operating cost of PV
c_p	Specific heat of the air
$C_{wt,d}$	Coefficient of blade drag
$C_{wt,l}$	Coefficients of blade lift
$C_{wt,t}$	Tangential force coefficient of wind turbine
C_{wt}	Operating cost of wind turbine
DR_{hvac}	HVAC-based demand response
DR_{lm}	Demand response of the lighting and miscellaneous loads
DR_{tes}	TES-based demand response
E_{bat}	Energy capacity of the battery
$F_{wt,ta}$	Average tangential force
h_c	Convective heat transfer coefficient
$H_{loss,pv}$	Array thermal loss coefficient
i	The notation for the i-th zone
$I_{d,ref}$	Diode reverse saturation current at reference conditions
I_d	Diode reverse saturation current
$I_{mx,ref}$	Current at maximum power point along current-voltage curve at reference conditions
$I_{pv,ref}$	Module photocurrent at reference conditions

I_{pv}	Module photocurrent
$I_{sc,ref}$	Short-circuit current at reference conditions
ice_{mode}	Ice storage operating mode
J	Coefficient of the motor inertia
j	The notation for the j-th zone which is an adjacent zone of the i-th zone
$j \in N_i$	All adjacent j-th zone of the i-th zone
k_b	Boltzmann constant in J/K
k_c	Constant coefficient in speed and torque characteristics equation
L_{dry}	Sensible heat flow from skin
L_{light}	Controlled lighting loads
L_{misc}	Controlled miscellaneous loads
L_{res}	Rate of respiratory heat loss
$L_{rsu,req}$	Rate of heat loss from the evaporation of regulatory sweating at the state of comfort
L_{sk}	Total evaporative heat loss from skin
$m(t)$	Total supplied mass airflow rate by the fan in kg/s
$m^d(t)$	Total desired mass airflow rate in kg/s
$m_{i,max}$	Max airflow rate at each zone, kg/s
m_i	Supplied airflow rate in i-th zone, kg/s
$m_i(t)$	Instantaneous total supplied airflow rate in i-th zone, kg/s
m_i^d	Desired airflow rate i-th zone, kg/s

$m_i^d(t)$	Instantaneous desired airflow rate in i-th zone, kg/s
n	Study period of the moving average
N_{rms}^*	Root mean square (RMS) value of the reference rotor speed, rpm
N_i	A set of $[i, j]$ that includes all combination of $[i, j]$ sets, but $i \neq j$
N_{rms}	Root mean square (RMS) value of the supplied rotor speed, rpm
$N_{s,pv}$	Number of individual cells in module
$N_{wt,bl}$	Blade number of wind turbine
p	Real-time electricity price
$P_{bat,c}$	Battery charging power
$P_{bat,d}$	Battery discharging power
$P_{bc,max}$	Maximum battery charging power
$P_{bc,min}$	Minimum battery charging power
$P_{bd,max}$	Maximum battery discharging power
P_{buy}	Power bought from grid
P_{fan}	Fan power, W
$P_{ice,c}$	Ice charging power
$P_{ice,d}$	Ice discharging power
P_{load}	Total electrical load of building
P_{loss}	Power loss due to conversion units
P_{pv}	Power generated from PV
$P_{sale,max}$	Allowed maximum power sold to grid
P_{sale}	Power sold to grid

p_{setc}	Allowable price for charging
p_{setd}	Allowable price for discharging
P_{wa}	Water vapor pressure in ambient air
P_{wt}	Power generated from wind turbine
PMV_{ave}	Average PMV value of zones in HVAC4
q_c	Electron charge constant
Q_i	The external heat sources from appliance and occupants in i-th zone, W
$C_{i,j}$	The wall capacitance between the i-th and j-th zone, J/K
R_{cl}	Ratio of clothed body
$R_{i,j}$	The wall thermal resistance between the i-th and j-th zone, K/W
R_i	The window thermal resistances in i-th zone, K/W
$R_{p,+ve}$	Error between maximum and RMS value of speed, torque and air-flow rate
$R_{p,-ve}$	Error between minimum and RMS value of speed, torque and air-flow rate
$R_{p,\%}$	Average ripple of speed, torque and airflow rate in %
$R_{p,ave}$	Actual average ripple of speed, torque and airflow rate
$R_{s,pv}$	Module series resistance in Ω
$R_{sh,pv}$	Module shunt resistance in Ω
R_{wt}	Radius of wind turbine
$S_{ice,max}$	Maximum allowed ice in tank
$S_{ice,min}$	Minimum allowed ice in tank

S_{ice}	Fraction of ice in the thermal energy storage (TES) tank
SOC_{req}	The required battery SOC
t	Time variable or time index
T_{air}	Air temperature
$T_{ceiling}$	The ceiling temperature of the zones, °C
$T_{cl,abs}$	Absolute value of clothing surface temperature
T_{cl}	Clothing surface temperature
T_{door}	Door outer layer temperature, °C
T_e	Electromagnetic torque
T_{floor}	The floor temperature of the zones, °C
$T_{hallway}$	The hallway temperature of the zones, °C
$T_{i,j}$	The instantaneous wall temperature calculated by equation (3.4), °C
T_i	The i-th zone temperature, °C
T_j	The j-th zone temperature, °C
$T_{L,rms}$	RMS value of load torque, Nm
$T_{m,ref}$	Module temperature at reference conditions in K
T_{mrt}	Mean radiant temperature
T_m	Mechanical torque generated by the motor shaft
T_m	Module temperature in K
T_{nor}	Normal cooling temperature set-point
$T_{oa,ave}$	Monthly mean outdoor air dry-bulb temperature

T_{oa}	Outdoor temperature or ambient temperature
$T_{op,up}$	Upper limit of zone operative temperature
T_{op}	Zone operative temperature
T_{SAT}	The supply air temperature, °C
T_{sn}	The set-points of thermostats in HVAC4
$T_{windows}$	Windows outer layer temperature, °C
Te_{rms}^*	RMS value of reference electromagnetic torque, Nm
Te_{rms}	RMS value of electromagnetic torque, Nm
$v(t)$	Supplied fan speed in percentage
$v^d(t)$	Desired fan speed in percentage
V_{local}	Local wind speed at the studied location
$V_{mx,ref}$	Voltage at maximum power point along current-voltage curve at reference conditions
$V_{oc,ref}$	Open-circuit voltage at reference conditions
V_{oc}	Open-circuit voltage
$V_{wt,a}$	Induced velocity

Chapter 1

Introduction

This chapter provides a brief introduction to the background, Energy Management System (EMS), Demand Response (DR), various types of Heating, Ventilation, and Air-Conditioning (HVAC) systems and motor drives, as well as the motivations, objectives, key contributions, and organization of this thesis.

1.1 Background

Currently, most countries generate their energy relying heavily on the oil, coal, and natural gas which are non-renewable and finite resources, i.e., those energy sources will reduce eventually, becoming costly, and cannot be recovered during a short period of time. With the global warming concern and energy crisis, the integration of renewable generation is increasing around the world. Solar and wind farms are progressively constructed in various countries to gradually replace the conventional energy generation methods. However, the increased penetration of solar photovoltaics (PVs) and wind turbines (WTs) threatens the stability of the conventional grid due to their intermittent nature and complicates the electricity price in the energy market.

In the USA, independent system operators (ISOs) and regional transmission organizations (RTOs) are responsible for maintaining the power balance between the supply and demand in the power grid. The energy market of the USA is categorized into two main groups: Short-term market and long-term market. The short-term market is composed of day-ahead and real-time markets which are forward energy markets used to schedule the resources and to maintain the grid reliability. Since

the energy market is moving towards liberalization for more efficient and economic market outcomes, a deregulated framework is employed in the USA for both day-ahead and real-time markets. In the deregulated regions, the wholesale market carries out and centers its activities around the ISOs and RTOs where the electricity suppliers and load serving entities will submit their bids in the day-ahead and real-time markets. On the other end, the long-term market is a capacity market operated by ISOs and RTOs to auction the commitment of a resource used to supply power at the capped price when the system emergency happens. Following the long-term prospective world trend of liberalizing the energy market, more consumers are encouraged to trade in the electricity market in the near future. Although a lot of excellent studies are available in the literature for electricity price, the statistical methods in economics, such as allocation of the price band, have been found to be more effective in simplifying the optimal power flow problems in the energy market.

Besides that, the energy storage system (ESS) is considered as one of the most important tools to address the intermittent issues of renewable energy resources and to enhance the overall stability and resilience of the grid. By using ESS, power plants avoid frequently ramping up and down for meeting the demand variations, thereby increasing their operating efficiency. ESS can be integrated for energy management in various ways. It is capable of storing and delivering power, acting as energy reserves for supporting short-term power supply, compensating for the intermittency of renewable generations, providing ancillary services, etc. Since operating distributed grid relies heavily on the market price and other economic dynamics, ESS can behave as an additional resource for the optimal dispatch schemes. Thus, it is important to have an effective EMS which ensures ESS's safe and optimal performance.

1.2 Introduction to Energy Management System and Demand Response

1.2.1 Energy Management System

The energy efficiency means using the same amount of energy to produce a more productive output. Optimizing EMS is one of the most effective and recognized

ways to achieve the energy efficiency of a system, to reduce the greenhouse effect, to lower the cost and consumption, as well as to slow the depletion of energy resources. An EMS is a computer-based system tool utilized by the utility grid or microgrid operators for monitoring, controlling, and optimizing the power generation, transmission, conversion, and storage systems [1], [2]. In recent studies, the EMS usually represents an optimizing process which aims to achieve the energy efficiency in the individual units of the system. Based on its applications, the EMS can also be called as the energy hub, Home Energy Management System (HEMS) or Building Energy Management System (BEMS).

The energy hub is defined as a conceptual entity which consists of various energy conversion and storage devices where the raw energy such as solar radiation, high-voltage electricity, natural gas, etc. are converted to the refined energy services needed by the consumers, e.g., low-voltage electricity, cooling and heating services, etc. [3]. An example of the energy hub framework is shown in Figure 1.1 where an energy hub consisting of photovoltaics, battery, heat pump, chiller, and boiler provides the electricity, cooling, and heating services to a group of buildings [4]. HEMS is specially designed for home users where the residential consumers are allowed to participate in Demand Side Management (DSM) programs. But, the domestic consumers normally face the problems caused by the uncertainties from renewable energy and users' behavior where consumers may prefer to maintain the highest level of comfort instead of the load curtailment for DR. BEMS is designed for the automated control and monitoring of building facilities which consume a significant amount of energy in the building such as HVAC, lighting, interior equipment, etc. BEMS is a broad concept of building automation whose scale can vary from a single building to a building cluster, e.g., school campuses, residential buildings, shopping malls, retail shops, office buildings, industry park, food street, etc. According to the report from [5], General Electric Company (GE) has proposed employing the BEMS or HEMS for houses to achieve the target of net-zero energy building in the residential sector as shown in Figure 1.2. This EMS framework includes smart meter, geothermal heat pumps, home energy manager, heat pump water heater, water filtration, energy storage, DR appliances, energy efficient lighting, small wind turbine, and PVs. The concept of net-zero energy building is defined as a building

Figure 1.1: Energy hub framework for the building cluster (Source: Adopted from [4]).

which has zero net energy consumption on an annual basis where the amount of energy used approximately equals to the amount of energy generated on-site, which is an ideal concept firstly introduced in 2000 and has become a mainstream idea since 2006 [6].

The objectives of a BEMS are: to provide a healthy and comfortable indoor environment, to ensure the occupants' safety, to make sure the building facilities are operated economically for both cost and energy savings [7]. Although BEMS control system has become much more complicated compared to that of the 1980s, rapid development in related technologies, such as information technology, advanced sensors, upgraded computers, and excellent controllers have made BEMS as a preferable tool for achieving the energy efficiency of the building [8]. Thanks to the advanced information technology, the building facilities in BEMS can be monitored and controlled through the internet. Furthermore, the fifth-generation (5G) cellular network technology is coming. Taking advantage of the internet of things (IoT) technology, remote control of BEMS on mobile devices can be achieved

Figure 1.2: Application of BEMS or HEMS framework in the residential sector (Source: Adopted from [5], [6]).

in the near future.

There are some benefits and difficulties from employing a BEMS. First of all, a BEMS can increase the energy efficiency of the buildings and improve the indoor environment. Moreover, the emergency situations, such as the fire, security issues, system fault, etc., can be automatically detected and systematically controlled. BEMS not only optimally runs the building facilities but also improves the life-span of some devices such as the battery energy storage unit. Besides that, using a BEMS may increase the initial investment cost for design and installation. The maintenance cost of a BEMS might be also raised in comparison with a simple management system. However, these initial cost and increased maintenance cost for BEMS can be recovered through the long-term benefits obtained from the improved energy efficiency and optimally operated facilities.

1.2.2 Demand Response

DSM is often composed of the DR and energy efficiency. Thus, DR is usually accompanied with optimizing EMS on the demand side for the energy efficiency of overall system operation. DR is defined as the activities performed by the consumers who reduce or shift their electricity consumption during peak-time in response to the changes in electricity price or other financial-based incentives [9].

Figure 1.3 summaries the various DSM categories where all DR programs can be categorized into four types, namely Energy-based DR, Capacity-based DR, Reserve-based DR, and Regulation-based DR [10]. For Energy-based DR, demand resources are offset by only reducing the energy demand during DR events. It is used by utilities to reduce the expensive cost of producing energy during peak periods such as ramping up the additional power plants to meet the unexpected higher demands in the day. For Capacity-based DR, demand resources are obligated during a specific time to provide the DR services when the system operator deploys. For Reserve-based DR, demand resources are obligated to provide the DR services deployed by the system operator when the reservation services are necessary for the system reliability. For Regulation-based DR, demand resources raise and reduce the load based on the real-time signals sending from the system operator to provide the regulation services needed for the grid such as frequency regulation, etc. It is employed to support the necessary services needed in the transmission of electric power for maintaining system reliability.

Utilities often offer two common ways to implement DR schemes on the demand side. One of them is the direct load control strategy where the power distributors or companies can remotely interrupt the consumers' loads which consume the high-power during peak periods, e.g., cycling HVAC and switching on/off water heaters. It can be achieved by using the load control devices such as the smart thermostats and other smart on/off switches. Another one is the dynamic pricing strategy, also called as the time-sensitive pricing. For example, time-of-use (TOU), the electricity price changes hourly or every half an hour to encourage consumer curtailing their load through the advanced metering infrastructure (AMI), such as the smart meters, during DR events. Other time-sensitive pricing programs including the critical peak price, critical peak pricing or rebates, real-time price, system peak response

Figure 1.3: Demand Side Management (DSM) categories (Source: Adopted from [10]).

transmission tariff, variable peak price, etc., can also be employed to shifting the consumers' loads [9], [10].

Due to the limitations of current electricity storages and transmission technologies, the energy supply and demand must be balanced. However, the electricity demand changes considerably with time and seasons. In the past, a balance between the supply and demand of electricity was accomplished by adjusting the generation of power plants only, which often calls for a significant investment in rarely used capital-intensive equipment or the dispatch of inefficient generators. Thus, DR was initially proposed by the utilities to improve the power system flexibility by temporarily lowering the peak power demand or shifting it from peak to non-peak periods. This can prevent the utilities from using inefficient power generation and costly investment of equipment for a short period of need.

In addition, DR can also be used to avoid the potential of blackouts in case where the load demands threaten to exceed supply resources on the grid. Nowadays, the utilities and system operators not only employ DR to improve the grid

reliability but also exploit its large potential in the energy market application [10]. In particular, DR can reduce the wholesale market price through flattening the demand curve which displaces costly peak energy generation and defers more expensive investment of new equipment for the increment of installed capacity. Furthermore, DR addresses the prevailing concerns in conventional power systems. For example, on the generation side, it flattens the demand curve and encourages the end-users to consume power in off-peak period to improve the overall power plant utilization rate. On the distribution side, DR lightens the stress condition in peak load period, which defers the heavy investment for the transmission infrastructure of the power grid. In the view of end-users, they are benefited from the DR schemes with direct cost saving by optimally managing their flexible loads and multi-energy storage units.

1.3 Introduction to Heating, Ventilation, and Air-Conditioning System and Motor Drives

The energy efficiency of the building receives much attention by researchers nowadays as buildings around the world account for 30% to 40% of the total energy consumption [11], [12]. In particular, the main energy consumer inside a typical building is the Heating, Ventilation, and Air-conditioning (HVAC) system. The energy consumption of fans and pumps in the HVAC system is of particular importance. For example, Figure 1.4 shows that fans and pumps constitute about 50% of the total energy consumption of a HVAC system in the typical governmental office building [13]. Their energy consumption is increased to around 60% in the commercial office buildings. In a typical hotel, about 70% of total HVAC energy is consumed by the fans and the pumps. The fans and the pumps consume even more in a typical shopping mall, around 75% of HVAC energy. As a result, the energy efficiency of the fans and pumps should be further investigated.

1.3.1 Types of the HVAC system

According to the various heat transfer medium, the HVAC system can be classified into four types, namely all water system, refrigerant system, all-air system, and

Figure 1.4: Annual operation electricity consumption of HVAC system in typical buildings in Beijing (Source: Adopted from [13]).

air-water system. In the all water system, both the indoor sensible and moisture load are removed by the water where the temperature and humidity of an indoor environment cannot be controlled independently from the ventilation system. The refrigerant system refers to the systems where heating and cooling are directly achieved through the refrigerant evaporation and condensation process, which is mainly used for the household application. The all-air system and the air-water system are the most common central air-conditioning system in the buildings around the world where both of the sensible and moisture load are controlled together by the HVAC system. The only difference between the all-air and the air-water systems is the heat transfer medium. The former one only uses the air as a heat transfer medium while the latter one uses both the air and water as the heat transfer medium. The air-water system is proved to be more energy efficient than the all-air system as the water has a better heat transfer capability than the air. In addition, the all-air system requires a larger cross-section area of the duct compared to the air-water system, thereby requiring more installation cost for construction of the air ducts.

1.3.1.1 Categories

Table 1.1 summarizes the main HVAC systems commonly used in the buildings, namely variable refrigerant flow (VRF), integrated fan coil unit (FCU) and outdoor air (OA) system, constant air volume (CAV), and variable air volume (VAV) [13].

Table 1.1: Categories of Current HVAC Systems [13].

Building type	Refrigerant system	Air-water system	All-air system
Residential buildings	Household air-conditioner, VRF system		
Small-scale commercial buildings	VRF system	FCU+OA system	CAV system
Large-scale commercial buildings		FCU+OA system	VAV system

Notes: Variable refrigerant flow (VRF), fan coil unit (FCU), outdoor air (OA), constant air volume (CAV), variable air volume (VAV).

The VRF system is often used in the residential buildings and small-scale commercial buildings. The VRF is also known as the variable refrigerant volume which is a technique developed by Daikin Industries, Ltd. in 1982 for the HVAC system [14]. The cooling and heating medium of a VRF system is the refrigerant which is conditioned by an outdoor condensing unit and is circulated in several indoor units within the building. A household air-conditioner is also one of the refrigerant-based direct evaporative cooling systems. The air-water system is often used in small-scale and large-scale commercial buildings. This type of HVAC systems normally consists of the FCU and OA processing units forming an FCU+OA system where the indoor space is cooled and dehumidified by the chilled water and cooled outdoor air in summer, while the indoor space is warmed with the hot water and heated outdoor air in winter. An FCU+OA system is widely used in China because of its superior performance over the all-air system in terms of requiring lower supply airflow rate and occupying fewer spaces.

For the all-air system, CAV is often used in the small-scale buildings while VAV is employed in large-scale commercial buildings. CAV is a HVAC technology which supplies a constant airflow at variable temperature. In a CAV system, the thermal loads of conditioned space are met by varying the supply air temperature or using an on/off control strategy. CAV system is often a good choice for small buildings because of its simplicity, low cost, and reliability. On the other end, the VAV system supplies a variable airflow at a constant temperature. Compared to the CAV

system, a VAV system has the following advantages such as more precise zone temperature control, reduced compressor wear and tear, less fan capacity, flexibility with load changes, simple to use outdoor air at the appropriate ambient temperature for zone cooling, large fan energy savings potential, etc. [15]. Therefore, a VAV system is more commonly used in large-scale buildings.

1.3.1.2 Schematic Diagram of a VAV system

Figure 1.5 shows a schematic diagram of a VAV HVAC system which consists of the VAV boxes, an air handling unit, and the OA controller [16]. VAV boxes, located at each zone of the conditioned spaces, are used to maintain the zone temperature at the desired temperature level by controlling the VAV-damper and reheating coils. VAV-damper controls the mass airflow rate that is supplied into the individual zone. The reheating coils are used to control the supply air temperature level. The air handling unit deals with the heat exchanges between the supply air and the chilled water. The chilled water passes through the cooling coils while the air flows through the cooling coil by the suction force of the fan. Then, the heat exchanges between the air and the chilled water take place. The variable frequency drive (VFD) drives a fan to the desired speed and controls the total airflow rate supplied to the zones. The OA controller maintains the return air and outdoor air in an appropriate ratio by manipulating two dampers in the air duct, where the upper damper controls the amount of outdoor air flowed into a HVAC system while the lower damper controls the amount of return air from the zones.

In fact, the fan driven by a VFD receives the control signal for the desired speed indirectly as the drive speed is often controlled by the physically dynamic changes of a duct pressure. For example, if the thermostat needs more cold air for cooling the space when temperature of a zone goes up, it would send a desired amount of airflow rate to the VAV box. Then, VAV-damper of a VAV box opens the damper position at the appropriate degrees to increase the supply airflow rate for a zone, which raises the airflow rate in the duct, thereby reducing the duct pressure. After that, a duct pressure sensor detects a decreased duct pressure, making commands to the VFD to raise its fan speed for recovering the duct static pressure to the prespecified set point.

Figure 1.5: A typical VAV HVAC system (Source: Adopted from [16]).

1.3.2 Types of the Motor Drive

Since the fans and pumps are driven by the electric motors that constitute about 50% – 75% of total energy consumption in the HVAC systems as shown in Figure 1.4, reducing the energy consumption of the drives becomes very important for reaching an overall energy efficiency of the HVAC system. It is commonly known that the electric drives can be grouped into two main types, namely DC drives and AC drives. In the past, DC drives dominated the variable-speed applications while AC drives were designed for the fixed-speed applications. DC drives have the strengths of accurate speed control over a wide range, high starting torque, simple design, etc. But they suffer from high initial and maintenance costs, required working in a clean environment, and low drive efficiency (typically 70–80%). On the other hand, AC drives have the advantages of low initial cost, low operation maintenance cost, rugged and reliable structure, high drive efficiency (typically 85–90%). But they have some vulnerabilities such as inability to operate at low speed, complex operating principle and position control, losses in the eddy current, etc. With the rapid development of science and technology, the DC drives are increasingly being displaced by the AC drives which can be effectively controlled at a much lower cost compared to the former one. Nowadays, DC drives are often employed in the high power variable-speed applications and special applications while

AC drives are dominating both fixed-speed and variable-speed applications. In the future, the power rating of a variable-speed AC drives would be increased for the wider applications while DC drives are likely to be used in the special applications where AC drives are not feasible.

AC drives are either synchronous or asynchronous. For a synchronous AC drive, the shaft rotation is synchronized with the supplying current frequency and the rotational period is the same as an integral number of AC cycle. The asynchronous drive is also called as induction machine (IM) where the torque is produced by the electromagnetic induction from the magnetic field of the stator winding and the electric current in the rotor. A three-phase IM is often used in a VFD system servicing for a fan or pump in the HVAC system. Although some single-phase drives and synchronous drives may be beneficial in certain circumstances, it is preferred to use the three-phase IM at most of the times due to the economic concerns.

1.4 Motivation

Buildings consume a significant amount of energy in the world, especially in the U.S. where the energy consumption of buildings occupies 33% to 41% of the total energy consumption of the entire nation [6]. The energy efficiency of the buildings can be improved in various ways. For example, buildings can be designed to fully utilize their available resources, e.g., air circulation in the HVAC system, reuse of wastewater, etc. [17]. However, those designs are often constructed in newer buildings due to the costly refurbishment of existing buildings. On the other end, integrating renewable energy, such as wind turbine (WT), PVs, biomass, fuel cell, hydroelectricity, etc., in the building can effectively reduce its grid dependency. Renewable energy sources are usually not solely integrated with the buildings due to their intermittent nature and lack of natural resources needed for energy production at sometimes. Therefore, a battery energy storage (BES) system is often used together with renewable generations to compensate for their side-effects, thereby ensuring the system efficiency and reliability.

A report from [18] shows that a HVAC system of the commercial building contributes 40% of its total energy consumption. Many good research works are carried

out to study the energy efficiency and DR of a HVAC system in the building. For example, several researchers focus on controlling HVAC system through adjusting zones' thermostats with a consideration of thermal comfort for a DR event while some researchers focus on the design of model predictive control (MPC) controllers by modeling the HVAC system as a non-linear RC-network model. However, those modeling and control algorithms are implemented on the HVAC system only, not considering its cooperation with other building facilities during the DR periods.

Although managing a HVAC system can reduce the overall building load demand, the HVAC load is still a major chunk of energy consumption in the building. Deploying thermal energy storage (TES) system can help to effectively reduce the overall load demand from the HVAC system during DR periods. There are numerous methods available in the literature for modeling and optimizing a TES system in the EMS framework. Some methods model and optimize the TES system in a similar way as the battery to charge or discharge the stored energy in a combined heating and power (CHP) connected microgrid. These models and algorithms may not be realistic when the energy conversions between electrical and mechanical energies are considered in the real practice as the energy losses during conversion process largely complicate the optimization problem. Moreover, the realistic considerations of different operating modes of TES working in a coordinated manner with BES and other DR programs in the building are missing in the literature. Apart from that, there are several other parameters missing in the literature which can affect the performance of TES in the building such as the Demand Responses (DRs) of HVAC, light, and miscellaneous loads. Those DR programs can reduce the cooling and heating loads of the building during DR events, thereby influencing the overall performance of TES. The ice storage system as one of the forms of TES is intensively studied in [19], [20] where the full ice storage strategy and partial ice storage strategy are investigated. Full and partial ice storage strategies refer to fully or partially charge the ice tank before a DR event respectively. The critical issue for deploying the ice storage system is that the full ice storage strategy provides a preeminent peak-load shaving but the highest total energy consumption at the end of a day, whereas the partial ice storage strategy, compared to the full ice storage strategy, offers a less peak-load reduction but a lower total energy consumption at

the end of a day. Hence, a proper trade-off between the peak-load reduction and energy consumption of the building with an ice storage system is necessary to be investigated.

Due to unawareness, hardware or software tools constraints in the past, small and medium-sized commercial buildings do not play many roles in the DR schemes. Thus, a large potential space is still available for the buildings to play roles in the DR scheme to benefit both the end-users and suppliers. A general trend shows that more and more utilities in different regions or countries start to offer DR schemes for their customers. Therefore, the key research problem is not only to optimize EMS for the energy efficiency of the building but also to coordinate building facilities with various DR programs. Hence, developing an effective BEMS framework for DSM is necessary for designing the DR programs and EMS control algorithms in the building.

Most of the previous research works discuss integrating renewable energy and multi-storage systems at the utility side but not at the consumer side with demand responsive building. In addition, those papers often model a TES as the mathematical model of the battery to charge or discharge the stored energy only, which ignores the different operating modes of a TES in the real practice. Since they focus on the system optimization for a microgrid instead of the DSM of a building, their optimization framework usually does not consider other DR programs available in the building, such as DR in HVAC, lighting, internal equipment, plug loads, etc. Thus, this thesis discusses how the EMS with multi-storage systems can be optimally and coordinately controlled in a demand responsive building by providing a price-based integrated automation model for managing various building loads, renewable energy, and multi-storage systems. The model presented is validated by the simulation environment conducted on EnergyPlusTM and CPLEX[®].

Since the energy efficiency of the buildings become increasingly important, most of the previous works focus on optimizing a building energy management system in terms of planning, scheduling, and dispatching the available resources of the buildings. However, the scope for the optimization of an energy management system reduces if the building design is fixed. Many previous works discuss the control of a HVAC system by varying the airflow rate of the air-conditioning system for getting

an optimal zone temperature. Since the variable airflow rate in the duct can influence the operation of a central fan driven by VFD, the drive control strategy for its particular application in this case is also important to the energy efficiency of a HVAC system. However, the drive performance under various HVAC operating status is often ignored in the literature. Thus, this thesis also studies the energy efficiency of an induction machine in the HVAC system since most of the fans and pumps are driven by the induction motors that constitute about 50% – 75% of total energy consumption in the HVAC system. An integrated HVAC system with model predictive flux control (MPFC) drive model [21] is built up in the Matlab/Simulink for investigating the drive performance in various scenarios.

1.5 Objectives

The main objective of this research work is to investigate, model, and optimize a building energy management system with the HVAC system for the energy efficiency and DR.

The objective in the first part of the study is to model a HVAC system for investigating the drive performance under various scenarios of HVAC load changes. It aims at studying the energy efficiency of a drive system in the application of a HVAC system. An integrated system with both HVAC and drive models are constructed in Matlab/Simulink. The end results will show the drive performance of a HVAC system in response to the changing ambient temperature and the varied amount of occupants.

The objective in the later part of the study is to accurately model the most realistic commercial building and then to develop an optimal coordinated control strategy for all building facilities under the building energy management system framework. It aims at minimizing the building's net operating cost with the help of PVs, WT, BES, TES, and other DR programs available in the building using TOU price which changes hourly basis at El Paso, Texas, USA. The building model is constructed systematically in EnergyPlus™ which is a simulation program used by engineers and researchers to model and simulate the energy consumption of building facilities as well as the water usages of the buildings. Then, the optimization

problem is formulated as a mixed-integer linear programming (MILP) problem solved by CPLEX solver. The end result will facilitate a smart decision process of identifying optimal battery operation and coordinated DR programs such as the TES-based DR, HVAC-based DR, and DRs in lights and miscellaneous loads in the building. This research work will investigate how the EMS with multi-storage systems can be optimally and coordinately controlled in the demand responsive building by providing a price-based integrated automation model for managing various building loads, renewable energy, and multi-storage systems.

1.6 Major contribution of the Thesis

The main contributions of this thesis are summarized as follows:

1. The first research work integrates a HVAC system model with an advanced IM control strategy, namely MPFC [21]. The simulations are carried out to investigate the drive performance of a HVAC system operating under different scenarios.
2. This thesis addresses the issue concluded in [19], [20]: The full ice storage strategy provides a preeminent peak-load shaving but the highest total energy consumption at the end of a day, whereas the partial ice storage strategy, compared to the full ice storage strategy, offers a less peak-load reduction but a lower total energy consumption at the end of a day. Hence, a smart price-priority strategy is developed for the ice storage system where the ice storage is coordinately controlled with other building facilities. The proposed method makes a proper trade-off between the peak-load reduction and the energy consumption in the building with the ice storage system.
3. A hybrid cooling-and-ventilation control algorithm is developed for a HVAC-based DR and its effectiveness is compared with the conventional global temperature adjustment [22]–[25] of all zones in the building.
4. This research work investigates how an EMS with multi-storage systems can be optimally and coordinately controlled in the demand responsive building by providing a price-based integrated automation model for managing various building loads, renewable energy, and multi-storage systems.

1.7 Organization of the Thesis

This thesis comprising 5 chapters are listed below:

Chapter 1: Introduction

This chapter provides a brief introduction to the EMS, DR, various types of HVAC systems and motor drives, as well as the motivations, objectives, key contributions, and organization of this thesis.

Chapter 2: Literature Review

This chapter explains the state-of-the-art about modeling and controlling of a HVAC system, the control strategies of the electric motor drives, the methods of optimizing an EMS framework, and DR strategies available in the literature.

Chapter 3: Model Predictive Control of Induction Machine for Energy Efficient HVAC Operation

In this chapter, a gray-box model for a HVAC system is developed in the Matlab/Simulink and a model predictive flux control (MPFC) [21] strategy is applied to control a central variable-speed fan plant which varies the airflow rates in the ventilation duct of a HVAC system for maintaining the zones' temperature. Scenarios including changes of ambient temperature and varied occupants in the zone are simulated for revealing the drive performance in those cases. The results show that the considerable energy losses are presented in the drive system when it operates at the low speed range during the partial-load condition of a HVAC system.

On the other end, this work has some challenges and limitations, such as inability to simulate a long study period needed by the HVAC model at an extremely small step size which is necessary for accurately controlling a drive. Moreover, a small gray-box HVAC model is constructed by the parameters obtaining from ASHRAE 2005 Handbook [26] instead of using the mean squared error approach or the least-square approach with experimental data, thereby not representing a typical HVAC system in the buildings around world. Since experimental data from a building is often difficult to be obtained because of the privacy and resources

constrains, an alternative way to get those valuable data is to use the building simulation software, such as ESP-r, TAS Engineering, TRNSYS, IDA ICE, Building Controls Virtual Test Bed (BCVTB), OpenStudio®, EnergyPlus™, etc. Hence, in Chapter 4, a medium-sized office building with a rooftop VAV type of HVAC system is systematically developed in EnergyPlus™ with the help of OpenStudio®, which represents the majority of office buildings in the USA.

Chapter 4: Smart Building Energy Management with Multi-storage Systems for Demand Response

This chapter sheds light on how the EMS with multi-storage systems can be optimally and coordinately controlled in the demand responsive building by providing a price-based integrated automation model for managing various building loads, renewable energy, and multi-storage systems by analyzing electricity price in the statistical methods of economics. The model presented is validated by the simulation environment conducted on EnergyPlus™ and CPLEX®. To mitigate the high energy consumption of full ice storage strategy and improve the peak-load reduction of partial ice storage strategy, a smart price-priority strategy is developed for the ice storage system where TES is coordinately controlled with other building facilities. The proposed control method makes a proper trade-off between the peak-load reduction and the energy consumption in the building with the ice storage system. In addition, a hybrid cooling-and-ventilation control algorithm is developed for the HVAC-based DR and its effectiveness is compared with the conventional global temperature adjustment of all zones in the building [22]–[25].

Chapter 5: Conclusions and Recommendations

In this chapter, the overall conclusions of this thesis are presented. Recommendations for the future research in the building automation with DR and multi-storage systems for handling the increasing penetration of electric vehicles (EVs) are discussed. The building model developed in EnergyPlus™ could be extended to study the performance of a physical drive system by using a BCVTB platform. Thus, the drive control technologies for different components of a HVAC system could be further investigated to improve the energy efficiency of several HVAC units such as pump, fan, chiller, compressor, etc.

Chapter 2

Literature Review

This chapter explains the state-of-the-art about modeling and controlling of a Heating, Ventilation, and Air-Conditioning (HVAC) system for the energy efficient operation, the control strategies of the electric motor drives, the methods of optimizing an Energy Management System (EMS) framework, and the Demand Response (DR) strategies available in the literature.

2.1 Types of Optimizing Energy Management System (EMS)

According to applications, optimizing EMS can be categorized into two types, namely on-line approach and off-line approach. For the on-line approach, the techniques including Lyapunov [27]–[29], model predictive control (MPC) [30], [31], simulation-based policy improvement (SBPI) [32]–[34] approaches, etc. can be exploited for the EMS optimization. The Lyapunov approach is a stochastic method developed based on the networked queuing system. Since a standard Lyapunov method cannot solve the time-coupled constraints in the optimization framework directly, the problem-solving process becomes complicated. The MPC approach is very good at operating an EMS of the microgrid to handle the uncertainties from renewable energy sources and building loads in a corresponding sampling time as the future system dynamics are predicted and optimized iteratively during the sampling process. On the other hand, SBPI is designed to improve the performance of the complex optimization problems, which is slightly different from the objectives of the MPC approach.

For the off-line approach, the techniques including mixed-integer linear programming (MILP), stochastic programming, genetic algorithms, particle swarm optimization (PSO), etc. can be used to optimize the EMS of the microgrid. Although the deterministic approach may not be very good at handling uncertainties from loads and renewable generations compared to the stochastic method, it is the mainstream of EMS optimization due to its simpler and faster computing capability. On the other hand, some stochastic methods have to solve the optimization problem by transforming a stochastic problem into the multiple deterministic problems, thereby increasing the computing complexity. The intelligent optimization including the genetic algorithms and particle swarm optimization uses the stochastic heuristic approach to find the local or global optimal solutions where those calculated results are probabilistic.

2.2 Optimization of Energy Management System (EMS) and Demand Response (DR)

2.2.1 Optimization at District Level

Considering various system scales, optimizing EMS and DR is grouped into two levels, namely the district level and building level. Optimizing EMS and DR at the district level refers to the algorithms or frameworks designed to optimally control the units of EMS for a group of buildings aiming at the energy efficiency and/or DR. The stochastic approach is often employed in the optimization framework for handling the uncertainties including system load and renewable energy generation. For example, Wakui et al. [35] develop a predictive management framework for the EMS with solar photovoltaics (PVs), heating unit, thermal energy storage (TES), and battery. This EMS is optimized by combining the two-stage stochastic MILP and rule-based controls, where the Monte Carlo (stochastic approach) is used to forecast the solar radiation, electric power, and hot water demands. Darivianakis et al. [4] develop a data-driven stochastic-based robust optimization for energy efficient buildings and districts. Various other optimization schemes including the deterministic approach, stochastic approach, distributional robust methods, and purely data-driven approaches are analyzed to address the building automation

control problems. It is concluded that their proposed unified data-driven control framework can effectively address the large-scale problems, such as cooperatively managing the aggregated energy demands of buildings in a district.

Another common way used for optimizing the operation of EMS in the microgrids is the MILP approach. Authors in [36] propose an optimization framework for the optimal energy dispatch in the EMS with multi-storage systems for the microgrid operating in grid-connected and islanded modes. It aims at minimizing the net operating costs of microgrids and enhancing the dispatch flexibility of generators, cooling and heat services in the day-ahead market. The dispatch models of the grid-connected and islanded microgrid are formulated as the MILP problems solved by GAMS. Their results show that the TES system can decouple the inflexible operating strategies of combined heating and power (CHP) and improve the system flexibility by joining the heat or ice storage tank in a combined dispatch network including power, cooling and heat energies. Furthermore, a temporally-coordinated operation method for the microgrid with multi-storage systems to handle various uncertainties in the system is developed in [37]. It aims at optimally coordinated dispatching of multiple energies in various timescales under the system consisting of CHP, energy conversion units, TES, and battery energy storage (BES). The problem is formulated as a two-stage stochastic programming problem which is then converted to a deterministic two-stage MILP equivalent problem solved by CPLEX and GAMS. Their proposed method shows superior performance over other strategies including the single-stage deterministic approach, single-stage stochastic approach, and two-stage deterministic approach.

A game theory approach is another method which is usually employed in optimizing EMS and DR programs at the district level. Liu et al. [38] propose a coalitional game theory approach to study the smart building cluster with DR programs. A hybrid energy sharing framework considering CHP and solar photovoltaic (PV) systems are constructed to investigate the energy trading in the building cluster where the energy sharing problem is solved by their proposed distributed optimal algorithm. It is shown that their proposed method can protect the PV prosumers' privacy as well as reduce their operating costs. Liu et al. [39] demonstrate the one-leader N-follower Stackelberg game theory used in multiparty

EMS framework to explore the energy trading among the microgrid operator and consumers with electricity and heat DR programs. The CHP is dynamically operated in the following electric load (FEL) mode or following thermal load (FTL) mode to maximize the operating profits of the microgrid operator. The optimization problem is formulated as a non-cooperative Stackelberg game and its solution, Stackelberg Equilibrium, is found by the proposed iterative algorithm instead of the common way called bilevel programming with Karush-Kuhn-Tucker condition. They prove the effectiveness of their proposed method in a real case study with six residential buildings.

Besides that, an economic dispatch model for Building Energy Management System (BEMS) considering uncertain generations from renewable energy and load demand is designed in [40]. The uncertainties are forecasted in every 10 minutes by the fuzzy prediction interval model which is trained by the PSO approach. They conclude that a proper policy for handling the uncertainties is important to guarantee the economic benefits of EMS. In another study, the joint-operation of buildings with PVs and battery storage system is studied in [41]. The cooperation between buildings with various uncertainties including building load and PV power generation is defined as a finite-stage event-based optimization problem under the Markov decision process (MDP) framework. Then, it is solved by an online SBPI approach focused on the improvement of policy. They find that the operating cost of building can be reduced by using the online SBPI approach which is also capable of handling the large-scale system in real time. Ondeck et al. [42] provide a simultaneous optimization framework for the design and operation of CHP with multi-storage systems in the residential EMS. Optimizing CHP plant is formulated as a multi-scale optimization problem solved by the bilevel decomposition algorithm with a hybrid cut method. They conclude that by using an appropriate TES, CHP plant is able to employ smaller equipment, thereby improving the overall operating efficiency of the plant and reducing the capital and operating costs.

Optimizing EMS and DR for participating energy market is also considered in numerous papers available in the literature. In [3], the authors consider the multi-energy scheduling problems in an energy hub which serves quantities of energy-users in the buildings where the energy hub is a concept that comprises various

energy conversion, power generation, and storage devices. A distributed auction mechanism is proposed for solving the above problem, which releases the computation burden in the centralized system by taking the advantage of shared auction's computation between the hub and users to solve the social welfare maximization problem. It is shown that their proposed distributed mechanism can reach the same outcome as the centralized mechanism in terms of the ex-post Nash Equilibrium. Moreover, two auction mechanisms for the energy tradings in a multi-energy district at the day-ahead and real-time markets respectively are designed in [43]. They mention that the developed auctions can economically maximize the social welfare among the participants. In another scheme, Alipour et al. [44] propose an $2m+1$ point estimation probabilistic scheduling scheme with DR programs to handle the load and price uncertainties in the power market. The optimization of an energy hub is formulated as a mixed-integer nonlinear problem which is then solved by GAMS. It is concluded that DR programs, regarding the thermal load curtailment, can be efficient in diminishing the energy hub's total cost and have a potential in the market participation. Shao et al. [45] expand the DR concept in a CHP system where DR strategies including energy substitution and load shifting are introduced in the heat and electricity integrated EMS. A real-time DR exchange market is constructed on the three levels, namely the transmission, distribution, and aggregator levels. The system optimization at the distribution level is formulated as a bilevel optimization problem solved by the primal-dual interior-point method. They also develop an optimal feasible region method to clear the real-time DR exchange market in the fast way that matches the clearing speed required in the real-time market.

2.2.2 Optimization at Building Level

Optimizing EMS and DR at the building level relates to a BEMS framework developed for optimally operating the building facilities to reach the targets of energy efficiency and/or DR. Some intelligent optimization approaches, such as knowledge-based [46] and machine learning [47], are introduced for the BEMS of a building. As an example, Zucker et al. [46] introduce a novel concept of cognitive system architecture for BEMS. The cognitive system optimizes the control strategies in

building system at both the automation level (i.e., logic conditions, scheduling, etc.) and process level (i.e., PID controllers, etc.). It is a software program which processes the building's sensor data; analyzes it with a knowledge base system provided by the experts or derived from data analysis; and executes the actions in an appropriate system to achieve the goals. It is mentioned by them that this cognitive system architecture can be integrated with the existing HVAC system and performed as an optimizer to reach the goals of indoor comfort and the energy efficiency of the system. Recently, artificial intelligence (AI) techniques are also applied to the development of a smart building. A lightweight electrical appliance activity detection approach to identify the appliances' characteristics in the smart building is explored in [47]. The continuous online learning and detection are achieved by using the multi-source fingerprint-weighting k-nearest neighbors' methods to group all appliance characteristics into two types of fingerprints called, the appliance-based fingerprint and the context-based fingerprint. The former fingerprint groups the appliance usage patterns based on the consumption data only. The context-based fingerprint considers the relationship between the user, appliance, and environment (i.e., time, weather, and temperature). They conclude that their proposed method outperforms the others in terms of detection accuracy.

Some other optimization techniques, such as stochastic approach [48], [49] and quadratic programming [50] are also discussed in the literature. In [48], Hemmati et al. propose an optimization framework for battery's charging or discharge regime as well as its optimal capacity which is optimally determined by considering the annual investment and operating cost of the system, i.e., \$/year. The problem is formulated as a stochastic MILP which is then solved by the advanced adaptive particle swarm optimization (AAPSO) algorithm. It is found that there is a decrease in 27.8% of the annual electricity bill for a home by installing the battery and PV system. The stochastic approach and genetic algorithm approach for improving the energy efficiency of an EMS are comparatively studied in [49]. In addition, an integrated energy management approach based on a multilevel characterization of different types of loads in a residential building by using Markovian processes for optimizing the EMS and DR is proposed. The EMS is optimized by considering the impact of weather, power generators from both renewable and nonrenewable

sources, storage systems, time-of-use (TOU) pricing, and comfort. Their results show that although the genetic algorithm is adequate for long planning periods and large number of controllable loads, it is not as robust as the Markov decision process approach. In [50], an optimization framework to dispatch the CHP with pipeline and building with TES taking consideration of the heat transfer process is discussed. The optimization problem is formulated as a quadratic objective with a linear constraints problem which is then solved by a CPLEX[®] solver. It is shown that the infeasible dispatch results would be obtained if the heat transfer process is not considered in the optimization problem.

In other studies, the nonlinear programming [51], [52] and linear programming [52] are also employed. In [51], the authors demonstrate a day-ahead multi-objective optimization framework for the BEMS considering the DR programs for TOU. The DR programs include adjustments of the indoor temperature, lighting illuminance, CO₂ concentration, and deferrable loads (e.g., washing machine, disinfection cabinet, and dishwasher). Then, the optimization problem is formulated as a multi-constraint nonlinear optimization problem which is solved by the Yalmip toolbox available in Matlab. It is shown that the overall building's economy and occupants' environment comfort can be optimized by their proposed optimization framework. Further on, a bi-level optimization framework for integrating a building to the smart grid is proposed by Razmara et al. [52]. This optimization is formulated as a hierarchical optimization problem where the building model is constructed as a linear programming problem which aims to find the minimized energy cost and is solved by Yalmip in Matlab. The distribution grid model is presented as a nonlinear model which aims to improve the load factor and is solved by GAMS. Their results show that this bi-level optimization framework can reduce the building's monthly bill by 25% in Winter compared to the unoptimized building loads.

Various DR programs are available for the building. For instance, Martirano et al. [53] study the building with mixed residential and commercial units where a well-organized microgrid aggregates the various users as a common electric, generation, and HVAC system. They construct a central building automation controller in EMS to manage various building's DR programs in a minute by minute timestep.

The DR programs which include adjusting the set-point temperature of the HVAC system or on/off HVAC system, optimally scheduling the operating cycles of dishwasher and washing machine, controls in the starting time of refrigerator's compressor, and smart controls of elevators are discussed. Xiong et al. [54] present a personalized shading control method to maximize the occupants' satisfaction and minimize the lighting energy consumption in the daylight office. Occupants are allowed to make their own decision in real time for balancing the visual comfort and energy consumption of the lighting within dynamic hidden optimal bounds.

2.2.3 EMS with HVAC-based Demand Response

DR is described as the shifting energy consumption of the users in response to different electricity rates or incentive payments. It is one of the promising solutions for improving the efficiency of power grid or microgrid [55]. Since the cooling and heating loads constitute a large portion of total electricity consumption in the buildings, optimizing the operation of HVAC system is a prevalent way to achieve the energy efficiency and DR in both residential and commercial sectors. This section discusses the state-of-the-art in the EMS optimization framework with integrated HVAC-based DR programs for reducing the peak demand during DR events, where HVAC-based DR refers to the DR programs, which is achieved by optimally operating a HVAC system during the DR events.

2.2.3.1 Residential Sector

In the literature, most of the related works focus on the residential sector because their load profiles can be easily generalized in the optimization framework of EMS. One of the most effective ways for implementing an HVAC-based DR is the on/off control strategy. The authors in [56] propose an on/off control algorithm in EnergyPlus to capture the HVAC performance in prevalent cycling on/off control strategies used in residential buildings. This controller is designed based on the adjustment of the cooling or heating set-points and temperature deadband of the HVAC system to achieve the on/off controls. Then, the results of EnergyPlus are compared with the field-collected data (empirical data) where the developed on/off control algorithm in EnergyPlus can accurately track the empirical data.

The heuristic [57] and deterministic [58] approaches are usually used for optimizing EMS with the HVAC-based DR in a residential building. In one of the attempts, a multistage EMS and Demand Responses (DRs) of the controllable appliance and HVAC system is introduced for the home-users where the problem is formulated as a mixed-integer combinatorial optimization problem solved by a metaheuristic algorithm [57]. The home EMS optimization is constructed in the three stages: In the first stage, the house load, PV power, electricity price, and outdoor air temperature are forecasted by the artificial neural network approach; in the second stage, the solutions of day-ahead scheduling for the house units are optimized by the natural aggregation algorithm; and in the third stage, the actual operation of house units are optimized by the natural aggregation algorithm together with a MPC controller which minimizes the deviation of actual and day-ahead forecasted house loads. In the end, they find that the natural aggregation algorithm evolution is superior to other heuristic optimization algorithms including the differential evolution algorithm and PSO algorithm. In another scheme, a deterministic unit commitment model is developed for optimizing the EMS where the probabilistic reserve constraints and the chance constraints of the limited controllability of the residential DR resources such as electric heating system, etc. are considered [58]. It aims at optimally scheduling the power plant with renewable generations and DR resources in the day-ahead scheme. It is concluded that their proposed method can reduce the operating cost by 7%–10%.

Sometimes, EMS optimization with DR programs of a residential building can be formulated as a convex optimization problem, namely second-order cone programming. A bi-level direct load control based DR optimization algorithm is introduced to investigate the possibility of combining the flexibility from multiple shared energy storage system units and HVAC units for DR in the residential building [59]. The objective of the algorithm is to minimize the peak-power demand during DR events with maintaining thermal comfort of the consumers. It is formulated as a bi-level optimization problem based on AC power flow equations constructed by the second-order conic programming, which is then solved by GAMS with MOSEK solver. It is shown that shared energy storage system (ESS) units can support the power demand from HVAC units during DR periods, thereby reducing power

dependence on the grid. In comparison with conventional DR programs focusing solely on reducing energy consumption, deploying ESS can effectively increase the average comfort of end-users.

In another attempt, a user-centric HVAC management framework is presented in [60] where a lightweight algorithm is developed to predict the cost of utilizing a HVAC system according to the historical data of temperature and HVAC usage, forecasted weather information, and utility pricing. In their proposed method, an averaged sectional model is firstly constructed based on sampled HVAC usage and building thermal factors, followed by a linear regression approach predicting the HVAC usage. After that, the cost function is minimized by the optimal set-point temperatures under certain user-defined constraints. The simulation results show that the proposed HVAC management framework is capable of providing the optimal solutions for set-point temperature and forecasting the cost of using the HVAC system.

2.2.3.2 Commercial Sector

Besides the residential DR, there are few commercial DRs available in the literature for managing the HVAC system. A transactive market mechanism is developed in [61] where it fully engages various sub-components in the HVAC system for DR of the commercial building. The HVAC system model of the commercial building is constructed by the RC-network model. The model parameters are identified from the measured data from the engineering building located on their campus. The transactive market mechanism is set up in a simulation environment using Building Controls Virtual Test Bed (BCVTB) where EnergyPlus is used for system calibration and Python is utilized for implementing the market mechanism. It is concluded that their proposed transactive control approach for DRs such as peak shaving, load shifting, and strategic conservation is very effective. In another study, Vrettos et al. [62] present a combination of robust and stochastic optimization framework to allocate the reserve capacities among the commercial buildings to provide the power system frequency reserves through the building HVAC system setpoints. A MPC method is used for controlling the HVAC and a reserve provision is supported by the dynamic heat pump control model. The results show that the

hybrid robust and stochastic approach is superior to the conventional fully robust approach in terms of performance and complexity. Lin et al. [63] address the question of how to do the DR of commercial building HVAC system for the ancillary services. The control system is designed by a two-layer architecture where the first layer optimizes the baseline power of HVAC in the building with a forecasted load. Another layer tracks scheduled baseline and ancillary service signal. It is concluded that the HVAC system of a commercial building can provide the ancillary services for 10 minutes up to 1 hour.

In addition, the common ways for optimizing EMS, such as stochastic programming, MILP, and heuristic approaches, are also discussed in the literature. A real-time HVAC control algorithm based on the Lyapunov optimization techniques is proposed to minimize the long-term total cost of the energy and thermal discomfort for the commercial building [64]. The optimization problem is formulated as a stochastic program which is solved by the proposed real-time HVAC control algorithm where predicting system parameters and knowing about stochastic information are not required, thereby simplifying the solving process of the problem. Moreover, a distributed implementation of the algorithm is designed to protect users' privacy and improve algorithmic scalability. Their results show that the proposed method can effectively reduce the energy cost with a minimum sacrifice of thermal comfort. Furthermore, a price-based DR framework for a HVAC system of the office building is introduced by Kim [65] where the optimal operation of the HVAC system is achieved by co-optimizing the energy cost and thermal discomfort of individual occupants. The optimal DR scheduling problem is formulated as a MILP problem through the artificial neural network models which are trained by the thermal discomfort votes from individual occupants and implemented explicitly using piecewise linear equations. It is concluded that the proposed method can effectively optimize a variable speed heat pump, minimize occupants' thermal discomfort, and reduce the risk of occupants' interruption to the optimum DR scheme. In another attempt, a heuristic-based EMS scheme for controlling the HVAC systems in classrooms of the university building is demonstrated in [66] where the energy minimization problem of a HVAC system is formulated as a MILP problem. Then, it is solved by the author developed heuristic-based algorithm due to the NP-hard nature in this optimization problem where the NP-hard nature refers to the

non-deterministic polynomial acceptable problems. It is shown that the proposed method can reduce the energy consumption of the HVAC in a university building by 19.75% during a week and maintain the users' comfort at the same time.

Various DRs of a HVAC system, including global temperature adjustment of all zones and systemically controlling other components in the cooling system, are discussed in [22]. According to the reports from [23]–[25], the global temperature adjustment of all zones in a building is the most effective way to achieve DR goal among the HVAC-based DRs. Recently, Sehar et al. [67] propose a peak-load reduction method by optimally controlling of cooling set points at each zone of the commercial building during the DR period, while maintaining occupant comfort measured by the predicted mean vote (PMV) index. They find that the demand rebound happens just after the HVAC-based DR, which would create a new additional peak-load point in the building.

2.2.4 EMS with TES-based Demand Response

Cooling demand of the building represents a significant proportion of total electrical demand during peak hours. Although managing the HVAC system can reduce the overall building load demand during DR periods, the HVAC loads are still the major chunk of energy in the building. Besides HVAC-based DR, locally using TES is shown to be beneficial and helpful for building owners or operators to lower their electricity bills. Employing the TES technology further helps to shift this amount of cooling demand from peak to non-peak periods, thereby helping to reduce the overall load demand from the HVAC system in DR events. This section discusses the state-of-the-art in EMS optimization framework with integrated TES-based DR programs for reducing the peak demand during DR periods. The TES-based DR refers to the DR programs implemented through the operation of a TES system such as ice storage, heat or cold water storage etc.

Much works have been done to investigate the benefits of TES for building integration. Li et al. [68] extensively review the various TES integration forms for the building and industry applications, such as integrating TES with hot water supply, HVAC, building construction, solar system, power production cycles, cogeneration,

etc. They also introduce different forms of TES including sensible, latent and sorption forms and summarize the performance enhancement of those forms. Naranjo Palacio et al. [69] analyze the impact of TES on minimizing the operating cost of the power system by reducing the peak load of the commercial buildings. The effects of a heuristic optimal TES allocation strategy on the power system's load factor, operating cost, ramping, and peak/valley ratio are intensively investigated. Their results show that for every 10% increase in the TES penetration level, the load factor can be improved by around 0.125, the operating cost is reduced by 0.9 – 1.5%, the ramping within the system is increased by 2.7, and the peak/valley ratio is decreased to 0.56 – 0.77.

In another study, Sehar et al. [19] study the application of ice TES for the peak-load shaving in large and medium-sized office buildings. A large office building and a medium-sized office building are modeled in the demand response quick assessment tool (DRQAT) with various weather data for representing the diverse climate zones. It is reported that a higher chiller energy consumption is found compared to the conventional non-storage systems due to the day and night operation of the chiller system. A summer with higher temperature and relative humidity climate would not only raise the cooling load of the building but also decrease the cooling of condenser water, thereby increasing the chiller energy consumption. In [20], the authors investigate the energy and peak power savings from the PVs and ice storage system in demand responsive building where two ice storage strategies, called full ice storage strategy and partial ice storage strategy, are compared for coordinating TES with PVs and DR. A medium-sized office building model is constructed in EnergyPlus where the building facilities including PVs, ice storage system, HVAC, lighting, and plug loads are coordinately controlled by the algorithm written in EnergyPlus runtime language (Erl). It is found that the building with full ice storage strategy provides the maximum peak-load savings at the expense of increased energy consumption at the end of a day, whereas deploying the partial ice storage strategy can reduce the energy consumption at the end of a day at the cost of increased peak demand. It also indicates that there should be a trade-off between the peak-load reduction and the energy consumption during a day when the ice storage system is integrated with the building. In [70], the ice storage system and PVs are

controlled in a coordinated manner with other DRs in the building for absorbing the plug-in electric vehicle (EV) penetrations. A real-world electrical distribution feeder is modeled in DEW Software [71] with its power flow applications, which serves a group of buildings modeled in EnergyPlus. It is shown from their research that the coordinated control of ice storage and PVs can fully absorb the plug-in electric vehicles as well as reduce the peak load by 13.4% and improve the load factor by 11%.

Besides the peak-load shaving, the TES system can also be used for the regulation services to the grid. The TES system in [72] is turned into a smart load for compensating the voltage and frequency fluctuations in the power system with intermittent renewable power. This converts a conventional refrigerator into an electric spring with the help of power electronics technology for the simulation studies on the stiff and weak grid scenarios. It is concluded that the TES with ice form can be utilized in the large buildings to reduce voltage and frequency fluctuations in the weak power grid. Rahnama et al. [73] propose a three-level hierarchical structure to aggregate the TES systems for providing upward and downward regulating power services in the smart grid. A hierarchical setup is developed where the aggregator acting as a central controller manages the flexible industrial thermal loads by a contract-based direct control policy. This central controller is designed for optimal power distribution by a robust MPC approach. Moreover, two aggregation methods including homogeneous aggregation and heterogeneous aggregation are discussed. It is revealed that heterogeneous aggregation is superior to the homogeneous aggregation in terms of operating cost, profits, energy consumption, and handling the unpredictable situations.

Literature review shows few ways for modeling a TES in the EMS framework. Bao et al. [74] propose a multi time-scale cooling and electricity coordinated scheduling and dispatching model for optimal microgrid operation where the status of ice storage is optimized considering four operating modes, namely air-conditioning mode, ice-making mode, ice-melting mode, and combined mode by air-conditioning and ice-melting. It is one of the few works which optimizes a EMS with considering various operating modes of TES while most of the others model a TES in the same way used for modeling a battery where the mathematical

model of a TES is built to charge or discharge the stored energy and is acted like a battery, e.g., [3], [36], [37], [43]. Since previous works [36], [37], [74] focus on the system optimization for microgrid instead of the Demand Side Management (DSM) of the buildings, their optimization framework does not consider other DR programs available in the building, i.e., DR in HVAC, lighting, internal equipment, plug loads, etc.

Most of the works in the literature often discuss integrating renewable energy and ESS at the utility side but not at the consumer side with demand responsive building. Therefore, the works of [19], [20], [70] provide a very good example of systematically modeling a building energy management system at the consumer side with PVs, TES, HVAC system, and DR programs where various operating modes of a TES system are considered. It is shown that employing PVs and strategically deploying DR and TES at the building level can help to mitigate the peak demand and energy consumption in the building. They provide this convenient BEMS framework for the people who are studying the DR potential and developing EMS algorithms for the building. However, their DR events are assumed to be within a fixed period (e.g., 2 – 5 pm), i.e., the coordinated controls of building facilities are constrained in a single period, which cannot reflect a real operation of the building facilities as the electricity price is hourly changed in the energy market of the USA. Moreover, the battery as another commonly used type of ESS is not studied in their framework. Hence, the optimal coordinated control of an EMS integrating renewable energy and multi-storage systems at the consumer side with demand responsive building is not fully investigated.

2.2.5 EMS with Multi-storage System and Demand Response

Buildings consume a significant amount of energy in the world, especially in the U.S. where the energy consumption of buildings occupies 33% to 41% of the total energy consumption of the entire nation [6]. The optimal operation of the EMS and DR is one of the most effective ways to improve the energy efficiency of a building. Some related works about the DRs in HVAC system are available in the literature. In [58], a deterministic unit commitment model is developed for the EMS where

the probabilistic reserve and opportunity constraints of the limited controllability of the residential DR resources are considered. Furthermore, a bi-level direct load control based DR optimization algorithm is proposed in [59], which is designed to investigate the possibility of combining the flexibility from multiple shared energy storage system units and HVAC units for the DR. In another scheme, Vrettos et al. [62] present a combination of robust and stochastic optimization framework to provide the power system frequency reserves through the building HVAC system setpoints. Motegi et al. [22] discuss the DR strategies in the HVAC system including global temperature adjustment of all zones and systematically controlling other components in the cooling system. According to the reports from [23]–[25], the global temperature adjustment of all zones in a building is the most effective way to achieve DR goal among the HVAC-based DRs. Although managing the HVAC system can reduce the overall building load demand, the HVAC loads are still the major chunk of energy in buildings.

Deploying TES system can help to effectively reduce the overall load demand from the HVAC system during the DR period. Much works have been done to investigate the benefits of TES in building integration. For example, Li et al. [68] extensively review the various TES and integration forms for the building and industrial applications. Naranjo Palacio et al. [69] analyze the impact of TES on minimizing the operating cost of the power system by reducing the peak load of the commercial buildings. In another attempt, the TES-based DR is studied in [19] where the application of ice storage for the peak-load shaving in large and medium-sized office buildings is investigated. It is reported that a higher chiller energy consumption is found compared to the conventional non-storage systems due to the day and night operation of the chiller system. Moreover, the energy and peak power savings from the PVs and ice storage system in demand responsive building are explored in [20] where the two ice storage strategies, called full ice storage strategy and partial ice storage strategy, are compared. It is concluded that the building with full ice storage strategy provides a preeminent peak-load shaving potential but the highest total energy consumption is found at the end of a day, which implies that there should be a trade-off between the peak-load reduction and the energy consumption during a day for the TES-based DR in a building. In [70],

the ice storage system and PVs are controlled in a coordinated manner with other DRs in the building to absorb the plug-in electric vehicle (PEV) penetration. It is shown from their research that the coordinated control of ice storage and PVs can fully absorb the PEV penetration as well as reduce the peak load by 13.4% and improve the load factor by 11%.

Literature review shows that there are studies that discuss the optimal operation of EMS with multi-storage systems (i.e., battery and ice storage). In [36], an optimization framework is developed for the optimal energy dispatch in the EMS with multi-storage systems for the microgrid operating in grid-connected and islanded modes. Then, a temporally-coordinated operation method is further proposed in [37] to handle various uncertainties in the microgrid with multi-storage systems. In another study, a simultaneous optimization framework is introduced to optimally design and operate the CHP with multi-storage systems in the residential EMS [42]. However, the ice storage in previous works is optimized in a similar way as the battery to charge or discharge the stored energy, and the different operating modes in the ice storage are usually neglected. In addition, Bao et al. [74] propose a multi time-scale cooling and electricity coordinated scheduling and dispatching model for optimal microgrid operation where the status of ice storage is optimized considering various operating modes. Although previous works address the optimization problem in the operation of EMS with multi-storage systems, its coordination with other DR resources (e.g., HVAC, lighting, plug loads, etc.) considering the various operating modes of ice storage at a building level is not systematically studied. Thus, Chapter 4 proposes a price-based integrated automation model to optimally and coordinately control the EMS with multi-storage systems in the demand responsive building.

2.3 Model, Control and Analysis of the Heating, Ventilation, and Air-Conditioning System

This section reviews our previous studies for the energy efficiency of a HVAC system, various ways to model a HVAC system, main control strategies for a variable air volume (VAV) HVAC system, and a new type of HVAC system widely used in the recent years.

2.3.1 Energy Efficiency of the HVAC System

Our previous works [75]–[77] have studied on the energy efficiency of a HVAC system in various aspects including the effect of contaminants in a chiller system, the HVAC system behavior under a multi-point sensing framework in the scenarios of changing ambient temperature, variable supply airflow rate, and time-varied occupants’ activities.

2.3.1.1 Contaminants in a Chiller System

The vapor compression cycle is a heat absorption and dissipation process which transfers the heat from one place to another. Figure 2.1 shows a schematic diagram of the vapor compression cycle in the chiller system including the main components of the compressor, condenser, expansion valve, and evaporator [75]. Firstly, the compressor increases the pressure and temperature of the gaseous refrigerant coming from the evaporator, thereby raising the boiling point of the refrigerant. Then, the gaseous refrigerant is converted to the liquid form by quickly cooling it in a condenser. Thus, there is a slight decrease in the refrigerant’s temperature in this state changes. Subsequently, the expansion valve releases high-pressured liquid, thereby reducing the temperature and boiling point of the refrigerant. Next, the evaporator turns the liquid form of the refrigerant into its gaseous-form or vapor where the surrounding heat is absorbed by the refrigerant in this process. The air across the evaporator is cooled and supplied to the conditioned space.

According to a report from the Building Construction Authority of Singapore [78], most of the newer constructed chiller systems fall under the quadrant A as shown in Figure 2.2 where a lower value of the y axis represents a more energy efficient system. With the increasing number of the service years, a few chillers with proper maintenance are located in the quadrant D while most of them are inappropriately maintained, thereby moving towards the quadrant C. Hence, it is necessary to continuously monitor and maintain the components of a HVAC system, especially for the chillers. Some fault detection tools are available in the literature. For example, Bashi et al. [79] design a fault detection algorithm for a HVAC system where the Gaussian-mixture distribution of unit parameters are estimated by the expectation-maximization algorithm. This algorithm is used to

Figure 2.1: The vapor compression cycle system in the chiller system (Source: Adopted from [75]).

Figure 2.2: Central chilled water HVAC system efficiency and chiller age (Source: Adopted from [78]).

continuously monitor the operating status of a HVAC system. The performance of the algorithm is studied based on both Monte Carlo simulations and real data obtained from the HVAC system. It is mentioned by them that the proposed algorithm can effectively monitor the system status and provide sufficient system information including the system fault, system modes, activation of a unit, etc.

From various investigations of the industrial chiller performance, the refrigerant contaminants have been recognized as one of the primary causes of efficiency loss. The contaminated refrigerants circulating in the vapor compression cycle would not only reduce the energy efficiency of the cycling process but also damage the equipment inside a HVAC system. The contaminants can be in the forms of solids, liquids and gaseous state. It is usually difficult to notice the existence of contaminants until the physical damage or obvious efficiency loss happened. It results in a high efficiency-loss of a chiller system even causes a major breakdown, thereby reducing the equipment lifespan and raising the maintenance cost.

Various contaminants are found in the refrigerant, such as oil, air, moisture, acids, particulate matters, etc. Oils are often used to lubricate the moving parts in the chiller system where a small amount of them may be leaked out and circulated with the refrigerant. Accumulated oil contaminants can change the refrigerants' properties, e.g., viscosity, enthalpy, heat transfer rate, and surface tension. Moisture contaminants could result in the ice formation in the expansion valve and evaporator. The formed ice can block the cooling coil and reduce the surface area for heat transfer. The mixed air contaminants and refrigerant form a non-condensable mixture which remains gaseous state during the vapor compression cycle, thereby increasing the pressure of heat exchanger and decreasing efficiency of the condensation process. Since contaminants in the vapor compression cycle can cause a significant loss in the energy efficiency or a major breakdown in a chiller system, Zhang et al. [75] analyze the refrigerant contaminants and reclamation service to prolong chiller lifespan and improve the energy efficiency of the chiller. This work investigates the possible impact of contaminants on the chiller system by formulating a vapor compression cycle model consisting of the compressor, evaporator, condenser, and expansion valve in Thermolib[®] which is an external library toolbox available in Matlab. The simulation results have demonstrated the

impact of contaminants on the refrigerant's enthalpy, system pressure, and overall heat transfer coefficient. It is found that contaminants dropping the enthalpy by 15% can decrease the coefficient of performance (COP) by 12% – 14.17% where the COP is subject to the change of the time-varied environment temperature.

2.3.1.2 HVAC System Behavior under a Multi-Point Sensing Framework

The sensor is one of the most important parts of the BEMS, which monitors the indoor environments of a building and provides the first-hand information to the system controllers. Various sensors are employed in a building, such as the temperature, humidity, illuminance, motion, CO₂, etc., which can be optimally mapped in the form of 2D or 3D deployment. The sensors' deployments are often optimized by two types of algorithms where one of them aims at the optimal disposition for the building energy and environmental management while the other one has the objective of minimizing the installation expenses [80].

A HVAC system often has problems with over-ventilation or under-ventilation. To address these issues, the demand controlled ventilation strategy is implemented in the building. But it usually operates based on solely monitoring CO₂ of a conditioned space, thereby maintaining the air quality of the indoor environment. Therefore, the harmful emissions from the building materials are often neglected [81]. In the earlier study, a parameter called total volatile organic compounds (VOC) is used to monitor the air quality of a zone, which indicates the concentration of all VOC species present in a zone. Although this indicator is helpful to maintain the level of VOC below the harmful level when demand controlled ventilation strategy is implemented, it is not reliable especially in the newly constructed buildings [82].

The occupancy information is another important factor directly affecting the energy consumption and performance of a HVAC system, which would result in the changes of heat loads, needed heating, cooling, or distribution of conditioned air, system running time, preferred temperature set points, etc. It is usually considered in two models, namely deterministic occupancy model and stochastic occupancy model. In the deterministic occupancy model, HVAC operating schedules of the standard workday and weekend load profiles are generated in advance [83]. On the

other hand, the dynamics schedules can be produced by the stochastic occupancy models using probabilistic approaches, e.g., Poisson processes and Markov chains [84].

Alternatively, using the occupancy sensors monitor the CO₂, VOC, motion, indoor temperature change, acoustic activity, etc., to detect the time-varied occupants in a conditioned space. Li et al. [85] propose a radio frequency identification based occupancy detection system to assist a demand-driven HVAC system. The proposed method can simultaneously detect and track numerous stationary and mobile occupants in the multi-zones of a building. The occupants are identified by the radio frequency identification tags which continuously record the location of occupants for supporting the energy efficient HVAC operation. It is concluded that the proposed occupancy detection system is also capable of classifying the detected occupants' simplified activities, such as walking and seated. In another attempt, Ploennigs et al. [86] demonstrate a scalable model-based virtual sensor which supports to analyze the energy consumption of a HVAC system at the zone-level using simple temperature sensors. Their results show that the proposed virtual sensors can effectively assist the decision-making process of optimizing a HVAC system while minimizing the monitoring cost of a building.

The single-point monitor scheme, i.e., one sensor per conditioned zone, is typically used in most of the commercial buildings for tracking and monitoring the indoor environment. It is however not very effective in comparison with the multi-point sensing system whereby a zone with multi-point sensors can provide a more sophisticated image of the climate in a conditioned space. The detailed image of the indoor environment can help to optimize and control the HVAC system for operating it in a more energy efficient way. Therefore, in the recent study, Zhang et al. [76] develop a multi-point sensing framework for investigating and supporting the energy efficient HVAC operation in the building. A typical office zone model is developed in FloVENT[®] to study the effect of occupants' dynamic activities by using a multi-point sensing system. The simulation results show that the proposed method can effectively identify the optimal monitoring positions for detecting the occupants' dynamic activities. It helps to minimize the number of sensors installed in the building and provides detailed indoor climate information

to support the HVAC system optimizer for more energy efficient operation. Then, Zhang et al. [77] further analyze the effects of changing ambient temperature and indoor supply airflow rates in the HVAC system of a building. It is concluded that the indoor temperature has a linear relationship with the time-varied outdoor temperature and changes non-linearly with the supply airflow rate.

2.3.2 Modeling of a HVAC System

In the literature, numerous HVAC models can be summarized into three categories, namely the mathematical model, empirical model, and hybrid model (i.e., white-box, black-box, and gray-box models). The mathematical model is a white-box model formulated based on the system characteristic and physical sciences such as the momentum conservation, universal laws, physical laws of mass conservation, energy balance, etc. This type of model is often in the form of time-domain differential equations which can be converted to the frequency-domain for controller designs. Generally, to model an entire HVAC system is very complex and time-consuming where the most sophisticated part is the building model associated with walls, floor, roof, windows, internal equipment, lighting, occupants' activities, and the heat gain from other resources. Hence, some building simulation software, e.g., ESP-r, TAS Engineering, TRNSYS, IDA ICE, BCVTB, OpenStudio®, EnergyPlus™, FloVENT®, etc., are developed to simplify the complexity of a modeling process. For example, the authors in [76], [77], [87], [88] use FloVENT® to build a HVAC system model under various scenarios while another paper [75] models a HVAC system by utilizing Thermolib® to analyze the effect of refrigerant contaminants for the energy efficiency of the chiller. The empirical model is a black-box model which is developed based on the experimental results or available data. This type of model can be built by various approaches, such as artificial neural network, support vector machine, fuzzy-logic approach, statistical and stochastic methods, etc. Compared to the white-box model, a black-box model is much easier to construct and is able to consider various uncertainties in the model. But it is less accurate than the former one.

The hybrid model is a gray-box model which combines the mathematical and empirical models. It improves the weaknesses of individual approaches where it

is simpler than a white-box model and is more accurate than a black-box model. Thus, the hybrid model is widely used in the literature for the controller designs and HVAC system optimization as it compensates the weaknesses of white-box and black-box models. In the earlier studies, the HVAC system is often built by a bilinear model [89]–[91]. Zaheer-Uddin et al. [89] design the robust decentralized controllers to handle the unknown disturbances and step changes in the desired set-points of a multi-zones heating system where the heating system is constructed by a bilinear model. The optimization problems are formulated as robust and nonlinear constrained servomechanism problems. The decentralized and centralized controllers are designed by solving the above problems. The simulation results show that the decentralized controller is superior to the centralized controller in terms of temperature regulation, economics, implementation, and maintenance. Arguello-Serrano et al. [90] develop a nonlinear disturbance rejection state feedback controller which regulates conditioned space and reject the disturbance components based on the Lyapunov stability theory. A bilinear model is used to present a VAV HVAC system where the state estimator is presented to estimate the on-line thermal load for the controller. It is concluded that the developed controller is capable of removing thermal disturbances in the conditioned space while keeping the thermal comfort at the same time, thereby improving the energy efficiency of a HVAC system. Semsar-Kazerooni et al. [91] demonstrate a control scheme for the nonlinear multiple-input-multiple-output HVAC system where an algorithm is proposed to decouple and track the disturbance of this nonlinear system. The HVAC system is formulated as a bilinear model instead of the linear first-order model or nonlinear single-input-single-output model because of that the bilinear model can best present a single zone HVAC system. It is concluded that their proposed algorithm can effectively regulate the output, decouple slowly time-varying disturbances, and prolong life-time of the actuators.

In recent years, the HVAC system is usually formulated as a RC-network model [16], [92], [93]. Deng et al. [92] propose a mean-field control methodology for the set-point temperature regulation in the large building where the distributed game theory approach is employed to optimize the problem with respect to the mean-field. The proposed control method is implemented on a non-linear RC-network model which is a gray-box model representing the HVAC system of a

large building. Their results show that the mean-field scheme can effectively track the zone's temperature while improving the energy efficiency of a HVAC system. Lin et al. [93] investigate various HVAC system modeling methods for the model predictive control application where the complexity of a HVAC model and the methods for identifying the unknown model parameters are discussed. Several non-linear RC-network models including the full-scale model, second-order model, and first-order model are compared. The end results show that the first-order and second-order models (i.e., the simplified forms of a full-scale model) are accurate enough to represent thermal dynamics of a HVAC system for the purpose of model predictive control application. Hao et al. [16] present a feed-forward architecture to control the central air supplying fan of a HVAC system for providing various ancillary services to the grid. A high fidelity non-linear characteristic of a building is formulated as a non-linear RC-network model where the parameters of a HVAC model are identified by the least-square approach with data collected from a real commercial building. It is concluded that fans of the HVAC systems in existing commercial buildings in the USA are able to satisfy about 70% of regulation reserve requirements in the frequency band from $\frac{1}{3 \text{ mins}}$ to $\frac{1}{8 \text{ s}}$ without additional investment for installing sensors and actuators. However, this HVAC system model ignores the energy consumption of chillers and cooling coils as well as the effect of indoor climate changes.

In addition, a semi-nonlinear thermal model for the building equipped with a HVAC system is developed in [87], [88] where the model is formulated by the ordinary differential equations with parameters as nonlinear functions of cooling air flow-rate and ambient temperature. To verify the performance of the proposed thermal model, authors build a three-roomed building in the computational fluid dynamics software called FloVENT® which is a white-box model continuously solving the Navier-Stokes equations for the temporal evolution of temperatures in the scenarios of various ambient temperatures and cooling air flow-rates. They propose two parameters estimation methods, namely offline parameter estimation and online parameter estimation. In the offline parameter estimation method, the problem is formulated as a nonlinear programming problem solved by a hybrid method consisting of the genetic algorithm and interior point approach. The online parameter estimation can further improve the prediction accuracy by recursively updating

parameters online using the extended Kalman filter approach. It is concluded that their proposed method addresses the problems associated with dynamically changing temperature and uncertainties in the HVAC system model by automatically updating the system parameters online to retain the prediction accuracy of the proposed thermal model.

2.3.3 HVAC Control Strategies

The prevailing control strategies of a VAV HVAC system are listed as follows:

1. Optimal start/stop control strategy
2. Duct static pressure reset control strategy
3. Supply air temperature reset control strategy
4. Demand controlled ventilation control strategy

The optimal start/stop control strategy is also called as the on/off control strategy which turns on/off the supply air at the appropriate time in each zone. The on/off time is controlled by the building automation system which calculates the optimal on/off time for each zone to reach the occupied set-point.

The duct static pressure reset control strategy maintains duct static pressure at the preset value by varying the supply airflow rate, i.e., fan speed. About 50% of the electrical power can be saved in the moderate thermal loads of building by using different control strategies, where the minimum airflow rate should not be set to too low because of the high power lost in variable frequency drive (VFD) at the low speed condition [94]. The duct static pressure reset control strategy can be implemented by resetting the static pressure with or without the terminal box feedback technique. Resetting the static pressure with the terminal box feedback technique directly controls the supply fan speed by the fan speed control algorithm and the real-time airflow rate demand at the terminal units [95]. The terminal unit is the component that contains the heating coil, cooling coil, and the automatic damper, which are used to control the zone temperature. Resetting the static pressure without the terminal box feedback technique avoids the inaccurate airflow

measurements existing at the terminal unit where the fan airflow station is created to calculate the airflow rate demand by utilizing the measured fan speed and fan head, instead of using real-time terminal unit measurements [96].

The supply air temperature reset control strategy aims to raise supply air temperature (SAT) during the partial load condition for reducing the energy consumption of the reheating coils in the VAV box. This strategy includes supplying the outdoor air directly to the conditioned space whenever the temperature of outdoor air is less than the set point of the SAT. Meanwhile, the compressor is shut down, the return air and the outdoor air damper are adjusted to maintain the desired SAT. The SAT has to follow the ASHRAE Standard 90.1 if the system operates the heating and cooling simultaneously at the zone level [97]. Literature review shows that the low SAT (between 7°C to 11°C) is able to largely reduce the fan power consumption, it scales down the size of an air handling unit and the VAV terminal units to reduce the installation cost at initial point [98]. However, there are some challenges encountered by using such low SAT. For example, the engineer has to consider the comfort of occupants as the supplied air temperature is too low for damping on the occupants directly. Another critical issue is that the low SAT can cause condensation problems on the air distribution systems, e.g., rusting diffusers, damaging surrounding ceiling systems, etc. The cold air distribution system design guide [99] is a powerful tool for the engineers to avoid the above issues when they plan to design a cold air supply HVAC system.

Since the supply air temperature is often associated with the operation of a vapor compression cycle system, numerous works are available in the literature to address the optimal control problems in such a system. In [100], a multiple-input-multiple-output model-based strategy is proposed to control the vapor compression cycle of a HVAC system. The techniques including Youla parameterization and Lyapunov-based approach are utilized where the former is used to modify a standard local controller network framework for gain-scheduling and the latter is employed for stabilizing the system. It is concluded that their developed nonlinear controller can effectively optimize the operation of an evaporator in the HVAC system while satisfying the cooling demand as well as guaranteeing the system

stability. A multiple single-input-single-output control scheme is developed to improve the energy efficiency of a vapor compression cycle where the relative gain array technique is used to sort the possible input-output pairs for the decentralized control [101]. It aims at maintaining superheat of the evaporator as well as maximizing the COP of a HVAC system. It is shown that their proposed method can ensure a good reference tracking of each output as well as provide the most effective matching for the input-output pairs. Although a variable speed control strategy for the compressor working in the partial load condition is superior to the on/off control strategy in terms of the energy efficiency in most of the cases [100], an on/off control strategy has to be implemented when the compressor's operating frequency is less than the minimum compressor operating frequency since it can only operate within a constrained frequency range [102].

The demand controlled ventilation control strategy is to automatically adjust the ventilation system according to the changed amount of occupants inside the zone. Current technologies available for detecting the number and distribution of the occupants is mainly based on detecting the moisture or CO₂ concentration in a particular area within the zone. This control strategy can be implemented by the direct digital control type of automation system which uses the computers to automatically manipulate the indoor environments of the building, e.g., a dual maximum baseline control logic approach [103].

2.3.4 New Type of HVAC system

Previously, most of the HVAC systems are designed in such a way that the refrigerator system is responsible to handle both temperature and humidity controls, e.g., to remove the heat and dehumidify the indoor air simultaneously. Hence, Liu et al. [104] provide a possible and effective solution to improve the energy efficiency of a HVAC system by introducing a temperature and humidity independent control of air-conditioning system (THIC) concept where the temperature and humidity of a conditioned space are controlled independently. A THIC HVAC system is the new type of HVAC system widely used in recent years. It is more energy efficient compared to the conventional HVAC system in terms of higher COP range of 8.5 – 9.0 [105]. In contrast, a conventional HVAC system has a COP range of

about 5.5 – 6.0 which is much lower than the THIC HVAC system. According to the reports from [104], the energy consumption of chiller in a THIC HVAC system can be reduced by up to 40% because of this COP difference. The considerable energy saving potential is come from the reduced cooling effort needed by the THIC HVAC system which requires a much smaller refrigerator working range as shown in Figure 2.3 [105]. In the conventional HVAC system, it is necessary to decrease the evaporating temperature to 5°C for dehumidifying the air by condensing process whereas a THIC HVAC system with the independent humidity control system does not need such a low temperature at the evaporating process, i.e., the refrigerator with a temperature of 16°C is good enough for the temperature control in that case, thereby avoiding the increase of cooling effort for further lowering down the evaporating temperature. However, a THIC HVAC system is hard to be modified from the existing conventional HVAC system when the building design is fixed because of the high rebuilding cost induced by the system replacement.

Figure 2.3: Refrigerator working range of the conventional HVAC system and the THIC HVAC system (Source: Adopted from [105]).

2.4 Model and Control of the Variable Frequency Drives (VFD)

Considering the economic aspects, the three-phase asynchronous AC drives (i.e., induction machines) are widely used in the VFD system servicing for a fan or pump

in the HVAC system. There are three main control platforms commonly used for controlling the speed or torque of an induction machine (IM), namely scalar control, direct torque control (DTC), and field oriented control (FOC). The scalar control is also called as V/Hz control where the speed of IM is controlled by varying the magnitude of stator voltage and frequency for keeping the air gap flux always at the desired level during steady state. The DTC technique was first developed by Dr. Takahashi in 1984 at Japan and FOC method was presented by Dr. F. Blaschke in 1971. Nowadays, these two techniques have become industry-standard approaches for regulating the torque of an IM [106], [107]. In the DTC method, the torque of a three-phase IM is directly controlled for the speed regulation where the magnetic flux and torque are estimated according to the measured voltage and current of a three-phase IM. FOC is also called as vector control where the stator current of an IM is visualized as a vector consisting of two orthogonal components. One component refers to the torque, and the other relates to the magnetic flux of the motor. The speed of IM is controlled by the corresponding current component calculated from the flux and torque references.

The scalar control method is a stable and simple control technique which can be easily implemented with very low cost. But it is used mainly in the low performance applications due to its intrinsic drawbacks, such as poor transient and sluggish responses, undesirable speed-accuracy during low speed operation, and inability for controlling torque and magnetic flux. Besides the scalar control, FOC and DTC are the two complex and high price control techniques widely used in the high performance applications. Table 2.1 summaries the advantages and disadvantages of these two control strategies. In general, DTC has very good dynamic torque response (e.g., excellent settling time and maximum overshoot), simple structure, small computational time, and implementable on low cost digital signal processor (DSP) platforms. Hence, it is often used in the high dynamic application. Unlike the DTC, FOC has slower torque response but uniform torque ripples, thereby usually employing the FOC approach for the reference generation.

In the earlier research, the basic DTC scheme is intensively studied and progressively modified to improve its dynamic performance, especially on the torque ripple minimization. In [106], a torque ripple control algorithm is developed to

Table 2.1: Comparison of Field Oriented Control (FOC) and Direct Torque Control (DTC) Methods [106], [107].

Item	Field Oriented Control (FOC)	Direct Torque Control (DTC)
Torque ripple	Low	High
Current harmonics	Low	High
Noise	High-frequency uniform noise	Irregular noise (maddening at low speed)
Dynamic response	Slow	Fast
Steady-state performance	Good	Not good
Computation time	Slow	Fast
Cost	High	Low
Application	Reference generation, communication, management of the user interface, for low-power drive applications	High dynamic application
Advantages	Good steady-state performance	High dynamic response
Disadvantages	Much tuning works for the PI controller, parameter sensitive, low dynamic performance, difficult to consider various nonlinear constrains in FOC	High torque and flux ripples, high average switching frequency, high current harmonics, poor performance at low speed

maintain the constant switching frequency while minimizing the torque ripple. It is mentioned that the proposed method is capable of improving the torque control characteristic as well as not deteriorating the capability of flux control. The performance of the DTC scheme for an induction machine are assessed in [107] where the principles, strategies, and problems associated with implementing DTC

are analyzed. The authors also discuss various ways to improve the basic DTC scheme, such as the rotor flux reference approach, improved stator flux estimator, stator flux vector control scheme, discrete space vector modulation technique, flux weakening approach, etc. The concept of DTC with its associated techniques is verified and analyzed by both simulations and experiments. It is concluded that although a DTC drive deteriorates at the low speed operation, the improved flux estimator can effectively enhance the drive performance. Furthermore, DTC is preferred for high dynamic application where the high current and torque ripple can be compensated by coupling the basic DTC scheme with the discrete space vector modulation technique.

Since the MPC approach becomes a mainstream type of control technique in the last decade, the basic DTC scheme evolves into the MPC-based DTC approach which is also named as model predictive torque control (MPTC) scheme. The authors in [108], [109] demonstrate the MPC scheme for a DTC drive that maintains the stator flux, motor torque, and the neutral point potential of an inverter in the defined hysteresis bounds while reducing the inverter's switching frequency. The MPC controller is designed based on an internal model of the drive which forecasts a number of potential switch transitions, deduces the output performances, and selects the optimal voltage vectors. The proposed method is confirmed by both simulations and experiments on a three-level voltage source inverter driving the squirrel-cage induction machine where the simulations are conducted by the Matlab/Simulink and the detailed standard DTC model is provided by ABB Ltd. [110]. It is shown that the developed MPC scheme inherits the fast dynamic response of a standard DTC scheme that bounds the torque, flux, and neutral point potential of an inverter. This scheme is also highly flexible where the drive performance for different objectives or applications can be simply varied by modifying the cost function of the internal model. Moreover, the MPC-based DTC scheme is capable of reducing the average inverter switching frequency while keeping the beneficial characteristics of the fast torque dynamic response, such as motor torque, length of stator flux, and neutral point potential of the inverter. However, their proposed approach may result in a considerable computational burden associated with the algorithms due to the intrinsic nature of the MPC approach. Later on, In another

attempt, Beerten et al. [111] develop a model-based predictive DTC scheme to compensate the time delay caused by the data processing in the increase of sampling frequency as well as diminishing the torque and flux ripples under various loads and speeds. Unlike the other MPC scheme, their proposed scheme only utilizes the historical data stored in the memories (e.g., electromagnetic torque, stator flux angle, and stator flux magnitude) for the prediction, no additional motor parameters are required. The proposed method is verified by the experiments. It is concluded that their prediction scheme can be easily extended to the existing DTC scheme. It can also improve the computation speed while the sampling frequency is increased, and significantly reduce both torque and flux ripples.

In the recent research, Zhang et al. [112] propose a torque ripple reduction strategy for a MPTC drive scheme where the control periods are divided into two intervals according to the principle of torque ripple minimization: One period is implemented with the optimally selected voltage-vector from the MPTC scheme while the other time interval is applied with a zero voltage-vector. The proposed strategy is verified by both simulations and experiments where the simulations are implemented by the Matlab/Simulink and the experiments are conducted on a two-level inverter-fed induction machine. It is shown that the proposed method can reduce the torque ripple and lower total harmonic distortion of the current while maintaining its intrinsic high dynamic performance. Then, an improved MPTC with duty cycle control scheme is further designed by them where the voltage vector and its duration are optimally selected at the same time while minimizing both torque and flux ripples [113]. The proposed method is also validated by both simulations and experiments. It is concluded that implementing the duty cycle control on the conventional MPTC scheme can effectively reduce the torque ripple at steady state and improve the low speed performance of a drive. After that, they introduce an improved MPTC with low complexity scheme for the induction machine [114]. It aims at reducing the torque ripple while lowering the complexity of the predictive structure as the MPTC often needs high computational ability to keep the torque ripple at the minimal level. Since the current prediction process is sophisticated, it is removed to reduce the complexity of a MPC controller in their approach. The proposed scheme is verified by the experiments conducted on an

induction drive. They mentioned that the developed scheme can accurately regulate the electromagnetic torque, thereby reducing the torque ripple significantly.

Although MPTC is a powerful control method used in the induction machines, it experiences cumbersome tuning processes for the weighting factor of the stator flux. It is shown that the output performance of a MPTC drive highly relies on the weighting factor where the improperly tuned weighting factor can deteriorate the drive performance significantly [115]. Therefore, to avoid this problem, a model predictive flux control (MPFC) approach for the control of induction machine is proposed in the following year [21].

In the MPFC approach, the stator flux vector is used as a control variable that simplifies the complicated predicting process for the stator current, thereby eliminating the weighting factor of the conventional MPTC approach. Both simulations and experiments are conducted to verify the proposed method. Their results show that the MPFC approach can achieve very good steady-state performance over a wide speed range while keeping the average switching frequency at the lower level. In addition, the MPFC approach eliminated the tedious tuning works for the weighting factor of MPTC and is much easier to be implemented in the practical application.

The main characteristics of MPTC and MPFC approaches are summarized and compared in Table 2.2 [21], [108], [109], [111]–[115]. In general, both MPTC and MPFC schemes are superior to the conventional DTC scheme in terms of much lower torque ripple, more precise control of the torque and flux, improved drive performance under low speed operation, lower Flux ripples, less violation of the hysteresis bound, keeping fast dynamic response while improving the steady-state performance. Therefore, both approaches are good alternatives to the conventional DTC scheme. MPTC is often used in the high-power application with limited switching frequency when the long prediction horizon is preferred. It can balance the switching losses and has high compatibility with various AC drives and different inverter types. With the simple structure, MPTC can be easily designed and implemented on the low cost DSP board. It is also applicable to the large-scale of three-phase AC drives. However, it is susceptible to the dead time effect of an inverter and sensitive to the variation of weighting factor. The tedious tuning

works for the weighting factor of the stator flux are often done by empirical procedure, which is inconvenient and time-consuming. In addition, the weighting factor must be tuned carefully as the improper tuning work can deteriorate the drive performance significantly. On the other end, MPFC takes full advantages of MPTC while compensating the weakness of MPTC, i.e., tuning the weighting factor of the stator flux. It eliminates the weighting factor from the cost function of MPTC and simplifies the complicated predicting process for the stator current. Figure 2.4 shows that MPFC scheme has a faster dynamic response comparing to FOC scheme while improving the steady-state performance of a MPTC drive [21]. However, all DTC-branched methods would suffer from poor low speed performance.

Figure 2.4: An comparison of short time response of torque for MPTC, MPFC, and FOC (Source: Adopted from [21]).

Table 2.2: Comparison of Model Predictive Torque Control (MPTC) and Model Predictive Flux Control (MPFC) Methods [21], [108], [109], [111]–[115].

Item	Model Predictive Torque Control (MPTC)	Model Predictive Flux Control (MPFC)
Flux ripples	Lower than DTC, but highly depend on the weighting factor of the stator flux	Lower than both DTC and MPTC
Current harmonics	Lower than DTC	Lower than MPTC
Steady-state performance	Better than DTC, similar to FOC	Better than MPTC
Computation time	Faster than FOC, slightly slower than DTC	Fast (41.51 μ s)
Cost of the platform	Low cost DSP board	Low cost DSP board
Average switching frequency	Lower than DTC	Lower than MPTC
Advantages	Balanced switching losses in DTC, highly compatible to various AC drives and inverter topologies, independent from the rating and drive characteristics, applicable to the large-scale of three-phase AC drives, simple controller design	Faster dynamic response than FOC while having the same steady-state performance of FOC, not required to tune the weighting factors of stator flux, low speed performance similar to MPTC
Disadvantages	Susceptible to the dead time effect of an inverter, sensitive to the variation of weighting factor, offline tuned weighting factor may deteriorate the time-varied drive performance, suffer from poor low speed performance	Suffer from poor low speed performance

Chapter 3

Model Predictive Control of Induction Machine for Energy Efficient HVAC Operation

3.1 Introduction

Recently, the energy efficiency of the building has been receiving much attention from the researchers. Many papers discuss the optimizations around the Heating, Ventilation, and Air-Conditioning (HVAC) system, such as sensors and thermostats in the system. The energy efficiency of the HVAC system can be improved by different methods, such as improving the operation of vapor compression cycle [100], [101], applying advanced HVAC fault detection [79], employing smart thermostat [60], and using various HVAC system controllers, e.g., the backstepping controller [91], robust decentralized controller [89], and Lyapunov-based nonlinear controller [90]. However, most of them do not consider the non-optimal energy usage at the motor-drives level, where the fans and pumps are powered by the induction machine (IM), consuming about 50% to 75% of total energy consumption in the overall HVAC system [13]. The various drive control strategies may render different energy savings by considering the losses of IM, e.g., switching, current and torque losses, in the different HVAC operating conditions, e.g., uncertainties in the ambient temperature, occupancy, etc. The large stator current ripples in the IM would cause high current harmonics, which is undesirable for the grid and IM, resulting in significant losses. The high torque ripples induce large torque losses and increase wear and tear on the IM that reduce the lifetime of IM. It also creates large speed

ripples, which deteriorate the energy efficiency of the overall HVAC system. As a result, it is important to investigate the different control strategies of IM for the HVAC system application. In this chapter, a gray-box HVAC model is built up and integrated with a recent (yr. 2016) developed drive control strategy, namely model predictive flux control (MPFC) [21] for investigating the drive performance during various HVAC scenarios.

The rest of the chapter is organized as follows. Section 3.2 describes a construction of the HVAC model in Matlab. Modeling of the MPC-based drive system is described in Section 3.3. Section 3.4 presents the simulation results for the integrated HVAC and drive system model, followed by discussions in Section 3.5.

3.2 Mathematical Model of a Heating, Ventilation, and Air-Conditioning (HVAC) system

The categorization of modeling of a HVAC system is described in Section 2.3.2. A gray-box model, non-linear RC-network [15], [16], [92], [93], is used for investigating the drive performance under different HVAC operating conditions in this chapter. The schematic diagram of a typical HVAC system (modified from [16]) is shown in Figure 3.1. A fan controller for the function of ancillary services in the original paper [16], is removed in this case, as only the HVAC portions are considered for investigating the drive performance. In Figure 3.1, $m(t)$ is the total supplied mass airflow rate by the fan in kg/s. $m^d(t)$ is the total desired mass airflow rate in kg/s. $v^d(t)$ is the desired fan speed in percentage (e.g., $v^d(t)=100$ means the fan is running at rated speed, $v^d(t)=50$ means the fan is running at half of the rated speed). $v(t)$ is the supplied fan speed in percentage. m_i^d is the desired airflow rate in the i-th zone. m_i is the supplied airflow rate in the i-th zone, and T_i is the i-th zone temperature in °C.

3.2.1 Airflow Rate Converter

The airflow rate converter in Figure 3.1 is used to convert the speed into supply airflow rate [16]:

$$m(t) = c_2 v(t), \quad (3.1)$$

Figure 3.1: Overview of a multi-zone HVAC model (Source: Modified from [16]).

where c_2 is a constant coefficient. In this case, the maximum airflow rate at each zone is limited to 0.25 kg/s, which is the same as that in [92]. There are in total of three zones in the HVAC system model. c_2 at full speed can be calculated as $(0.25 \text{ kg/s}) \times (3 \text{ zones}) = c_2 \times (100) \Rightarrow c_2 = 0.0075 \text{ kg/s}$.

3.2.2 Speed Converter

The speed converter in Figure 3.1 is used to convert the desired mass airflow rate, $m^d(t)$ to the desired fan speed, $v^d(t)$. This conversion equation is given as

$$\tau_2 \frac{dv^d(t)}{dt} + v^d(t) = \frac{m^d(t)}{c_2}, \quad (3.2)$$

where τ_2 is the time constant, $\tau_2=10 \text{ s}$ [16].

3.2.3 Thermostat

There are many ways to model the thermostat of a HVAC system, e.g., a smart thermostat is proposed in [60] considering the use of the model predictive control (MPC) strategy for the energy efficiency of the HVAC system. Since the objective is focused on studying the drive performance, a classic PI controller is used in

this chapter with the parameter of $Kp \approx -4.194$ and $Ki \approx -0.011$ to reduce the complexity of modeling a smart thermostat.

3.2.4 Thermal Dynamic Model

The thermal dynamic model in Figure 3.1 is a gray-box model, namely “RC-network” model. It has been well-used in the various papers [15], [16], [92], [93]. Hence, a mathematical HVAC model is given as

$$C_i \frac{dT_i}{dt} = \frac{T_{oa} - T_i}{R_i} + \sum_{j \in N_i} \frac{T_{i,j} - T_i}{R_{i,j}} + c_p m_i (T_{SAT} - T_i) + Q_i, \quad (3.3)$$

$$C_{i,j} \frac{dT_{i,j}}{dt} = \frac{T_i - T_{i,j}}{R_{i,j}} \frac{T_j - T_{i,j}}{R_{i,j}}, \quad (3.4)$$

where i denotes the i -th zone; j denotes the j -th zone which is adjacent to the i -th zone; C_i is the i -th zone capacitance in J/K ($C_i = 7.8 \times 10^5$ J/K); T_{oa} is the outdoor air temperature (ambient temperature); R_i is the window thermal resistance in the i -th zone; $T_{i,j}$ is the instantaneous wall temperature calculated by (3.4); $R_{i,j}$ is the wall thermal resistance between the i -th and the j -th zone; N_i is a set of $[i, j]$ defined in the paper [92], which includes all combination of $[i, j]$ sets where $i \neq j$; $j \in N_i$ indicates all adjacent zones of the i -th zone; c_p is the specific heat of the air ($c_p = 1.005 \times 10^3$ J/(kg · K)); m_i is the supplied airflow rate in the i -th zone; T_{SAT} is the supply air temperature (12.8°C); Q_i is the external heat sources from appliance and occupants in the i -th zone; $C_{i,j}$ is the wall capacitance between the i -th zone and j -th zone; and T_j is the j -th zone temperature.

3.2.5 Single Zone Model

3.2.5.1 Zone Size

A schematic diagram of a single zone is shown in Figure 3.2(a). It has a size of 5 m × 5 m × 3 m, and consists of a HVAC supply, a door and two windows. The designed door size is 970 mm × 2080 mm (2.0176 m²) and a single window size is 1.35 m² for the operable glazing windows stated in ASHRAE 2005 Handbook respectively [116].

3.2.5.2 Parameters of Thermal Resistance (R) and Capacitance (C)

The thermal resistance (R) and capacitance (C) of the wall are $0.18 \text{ m}^2 \cdot \text{K/W}$ and $149.83 \times 10^3 \text{ J/K/m}^2$ respectively for the “200 mm concrete block” type of the concrete wall stated in chapter 30 of the ASHRAE 2005 Handbook [26]. Similarly, the “opaque spandrel glass” type of the windows are used in this chapter, which have the parameter of $R = 0.01 \text{ m}^2 \cdot \text{K/W}$ and $C = 14.1 \times 10^3 \text{ J/K/m}^2$. The “slab doors (wood slab in wood frame)” type of the door are applied in the model with parameters of $R = 0.33 \text{ m}^2 \cdot \text{K/W}$ and $C = 50.49 \times 10^3 \text{ J/K/m}^2$.

3.2.6 Three Zones Model

A three zones model in Figure 3.2(b), is formed by three identical single zone model in Figure 3.2(a) with parameters in Section 3.2.5.2 and Table 3.1. The supply airflow rate at each zone can be estimated as

$$m_i(t) = a_i m(t) \text{ where, } a_i = \frac{m_i^d(t)}{m^d(t)} \text{ \& } m^d(t) = \sum_{i=1}^n m_i^d(t), \quad (3.5)$$

$m_i(t)$ is the instantaneously supplied airflow rate in i-th zone; a_i is the required airflow rate ratio in the HVAC system; and $m_i^d(t)$ is the instantaneously desired airflow rate in i-th zone. In this case, $n = 3$ for the three zones model.

The power consumption of a fan can be expressed by [16], [117], [118]

$$P(t) = c_1 [v(t)]^3, \quad (3.6)$$

where $P(t)$ is the fan power consumption in W, c_1 is a constant coefficient for the fan power estimation in W, and (3.6) is deduced by the fan law stated in [119]. In

Table 3.1: Other HVAC Parameters for (3.3) and (3.4).

Symbol	Definition	Parameters
$m_{i,max}$	Max airflow rate limit at each zone	0.25 kg/s
$T_{ceiling}$	Zone ceiling temperature	T_{oa}
T_{floor}	Zone floor temperature	25 °C
$T_{hallway}$	Hallway temperature	25 °C
$T_{windows}$	Windows outer layer temperature	T_{oa}
T_{door}	Door outer layer temperature	25 °C

3.2(a) Single zone model.

3.2(b) Three zones model.

Figure 3.2: The schematic diagram of the single zone model and the three zones model.

this case, a 2.2 kW induction machine is used for the airflow supply in the HVAC system, and c_1 can be calculated as $2.2 \times 10^3 = c_1[100]^3 \Rightarrow c_1 = 0.0022$ W.

3.3 Model Predictive Flux Control (MPFC) of Induction Machine (IM) Model

The fan plant in Figure 3.1, is discussed in this section. Most of the prior works consider this fan plant as a first-order transfer function, e.g., in [16], [117]. However, when this fan plant is looked into details, a lot of optimization regarding the drive itself could be found out. In this section, a detailed drive model is built up for investigating the drive performance under various HVAC operating scenarios described in Section 3.4.

3.3.1 Dynamic Equation of Induction Machine

The dynamic equation can be expressed as a state space model in the stationary reference frame [21]:

$$\begin{aligned}\dot{x} &= Ax + Bu \\ A &= \begin{bmatrix} -\lambda(R_s L_r + R_r L_s) + j\omega_r & \lambda(R_r - jL_r \omega_r) \\ -R_s & 0 \end{bmatrix} \\ B &= [\lambda L_r \quad 1]^T \\ \lambda &= 1/(L_s L_r - L_m^2)\end{aligned}\tag{3.7}$$

where $x = [i_s \quad \Psi_s]^T$ is a state vector; i_s is the stator current; Ψ_s is the stator flux of the IM; u is the selected stator voltage vector for the 2-level voltage source inverter; R_s and R_r are the stator resistance and rotor resistance of IM respectively; L_s and L_r are the stator inductance and rotor inductance respectively; and ω_r is the rotor speed.

The discretized IM model can be express as [112], [113]:

$$\begin{cases} x_p^{k+1} = x^k + T_s(Ax^k + Bu^k) \\ x^{k+1} = x_p^{k+1} + \frac{T_s}{2}A(x_p^{k+1} - x^k) \end{cases}\tag{3.8}$$

where k is the time instant; x_p^{k+1} is the predictor-corrector of state vector; x^{k+1} is the predicted state vector for the stator current and flux; and T_s is the sampling time of the system (or the drive control period).

The predicted rotor flux (Ψ_r^{k+1}) and electromagnetic torque (T_e^{k+1}) can be express as [21], [112], [113], [115]:

$$\Psi_r^{k+1} = \frac{L_r}{L_m} \Psi_s^{k+1} - \frac{1}{\lambda L_m} i_s^{k+1}\tag{3.9}$$

$$T_e^{k+1} = \frac{3}{2} N_p \Psi_s^{k+1} \otimes i_s^{k+1} \quad (3.10)$$

where N_p is the pole pair of the IM and “ $\otimes$ ” is the symbol for cross product.

3.3.2 Design of Model Predictive Flux Control

The overall control diagram of MPFC is shown in Figure 3.3 where the motor, current and voltage vector applied to the drive at time k are used to predict the stator and rotor flux at time $k+1$ and also stator flux at time $k+2$. Then the reference torque and flux magnitude are converted to form a new reference flux, containing both magnitude and angle of flux. Finally, this new reference flux is compared with the estimated stator flux at time $k+2$ to provide an optimal voltage vector to the 2-level voltage source inverter (VSI). This MPFC strategy is proved to be much better than the conventional direct torque control (DTC), field oriented control (FOC), and model predictive torque control (MPTC) approaches [21]. In Figure 3.3, the state voltage vector (u^k), stator current (i_s^k), and rotor speed (ω_r) at time instant k are substituted in (3.8) and (3.9) to obtain the predictive values of Ψ_s^{k+1} , Ψ_r^{k+1} and i_s^{k+1} . Then, Ψ_r^{k+2} is estimated by the current model [21], [115]:

$$\Psi_r^{k+2} = \Psi_r^{k+1} + T_s \left[R_r \frac{L_m}{L_r} i_s^{k+1} - \left(\frac{R_r}{L_r} - j\omega_r^k \right) \Psi_r^{k+1} \right] \quad (3.11)$$

which is used to calculate the angle of the reference stator flux in (3.12). With the inputs of reference torque (T_e^{ref}) and the magnitude of reference stator flux ($|\Psi_s^{ref}| = 0.91$ Wb), the Ψ_s^{ref} can be estimated as $\Psi_s^{ref} = |\Psi_s^{ref}| \angle \Psi_s^{ref}$, where $\angle \Psi_s^{ref}$ is evaluated by [21], [115]:

$$\angle \Psi_s^{ref} = \angle \Psi_r^{k+2} + \sin^{-1} \left(\frac{T_e^{ref}}{\frac{3}{2} N_p \lambda L_m |\Psi_r^{k+2}| |\Psi_s^{ref}|} \right) \quad (3.12)$$

Afterwards, the cost function minimization block in Figure 3.3 compares Ψ_s^{ref} and Ψ_r^{k+2} by the cost function of $J_1 = |\Psi_s^{ref} - \Psi_r^{k+2}|$, where Ψ_r^{k+2} is calculated by the voltage model: $\Psi_s^{k+2} = \Psi_s^{k+1} + T_s (u^{k+1} - R_s i_s^{k+1})$ [21], [115].

Finally, an optimal voltage vector ($u_{opt} = u^{k+1}$) corresponding to the minimum cost of J_1 is selected and supplied to the 2-level voltage source inverter. The detailed construction of MPFC, parameters of the IM (i.e., stator resistance and inductance, etc.), and the comparisons between the MPFC with other MPC-based drive control strategies can be found in [21].

Figure 3.3: The control diagram of model predictive flux control (MPFC) (Source: Adopted from [21]).

3.3.3 Fan Load and Mechanical IM Model

The fan load is expressed as the torque-speed characteristic of the fan or pump type of load in (3.13) [120]. It is a simple swing equation type model where the damping term is ignored to simplify the problem.

$$T_m = k_c \omega_r^2 \quad (3.13)$$

where $\omega_r \approx 157.08$ rad/s (1500 rpm, full speed), $T_m \approx 14$ Nm (2 kW of IM at full speed) is the maximum load torque, and k_c is a constant coefficient which can be estimated by $14 = k_c(157.08)^2 \Rightarrow k_c \approx 5.67 \times 10^{-4}$.

The mechanical model of IM can be expressed as [121]–[123]

$$J \frac{d\omega_r}{dt} = T_e - B\omega_r - T_m \quad \text{and} \quad \frac{d\theta_r}{dt} = \omega_r \quad (3.14)$$

where J is the coefficient of the motor inertia ($J = 0.01$ kg · m²); ω_r is the rotor speed; θ_r is the rotor angular position; T_e is the electromagnetic torque; T_m is the mechanical torque generated by the motor shaft (load torque); and B is the viscous friction coefficient ($B = 0$, ignored).

3.4 Simulation Results

This MPFC drive model in Section 3.3 is integrated with a HVAC system model in Section 3.2 as shown in Figure 3.4.

Figure 3.4: Overview of the MPFC drive model in the HVAC system.

In order to reduce the calculation time, the simulation time of this integrated MPFC and HVAC model is set as 2500 s (≈ 42 mins), with a base sampling frequency of 10 kHz [113]. The simulation is carried out based on the three HVAC cases in Table 3.2 where the initial zone temperature is at 26 °C. The individual zone temperature is set as 25 °C. Q1, Q2, and Q3 represent the heat emitted by the occupants in zones 1, 2, and 3 respectively in Figure 3.2(b). One person is estimated to generate 80 W of heat in the zone.

Table 3.2: The Three HVAC Scenarios for Investing the Changes of Ambient Temperature and Occupancy.

HVAC Case	Ambient Temperature, T_{oa}	External Heat (Occupancy)		
		Q1	Q2	Q3
Case 1	30 °C	80 W $\times$ (1)	80 W $\times$ (1)	80 W $\times$ (1)
Case 2	25 °C	80 W $\times$ (1)	80 W $\times$ (1)	80 W $\times$ (1)
Case 3	25 °C	80 W $\times$ (4)	80 W $\times$ (1)	80 W $\times$ (1)

The examples of motor output performance is shown in Figure 3.5 for the HVAC Case 1. Their responses in the other two HVAC cases are similar to those in the HVAC Case 1 but with different response time. Therefore, only HVAC Case 1 is presented as an example in this chapter. The “Phase 1” and “Phase 2”, in Figure 3.5, indicate the full speed performance at the beginning when the zone temperature is at 26 °C, and the steady-state performance at the partial-load condition where the zone temperature has reached the set-point temperature of 25 °C, respectively. The phase 1 at Case 1, Case 2, and Case 3 are defined as the 80 s $\sim$ 739 s, 80 s $\sim$ 399 s, and 97 s $\sim$ 398 s respectively. Phase 2 is measured at the steady-steady period of 1994 s $\sim$ 2500 s in all cases. Figure 3.5 shows that the drive control works well as the oscillations of the stator phase current and electromagnetic torque have followed the changes in the motor speed. There is an overshoot in the motor speed presented between 500 s and 1000 s. It is caused by the proportional-integral (PI) controller that is used to function as a speed regulator. The other detailed analyses of the data collected from the simulation are discussed in Sections 3.4.1 and 3.4.2.

Figure 3.5: Motor output performance at HVAC Case 1.

The reference tracking, speed and torque ripples in Tables 3.3 and 3.4 are calculated by (3.15):

$$\begin{aligned}\xi_{rms} &= \frac{|\beta_{rms} - \beta_{rms}^*|}{\beta_{rms}^*} \times 100\% \\ R_{p,\%} &= \frac{R_{p,ave}}{\beta_{rms}} \times 100\% \quad ; \quad R_{p,+ve} = \beta_{max} - \beta_{rms} \\ R_{p,ave} &= \frac{R_{p,+ve} + |R_{p,-ve}|}{2} \quad ; \quad R_{p,-ve} = \beta_{min} - \beta_{rms}\end{aligned}\tag{3.15}$$

where β is a symbol that represents the speed (N) in Table 3.3, and the torque (T_e) in Table 3.4 respectively. ξ_{rms} is the approximated RMS error that investigates the error between the RMS values of the supplied and reference speed, as well as the approximated RMS error that calculates the error between the RMS values of the

Table 3.3: Motor Speed Under Different Cases in Two Steady-State Periods.

HVAC Case	Phase	N_{rms}	N_{rms}^*	ξ_{rms}	$R_{p,ave}$	$R_{p,\%}$
Case 1	Phase 1	1495 rpm	1500 rpm	0.33%	4 rpm	0.27%
	Phase 2	854.5 rpm	854.4 rpm	0.01%	14.7 rpm	1.72%
Case 2	Phase 1	1495 rpm	1500 rpm	0.33%	4 rpm	0.27%
	Phase 2	459.4 rpm	459.4 rpm	0.00%	6.4 rpm	1.39%
Case 3	Phase 1	1495 rpm	1500 rpm	0.33%	4 rpm	0.27%
	Phase 2	498.5 rpm	498.5 rpm	0.00%	6.65 rpm	1.33%

supplied and reference torque. $R_{p,\%}$ shows the percentage of speed, and torque ripple respectively. $R_{p,ave}$ is the actual average speed and torque ripple. $R_{p,+ve}$ is the error between the maximum and RMS values of the speed and torque within a specific time period. $R_{p,-ve}$ is the error between the minimum and RMS values of the speed and torque within a specific time period.

3.4.1 Speed Performance of an Induction Machine

The speed performance, according to the different HVAC cases are recorded in Table 3.3, where N_{rms} is the RMS value of the supplied speed and N_{rms}^* is the RMS value of the reference speed. In phase 1, the IM is running at the full speed with speed ripple around 0.27% in all three HVAC cases. The reference tracking error (ξ_{rms}) is slightly larger than that in phase 2. In phase 2, the IM runs at steady state under different HVAC cases. When the ambient temperature decreased by 5 °C (from Case 1 to Case 2), the speed in steady state is reduced by almost 46%, and the speed ripple is reduced by around 0.33%. Compared to Case 2, the occupants of Case 3 are increased by 3 persons in zone 1 leading to an increase of 8.6% in required speed and a decrease in the speed ripple by 0.06%. It is noticed that a HVAC system in the partial load condition that the drive runs below full speed would increase the speed ripple of a drive accordingly.

3.4.2 Torque Performance of an Induction Machine

The torque performance, according to the different HVAC cases, are recorded in Table 3.4, where Te_{rms} is the RMS value of the supplied torque, and Te_{rms}^* is the

Table 3.4: Electromagnetic Torque of the Induction Machine Under Different Cases in Two Steady-State Periods.

HVAC Case	Phase	$T_{e_{rms}}$	$T_{e_{rms}}^*$	ξ_{rms}	$R_{p,ave}$	$R_{p,\%}$
Case 1	Phase 1	14.3 Nm	14.00 Nm	2.14%	6.81 Nm	47.65%
	Phase 2	5.20 Nm	4.95 Nm	5.01%	8.50 Nm	163.71%
Case 2	Phase 1	14.30 Nm	14.00 Nm	2.14%	6.81 Nm	47.65%
	Phase 2	5.32 Nm	1.97 Nm	170.45%	8.59 Nm	161.61%
Case 3	Phase 1	14.30 Nm	14.00 Nm	2.14%	6.81 Nm	47.65%
	Phase 2	5.33 Nm	2.30 Nm	132.32%	8.71 Nm	163.34%

RMS value of the reference torque. The RMS error and ripples are calculated by (3.15). In phase 1, the RMS error and torque ripple are the same in all cases, with the values of 2.14% and 47.65% respectively. In phase 2, comparing to Case 1, the decrease of ambient temperature in Case 2 causes a large torque tracking error (170.45%), and slightly decrease of 2.09% torque ripple. Considering the occupancy, the increased occupants in zone 1 leads to a decrease of 38.13% RMS error (Case 3 vs. Case 2), and a small increase of torque ripple of 1.73%.

3.4.3 Torque Loss and Fan Power

The fan load, power consumption of the fan (P_{fan}), and the calculated torque loss are recorded in Table 3.5 where the torque loss, $T_{loss,\%} = (T_{e_{rms}} - T_{L,rms})/T_{e_{rms}}$, and $T_{L,rms}$ is the RMS value of the load torque. The fan load torque and the power consumption corresponding to the time in HVAC Case 1 are shown in Figure 3.6. The estimated fan power and the real power are the same in all HVAC cases. The estimated fan power is evaluated by (3.6). The real fan power is calculated by the load torque multiplying the motor speed.

In phase 1, the fan runs at full speed with the power consumption of 2177 W and torque loss of 2.73% in all cases. The maximum rating of the IM is 2 kW which is slightly higher than the fan power consumption in this case. This may be caused by a non-optimal tuned PI-controller (speed regulator) in the MPFC model or the characteristic of IM used in the system. In phase 2, the IM reaches steady state in

Table 3.5: Fan Load and Fan Power.

HVAC Cases	Phases	$T_{L,rms}$	$T_{e,rms}$	$T_{loss,\%}$	P_{fan}
Case 1	Phase 1	13.91 Nm	14.30 Nm	2.73%	2177 W
	Phase 2	4.545 Nm	5.20 Nm	12.51%	406.7 W
Case 2	Phase 1	13.91 Nm	14.30 Nm	2.73%	2177 W
	Phase 2	1.314 Nm	5.32 Nm	75.29%	63.22 W
Case 3	Phase 1	13.91 Nm	14.30 Nm	2.73%	2177 W
	Phase 2	1.547 Nm	5.33 Nm	71.00%	80.77 W

Figure 3.6: Fan load and power consumption at HVAC Case 1.

each case, the torque loss is increased by 62.77%, and the fan power consumption is decreased by 84.46% in Case 2 comparing to that of Case 1. Compared to Case 2, Case 3 indicates a slight decrease in torque loss of 4.29% and an increase of 27.76% fan power consumption.

3.5 Discussion

3.5.1 Summary

This chapter integrates a HVAC system model with an advanced IM control strategy, namely MPFC. The simulations are carried out to investigate the drive level performance of a HVAC operating under different scenarios. The results show that the percentage of speed ripple is the lowest at full speed ($\approx 0.27\%$). The ambient temperature and occupancy changes would not affect the speed ripple too much when the machine operates at the steady state during phase 2. On the other end, the speed ripple during full speed is slightly lower than that in the partial-load speed. Although decreasing in ambient temperature may largely reduce the power consumption of a HVAC system, it also results in a considerable increase of torque loss (i.e., energy loss) during the drive's operation. The change of occupancy is another very important factor for the HVAC engineer to consider, as in this case, there are only 3 occupants more in one zone, which is able to cause an increase of 27.76% total fan power consumption. The one could expect that if there are 3 occupants more in each zone, the power consumption would be even higher. Therefore, the demand controlled ventilation (DCV) strategy [15], [103] is necessary to be implemented for continuously monitoring the occupancy status. In order to achieve more energy efficient HVAC operation inside the building, a multi-point sensor concept in [76], [77] can be considered further, as it gives not only the comfort to occupants but also reduced the energy consumption of the system. On the other hand, one technique may not be suitable for all applications, which is shown in [113] where their proposed control method is not good at the high-speed operation in terms of current total harmonic distortion (THD). Therefore, a hybrid drive control strategy for the HVAC application can be studied in future research.

3.5.2 Challenges and Limitations

The HVAC model integrated with a MPC-based drive model in Chapter 3 forms a typical numerical simulation problem, namely stiff equation. In mathematics, the stiff equation is defined as a differential equation which is solved by certain numerical methods where the solution is numerically unstable unless taking an

extremely small timestep (i.e., step size) for the calculation. In this case, the timestep of a MPC-based drive model must not exceed 0.0001 second (i.e., 10 kHz [21], [113]) to ensure the minimum required accuracy for a solution while a HVAC system is often controlled in the timestep of 1–10 minutes. Compared to the timestep of a HVAC system for hourly simulation, the step size of a drive model is extremely small. Hence, the existing huge timestep difference between the HVAC system and MPC-based drive system results in a computation challenge where a normal computer often cannot afford to this joined simulation because of the limited memory size and extremely long computing time. For example, previously, an integrated HVAC and drive systems with a study period of 1 hour was simulated and the timestep was set to 0.00005 second (i.e., 20 kHz [21], [113]) for obtaining more accurate drive performance. However, the computer has got stuck after 3 days calculation caused by the limited memory size. Subsequently, the computers with a larger memory size were used for this simulation. It is still difficult to obtain full simulation results.

As a result, the previous model is constrained to be simulated at a timestep of 0.0001 second for the study period of 42 minutes, thereby resulting in a considerable variation in the simulation results, e.g, torque ripple. The authors in [21], [113] indicate that decreasing the timestep from 0.0001 second to 0.00005 second can effectively reduce the torque ripple with a slight increase of the switching loss in the devices. Analyzing a drive with hourly HVAC system performance seems to be impractical by solely using the simulation model in this case. Hence, a physical drive system is needed to be set up in the laboratory for studying the hourly integrated system performance with a much smaller control timestep. By coupling a physical drive system with a simulation model of the HVAC system, the control timestep of a drive can be set small enough which improves the accuracy of results as well as mitigates computation burden of the computer.

Furthermore, the HVAC model in Chapter 3 is limited to three small zones and ignores the effect of chillers and cooling coils on power consumption, thereby not representing a systematical HVAC system in the building. It is constructed by the parameters obtained from the ASHRAE 2005 Handbook [26], which is different from the mainstream approach in the literature where all parameters of

a HVAC model (i.e., RC-network) are often identified by the mean squared error approach/least-square approach with experimental data. Since experimental data from a building is often difficult to be obtained because of the privacy and resources constrains, an alternative way to get those valuable data is to use the building simulation softwares, such as ESP-r, TAS Engineering, TRNSYS, IDA ICE, Building Controls Virtual Test Bed (BCVTB), OpenStudio[®], EnergyPlus[™], etc. Those softwares, which are well-accepted in the industry, are shown to be effective and accurate for representing the real characteristic of a building with the HVAC system.

For a continuous study of the energy efficiency and Demand Response (DR) in the building, in Chapter 4, a medium-sized office building with a rooftop variable air volume (VAV) type of HVAC system is constructed systematically in EnergyPlus[™] with the help of OpenStudio[®], which represents the majority of office buildings in the USA. For future research, this building model can be extended to study the performance of a physical drive system described in Chapter 3. The drive control technologies for different components of a HVAC system could be further investigated to improve the energy efficiency of several HVAC units such as pump, fan, chiller, compressor, etc. This extension could be implemented on the BCVTB platform. BCVTB, developed by the Lawrence Berkeley National Laboratory (LBNL), is a software that connects the simulation program and hardware for co-simulation. It is also a middleware that functions as a bridge between one or more software to overcome and complement the disadvantages of each simulation tool. In this case, the BCVTB (Ptolemy II model) can provide the platform for a building model constructed in EnergyPlus[™] to communicate with hardware, i.e., a physical drive system.

Chapter 4

Smart Building Energy Management with Multi-storage Systems for Demand Response

This chapter sheds light on how the Energy Management System (EMS) with multi-storage systems can be optimally and coordinately controlled in the demand responsive building by providing a price-based integrated automation model for managing various building loads, renewable energy, and multi-storage systems. The model presented is validated by the simulation environment conducted on Energy-PlusTM and CPLEX[®]. The main contribution of this chapter can be summarized as follows. This chapter addresses the issue concluded in [19], [20]: The full ice storage strategy provides a preminent peak-load shaving but the highest total energy consumption at the end of a day, whereas the partial ice storage strategy, compared to the full ice storage strategy, offers a less peak-load reduction but a lower total energy consumption at the end of a day. Hence, a smart price-priority strategy is developed for the ice storage system where the ice storage is coordinately controlled with other building facilities. The proposed method makes a proper trade-off between the peak-load reduction and energy consumption in the building with the ice storage system. In addition, a hybrid cooling-and-ventilation control algorithm is developed for the HVAC-based Demand Response (DR) and its effectiveness is compared with the conventional global temperature adjustment [22]–[25] of all zones in the building.

The rest of the chapter is organized as follows. The proposed method is described in Section 4.1. Section 4.2 presents the results of implementing the proposed

method, followed by the discussions in Section 4.3.

4.1 Proposed Method

4.1.1 Commercial Building Model

4.1.1.1 Building Envelope

A medium-sized office building with installed solar photovoltaics (PVs) and wind turbines (WTs) is firstly drawn by SketchUp[®] in agreement with the commercial reference buildings provided by U.S. Department of Energy [124]. Then, it is further extended by using OpenStudio[®] and EnergyPlus[™] based on the works of Sehar et al. [20], [67]. The building has the dimension of 49.91 m $\times$ 33.27 m $\times$ 11.89 m as shown in Figure 4.1. SketchUp[®], developed by Trimble Inc., is a 3D drawing software which is compatible with the OpenStudio[®] [125]. OpenStudio[®], developed in collaboration by National Renewable Energy Laboratory (NREL) and Lawrence Berkeley National Laboratory (LBNL) et al., is a software tool which supports the whole building energy modeling using EnergyPlus[™], especially for modeling and visualizing the Heating, Ventilation, and Air-Conditioning (HVAC) system [126]. EnergyPlus[™], developed in collaboration with NREL and various U.S. Department of Energy's National Laboratories, et al., is a whole building energy simulation program that is used to model the energy consumption for HVAC, lighting, and other loads available in the building as well as the building's water usage [127].

This building model represents the majority of office buildings in the USA [20], [124]. It consists of three storeys with 4 perimeter-zones and 1 core-zone on each floor. The zones facing South-direction include Z_{top1} , Z_{mid1} and Z_{bot1} . The zones facing East-direction consist of Z_{top2} , Z_{mid2} and Z_{bot2} . The zones facing North-direction are constituted by Z_{top3} , Z_{mid3} and Z_{bot3} . The zones facing West-direction are comprised of Z_{top4} , Z_{mid4} and Z_{bot4} . The location of these perimeter-zones is mapped in Figure 4.1. The core-zones at three levels are named as $Core_{top}$, $Core_{mid}$ and $Core_{bot}$. Therefore, there is a total of 15 zones in the building where each core-zone occupies about 983.54 m² and each zone facing South-direction or North-direction has an area of 207.22 m² while each zone facing West-direction or East-direction occupies about 131.26 m². In this chapter, the study location is at El Paso, Texas, USA, with statistical weather data available in [127].

Figure 4.1: Overview of the three storeys medium-sized office building with integrated PVs and Wind Turbines (WTs).

4.1.1.2 Solar Photovoltaics (PVs) Model

The same solar photovoltaic (PV), LG230M1C, from [20] is used in this chapter where the installation method of PVs is modified due to the change of study location. In this case, the studied model is located at El Paso, Texas, USA with a latitude of 31.8° and a longitude of -106.4° . The best tilt angle is 4.96° calculated by (4.1) which is often used to calculate a fixed tilt angle designed for the summer day [128].

$$Tilt = Latitude \times 0.92 - 24.3 \quad (4.1)$$

To avoid the shading effect of the installed PV arrays, an inter-row spacing of 0.25 m is used. It is calculated by the solar shading calculator provided by RBI Solar Inc. [129]. In this case, it is assumed that PV covers 65% of the building roof area. Therefore, the calculated maximum allowable PV arrays are 570 PV modules (19 parallel strings of 30 modules in series). The maximum output of the PV panels is about 131.1 kW.

The equivalent one-diode model, available in EnergyPlus™, is used to model the PV arrays installed on the roof. It is also known as the TRNSYS PV model

which predicts the electrical performance of the PV arrays [130]. Figure 4.2 shows the equivalent one-diode circuit model used to represent the PV arrays where the solar radiation varies the strength of a current source while the diode's current-voltage characteristics are dependent on the temperature. The current-voltage characteristic of a PV is determined as follows:

$$I = I_{pv} - I_d \left[\exp \left(\frac{q_c}{\lambda_{pv} k_b T_m} (V + I R_{s,pv}) \right) - 1 \right] \quad (4.2)$$

$$I_{pv} = I_{pv,ref} \frac{\Gamma_e}{\Gamma_{e,ref}} \quad (4.3)$$

$$I_d = I_{d,ref} \left(\frac{T_m}{T_{m,ref}} \right)^3 \quad (4.4)$$

$$T_m = T_{oa} + \frac{1 - \frac{\eta_{c,pv}}{\alpha_{pv}}}{\Gamma_e \alpha_{pv} / H_{loss,pv}} \quad (4.5)$$

where V is the load voltage; I is the current flowing through the load and PV; I_{pv} is the module photocurrent; I_d is the diode reverse saturation current; q_c is the electron charge constant; λ_{pv} is the empirical PV curve-fitting parameter; k_b is Boltzmann constant; T_m is the module temperature; $R_{s,pv}$ is the module series resistance; $I_{pv,ref}$ is the module photocurrent at reference conditions; Γ_e is the total radiation incident on PV array; $\Gamma_{e,ref}$ is the radiation incident at reference conditions; $I_{d,ref}$ is the diode reverse saturation current at reference conditions; $T_{m,ref}$ is the module temperature at reference conditions; T_{oa} is the ambient temperature; $\eta_{c,pv}$ is the module conversion efficiency; α_{pv} is the module transmittance absorptance product; and $H_{loss,pv}$ is the array thermal loss coefficient.

Since the current-voltage characteristic of a PV is determined by the parameters of $I_{pv,ref}$, $I_{d,ref}$, λ_{pv} , and $R_{s,pv}$ which can be calculated by substituting the current and voltage into (4.2) in the following scenarios: open-circuit, short-circuit and maximum power conditions. Thus, the following three equations are derived:

Under the open-circuit condition:

$$\frac{V_{oc,ref}}{R_{sh,pv}} = I_{pv,ref} - I_{d,ref} \left[\exp \left(\frac{q_c}{\lambda_{pv} k_b T_{m,ref}} V_{oc,ref} \right) - 1 \right] \quad (4.6)$$

Under the short-circuit condition:

$$I_{sc,ref} + \frac{I_{sc,ref} R_{s,pv}}{R_{sh,pv}} = I_{pv,ref} - I_{d,ref} \left[\exp \left(\frac{q I_{sc,ref} R_{s,pv}}{\lambda_{pv} k_b T_{m,ref}} \right) - 1 \right] \quad (4.7)$$

Figure 4.2: An equivalent one-diode circuit model for prediction of the PV's electrical performance [131].

Under the maximum power condition:

$$I_{mx,ref} + \frac{V_{mx,ref} + I_{mx,ref}R_{s,pv}}{R_{sh,pv}} = I_{pv,ref} - I_{d,ref} \left[\exp \left(\frac{q_c}{\lambda_{pv}k_bT_{m,ref}} (V_{mx,ref} + I_{mx,ref}R_{s,pv}) \right) - 1 \right] \quad (4.8)$$

where $V_{oc,ref}$ is the open-circuit voltage at reference condition; $R_{sh,pv}$ is the module shunt resistance; $I_{sc,ref}$ is the short-circuit current at reference condition; $I_{mx,ref}$ is the current at maximum power point along the current-voltage curve at reference condition; and $V_{mx,ref}$ is the voltage at maximum power point along the current-voltage curve at reference condition. After that, (4.6) to (4.8) can be rewritten as

$$I_{pv,ref} \approx I_{sc,ref} \quad (4.9)$$

$$\lambda_{pv} = \frac{q_c(V_{mx,ref} - V_{oc,ref} + I_{mx,ref}R_{s,pv})}{k_bT_{m,ref} \ln \left(1 - \frac{I_{mx,ref}}{I_{sc,ref}} \right)} \quad (4.10)$$

$$I_{d,ref} = \frac{I_{sc,ref}}{\exp \left(\frac{q_c V_{oc,ref}}{\lambda_{pv}k_bT_{m,ref}} \right)} \quad (4.11)$$

The estimated temperature coefficient of open-circuit voltage at the reference open-circuit condition (δ_{oc}^*) is given by

$$\frac{\partial V_{oc}}{\partial T_m} = \delta_{oc}^* = \frac{\lambda_{pv}k_b}{q_c} \left[\ln \left(\frac{I_{sc,ref}}{I_{d,ref}} \right) + \frac{T_m \delta_{sc}}{I_{sc,ref}} - \left(3 + \frac{q_c \varepsilon_b}{A_{coe}k_bT_{m,ref}} \right) \right] \quad (4.12)$$

where

$$A_{coe} = \frac{\lambda_{pv}}{N_{s,pv}} \quad (4.13)$$

V_{oc} is the open-circuit voltage; δ_{sc} is the temperature coefficient of the short-circuit current; ε_b is the semiconductor bandgap; and $N_{s,pv}$ is the number of individual cells in the module.

EnergyPlus uses an iterative search routine for (4.9) to (4.12) to determine the value of $R_{s,pv}$ which lies between 0 and the value resulting in $\lambda_{pv} = N_{s,pv}$. In this process, the calculated value of δ_{oc}^* and the catalog value of δ_{oc} are iteratively compared until $R_{s,pv}$ and λ_{pv} converge where δ_{oc} is the temperature coefficient of the open-circuit voltage given by the manufacturer's datasheet. Once the value of $R_{s,pv}$ is confirmed, the other parameters including $I_{pv,ref}$, $I_{d,ref}$, and λ_{pv} can be obtained subsequently. In other words, the current-voltage characteristic of a PV model is calculated by (4.2) to (4.5) with the parameters including $I_{pv,ref}$, $I_{d,ref}$, λ_{pv} , $R_{s,pv}$, and T_m estimated in (4.9) to (4.12).

4.1.1.3 Wind Turbine (WT) Model

The building rooftop is installed six Aeolos-V 10 kW vertical wind turbines with the rotor height of 6 m and the rotor diameter of 5.5 m [132]. The vertical wind turbine is an ideal choice for the rooftop mounted WTs in terms of lower noise level compared to the horizontal WTs. Another advantage is that they can be powered by the wind coming from all directions. In order to avoid the aerodynamic interference coming from the adjacent WTs, the inter-space between the WTs is calculated as 4 times of rotor diameter [133]. Therefore, the maximum of six 10-kW WTs are modeled in the EnergyPlus™. The WTs in Figure 4.1 are used to display the location of wind turbine (WT) purpose as the wind turbine model available in EnergyPlus™ does not require the detailed 3D drawing of WTs in the building envelop as PV does. The maximum output of the WTs is about 60 kW. The mathematical model for a vertical wind turbine is described as follows:

The generated wind power (P_{wt}) is given by [130]

$$P_{wt} = N_{wt,bl} F_{wt,ta} \omega_{wt} \quad (4.14)$$

where

$$F_{wt,ta} = \frac{1}{4\pi} C_{wt,t} \rho_{rh} A_{wt,c} \left(\int_0^{2\pi} (\omega_{wt} R_{wt})^2 + \int_0^{2\pi} V_a^2 \right) \quad (4.15)$$

$$C_{wt,t} = C_{wt,l} \sin \alpha_{wt} + C_{wt,d} \cos \alpha_{wt} \quad (4.16)$$

$$\alpha_{wt} = \tan^{-1} \left[\frac{\sin \theta_{wt}}{(\omega_{wt} R_{wt} / V_{local}) / (V_{wt,a} / V_{local}) + \cos \theta_{wt}} \right] \quad (4.17)$$

$$V_{wt,a} = \frac{2}{3} V_{local} \quad (4.18)$$

P_{wt} is the power generated by the wind turbine; $N_{wt,bl}$ is the blade number of the wind turbine; $F_{wt,ta}$ is the average tangential force; ω_{wt} is the angular velocity of the wind turbine; $C_{wt,t}$ is the tangential force coefficient of the wind turbine; ρ_{rh} is the local air density at the rotor height; $A_{wt,c}$ is the blade chord area of the wind turbine; R_{wt} is the radius of the wind turbine; $V_{wt,a}$ is the induced velocity; $C_{wt,l}$ is the coefficient of the blade lift; $C_{wt,d}$ is the coefficient of the blade drag; α_{wt} is the blade's angle of attack; V_{local} is the local wind speed at the studied location; and θ_{wt} is the azimuth angle of a vertical axis wind turbine.

4.1.1.4 Battery Energy Storage Model

The simple energy balance model, available in EnergyPlusTM, is used to represent a battery energy storage (BES) system in this study. The battery, Intensium[®] Max+ 20E [134], is modeled in the EnergyPlusTM with a capacity of 2360 kWh and a cycle efficiency of 96%. The rated charge or discharge value is limited at 285 kW. In this study, it is assumed that the battery can support at least 5.5 hours in its desired discharge rate. The mathematical model of a battery is described as follows:

$$E_{bat}(t) = E_{bat}(t-1) + \left[P_{bat,c}(t) \eta_s - \frac{P_{bat,d}(t)}{\eta_s} \right] \quad (4.19)$$

where E_{bat} is the battery's energy capacity; $P_{bat,c}$ and $P_{bat,d}$ are the charge and discharge power of the battery respectively; η_s is the battery's efficiency; and t is the time index.

4.1.1.5 HVAC with Ice Storage System Model

This section modifies the building model constructed in [20], [67]. In the original building model, it is equipped with a rooftop direct expansion (DX) variable air volume (VAV) type of the HVAC system with an ice storage tank at each floor, i.e., the total of the three HVAC systems, where the ice storage tanks are considered as the thermal energy storage (TES) devices to shift the demanded cooling load during the peak hours. An additional HVAC system with an ice storage tank is added in this section, named it as HVAC4, to study the hybrid cooling-and-ventilation control algorithm developed in the latter part of this chapter. It is assumed that the HVAC4 supplies the less-important area consisting of the perimeter-zones facing South-direction and North-direction (i.e., about 15.67% of the building area). The remaining three HVAC systems in [20], [67], namely HVAC1, HVAC2 and HVAC3, are modified accordingly in such a way that: HVAC1 supplies for the zones including $Core_{bot}$, Z_{bot2} and Z_{bot4} , HVAC2 supplies for the zones including $Core_{mid}$, Z_{mid2} and Z_{mid4} , and HVAC3 supplies for the zones including $Core_{top}$, Z_{top2} and Z_{top4} .

The HVAC systems are firstly designed in OpenStudio[®] and modified later in EnergyPlus[™] for integrating the TES devices. For example, the HVAC4 system is firstly drawn in OpenStudio[®] as shown in Figure 4.3. In the air-loop diagram, the main components of a HVAC system include the outdoor air handling unit, single-speed electric DX air cooling coil, electric air heating coil, variable speed central fan, and air terminal units. The outdoor air handling unit controls the mixed ratio of the outdoor air and indoor air. The single-speed electric DX air cooling coil and electric air heating coil are responsible for adjusting the supply air temperature by cooling and heating air in the duct respectively. The variable speed fan regulates the total airflow rate of air in the duct. The air terminal units take charge of controlling their respective zone temperature.

To integrate the TES device into a HVAC system, the single-speed electric DX air cooling coil model drawn in OpenStudio[®] is replaced by the packaged thermal storage cooling coil model available in EnergyPlus[™]. Subsequently, the ice storage system is constructed in the same way discussed in [20], [70]. This packaged model simulates the thermal performance of the DX type of the central air conditioning system integrated with the TES tank. The main parts of this integrated package

Figure 4.3: The schematic diagram of HVAC4 drawn in OpenStudio®.

include the condenser, compressor, evaporator, and TES tank exposing to the ambient as shown in Figure 4.4.

This packaged model can operate in the following modes [130]:

0. OFF-mode
1. Cooling-only mode
2. Cool-and-charge mode

Figure 4.4: Packaged thermal storage cooling coil model (Source: Adopted from [130]).

3. Cool-and-discharge mode
4. Charge-only mode
5. Discharge-only mode

The detailed operation modes of the packaged thermal storage cooling coil model are documented in the reference [130].

4.1.1.6 Building Operation, Internal Loads, and Outdoor Environments

Building Operation: In a typical weekday, the HVAC system is turned on from 6 am to 10 pm and the thermostats are scheduled as 24 °C from 6 am to 9 pm while 27 °C is applied before 6 am and after 9 pm during daily normal processes as shown in Figure 4.5.

Internal Loads: In EnergyPlus™, the power consumption of lighting, miscellaneous (misc.) loads, occupancy, and elevators are calculated as a fraction of the

Figure 4.5: The normal operating schedules of the HVAC system. Plot (I): HVAC on/off status. Plot (II): Thermostats' set-points of the HVAC system.

designed power level. These fractions for a typical medium-sized office building are presented in Figure 4.6. The average power density of 16.89 W/m^2 and 10.76 W/m^2 are applied to the lighting system and the miscellaneous loads respectively. The miscellaneous loads include operating equipment and other plug loads in the medium-sized office building. The building average occupancy density is designed with $18.58 \text{ m}^2/\text{person}$ in this study. The elevator is located in the core-zone area with the designed power level of 32.11 kW .

Outdoor Environments: In Figure 4.7, the outdoor environments including the sky clearness factor and outdoor air temperature are presented. The sky clearness factor is used to determine sky type and luminous efficacy of solar radiation, which indicates an overcast sky if the value is close to 1 while a clear sky is presented if the value is greater than 6 [130]. It is shown that the maximum point of the sky clearness factor is at around 11:30 am. It implies that a clear sky with the maximum solar radiation could be expected at around 11:30 am where the cooling load of the building could be increased while giving a maximum solar power generation. For the study day, the maximum outdoor air dry-bulb temperature is about 34.4°C

Figure 4.6: Time-varied fraction of building internal loads.

Figure 4.7: Outdoor environments. Plot (I): Sky clearness factor. Plot (II): Outdoor air temperature.

which occurs at around 5 pm while the minimum values, 23.3 °C, are found from 5 am to 8 am.

4.1.2 Allocation of Price Band

The real-time price of electricity data in Texas, USA is obtained from [135]. The price bands are allocated by the moving average approach since the price is volatile for hourly updates in the USA markets. They can provide the appropriate price guideline to the EMS for optimal building operation as the calculated price boundaries narrow or widen naturally with the dynamic real-time price. The similar concept has been used in developing the optimal control of charging the electric vehicle (EV) [136]. Historical price data up to 12 hours ($n = 12$) is used to obtain the first value of the exponential moving average (EMA) in (4.20). After that, the price boundaries are calculated by (4.21) to (4.24).

$$\bar{p}_{ema}(t) = \begin{cases} \bar{p}_{sma}(n) = \frac{1}{n} \sum_{i=1}^n p_i & (t = 1) \\ \bar{p}_{ema}(t-1) + \alpha \cdot \varphi & (t > 1) \end{cases} \quad (4.20)$$

$$\varphi = p(t) - \bar{p}_{ema}(t-1) \quad \alpha = 2/(n+1) \quad (4.21)$$

$$\sigma_p(t) = \begin{cases} \sqrt{\frac{1}{n} \sum_{i=1}^n [p_i - \bar{p}_{sma}(n)]^2} & (t = 1) \\ \sqrt{(1-\alpha) \cdot [\sigma_p(t-1) + \alpha \cdot \varphi^2]} & (t > 1) \end{cases} \quad (4.22)$$

$$B_{U1}(t) = \bar{p}_{ema}(t) + \frac{\sigma_p(t)}{2} \quad (4.23)$$

$$B_{U2}(t) = \bar{p}_{ema}(t) + \sigma_p(t) \quad (4.24)$$

where $\bar{p}_{ema}$ and $\bar{p}_{sma}$ are the EMA and simple moving average (SMA) of real-time price respectively; n is the study period of the moving average; p is the real-time electricity price; and σ_p is the standard deviation from the exponential moving average of the real-time price. B_{U1} and B_{U2} are the 1st-boundary and 2nd-boundary of the electricity price respectively.

4.1.3 Battery Optimization by Deterministic Approach

The optimal operation of a battery in EMS with ice storage, PVs, and WTs can be formulated as a mixed-integer linear programming (MILP) problem in (4.25) to (4.30) and (4.32) to (4.40).

The net operating cost function (J):

$$\begin{aligned} \min J(t) = & C_{bat}(t) + C_{ice}(t) + C_{grid}(t) \\ & + C_{pv}(t) + C_{wt}(t), \end{aligned} \quad (4.25)$$

$$C_{bat}(t) = C_{cp,bat} + C_{o,bat} * [P_{bat,c}(t) + P_{bat,d}(t)] \quad (4.26)$$

$$C_{ice}(t) = C_{cp,ice} + C_{o,ice} * [P_{ice,c}(t) + P_{ice,d}(t)] \quad (4.27)$$

$$C_{grid}(t) = p(t) * [P_{buy}(t) - P_{sale}(t)] \quad (4.28)$$

$$C_{pv}(t) = C_{cp,pv} + C_{o,pv} * P_{pv}(t) \quad (4.29)$$

$$C_{wt}(t) = C_{cp,wt} + C_{o,wt} * P_{wt}(t) \quad (4.30)$$

The capital cost $C_{cp,m}$ ($m \in$ symbols $\{bat, ice, pv, wt\}$) [36]:

$$C_{cp,m} = C_{in,m} l (1 + l)^{n_m} / [(1 + l)^{n_m} - 1] \quad (4.31)$$

Power balance:

$$\begin{aligned} P_{load}(t) = & P_{bat,d}(t) - P_{bat,c}(t) + P_{buy}(t) - P_{sale}(t) \\ & + P_{pv}(t) + P_{wt}(t) - P_{loss}(t) \end{aligned} \quad (4.32)$$

Constraints:

$$0.2E_{cap} \leq E_{bat} \leq E_{cap} \quad (4.33)$$

$$E_{bat}(t) = E_{bat}(t - 1) + [P_{bat,c}(t)\eta_s - \frac{P_{bat,d}(t)}{\eta_s}] * \tau_m \quad (4.34)$$

$$At \text{ most one of } [P_{bat,d}(t) , P_{bat,c}(t)] > 0 \quad (4.35)$$

$$At \text{ most one of } [P_{buy}(t) , P_{sale}(t)] > 0 \quad (4.36)$$

Boundaries:

$$P_{bc,min}(t) \leq P_{bat,c}(t) \leq P_{bc,max}(t) \quad (4.37)$$

$$0 \leq P_{bat,d}(t) \leq P_{bd,max}(t) \quad (4.38)$$

$$0 \leq P_{buy}(t) \leq P_{buy,max} \quad (4.39)$$

$$0 \leq P_{sale}(t) \leq P_{sale,max}(t) \quad (4.40)$$

where J is the building's net operating cost. C_{bat} , C_{ice} , C_{grid} , C_{pv} , and C_{wt} are the costs of the battery, ice storage, net purchased cost from the grid, PVs, and WTs respectively. $C_{o,bat}$, $C_{o,ice}$, $C_{o,pv}$, $C_{o,wt}$ are the operating costs of the battery, ice, PVs, and WTs respectively. $C_{cp,bat}$, $C_{cp,ice}$, $C_{cp,pv}$, $C_{cp,wt}$ are the capital costs of the battery, ice, PVs, and WTs respectively. $C_{in,m}$ is the initial investment cost of the units. $C_{cp,m}$ is the capital cost of units. l is the interest rate. n_m is the life span of

the units. $P_{ice,c}$ and $P_{ice,d}$ are the charge and discharge power of the ice respectively. P_{buy} and P_{sale} are the power bought from and sold to the grid respectively. P_{pv} and P_{wt} are the renewable energy generated by PVs and WTs respectively. P_{load} is the total power demand of the whole building. P_{loss} is the power loss caused by power conversion. E_{cap} is the maximum energy capacity of the battery. τ_m is the time constant. $P_{bc,min}$ and $P_{bc,max}$ are the minimum and maximum of the battery charging power respectively. $P_{bd,max}$ is the maximum battery discharging power. $P_{buy,max}$ is the maximum power that can be purchased from the grid. $P_{sale,max}$ is the maximum allowable power sold to the grid.

The boundary parameters $P_{bd,max}$, $P_{sale,max}$ and $P_{bc,min}$ are determined as follows:

- 1) Firstly, p_{setc} and p_{setd} are the user-defined basic allowable prices for charging and discharge respectively.
- 2) If $p \geq p_{setd}$, battery is allowed to discharge at rated power ($P_{bd,max} = P_{peak}$). Otherwise, no discharge is allowed ($P_{bd,max} = 0$).
- 3) If $p > B_{U2}$, battery is allowed to discharge for selling power ($P_{sale,max} = P_{bd,max}$). Otherwise, no selling is allowed ($P_{sale,max} = 0$).
- 4) If $p \leq p_{setc}$, battery is allowed to charge up to 90% of state of charge (SOC) from the grid power. Otherwise, the battery is only charged from PVs and WTs when surplus power exists ($P_{bc,min} = 0$).
- 5) It is assumed that the building can only allow to buy $P_{buy,max}$ of power from the grid. Thus, the battery charging power is calculated as follows:
 - If $P_{buy,max} - P_{load} + P_{pv} + P_{wt} - P_{loss} \leq P_{peak}$, the battery is charged at the power of $P_{bc,min} = P_{buy,max} - P_{load} + P_{pv} + P_{wt} - P_{loss}$.
 - Otherwise, the battery is charged at the rated power P_{peak} .

4.1.4 Smart Price-priority Strategy

4.1.4.1 Algorithm 1: Smart price-priority strategy for coordinated control of ice storage with DR_{lm} and DR_{hvac} events

Algorithm 1 shows the proposed smart price-priority strategy for coordinated control of ice storage with the HVAC-based DR (DR_{hvac}) as well as the Demand Responses (DRs) of the lighting and miscellaneous loads (DR_{lm}). The algorithm is explained as follows:

- The input variables are: Real-time electricity price (p), allowable price for charging (p_{setc}), exponential moving average of electricity price ($\bar{p}_{ema}$), 1st-boundary (B_{U1}), 2nd-boundary (B_{U2}), time index (t), fraction of ice in the TES tank (S_{ice}), minimum allowed ice in tank ($S_{ice,min}$), and maximum allowed ice in tank ($S_{ice,max}$).
 - The outputs are: Ice storage operating mode (ice_{mode}), demand response of the lighting and miscellaneous loads (DR_{lm}) status, and HVAC-based demand response (DR_{hvac}) status.
- 1) The algorithm first calculates $\bar{p}_{ema}$, B_{U1} , and B_{U2} by (4.20) to (4.24) and check the percentage of ice in tank S_{ice} at time t .
 - 2) For the working hours (6 am to 10 pm), if $S_{ice,min} < S_{ice} < S_{ice,max}$, ice storage is available, the price band allocation method is applied as follows:
 - i) If $p > B_{U2}$, which means the electricity is too high, the algorithm tries to operate ice storage in discharge-only mode with a DR_{lm} program. In this case, DR_{hvac} is not necessary as the ice storage takes the most responsibilities for the HVAC loads. Therefore, only DR_{lm} is considered to further reduce the building loads in this period.
 - ii) If $B_{U1} < p \leq B_{U2}$, the electricity price is slightly lower than the previous condition, the ice storage is switched to the cool-and-discharge mode with a DR_{hvac} program. Because the lighting and miscellaneous loads would have the first priority to be retained compared to the HVAC loads in the lower price period as people's works mostly rely on the lighting,

plug loads, equipment, etc. Thus, only the DR_{hvac} program is triggered at this stage to compensate for the cost of providing cooling service from the grid power.

- iii) Next, if $\bar{p}_{ema} < p \leq B_{U1}$, price further decreases, the cool-and-discharge mode without other DRs is carried out to ensure the good working environment where the required power for HVAC loads is shared by the grid and ice storage system.
 - iv) If $p \leq \bar{p}_{ema}$, price becomes reasonable, the cooling-only mode is operated for the normal cooling process without any DR programs.
 - v) Besides, if $p \leq p_{setc}$, the ice storage is allowed for charging back to the required status, therefore, the cool-and-charge mode is operated during the working hours.
 - vi) If $S_{ice} \leq S_{ice,min}$ or $S_{ice} = S_{ice,max}$, ice storage is not available for discharging or charging, the system is switched to the normal cooling process, i.e., cooling-only mode.
- 3) For the non-working hours, the HVAC system is turned off.
- i) Then, the ice storage is switched to charge-only mode only if $p \leq p_{setc}$ and $S_{ice} < S_{ice,max}$ where the price is acceptable and the storage is not full.
 - ii) Otherwise, the ice storage system operates in the OFF-mode.
- 4) At the end, Algorithm 1 checks for the simultaneous charging commands from the battery and ice storage. In this case, the battery is allowed to charge first before the ice storage to avoid the peak load caused by charging them concurrently.

Algorithm 1: Smart price-priority strategy for coordinated control of ice storage with DR_{lm} and DR_{hvac} events

Input: $p, p_{setc}, \bar{p}_{ema}, B_{U1}, B_{U2}, t, S_{ice}, S_{ice,min}, S_{ice,max}$,

Output: $ice_{mode}, DR_{lm}, DR_{hvac}$

```

1: Initialization: Define working hours (6 am to 10 pm) of HVAC system
2: for  $t = 1$  to 24 do
3:   Calculate  $\bar{p}_{ema}, B_{U1}$  and  $B_{U2}$  by (4.20) to (4.24)
4:   Check the fraction of ice available in the tank ( $S_{ice}$ ).
5:   if HVAC operates in working hours then
6:     HVAC system is turned on.
7:     if  $S_{ice,min} < S_{ice} < S_{ice,max}$  then
8:       if  $p > B_{U2}$  then
9:          $DR_{hvac} = \text{OFF-mode}; DR_{lm} = \text{ON-mode}$ 
10:         $ice_{mode} = \text{discharge-only mode}$ 
11:       else if  $B_{U1} < p \leq B_{U2}$  then
12:          $DR_{hvac} = \text{ON-mode}; DR_{lm} = \text{OFF-mode}$ 
13:          $ice_{mode} = \text{cool-and-discharge mode}$ 
14:       else if  $\bar{p}_{ema} < p \leq B_{U1}$  then
15:          $DR_{hvac} = \text{OFF-mode}; DR_{lm} = \text{OFF-mode}$ 
16:          $ice_{mode} = \text{cool-and-discharge mode}$ 
17:       else if  $p \leq \bar{p}_{ema}$  then
18:          $DR_{hvac} = \text{OFF-mode}; DR_{lm} = \text{OFF-mode}$ 
19:          $ice_{mode} = \text{cooling-only mode}$ 
20:       end if
21:       if  $p \leq p_{setc}$  then
22:          $ice_{mode} = \text{cool-and-charge mode}$ 
23:       end if
24:     else
25:        $ice_{mode} = \text{cooling-only mode}$ 
26:     end if
27:   else
28:     HVAC system is turned off.
29:     if  $p \leq p_{setc}$  and  $S_{ice} < S_{ice,max}$  then
30:        $ice_{mode} = \text{charge-only mode}$ 
31:     else
32:        $ice_{mode} = \text{OFF-mode}$ 
33:     end if
34:   end if
35:   Check battery status, ice storage stop charging when battery needs to charge.
36: end for
37: return  $ice_{mode}, DR_{lm}, DR_{hvac}$ 

```

4.1.4.2 Algorithm 2: Control algorithm for DR_{hvac} and DR_{lm} events

Before introducing the proposed Algorithm 2 for implementing the DR in the events of DR_{hvac} and DR_{lm} , the standards for natural ventilation and thermal comfort model are presented as follows:

Standards for Natural Ventilation: Algorithm 2 shows a demand responsive control algorithm for DR_{hvac} and DR_{lm} events where a hybrid cooling-and-ventilation strategy for DR_{hvac} is developed by considering 90% acceptability under ASHRAE Standard 55-2010 [137]. This DR_{hvac} program applies to the HVAC4 system which occupies 15.67% of the entire building area. In the DR_{hvac} period, the zone operative temperature (T_{op}) can be calculated by (4.41) [127]. Next, the 90% acceptability limit is formulated in (4.42), which forms an upper boundary of the zone operative temperature for a typical summer day.

$$T_{op} = 0.31 * T_{oa,ave} + 17.8 \quad (4.41)$$

$$T_{op,up} = 0.31 * T_{oa,ave} + 17.8 + 2.5 \quad (4.42)$$

where $T_{oa,ave}$ is the monthly mean outdoor air dry-bulb temperature and $T_{op,up}$ is the upper limit of the zone operative temperature under 90% acceptability standard.

Thermal Comfort Model: The thermal comfort model allows one to conduct an energy analysis on the zones of building while determining whether the environmental control strategy is sufficient to make the occupants thermally comfortable. The Fanger's comfort model is the first thermal comfort model developed in 1967 and then updated subsequently [138]. It introduces a predicted mean vote (PMV) index to indicate the occupants' thermal comfort in a zone. The PMV index has the following thermal comfort indications: +1, +2, +3, -1, -2, and -3 represent slightly warm, warm, hot, slightly cool, cool and cold conditions respectively. This PMV can be calculated as follows [67], [138].

$$PMV = (0.303 \times e^{-0.036 \times \Upsilon_{mr}} + 0.028)(\Upsilon_{occ} - L_{sk} - L_{res} - L_{dry}) \quad (4.43)$$

where

$$\Upsilon_{occ} = \Upsilon_{mr} - \Upsilon_{hl} \quad (4.44)$$

$$L_{sk} = L_{rsw,req} + 0.00305 * (5733.0 - 6.99 * \Upsilon_{occ} - P_{wa}) \quad (4.45)$$

$$\begin{cases} L_{rsw,req} = 0.42 * (\Upsilon_{occ} - 58.2) & \text{for}(\Upsilon_{occ} > 58.2) \\ L_{rsw,req} = 0 & \text{for}(\Upsilon_{occ} \leq 58.2) \end{cases} \quad (4.46)$$

$$L_{res} = (1.7 * 10^{-5}) * \Upsilon_{mr} * (5867 - P_{wa}) + (1.4 * 10^{-3}) * \Upsilon_{mr} * (34 - T_{air}) \quad (4.47)$$

$$L_{dry} = R_{cl} * h_c * (T_{cl} - T_{air}) + 3.96 * R_{cl} * [(0.01 * T_{cl,abs})^4 - (0.01 * T_{mrt})^4] \quad (4.48)$$

PMV is the predicted mean vote index; Υ_{mr} is the metabolic rate per unit area; Υ_{hl} is the rate of heat loss due to the performance of work; Υ_{occ} is the internal heat production rate of an occupant per unit area; h_c is the convective heat transfer coefficient; L_{sk} is the total evaporative heat loss from skin; L_{res} is the rate of respiratory heat loss; L_{dry} is the sensible heat flow from skin; $L_{rsw,req}$ is the rate of heat loss from the evaporation of regulatory sweating at the state of comfort; P_{wa} is the water vapor pressure in ambient air; R_{cl} is the ratio of clothed body; T_{cl} is the clothing surface temperature; T_{air} is the air temperature; $T_{cl,abs}$ is the absolute value of clothing surface temperature; and T_{mrt} is the mean radiant temperature.

By utilizing the standards for natural ventilation and PMV index of Fanger's thermal comfort model, a hybrid cooling-and-ventilation strategy for the DR_{hvac} event is developed in Algorithm 2 which also supports for the DRs of the lighting and miscellaneous loads in the DR_{lm} event. The algorithm is explained as follows:

- The input variables are: HVAC-based demand response (DR_{hvac}) status, demand response of the lighting and miscellaneous loads (DR_{lm}) status, zone operative temperature (T_{op}), upper limit of zone operative temperature ($T_{op,up}$), time index (t), average PMV value of zones in HVAC4 (PMV_{ave}), normal cooling temperature set-point (T_{nor}), controlled lighting loads (L_{light}), controlled miscellaneous loads (L_{misc}), reduced lighting load (μ_{light}), and reduced miscellaneous load (μ_{misc}).
- The outputs are: Controlled lighting loads (L_{light}), controlled miscellaneous loads (L_{misc}), HVAC4 operating status (λ_{hvac4}), nature ventilation status in HVAC4 (λ_{nv}), and the set-points of thermostats in HVAC4 (T_{sn}).

1) The algorithm first calculates T_{op} and $T_{op,up}$ by (4.41) and (4.42).

- 2) Then, PMV_{ave} at time t is evaluated according to the PMV index (calculated by (4.43) to (4.48)) of each zone in the system of HVAC4.
- 3) Next, Algorithm 2 continuously obtains the sensor data, L_{light} , L_{misc} , and T_{nor} from EnergyPlus™. Then, it checks the status of DR_{hvac} and DR_{lm} from Algorithm 1 at time t .
- 4) If $DR_{lm} = \text{ON-mode}$, the DRs of the lighting and miscellaneous loads are activated, the controlled lighting and miscellaneous loads are reduced by μ_{light} and μ_{misc} respectively at time t . Otherwise, no reduction is made on lighting and miscellaneous loads.
- 5) If $DR_{hvac} = \text{ON-mode}$, a HVAC-based DR for the system of HVAC4 is called up where a hybrid cooling-and-ventilation strategy is carried out in such DR event.
 - i) In this case, the natural ventilation is switched on in the system of HVAC4 by setting $\lambda_{hvac4} = \text{OFF-mode}$, $\lambda_{nv} = \text{ON-mode}$, and $T_{sn} = T_{op}$ when $PMV_{ave}^t \leq 0.1$ and none of zones' temperature in the system of HVAC4 exceeds $T_{op,up}$.
 - ii) Otherwise, the cooling service is turned on by setting $\lambda_{hvac4} = \text{ON-mode}$, $\lambda_{nv} = \text{OFF-mode}$, and $T_{sn} = T_{op,up}$. The above commands ensure all zones' temperature not exceeding the upper limit of $T_{op,up}$ by switching the system of HVAC4 between the cooling and natural ventilation modes during the DR_{hvac} period.
- 6) In the normal cooling process, the system of HVAC4 operates in the setting of $\lambda_{hvac4} = \text{ON-mode}$, $\lambda_{nv} = \text{OFF-mode}$, and $T_{sn} = T_{nor}$.
- 7) Since a demand rebound usually occurs after a DR_{hvac} event [67], it is not recommended to set back the thermostat to its normal operating temperature directly. Thus, if $T_{sn}^{t-1} - T_{nor}^t \geq 3$, which implies that the temperature difference between the previous and current intended set-point of thermostats is relatively high, set $T_{sn} = T_{op}$ and keep it for 2 hours before recovering back to T_{nor} where T_{op} is the zone operative temperature calculated by (4.41).

Algorithm 2: Control algorithm for DR_{hvac} and DR_{lm} events

Input: DR_{hvac} , DR_{lm} , T_{op} , $T_{op,up}$, t , PMV_{ave} , T_{nor} , L_{light} , L_{misc} , μ_{light} , μ_{misc}

Output: L_{light} , L_{misc} , λ_{hvac4} , λ_{nv} , T_{sn}

```

1: Initialization: Find  $T_{op}$  and  $T_{op,up}$  by (4.41) and (4.42)
2: for  $t = 1$  to 24 do
3:   Calculate PMV index [67] for each zone and estimate  $PMV_{ave}^t$ 
4:   Get sensor data,  $L_{light}^t$ ,  $L_{misc}^t$ , and  $T_{nor}^t$  from building model in EnergyPlus™.
   Check DR status,  $DR_{hvac}$  &  $DR_{lm}$ , from Algorithm 1
5:   if  $DR_{lm} = \text{ON-mode}$  then
6:      $L_{light}^t = L_{light}^t (1 - \mu_{light})$ ;  $L_{misc}^t = L_{misc}^t (1 - \mu_{misc})$ 
7:   end if
8:   if  $DR_{hvac} = \text{ON-mode}$  then
9:     if ( $PMV_{ave}^t \leq 0.1$ ) and (any zone temperature in the system of HVAC4
   at time  $t$  must not exceed  $T_{op,up}$ ) then
10:       $\lambda_{hvac4}^t = \text{OFF-mode}$ ;  $\lambda_{nv}^t = \text{ON-mode}$ ;  $T_{sn}^t = T_{op}$ 
11:    else
12:       $\lambda_{hvac4}^t = \text{ON-mode}$ ;  $\lambda_{nv}^t = \text{OFF-mode}$ ;
13:       $T_{sn}^t = T_{op,up}$ 
14:    end if
15:  else
16:     $\lambda_{hvac4}^t = \text{ON-mode}$ ;  $\lambda_{nv}^t = \text{OFF-mode}$ 
17:    if  $T_{sn}^{t-1} - T_{nor}^t \geq 3 \text{ }^\circ\text{C}$  then
18:      Hold  $T_{sn}^t = T_{op}$  for 2 hours before back to  $T_{nor}^t$ 
19:    else
20:       $T_{sn}^t = T_{nor}^t$ 
21:    end if
22:  end if
23: end for
24: return  $L_{light}$ ,  $L_{misc}$ ,  $\lambda_{hvac4}$ ,  $\lambda_{nv}$ ,  $T_{sn}$ 

```

This gradually step-down process can effectively reduce the demand rebound effect.

4.2 Results

The proposed smart price-priority strategies, Algorithms 1 and 2, are written in the EMS module of EnergyPlus™ where EnergyPlus Runtime Language (Erl) is used to run the control algorithms based on IF-THEN-ELSE statements and other logic structures [127]. However, EnergyPlus™ alone is not capable of providing

the deterministic optimization for the battery. Thus, CPLEX[®] is used to solve the MILP problem formulated by (4.25) to (4.40) in Section 4.1.3. The simulation time step is set as 1 min/timestep because it is the minimum time step allowed in EnergyPlus[™] to provide the highest resolution of solutions.

In this section, the DR types in the building are categorized as the TES-based DR (DR_{tes}), HVAC-based DR (DR_{hvac}), lighting and miscellaneous loads DR (DR_{lm}). The building studied here is integrated with PVs, WTs, battery, and ice storage system as discussed in Section 4.1.1. There are four ice storage systems having a total capacity of 26.9 GJ. The rated total storage discharging capacity is about 1245.07 kW (mechanical power) with a coefficient of performance (COP) of 3.5. The ice storage devices are constructed in the same way discussed in [20], [70]. The parameters used in the simulations are listed in Tables 4.1 to 4.3 where p_{setc} is a user-defined value that allows the battery and ice storage to charge from the grid power. In this case, it is assumed that the storage units can use the grid power for charging only if electricity price equals or falls below \$0.027/kWh. p_{setd} is estimated as $p_{setd} = (C_{o,bat} + p_{setc}) \times 2$, to compensate the cost of power bought from the grid. It is assumed that the battery has an initial SOC of 90% which would allow the ice storage system charging to the required level before a DR_{tes} event comes since they are not allowed charging simultaneously.

Table 4.1: Parameters of PV Module: LG230M1C [20].

Item	Parameter	Item	Parameter
α_{pv}	0.9	$I_{mx,ref}$	7.81 A
ε_b	1.12 eV	$V_{mx,ref}$	29.5 V
$R_{sh,pv}$	1 M Ω	δ_{sc}	0.001 A/K
$I_{sc,ref}$	8.37 A	δ_{oc}	-0.124 V/K
$V_{oc,ref}$	36.6 V	$T_{oa,noct}^1$	20 °C
$T_{m,ref}$	25 °C	$T_{m,noct}^2$	45 °C
Number of cells in series	60	$\Gamma_{e,noct}^3$	800 W/m ²
Active area	1.6 m ²	$\Gamma_{e,ref}$	1k W/m ²
Total heat capacity	50k J/m ² K	$H_{loss,pv}$	30 W/m ² K

¹ $T_{oa,noct}$ is the ambient temperature under nominal operating cell temperature (NOCT) test

² $T_{m,noct}$ is the cell temperature under NOCT test

³ $\Gamma_{e,noct}$ is the insolation under NOCT test

Table 4.2: Parameters of Wind Turbine.

Description	Parameters
Rated rotor speed	260 rev/min
Rotor diameter	5.5 m
Rotor height	6 m
Number of blades	3
Rated power	10 kW
Rated wind speed	11 m/s
Cut-in wind speed	2.5 m/s
Cut-out wind speed	52.5 m/s
Fraction system efficiency	0.96
Maximum tip speed ratio	5
Annual local average wind speed	3.853 m/s
Height for local average wind speed	10 m
Blade chord area	2.08 m ²
Coefficient of blade drag	0.9
Coefficient of blade lift	0.05

Table 4.3: List of Other Parameters [36], [136].

Parameter	Value	Parameter	Value
$C_{o,bat}$	\$0.0011 /kWh	$C_{in,bat}$	\$97.12 /kW
$C_{o,ice}$	\$0.0002 /kWh	$C_{in,ice}$	\$65.23 /kW
$C_{o,pv}$	\$0.0019 /kWh	$C_{in,pv}$	\$289.90 /kW
$C_{o,wt}$	\$0.0021 /kWh	$C_{in,wt}$	\$1594.45 /kW
n_{bat}	25 years	E_{cap}	2360 kWh
n_{ice}	20 years	l	1.5%
n_{pv}	25 years	η_s	96%
n_{wt}	20 years	τ_m	0.017
μ_{light}	10% [20], [127]	p_{setc}	\$0.027 /kWh
μ_{misc}	10% [20], [127]	p_{setd}	\$0.0562 /kWh
SOC_{req}	90%	$S_{ice,min}$	1%
P_{peak}	285 kW	$S_{ice,max}$	77.5%
$P_{buy,max}$	450 kW		

The case studies are summarized in Table 4.4. It is assumed that the allowed demand response time for DR_{lm} and DR_{hvac} events are limited to 3 hours and 4 hours per day respectively [20], [67], [70], [139]. The various cases are explained as follows:

Table 4.4: Cases and Their Descriptions.

Case	Description
base1	Base load without PV, WT, storage systems, and DRs
base2	Consider building with PV and WT only
base3	Consider building with PV, WT and battery only
c1	Smart coordinated control of facilities in building (proposed)
c2	Uncoordinated control of battery
c3	Uncoordinated control: full TES with DR_{lm}
c4	Uncoordinated control: partial TES with DR_{lm} and DR_{hvac}
c5	Consider global temperature adjustment of building for DR_{hvac}

base1: It is the base load of the building without installing PVs, WTs, and energy storage systems.

base2: It considers the building integrated with PVs and WTs only.

base3: It is the case that building integrated with PVs, WTs, and battery storage where the battery is optimized by MILP model in Section 4.1.3.

c1: It validates the proposed smart coordinated controls of the building facilities including PV, WT, battery, ice storage, DR_{hvac} , and DR_{lm} . This optimal coordinated control method is described in Sections 4.1.2 to 4.1.4.

c2 It considers the uncoordinated control of battery in the building when other facilities are optimally controlled by the proposed method. In this case, the battery discharges at rated power when $p \geq p_{setd}$ and charges at rated power when $p \leq p_{setc}$.

c3 It considers uncoordinated control of TES with other DRs where the ice storage is fully charged before the DR_{tes} event (full ice storage strategy [19], [20]). In the DR_{tes} period, the ice storage operates in the discharged only mode. DR_{lm} is activated at the beginning of DR_{tes} event and ended at 3 hours later. DR_{hvac} is not necessary here as the ice storage handles most of the cooling load in this case.

- c4 It considers uncoordinated control of TES with other DRs where the ice storage is partially charged at 55% of the full tank before the DR_{tes} event (partial ice storage strategy [19], [20]). In the DR_{tes} period, the ice storage operates in the cool-and-discharge mode. DR_{lm} and DR_{hvac} are both activated at the beginning of DR_{tes} event and ended at 3 hours and 4 hours later respectively.
- c5 It shows another DR_{hvac} program available in the literature to evaluate the effectiveness of the developed DR_{hvac} program. In this case, the conventional global temperature adjustment of all zones in a building by 3°C [22]–[25] is considered for the DR_{hvac} event when other facilities are optimally controlled by the proposed method.

Figure 4.8 shows the price bands calculated by (4.20) to (4.24) where the real-time electricity price in a typical summer day at Texas, USA is taken from [135]. It contains the variables: Real-time electricity price (p), exponential moving average of electricity price ($\bar{p}_{ema}$), 1st-boundary (B_{U1}), 2nd-boundary (B_{U2}), allowable price for charging (p_{setc}), and allowable price for discharging (p_{setd}). From Figure 4.8, it is noticed that $p > B_{U2}$ locates in the periods, 6–7 am, 9–10 am, and 1–2 pm. The p in price band $B_{U1} < p \leq B_{U2}$ is observed in the periods, 7–9 am, 10 am–12 nn. During the HVAC’s working hours, $p \leq \bar{p}_{ema}$ is in the periods, 12 nn–1 pm, 2

Figure 4.8: The electricity price with calculated price band.

pm–10 pm. These estimated price bands are used to optimally coordinated control of the building facilities.

Figure 4.9 displays the proposed optimal coordinated controls of the battery, ice storage, DR_{lm} , and DR_{hvac} events in the demand responsive building. The variables in Figure 4.9 include the state of charge (SOC), demand response of the lighting and miscellaneous loads (DR_{lm}), HVAC-based demand response (DR_{hvac}), and ice storage operating mode (ice_{mode}). The ice_{mode} has the following operation modes: $ice_{mode} = 0 \Rightarrow$ OFF-mode, $ice_{mode} = 1 \Rightarrow$ cooling-only mode, $ice_{mode} = 2 \Rightarrow$ cool-and-charge mode, $ice_{mode} = 3 \Rightarrow$ cool-and-discharge mode, $ice_{mode} = 4 \Rightarrow$ charge-only mode, and $ice_{mode} = 5 \Rightarrow$ discharge-only mode. Figure 4.9 depicts that

Figure 4.9: The proposed coordinated controls of demand responsive building loads based on price band. Plot (I): The coordinated controls of ice storage, DR_{lm} , and DR_{hvac} events in building. Plot (II): The coordinated control of battery's status in percentage where negative (-ve): charge; positive (+ve): discharge.

DR_{tes} event happens in the periods 6 am–12 nn and 1–2 pm when $p > \bar{p}_{ema}$. In the DR_{tes} period, DR_{lm} event is actuated in a coordinated manner with the ice storage which operates in the discharge-only mode during the periods, 6–7 am, 9–10 am, and 1–2 pm when $p > B_{U2}$. At the same time, the battery discharges at the rated power for selling any excess power to the grid. On the other hand, the DR_{hvac} event is activated corresponding to the ice storage operating in the cool-and-discharge mode during the periods 7–9 am and 10 am–12 nn when $B_{U1} < p \leq B_{U2}$. Meanwhile, the battery is optimally discharged to satisfy the rest of building loads where the discharged power is not for selling.

Figure 4.10 presents the control process of the HVAC systems in the DR_{hvac} event where the hybrid cooling-and-ventilation strategy (Algorithm 2) is implemented on the system of HVAC4, whereas other HVAC systems operate as usual. In Figure 4.10, T_{sn} and T_{nor} represent the set-points of thermostats in HVAC4 and the normal cooling temperature set-point respectively. In the first DR_{hvac} period (7–9 am), the natural ventilation on HVAC4 is turned on at 7 am with the settings of $\lambda_{hvac4}^t = \text{OFF-mode}$, $\lambda_{nv}^t = \text{ON-mode}$, $T_{sn} = T_{op}$ when the value of $PMV_{ave} \leq 0.1$. In this case, $T_{op} = 26.5^\circ\text{C}$ calculated by (4.41). At around 8 am later, one of zones in the HVAC4 system reaches the upper-temperature limit, $T_{op,up} = 29^\circ\text{C}$ calculated by (4.42). Thus, HVAC4 is turned on with the following settings of $\lambda_{hvac4}^t = \text{ON-mode}$, $\lambda_{nv}^t = \text{OFF-mode}$, $T_{sn} = T_{op,up}$ in the rest of first DR_{hvac} period. The second DR_{hvac} occurs in 10 am–12 nn where the same setting of $\lambda_{hvac4}^t = \text{ON-mode}$, $\lambda_{nv}^t = \text{OFF-mode}$, $T_{sn} = T_{op,up}$ is used since $PMV_{ave} \not\leq 0.1$. After the DR_{hvac} event, T_{sn} is set to T_{op} (26.5°C) for two hours after the DR_{hvac} event as $T_{sn}^{t-1} - T_{nor}^t \geq 3^\circ\text{C}$. This control process is used to release the effect of demand rebound [67] accompanied with the DR_{hvac} event.

Figure 4.11 shows the net purchased power of base1, base2, base3, and the proposed method where negative (-ve): exporting power and positive (+ve): importing power. It is noticed that the building with PV and WT only (base2) helps to reduce the base load (base1) from 6 am–7 pm and around 9–10 pm. The excess powers are sold to the grid during 0–6 am and 10 pm–0 am. Comparing to base2, the proposed method can largely reduce the power demand in the periods of 6 am–12 nn and 1–3 pm. Comparing to base3 where the building integrated with

Figure 4.10: The status of the HVAC systems and calculated average of PMV in the system of HVAC4. Plot (I): The on/off status of HVAC4 and other HVAC systems in building. Plot (II): Calculated average PMV value at the zones in HVAC4. Plot (III): Thermostats' set-points of the HVAC systems.

PV, WT, and battery only, the proposed method extends the zero net purchased power until 3 pm. More powers are sold to the grid during 6–7 am, 9–10 am, and 1–2 pm. These indicate that implementing the additional DR_{tes} , DR_{lm} and DR_{hvac} programs can prolong the battery discharging time and further reduce the building's net operating cost.

Figure 4.12 compares the proposed method in c1 with the uncoordinated control of battery, ice storage, DR_{lm} , and DR_{hvac} in the cases c2, c3, c4. It is noticed that the uncoordinated control of battery in c2 causes the battery using up its energy at the early 12 nn, which results in a large amount of power purchased during 1–3 pm when the electricity price is still relatively high. Thus, a higher building's net operating cost would be expected in c2. Comparing to the uncoordinated control

Figure 4.11: The net purchased power of cases: base load, base with PV + WT, proposed method, and battery only. Plot (I): Net purchased power of base load with or without power generated by PV and WT. Plot (II): Proposed method vs. Base with PV + WT and Battery only.

of TES with DR_{lm} and DR_{hvac} in c3 and c4, c1 has more power selling in the peak periods 9–10 am and 1–2 pm due to the optimally coordinated controls of all building facilities. Before 5 am, the energy consumption of c1 for ice charging is in between of c3 and c4 because of the price-priority strategy in c1 that makes a proper trade-off between the energy consumption and operating cost.

In Figure 4.13, the building load profiles of c1 and c5 are compared. It is noticed that c1 and c5 have similar loading profiles except for the periods 7–9 am and 10 am–1 pm. This is caused by the different DR_{hvac} programs implemented in the coordinated controls of facilities. At 12 nn, there is a peak demand in c5 where the thermostat is directly set back to the normal temperature after the DR_{hvac} event. This is the demand rebound effect described in [67]. On the other hand,

Figure 4.12: The comparison of the proposed method in c1 with the uncoordinated controls in c2, c3, and c4. Plot (I): Battery charge or discharge status where negative (-ve): charge, positive (+ve): discharge. Plot (II): Battery's SOC. Plot (III): Net purchased power from grid.

the demand rebound in c1 is found much lower than c5. One of the reasons is that DR_{hvac} program in c1 deals with this demand rebound effect by gradually decreasing the set-points of thermostats after the DR_{hvac} event.

The building's net operating cost of all cases are summarized in Figure 4.14 which consists of the operating cost of battery (C_{bat}), operating cost of ice (C_{ice}), operating cost of PV (C_{pv}), operating cost of wind turbine (C_{wt}), and net power cost from grid (C_{grid}). It is shown that the proposed method in c1 has the lowest cost among the others. The uncoordinated control of battery in c2 and the uncoordinated control of ice storage with DR_{lm} and DR_{hvac} in c3 and c4, would increase the building's net operating cost accordingly. This is caused by the improper power trading between the building and grid in c2, c3, c4 due to the uncoordinated con-

Figure 4.13: Building load profiles of the hybrid cooling-and-ventilation strategy in c1 and the conventional global temperature adjustment of all zones in the building for HVAC-based DR in c5.

Figure 4.14: The building's net operating cost in various cases.

trols of building facilities. The DR_{hvac} programs in c1 and c5 have a similar net operating cost. It indicates that the hybrid cooling-and-ventilation strategy applied on 15.67% of building area would have similar cost-effectiveness of the global temperature adjustment strategy where the whole building area is affected in the DR_{hvac} event.

Figure 4.15 shows the building's electric load profiles in various cases. In Figure 4.15, comparing to base1–base3, the building with ice storage system in c1–c5

Figure 4.15: Building's electric load profiles in various cases.

would increase the HVAC load of building. As a result, the total energy consumption of the building is increased by installing the ice storage system for DR_{tes} . Comparing c3 and c4, the full ice storage strategy in c3 shows a higher energy consumption but a lower net operating cost, whereas the partial ice storage strategy in c4 has a lower energy consumption but a higher net operating cost. Thus, this chapter introduces the optimal coordinated control method in c1 which can make a proper trade-off between the energy consumption and the net operating cost among these two different ice storage strategies with DR_{lm} and DR_{hvac} events.

Figure 4.16 shows the building's energy resources profiles in various cases that are used to satisfy the building's electric loads. In Figure 4.16, the largest energy sold to the grid is found in c2, but the net operating cost is the highest among other buildings with the storage systems. This shows the importance of coordinated controls for battery optimization in Section 4.1.3.

4.3 Discussions

This chapter has extended the works of [20], [67] to provide a price-based integrated automation model for managing various building facilities. The authors have focused on the issues discussed in [19], [20]: The full ice storage strategy can provide a preminent peak-load shaving during the TES-based DR events but has the highest energy consumption in a day while the partial ice storage strategy has

Figure 4.16: Building's energy resources profiles in various cases.

the lowest energy consumption in a day but unfortunately offer a less peak-load reduction during the TES-based DR events. Thus, a smart price-priority strategy is developed for the ice storage system which operates in a coordinated manner with other building facilities. The proposed method shows a proper trade-off between the peak-load reduction (in terms of net operating cost) and energy consumption in the building. In addition, a hybrid cooling-and-ventilation control algorithm is developed for a HVAC-based DR event. The simulation results show that the proposed hybrid cooling-and-ventilation has a similar performance in that of the conventional global temperature adjustment of all zones in the building, in terms of net operating cost and energy consumption. The future work will integrate the electric vehicle charging model (e.g., [70], [139], [140]) in this price-based integrated automation model to further explore the DR potentials with the increasing trend of electric vehicle penetration in the building.

Chapter 5

Conclusions and Recommendations

This chapter gives an overall conclusion of this thesis. The recommendations for further research in the field of building energy management and Demand Response (DR) are discussed.

5.1 Conclusions

Since the energy efficiency of the building becomes more and more essential around the world, a majority of previous works are carried out based on the planning, scheduling, and dispatching the building's facilities and resources for optimizing the energy consumption of the building. However, if the building design is fixed, the scope for optimizing the energy management system will be reduced. Nowadays, the variable air volume (VAV) type of the centralized Heating, Ventilation, and Air-Conditioning (HVAC) system is widely used in the medium and large size commercial buildings where the building temperature is regulated by the variable airflow rate at a constant supply air temperature. This variable airflow rate in the duct is directly achieved by the operation of a central fan driven by the variable frequency drive (VFD). Thus, the drive control strategy for such application becomes another important factor to improve the energy efficiency of a HVAC system. However, the drive performance study under various HVAC conditions is lacking in the literature.

Chapter 3 has introduced an integrated HVAC and drive model to investigate the drive performance in the HVAC system. It throws light on the energy efficiency

of an induction machine controlled by a model predictive control (MPC) based approach for the central fan application in a HVAC system. Currently, this study is lacking in the literature where the energy efficient HVAC and drive performance are usually studied and considered separately in the previous research works. In Chapter 3, the HVAC system is constructed by a RC-network model which is a gray-box model commonly used in the literature for the controller and algorithm designs. The induction machine is controlled by the model predictive flux control (MPFC) approach developed by Zhang et al. [21] in the recent year. This integrated HVAC and MPFC drive model is constructed in Matlab/Simulink. The simulations have been carried out to study the drive performance under various scenarios in the HVAC system. Although the poor drive performances are observed from the simulation results due to a bigger step size adopted, it presents that the energy efficiency of the drive should not be ignored or considered separately as it is a part of the whole HVAC system. It has also shown that a single drive control strategy cannot guarantee the drive performance under all speed ranges in various scenarios. Different drive control strategies for their respective working range could be studied further to develop a hybrid drive control strategy that would be capable of improving the drive performance at both the full speed and partial-load speed for a central fan application in the HVAC system.

Besides improving the energy efficiency of system components in a HVAC system, optimizing the Building Energy Management System (BEMS) and DR of a building is another most essential way to reduce the building's electricity bill. Previously, many excellent studies concentrate on regulating the HVAC system by changing thermostats of the zones based on the occupants' thermal comfort during a DR event. Some works are related to the MPC controller designs for a HVAC system. However, those studies are restricted to the HVAC system itself, not taking the other building facilities into account during a DR event. Solely optimizing the operation of a HVAC system during the DR event has its own limitations on reducing the building's operating cost. It is often observed that the HVAC load is still a major chunk of energy consumption in the building, even after a HVAC-based DR.

Hence, the thermal energy storage (TES) system is deployed to compensate the remaining HVAC loads for a DR event. The previous works considering both

battery energy storage (BES) and TES in the Energy Management System (EMS) framework usually model and optimize a TES system in the similar way as the battery to charge or discharge the stored energy. However, it is not practical for a real TES system as the energy conversions between electrical and mechanical energies can largely complicate the optimization problem. In addition, a real TES system usually has few operating modes that are often missing in the previous research works. Most importantly, a majority of previous research works discuss integrating renewable energy and multi-storage systems at the utility side but not at the consumer side with demand responsive building. Since they focus on the system optimization for a microgrid instead of the Demand Side Management (DSM) of a building, their optimization framework usually does not consider other DR programs available in the building, such as the Demand Responses (DRs) of HVAC, lighting, internal equipment, plug loads, etc. Those DR programs can change the building's internal thermal loads which not only has an impact on the energy consumption of a HVAC system but also influence the operation of a TES system during a DR event.

Chapter 4 of this thesis sheds light on how the EMS with multi-storage systems can be optimally and coordinately controlled in a demand responsive building by providing a price-based integrated automation model for managing various building loads, renewable energy, and multi-storage systems. This work focuses on the optimization of an EMS framework for the DSM instead of the utility side optimization. It aims at accurately modeling the most realistic commercial building model with the HVAC system, developing an optimal coordinated control strategy for all building facilities in the building energy management system, and minimizing the building's net operating cost with the help of solar photovoltaics (PVs), wind turbine (WT), BES, TES, and other DR programs available in a building using the time-of-use (TOU) price. In addition, Chapter 4 extends the works of [20], [67] and addresses their presented issues for deploying the ice storage system, i.e., the dilemma of using a single full or partial ice storage strategy in the DR event.

The system model is firstly constructed in EnergyPlusTM. Then, it is optimized by a smart price-priority strategy developed in EnergyPlusTM using EnergyPlus runtime language (Erl) and solving a mixed-integer linear programming (MILP)

problem in CPLEX solver. The smart price-priority strategy is responsible to make a smart decision for coordinated control of the TES device, battery, HVAC-based DR, and the DRs of lighting and miscellaneous loads. The deterministic approach, i.e., MILP problem solved by CPLEX, is taken charge of optimizing other building facilities including the battery, PVs, and wind turbines.

The simulation results have shown that the proposed smart price-priority strategy and deterministic approach can make a proper trade-off between the peak-load reduction and energy consumption in a building where the issues concluded in [19], [20] are addressed. It is an intermediate way to optimally dispatch the ice storage together with other building's DR programs. In other words, the proposed method can minimize the building's net operating cost while maintaining the building's energy consumption in a day at the lowest as possible. Moreover, a hybrid cooling-and-ventilation control algorithm has been developed for the HVAC-based DR and its effectiveness is compared with the conventional global temperature adjustment [22]–[25] of all zones in the building. The results have shown that the proposed hybrid cooling-and-ventilation strategy can ensure the cooling comfort unaffected at most of the building areas during a HVAC-based DR event while maintaining the similar energy consumption and building's net operating cost of the conventional HVAC-based DR programs where the whole building temperature is changed for the DR of the HVAC system.

Besides, Chapter 4 also provides a systematical model for a HVAC system which can be used for further studies on the drive performance in Chapter 3. This HVAC system model can generate valuable data to identify the parameters of a RC-network model developed in Chapter 3. Alternatively, it can also be used directly for the drive performance studies by linking it with a physical or simulated drive system together under the Building Controls Virtual Test Bed (BCVTB) platform. In addition, this research work provides additional studies on the building's net operating cost, battery system, wind turbine, and various DRs in the building. It also gives a further understanding of the loading profiles, electricity cost, and energy consumption for the building owner or operator to consider using the different energy management system strategies in their building.

The knowledge obtained in this work will also help researchers to develop their own improved energy management system in the building.

The study of Chapter 4 has also shown that the DR programs may affect the occupants' comfort such as the illuminating, cooling and heating. A larger single storage system or multi-storage system would obviously reduce the side effect of the DR programs. It extends to other important questions that the building operators have to decide whether using a single large storage system, i.e., BES or TES, or adopting both systems to offset any discomfort caused by the DR programs. How to optimally select the type of storage system, system capacity, and the DR programs becomes extremely important to the building operators. For example, if a single BES system with a large enough capacity can satisfy all the building loads during the peak hours, the occupants' comfort would not be affected as it may not need any DR programs in that periods. But the initial investment cost of the single BES system is the highest. If a single TES system with a large enough capacity can satisfy all the cooling and heating loads in the building during the peak hours, the thermal comfort of the occupants would not be affected. The other occupants' comfort such as the illuminating may be deteriorated as the DR programs may be activated to further cut down the building's net operating cost during the peak hours. The initial investment cost for a single TES system would be much lower than that for a single BES system in the same building. Adopting DR programs without considering any storage systems would definitely avoid the initial investment cost for the storage systems. However, the occupants would suffer more discomforts coming from the DR programs in the building. Thus, an optimal balance must be found between the type of storage system, system capacity, and DR programs in the specific building.

5.2 Recommendations for future works

The recommendations for some possible future works related to this thesis are presented as follows:

1. The research work in Chapter 3 is carried out on the basis of simulations, thereby having some challenges and limitations for studying the drive performance under various scenarios in the HVAC system. One of the challenges is

that the integrated HVAC and MPC-based drive model results in a typical numerical simulation problem, namely stiff equation. The stiff equation is a differential equation which is solved by certain numerical methods where an extremely small timestep (i.e., step size) must be used to ensure the stability and accuracy of the solution.

In this particular case, the drive model needs a timestep of at least 10 kHz [21], [113] (i.e., timestep = 0.0001 second) to secure the stable and accurate control of a drive in the MPC approach. On the other hand, the HVAC system requires a timestep of 1–10 minutes which is good enough for controlling a HVAC system. In this case, a timestep of 10 kHz has to be used for simulating the integrated HVAC and drive system model in a study period of 42 minutes, i.e., this integrated model has to be calculated by 2.52×10^7 times to complete this simulation process. Thus, it results in a computation challenge in the simulation process where a normal computer often cannot afford to this joined simulation due to the limited memory size and extremely long computing time.

As a result, analyzing a drive with hourly HVAC system performance seems to be impractical by solely using the simulation model in this case. Hence, in the future study, a physical drive system is needed to be set-up in the laboratory for studying the hourly integrated system performance with a much smaller control timestep such as the timestep of 20 kHz for a MPC-based approach. By coupling a physical drive system with a simulation model of the HVAC system, the control timestep of a drive can be set small enough which improves the accuracy of results as well as mitigates the computation burden of the computer.

2. The model developed in Chapter 4 can be extended to study the performance of a physical drive system described in Chapter 3. The drive control technologies for different components of a HVAC system could be further investigated to improve the energy efficiency of several HVAC units such as pump, fan, chiller, compressor, etc. This extension could be implemented on the BCVTB platform. BCVTB, developed by the Lawrence Berkeley National Laboratory

(LBNL), is a software that connects the simulation program and hardware for co-simulation. It is also a middleware that functions as a bridge between one or more software to overcome and complement the disadvantages of each simulation tool. In this case, the BCVTB (Ptolemy II model) could provide the platform for a building model constructed in EnergyPlusTM to communicate with the hardware, i.e., a physical drive system.

3. Due to technological advances and environmental concerns, the penetration of electric vehicles (EVs) is growing fast. The public charging infrastructure is necessary to be in conjunction with residential plug-in electric vehicle (EV) charging to reduce the range anxiety of the electric vehicles and promote their adoption. Few feasible options including integrating renewable energy, implementing DR programs, and dispatching energy storage devices could effectively minimize the impact of widespread EV penetration on the power grid. Thus, future work could consider EV charging model in the developed building model to further explore the DR potentials with the increasing trend of EV penetration in the building. It could facilitate further exploration of the Buildings-to-Grid (B2G) concept.
4. Much works in the literature have proved that the energy storage system can effectively reduce the building's net operating cost and reduce the discomfort caused by the DR programs. It is believed that most of the building operators would have a question on how to select the energy storage systems for minimizing their daily net operating costs. Different types of building may need their respective optimal installation or operation of the BES, TES or multi-storage system. Thus, in the future work, it is recommended to develop an algorithm or framework which can help the building operators to make the optimal selection of the system capacity, the type of storage system, and the operation of the DR programs for the specific application.

Author's Publications

Journal Publications

1. **H. Zhang**, P.L. So, and A. Ukil, "Smart Building Energy Management with Multi-storage Systems for Demand Response," *IEEE Transactions on Sustainable Energy*, 2019. (under revision)

Conference Publications

1. **H. Zhang** and A. Ukil, "Model Predictive Control of Induction Machine for Energy Efficient HVAC Operation," in *2018 IEEE Innovative Smart Grid Technologies –Asia (ISGT Asia)*, 2018, pp. 1068–1073
2. **H. Zhang**, A. Ukil, and Y. Li, "Analyzing refrigerant contaminants and reclamation service to prolong chiller lifespan and improving chiller energy efficiency," in *IECON 2017 – 43rd Annual Conference of the IEEE Industrial Electronics Society, 2017*, pp. 7085–7090.
3. **H. Zhang** and A. Ukil, "Analysis of ambient temperature effects and air-flow rate for energy efficient HVAC in buildings," in *2016 IEEE Region 10 Conference (TENCON)*, 2016, pp. 441–446.
4. **H. Zhang** and A. Ukil, "Framework for multipoint sensing simulation for energy efficient HVAC operation in buildings," in *IECON 2015 – 41st Annual Conference of the IEEE Industrial Electronics Society, 2015*, pp. 000398–000403.

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