Model predictive control for energy efficiency and occupant well-being optimisation in tropical buildings

Yang, Shiyu

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**MODEL PREDICTIVE CONTROL FOR ENERGY
EFFICIENCY AND OCCUPANT WELL-BEING
OPTIMISATION IN TROPICAL BUILDINGS**

**YANG SHIYU
SCHOOL OF MECHANICAL AND AEROSPACE ENGINEERING
MARCH 2020**

**Model Predictive Control for Energy
Efficiency and Occupant Well-being
Optimisation in Tropical Buildings**

Yang Shiyu

School of Mechanical and Aerospace Engineering

A thesis submitted to the Nanyang
Technological University Singapore in
partial fulfilment of the requirement for
the degree of Doctor of Philosophy

March 2020

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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Yang Shiyu

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.

17/Mar/2020

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Date

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Assoc Prof Wan Man Pun

Authorship Attribution Statement

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

Chapter 3 is published as:

- (1) Yang, S., Wan, M.P., Ng, B.F., Zhang, T., Babu, S., Zhang, Z., Chen, W., Dubey, S. (2018). A state-space thermal model incorporating humidity and thermal comfort for model predictive control in buildings. *Energy and Buildings*, 170, 25-39.
- (2) S. Yang, M. P. Wan, B. F. Ng, Z. Zhang, A. Lamano, W. Chen. (2018) “Modelling and model calibration for model predictive occupants comfort control in buildings. In Proceedings of IBPC 2018, Syracuse, NY, USA.

The contributions of the co-authors for Paper (1) are as follows:

- Prof Wan provided the initial project direction.
- I prepared the manuscript drafts. The manuscript was revised together with Prof Wan and Prof Ng.
- I developed the building modelling method for buildings with fan coil unit air-conditioning systems and the model predictive control formulation. I also performed the simulation to study the performance of the developed building model and model predictive control.
- I performed data analysis together with Ms. Chen to evaluate the performance of the developed building model and model predictive control.
- Mr. Babu and Ms. Zhang Zhe assisted in the extraction of measured data in the test facility.
- Dr. Zhang Tian and Dr. Dubey assisted in the weather data for simulation.

The contributions of the co-authors for Paper (2) are as follows:

- Prof Wan provided the initial project direction.
- I prepared the manuscript drafts. The manuscript was revised with Prof Wan and Prof Ng.

- I developed the modelling method for buildings with active chilled beam air-conditioning systems. I also performed the model calibration and validation to refine the developed building model.
- I performed simulation and data analysis together with Ms. Chen to evaluate the performance of the developed building model.
- Mr. Lamano and Ms. Zhang Zhe assisted in the extraction of measured data in the test facility.

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- (3) Yang, S., Wan, M. P., Ng, B. F., Dubey, S., Henze, G. P., Rai, S. K., Baskaran, K. (2019). Experimental study of a model predictive control system for active chilled beam (ACB) air-conditioning system. *Energy and Buildings*, 203, 109451.

The contributions of the co-authors for Paper (3) are as follows:

- Prof Wan provided the initial project direction.
- I prepared the manuscript drafts. The manuscript was revised with Prof Wan, Prof Ng and Prof Henze.
- I developed the MPC system and lead the experimental setup and experimental study.
- I performed data analysis together with Ms. Chen to evaluate the performance of the developed MPC system.
- Dr. Dubey, Mr Rai and Mr. Baskaran assisted in the experimental setup.

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- (4) Yang, S., Wan, M. P., Ng, B. F., Dubey, S., Henze, G. P., Chen, W., Baskaran, K. (2020). Experimental study of model predictive control for an air-conditioning system with dedicated outdoor air system. *Applied Energy*, 257, 113920.

The contributions of the co-authors for Paper (4) are as follows:

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- I prepared the manuscript drafts. The manuscript was revised with Prof Wan, Prof Ng and Prof Henze.

- I developed the MPC system and lead the experimental setup and experimental study.
- I performed data analysis together with Ms. Chen to evaluate the performance of the developed MPC system.
- Dr. Dubey and Mr. Baskaran assisted in the experimental setup.

12/Mar/2020

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Date

杨诗雨

.....

Yang Shiyu

Abstract

Conventional building automation and control (BAC) systems employ reactive feedback control, such as proportional-integral-derivative (PID), which limits the efficiency in managing building energy and dealing with the contrasting need for human well-being and energy efficiency. Model predictive control (MPC), which brings forward prediction and optimization capabilities on the principles of closed-loop control to BAC, gains extensive attention as a solution to such limitations, allowing optimisation of building energy efficiency and indoor climate.

This study proposes an MPC system based on a building-physics-based modelling approach to formulating a state-space model (SSM) that captures the building dynamics and quantitative occupant comfort indices. The system incorporates real-time optimization for energy efficiency and occupant comfort, which requires less than 0.1 s for solving the optimisation problem in each control interval. The proposed MPC system was implemented in two test buildings, the Building and Construction Authority (BCA) SkyLab and Lecture Theatre 3 (LT3) on the campus of NTU. The control characteristics and performance of the MPC system were evaluated and compared to conventional BAC systems under different air-conditioning and mechanical ventilation (ACMV) systems including fan coil unit (FCU), active chilled beam (ACB), air-handling unit (AHU) as well as separate sensible and latent cooling (SSLC) with dedicated outdoor air system (DOAS). The MPC system achieved 15 – 20% of electricity savings for the ACMV systems with improved occupant comfort, compared to conventional BAC systems. The MPC system was further developed to perform coordinated control of multiple building systems (air-conditioning, lighting and shading) by incorporating extra models for predicting indoor lighting power and visual comfort. The MPC system achieved

up to 20.3% of building electricity savings with great improvements in thermal and visual comfort.

In order to enhance the adaptability of the MPC system to the transient nature of building operation, machine learning (ML) technology was adopted to develop an adaptive ML-based building model, which was initialised by historical building operation data and continuously updated using online building operation data. An adaptive MPC system employing such model was developed and implemented in a test office. The MPC system achieved 59% cooling energy saving compared to the conventional thermostat control. This study also explored the feasibility of developing a full ML controller by supervised learning of the control laws of the MPC system using the building operation data generated by the MPC system. The ML controller retained the high thermal comfort performance and 86% of the energy saving performance of the master MPC system.

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Nomenclature

Abbreviation	Description	Unit
ACB	Active Chilled Beam	-
ACMV	Air-Conditioning and Mechanical Ventilation	-
AHU	Air-Handling Unit	-
AMPC	Adaptive Model Predictive Control	-
ANN	Artificial Neural Network	-
API	Application Programming Interface	-
BAC	Building Automation and Control	-
BCA	Building and Construction Authority	-
BMS	Building Management System	-
BTU	British Thermal Unit	-
CAV	Constant Air volume	-
COP	Coefficient of Performance	-
CSD	Constant Speed Drive	-
DALI	Digital Addressable Lighting Interface	-
DAQ	Data Acquisition	-
DDC	Direct Digital Control	-
DGP	Daylight Glare Probability	-
DGU	Double Glazed Unit	-
DOAS	Dedicated Outdoor Air System	-
EC	Electrochromic	-
FAD	Fresh Air Damper	-
FCU	Fan Coil Unit	-
FDM	Finite Difference Method	-
HDR	High Dynamic Range	-
HVAC	Heating, Ventilation, and Air Conditioning	-
I/O	Input/Output	-
LDR	Low Dynamic Range	-
LED	Light-Emitting Diode	-
MAD	Mean Absolute Deviation	-
MAE	Mean Absolute Error	-
MAPE	Mean Absolute Percentage Error	-

ML	Machine Learning	-
MPC	Model Predictive Control	-
NAC	North Academic Complex	-
NARX	Nonlinear Autoregressive Exogenous	-
NTU	Nanyang Technological University	-
OPC	Open Platform Communication	-
P	Proportional	-
PAU	Primary Air-handling Unit	-
PI	Proportional-Integral	-
PID	Proportional-Integral-Derivative	-
PLC	Programmable Logic Controller	-
PMV	Predicted Mean Vote	-
PPD	Predicted Percentage of Dissatisfied	-
PWA	Piecewise Affine	-
RAD	Return Air Damper	-
RC	Resistance-Capacitance	-
RH	Relative Humidity	-
SD	Standard Deviation	-
SHGC	Solar Heat Gain Coefficient	-
SISO	Single-Input-Single-Output	-
SQP	Sequential Quadratic Programming	-
SSE	Sum-Square Error	-
SSLC	Separate Sensible and Latent Cooling	-
SSM	State-Space Model	-
THPL	Temperature-Humidity-Pressure-Lux	-
VAV	Variable Air Volume	-
VLT	Visible Light Transmittance	-
VSD	Variable Speed Drive	-
WWR	Window-To-Wall Ratio	-
Symbol	Description	Unit
$\widehat{PMV}$	Normalised PMV	-
$\hat{Q}$	Normalised heat flowrate	-
$\dot{m}$	Mass flow rate	kg/s

<i>A</i>	Area	m ²
<i>A</i>	State matrix	-
<i>B</i>	Input matrix	-
<i>c</i>	Coefficient	-
<i>C</i>	Thermal capacitance	J/K
<i>C</i>	Output matrix	-
<i>conc</i>	CO ₂ concentration	m ³ /m ³
<i>CONS</i>	Constant	-
<i>D</i>	Feedthrough matrix	-
<i>dls</i>	Daylight sensor	-
<i>E</i>	Illuminance	lux
<i>ECR</i>	Equal Concern for the Relaxation	-
<i>EP</i>	Electric power	W
<i>f()</i>	Function	-
<i>f</i>	Factor	-
<i>G</i>	Volume flow rate	m ³ /s
<i>h</i>	Heat transfer coefficient	W/K-m ²
<i>H</i>	Enthalpy	J
<i>hod</i>	Hour of the day	-
<i>I</i>	Irradiance	W/m ²
<i>Ins</i>	Insulation	clo
<i>J</i>	Objective function	-
<i>k</i>	Index variable	-
<i>Kt</i>	Sky clearness index	-
<i>L</i>	Latent heat of water	J/kg
<i>ℓ</i>	Cost function	-
<i>LE</i>	Luminous efficacy	lux/W
<i>m</i>	Mass	kg
<i>M</i>	Metabolic rate	W
<i>N</i>	Prediction horizon	-
<i>os</i>	Operation status	-
<i>p</i>	Pressure	Pa
<i>PMV</i>	Predicted mean vote	-

PWC	Atmospheric perceptible water content	-
Q	Heat flow rate	W
q	Heat flux	W/m ²
R	Thermal resistance	K/W
r	Reflectivity of visual light	%
RH	Relative humidity	%
S	Source volume generation rate	m ³ /s
t	Time	s
T	Temperature	K
u	Input variable	-
VLT	Visible light transmittance	%
W	Weighting factor	-
x	State variable	-
y	Output variable	-
α	absorptance	%
ϵ	Slack variable	-
σ	Stefan-Boltzmann constant	-
$\mathcal{U}$	Constraints of inputs	-
$\mathcal{X}$	Constraints of states	-
$\mathcal{Y}$	Constraints of outputs	-
ε	Surface emittance	%
θ	Angle	°
τ	Transmittance	%
ψ	Humidity ratio	kg/kg
Subscript	Description	Unit
abs	Absorbed	-
air	Air	-
$alti$	Solar altitude	-
am	Air mass	-
$beam$	Solar beam	-
CB	Chilled beam	-
cb	Circumsolar brightening	-
clo	Cloth	-

<i>cond</i>	Conduction	-
<i>conv</i>	Convection	-
<i>cw</i>	Chilled water	-
<i>dif</i>	Diffuse	-
<i>diff</i>	Difference	-
<i>dir</i>	Direct	-
<i>dl</i>	Daylight	-
<i>em</i>	Exterior thermal mass	-
<i>env</i>	Envelope	-
<i>es</i>	Exterior surface	-
<i>et</i>	Extraterrestrial solar irradiance	-
<i>evap</i>	Evaporation	-
<i>fa</i>	Fresh air	-
<i>gap</i>	Air gap	-
<i>glo</i>	Global	-
<i>gro</i>	Ground	-
<i>hb</i>	Horizon brightening	-
<i>hor</i>	Horizon	-
<i>i</i>	Index	-
<i>im</i>	Interior thermal mass	-
<i>inc</i>	Incident	-
<i>incl</i>	Inclined	-
<i>int</i>	Internal	-
<i>is</i>	Interior surface	-
<i>j</i>	Index	-
<i>k</i>	Index	-
<i>l</i>	Index	-
<i>lig</i>	Lighting	-
<i>ma</i>	Mixed air	-
<i>max</i>	Maximum	-
<i>mea</i>	Measurement	-
<i>min</i>	Minimum	-
<i>moi</i>	Moisture	-

<i>mr</i>	Mean radiant	-
<i>n</i>	Number	-
<i>o</i>	Outdoor	-
<i>occ</i>	Occupants	-
<i>pred</i>	Prediction	-
<i>ra</i>	Return air	-
<i>rad</i>	Radiation	-
<i>ref</i>	Reference	-
<i>res</i>	Respiration	-
<i>sa</i>	Supply air	-
<i>sb</i>	Sky brightness	-
<i>sen</i>	Sensible	-
<i>skin</i>	Skin surface	-
<i>sol</i>	Solar radiation	-
<i>sp</i>	Set point	-
<i>sur</i>	Surface	-
<i>t</i>	Time	-
<i>the</i>	Thermal	-
<i>tilt</i>	Tilt	-
<i>tra</i>	Transmitted	-
<i>vap</i>	Vapour	-
<i>win</i>	Window	-
<i>work</i>	External work	-
<i>wp</i>	Work plane	-
<i>z</i>	Thermal zone	-
<i>zen</i>	Solar zenith	-

Part I Introduction and Literature Review

Chapter 1 Introduction

1.1 Background and motivations

The proportion of the world's population living in urbanised areas is continuously increasing and has reached 55% [1.1]. The number is forecasted to keep increasing and reaching 68% by 2050 [1.1]. The growth of the urban population results in an increase in the density of urban buildings, which are increasingly relying on different building services to provide comfortable and healthy indoor environments [1.2]. The growing demand for the built environments leads to the building sector being the largest energy consumer worldwide. In the U.S., the energy consumption of the building sector accounts for 39% of the total final energy of the nation [1.3]. In E.U., the building sector also consumes the largest portion of energy, around 40% of the total final energy consumption or 55% of electricity consumption [1.4]. In Singapore, 37% of the nation's electricity is consumed by the building sector [1.5] as shown in Figure 1.1. The energy consumed by buildings is largely attributed to heating, ventilation, and air-conditioning (HVAC) that accounts for around 50% of the final energy consumption in buildings, followed by lighting systems, which constitutes 20% of the remaining energy consumption in buildings worldwide [1.2][1.6][1.7]. In Singapore, the energy consumption of air-conditioning and mechanical ventilation (ACMV) systems takes up 70% of the electricity in buildings, due to the hot and humid tropical coastal climate [1.8], followed by lighting systems that consume 15% of building electricity.

Figure 1.1 Breakdown of electricity consumption of the nation and building sector in Singapore [1.5][1.8]

Various efforts have been taken in different countries to drive buildings to be more energy-efficient. The U.S. has proposed to achieve net-zero-energy for all new federal buildings by 2030 [1.9]. E.U. requires all new buildings to be nearly net-zero-energy by the end of 2020 and all new public buildings must be nearly net-zero-energy by 2018 [1.10]. In Singapore, a national target to green at least 80% of Singapore's building stock by 2030 was set to address the growing energy consumption in buildings [1.11]. To achieve the targets, one promising direction is to upgrade current building automation and control (BAC) systems or building management systems (BMS), which are often criticised for inefficiency in building energy management [1.12].

Conventional feedback control strategies including on/off, proportional (P), proportional-integral (PI), and proportional-integral-derivative (PID) are widely used in current BAC practice. The conventional feedback control is based on the so-called 'respond-to-current-state' reactive control approach [1.13]. For instance, a PID controller calculates an error between the desired set point and a measured process variable and generates a correction for control signals based on the error. However, due to the simplicity and absence of knowledge of the controlled

system in the reactive control approach, the control performance of the conventional control is poor for dynamic systems. Thus, it is challenging for BAC systems employing conventional feedback control to handle building dynamics in managing building energy and indoor environment. In buildings, ACMV systems are typically regulated to achieve a temperature set point of room air in spite of the fact that thermal comfort is determined by many factors including room air temperature, humidity, radiant temperature, air velocity, occupants' metabolic rate and clothing insulation. Thus, indoor conditions regulated by conventional feedback control always have a certain deviation to the actual thermal neutral. In addition, the conventional feedback control including the above-mentioned PID is a non-integrated control approach and typically for Single-Input-Single-Output (SISO) systems. Thus, the conventional control is not able to perform coordinated control of multiple systems, such as ACMV, lighting and shading systems in buildings.

Model predictive control (MPC) provides an alternative to the current conventional feedback control [1.14]. MPC exploits a building model and measured/predicted disturbances (internal and external loads) to perform anticipation of future responses of the building. MPC minimises a cost function to obtain the best control strategies in a prediction horizon with the model-based prediction capacity. By employing a comprehensive thermal sensation model such as predicted mean vote (PMV), MPC is capable of optimising the real thermal comfort in buildings instead of a single temperature set point in conventional BAC systems. By employing multiple terms in a cost function, MPC is able to perform multi-objective (e.g., thermal comfort, visual comfort and energy saving) optimisation and coordinated control of multiple building systems (e.g., ACMV, lighting and shading systems). Thus, MPC for BAC applications is an attractive direction to promote building efficiency toward the next stage.

Many previous studies had used MPC for controlling building systems, especially for HVAC/ACMV systems, and demonstrated its capability to achieve substantial energy saving and significant improvement of human comfort. However, the application of MPC to buildings in tropical Singapore is rarely studied. Due to the hot and humid climate with high solar radiation, advanced building systems including separate sensible and latent cooling (SSLC), automated lighting and automated shading are needed for buildings in tropical Singapore. Thus, this thesis investigates the applications of MPC to control these systems including SSLC, automated lighting and automated shading in tropical buildings for optimizing energy efficiency and occupant well-being.

1.2 Objectives and research scope

The objective of this thesis is to investigate the application of MPC to control the service systems in tropical buildings by developing intelligent BAC systems using model predictive control technology and evaluating the control performance. The research scope of the thesis includes the following:

- i. Develop a simplified building-physics-based model capturing building dynamics and human comfort for real-time optimisation and control.
- ii. Develop an MPC system for coordinated building services control including ACMV, lighting and shading systems based on the developed building model
- iii. Implement the MPC system in real buildings for controlling different building systems including conventional single-coil ACMV systems [fan coil unit (FCU) and air-handling unit (AHU)], separate sensible and latent cooling (SSLC) air-conditioning systems

[active chilled beam (ACB) and dedicated outdoor air system (DOAS)], automated dimming system and automated shading system to investigate the control performance.

- iv. Further develop the MPC system by merging MPC and machine learning (ML) technologies in two approaches, 1) employ ML-based building model instead of a physics-based building model for constructing MPC, and 2) approximate the control laws of MPC using ML without the need of solving the optimisation problem. The two approaches to merge ML and MPC technologies for BAC applications are validated through experiments.

1.3 Thesis Outline

This thesis contains five parts. Part I presents an introduction and literature review for this study. Chapter 2 reviews the theory of MPC and its application for BAC, discusses the research gaps in the literature and summarizes the novelties of this study. The comparison of MPC and conventional control is illustrated. Methodologies for developing MPC for BAC applications including building modelling and MPC formulation are introduced.

Part II presents the procedure of developing an MPC controller for optimising building energy consumption and indoor thermal comfort. Chapter 3 proposes a building-physics-based modelling approach to develop an integrated linear state-space model (SSM) capturing building dynamics and thermal comfort. The developed SSM was calibrated and validated against the measured building data. A multi-objective MPC formulation was developed to optimise building energy efficiency and indoor thermal comfort. An MPC controller using the developed SSM and MPC formulation was developed and tested by several simulation cases based on the physical model of a test facility [Building and Construction Authority (BCA) SkyLab].

Chapter 3 presents the implementation of MPC, which is developed based on the SSM and MPC formulation described in Part II, for controlling conventional single-coil air-conditioning systems (FCU and AHU) and SSLC air-conditioning systems (ACB and DOAS). Chapter 4 develops an MPC system for controlling FCU and ACB air-conditioning systems and the MPC controllers were implemented in the SkyLab test facility. The MPC controller for the FCU is the same as that developed in Part II. The MPC controller for the FCU system was further developed for controlling the ACB system. The control performance of the MPC system was compared to the original conventional control based BMS. Chapter 5 develops an MPC system for controlling an AHU and DOAS air-conditioning systems, respectively. The MPC system was implemented in Lecture Theatre 3 (LT3) in the North Academic Complex building on the campus of Nanyang Technological University (NTU). The MPC controller for the AHU employs the same MPC formulation as proposed in Part II and an SSM of the test room (LT3). The MPC controller for AHU was further developed for controlling the DOAS air-conditioning system. The control performance of the MPC system was compared to the original conventional control based BMS of the test building.

In Part IV, an MPC system is developed for coordinated control of multiple building systems including ACMV, lighting and shading systems. The MPC system was implemented in the SkyLab test facility. In addition to the SSM of the test facility, a lighting power prediction and a visual comfort prediction models were also developed for constructing the MPC system. The MPC system was implemented in SkyLab to regulate the ACB system and an electrochromic (EC) window coordinating with an automated dimming system to optimise the building energy consumption, indoor thermal comfort and indoor visual comfort. The control performance of the MPC system was compared to the original conventional BMS of SkyLab.

Part V investigates the merging of MPC and ML techniques for BAC applications. Chapter 7 proposes an MPC with an adaptive ML-based model for BAC applications by combining MPC, ML and adaptive modelling techniques. The adaptive ML-based model is initially trained using historical building operation data and is continuously updated using online building operation data as the MPC system is operating. The MPC controller was implemented in an office on the campus of NTU to control a variable air volume (VAV) box. The control performance of the MPC controller was compared to the original thermostat in the office. Chapter 8 develops an ML controller, which was trained by supervised learning based on the measured building operation data of the MPC controller developed in Chapter 7 to approximate the control laws of the MPC controller. The ML controller could generate near-optimal control for buildings based on measured inputs directly without the need to solve the optimisation problem. The ML controller was implemented in the same office as used in Chapter 7. The control performance of the ML controller was compared to the thermostat and the MPC controller.

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Chapter 2 Literature Review

2.1 Conventional control

The current practice of BAC systems is the conventional feedback control scheme including on/off control, P control, PI control, PID control, etc. [2.1][2.2]. Conventional feedback control has been widely used in BAC systems, typically working as thermostat, humidistat and pressostat [2.3], for decades due to the simplicity of its control logic. On/off control, which is the simplest closed-loop control, uses simple logic (if...else...) to switch on/off of a controlled system according to the lower/upper threshold of a measured feedback variable [2.4]. P/PI/PID controllers calculate an error value, which is the difference between the desired set point and a measured process variable, and apply a correction for control signals based on the parameters in P/PI/PID controllers [2.4] as illustrated in Figure 2.1. The simple logic behind the conventional control allows it to be largely used for controlling cooling coils, heaters, dampers and fans in buildings.

Figure 2.1 Concept of PID control

However, the simplicity in the control logic of the conventional control results in several limitations. Firstly, due to the simple reactive control approach without knowledge of the controlled system, conventional feedback control has poor control performance for dynamic systems [2.5]. Many studies had [2.6][2.7][2.8] tried to solve this issue by tuning parameters

in the conventional feedback controllers. However, the parameters tuning procedure could be time-consuming and re-tuning is required for large ACMV systems with multiple conventional feedback controllers as mentioned by Guo et al. [2.9]. Secondly, conventional feedback control is not able to handle disturbances as the feedback is only the error between the set point and the measured state of the controlled system. Thus, for buildings controlled by conventional feedback controllers, disturbances such as change of weather and internal load could cause large fluctuation of indoor conditions. Next, the way to control indoor environment by conventional feedback control is usually to pursue a set point of room air temperature without considering other key factors affecting occupants' thermal sensation including humidity, radiant temperature, air velocity, occupants' metabolic rate and clothing insulation. Besides, conventional control is typically used for a single-input-single-output (SISO) system without considering interactions between different systems [2.4]. The limitations of conventional control could lead to buildings operating at low energy efficiency and poor indoor environments [2.3][2.10].

2.2 Model predictive control

MPC is an advanced process control technology, which has been widely applied to industry [2.11]. The key feature of MPC is that it exploits a predictive model of the controlled system to anticipate and optimise future responses of the controlled system in a prediction horizon (t , $t+k$) incorporating predicted/measured disturbances (e.g., weather and internal loads), as shown in Figure 2.2. This means that MPC is capable of considering future information for optimisation and control. Thus, MPC could generate the optimal future control inputs for the controlled system in the prediction horizon with the prediction ability and minimising a cost function. A key feature of MPC differentiating it from other optimal control technologies is that it merges the principles of both feedback control and optimisation. MPC employs a

receding optimisation technique to repeat the optimisation procedure at each control interval to avoid the accumulation of control errors. At each control interval before the optimisation, the measured outputs of the controlled system could be fed back to MPC to update the state parameters of the predictive model to compensate for the prediction errors in the last control interval. A general MPC problem is described by Equations (2.1), (2.2) and (2.3).

$$\text{Minimise} \quad J = \sum_t^{t+n} \ell(x(t), u(t), y(t)), \quad (2.1)$$

$$\text{Subject to} \quad u(t+k) \in \mathcal{U}, x(t+k) \in \mathcal{X}, y(t+k) \in \mathcal{Y}, \quad (2.2)$$

and,

$$x(k+1) = f(x(t), u(t)); y(k) = f(x(t), u(t)). \quad (2.3)$$

In Equations (2.1) - (2.3), symbols x , u , y , N , t , k , $f()$, ℓ , $\mathcal{U}$, $\mathcal{X}$ and $\mathcal{Y}$ refer to state variable, input variable, output variable, prediction horizon, current time, index of time, function, cost function, constraints of inputs, constraints of states, constraints of outputs, respectively.

Figure 2.2 Concept of model predictive control

The framework and key elements of MPC for BAC applications are illustrated in Figure 2.3. MPC for BAC applications employs a building model for predicting future responses of the building. Three modelling approaches, including white-box, grey-box and black-box, are widely used for constructing building models for MPC. An objective function is employed in an MPC controller, which is often formulated in a linear or quadratic form. The objective function could include multiple terms such as indoor temperature, thermal comfort, indoor air quality and energy consumption for performing multi-objective optimisation. For MPC employing a linear building model, linear or quadratic programming is often used for solving the linear optimisation problem. For MPC employing a nonlinear building model, nonlinear optimisation approaches such as mixed-integer programming, sequential quadratic programming and genetic algorithm are used for solving the nonlinear optimisation problem. External and internal disturbances are often integrated into MPC for building control. External disturbances include outdoor air temperature, humidity, solar radiation and dynamic energy price. Internal disturbances include occupancy, lighting and plug loads. For buildings, the

constraints are the capacities of building systems (e.g., cooling power of ACMV system and power capacity of lights), actuator ranges (e.g., the opening of water valves and speed of fans) and requirements of room conditions (e.g., indoor air temperature, thermal comfort and indoor air quality).

Figure 2.3 Framework and key elements of MPC for BAC applications

2.2.1 BAC application

Numerous previous studies of MPC for BAC applications could be found in the literature and most of the studies had focused on the application of MPC to the control of HVAC/ACMV systems. MPC has been used to control different HVAC/ACMV systems including chillers [2.12], variable air volume (VAV) boxes [2.13][2.14], fan coil units (FCU) [2.15], air-handling units (AHU) [2.16][2.17], heat pumps [2.18][2.19], ceiling radiant cooling [2.20][2.21] and floor radiant heating [2.22], etc. However, the study of MPC for the separate sensible and latent cooling (SSLC) air-conditioning systems is lacking in the literature. The SSLC air-

conditioning system can decouple the sensible and latent loads in ACMV systems, providing extra flexibility to achieve better thermodynamic efficiency and adjustability for different sensible heat ratio as compared to the conventional FCU and AHU air-conditioning systems [2.23][2.24]. These features of the SSLC air-conditioning system make it suitable for buildings in tropical Singapore where the climate is hot and humid. The active chilled beam (ACB) and dedicated outdoor air system (DOAS) are two popular SSLC air-conditioning systems which employ separate cooling coils to deal with the sensible and latent loads. However, a more sophisticated control than the conventional feedback control is needed to handle the dynamics of multiple cooling coils in ACB and DAOS air-conditioning systems. Thus, it is meaningful to investigate the application of MPC to ACB and DOAS air-conditioning systems to fulfill the full potential.

Besides the ACMV systems, shading and lighting are the other two systems affecting building energy efficiency and human comfort. The heat gain from windows accounts for a large portion (around 30% [2.25][2.26]) of the building cooling load, especially for the buildings in tropical Singapore where the climate is hot and humid with high solar radiation. The lighting accounts for 15% of the energy consumption in buildings in tropical Singapore [2.27] and it has a large potential in reducing its energy consumption by making use of the abundant daylight. Thus, it is also necessary to employ MPC for controlling shading and lighting systems. A few studies used MPC to control shading systems for reducing cooling loads and optimizing indoor visual conditions in buildings. For instance, Huchuk et al. [2.28] [2.29] developed an MPC controller for roller blinds in an office and the simulation results showed up to 35% reduction of cooling energy achieved by the MPC controller as compared to manual control. Lamano et al. [2.30] developed an MPC controller to optimize the operation of Venetian blinds in an office environment and the simulation results showed that the MPC controller achieved around 10%

reduction of building electricity and maintained daylight glare probability (DGP) below 0.35 throughout the year.

However, most previous studies of MPC for BAC applications including the above-mentioned studies only focused on the control of a single system in buildings. The application of MPC to the coordinated control of different building systems including ACMV, lighting and shading is rarely studied. As one of the advantages of MPC over the conventional feedback control is its ability to control multiple systems in a coordinated way [2.5], MPC has potential to achieve even more energy savings and better occupant well-being by extending the control from a single system to multiple systems such as ACMV, lighting and shading in buildings. Thus, it is necessary to investigate the performance of MPC for coordinated control of multiple building systems to maximize building performance.

MPC has also been employed to manage the demand response for buildings [2.31][2.32]. The idea of demand response management is to shift cooling/heating loads of buildings taking advantage of building thermal mass and dynamical energy prices to reduce energy bills without sacrificing human comfort [2.33]. However, the electricity tariff in Singapore for low-tension supplies is constant within a day [2.34] and it applies to the test buildings used in this study. Therefore, the application of MPC to demand response management for buildings is not studied in this research work.

2.2.2 Building model

MPC requires a building model to predict building responses for optimisation and control. The building model usually includes the building dynamics model (e.g., room air, walls, roofs, floors, windows, ACMV and lighting) and human comfort (e.g., thermal comfort and visual

comfort) model. The building modelling approaches could be classified into three categories, viz. white-box, grey box and black-box as shown in Figure 2.4.

Figure 2.4 Comparison of different building modelling approaches

2.2.2.1 White-box and grey-box models

White-box and grey-box models are built based on building physics including heat and mass transfers in buildings and building systems. White-box models are usually developed in the form of differential equations based on building physics and the parameters of these differential equations are determined by the building information including dimensions and materials of building structures etc. Similar to a white-box model, a grey-box model also relies on the building physics [2.35][2.36]. Grey-box models are also developed in the form of differential equations but the parameters are identified using building operation data obtained from real building measurements or building energy simulation tools. The modelling approach using building physics ('physics-based' modelling) has been widely used in many building performance simulation tools, including EnergyPlus [2.37] and TRNSYS [2.38]. However, models developed in these tools, and their accompanying solutions, contain numerous

nonlinearities that complicate and are prohibitive to real-time control and optimisation [2.39]. Besides, the use of the models developed in these tools for MPC may not necessarily end up in good control performance [2.40]. An alternative approach would be developing simplified building-physics-based models, which are of medium to high fidelity and computationally more efficient [2.39].

The thermal RC network is one of the most popular simplified modelling approaches to represent building thermodynamics. Figure 2.5 shows a typical thermal RC model of an exterior wall. The wall is modelled as one thermal capacitance (C_1) and two thermal resistances (R_1 and R_2). R_3 and R_4 refer to air film resistances of the exterior surface and interior surface of the wall. For a white-box model, the R and C parameters are derived directly from the detailed physical structures and material properties of the building. For a grey-box model, the R and C parameters are identified based on building operation data. The thermal RC model has been applied to build both full-scale [2.41] and reduced-order [2.35] building models.

Figure 2.5 A thermal RC representation of a wall

The thermal RC model has been used in many previous studies to construct MPC controllers for building control. Dong and Lam [2.42] developed a thermal RC building model for a

residential house using 1C to represent the air of each room and using 3R2C network to represent each building structure including walls and floors. The model parameters of the thermal RC building model are estimated using experimental building operation data and the thermal RC model is used to construct an MPC controller for controlling the HVAC system of the house. Dobbs and Hincey [2.43] developed a detailed thermal RC model with 41 states for a room and used it to construct an MPC controller for controlling a heating system. Sturzenegger et al. [2.41] developed a Building Resistance-Capacitance Modelling (BRCM) toolbox which can generate a detailed thermal RC model from building data including geometry, construction and systems. A thermal RC model of an office building is generated using the toolbox to construct an MPC controller for controlling the HVAC system of the building [2.44]. Hu and Karava [2.45] developed a detailed thermal RC model for a mixed-mode building and constructed an MPC controller using the developed thermal RC model for controlling the mixed cooling system for the building. Zong et al. [2.46] developed a thermal RC model, which used 1C to represent room air and 1R to present each wall, floor or roof, for a residential house and used the RC model to construct an MPC controller for controlling the heating system of the house. Viot et al. [2.47] developed a thermal RC model for a conference room and four thermal capacitances were used to represent the room air, floor slab, exterior walls and interior walls. The thermal RC model was used to construct an MPC controller for controlling the floor heating system of the room [2.48].

However, in most of the previous studies including the studies discussed above, the focus had been on the prediction of indoor temperature while the modelling of indoor humidity and mean radiant temperature is seldom covered. It has been shown that latent loads can take up a significant portion of annual energy consumption (up to 60%) by ACMV systems in commercial buildings situated in the tropics [2.49]. Besides, indoor humidity and mean radiant temperature are the key factors for the evaluation of indoor thermal comfort especially for

buildings in tropical Singapore as the climate is hot and humid with high solar radiation. Thus, it is necessary to include humidity and mean radiant temperature in the building model for BAC applications.

2.2.2.2 Black-box model

In a black-box model, the structure and parameters are identified directly from building operation data [2.50][2.51], which are usually obtained by experimental tests or generated by building energy performance simulation tools. Thus, a black-box model is also called a data-driven model. A black-box model is usually developed using the machine learning (ML) technique in many model types including subspace [2.52], regression tree [2.53], support vector machine [2.54], fuzzy logic [2.55] and artificial neural network (ANN) [2.56], etc. As the building model developed using ML (or ‘ML-based building model’) does not require the expertise in building physics and detailed building information, it could be constructed with less effort as compared to the physics-based models [2.57]. The ML-based building models have been used to predict indoor environments [2.58], energy consumptions [2.59], occupancy behaviours [2.60][2.61], and weather conditions [2.62] for buildings.

ANN is one of the most most popular ML-based models for building modelling due to its capacity for constructing accurate models for linear and nonlinear systems [2.63]. ANN is a highly accurate and efficient computing system with several simple neurons in multiple layers inspired by the biological neural network that constitutes animal brains as shown in Table 2.1. An ANN is usually composed of input layers, hidden layers and output layers. It receives inputs from one or more sources. The node multiplies each of these inputs by a weight. Then it adds the multiplications and passes the sum to an activation function. In this way, the data are passed to the next layer until the output layer. The schematic of an ANN model is shown in Figure 2.6.

Figure 2.6 Schematic of an ANN model

Table 2.1 Comparison of artificial and biological neural networks [2.69]

Biological neural network	Artificial neural network
Soma	Node
Dendrites	Input
Synapse	Weights or Interconnection
Axon	Output

For building modelling, the model structure of a nonlinear autoregressive exogenous (NARX) is one of the commonly used ANN models [2.64]. A NARX ANN model is a time-series, recurrent and dynamic neural network for modelling dynamical systems. NARX ANN could be algebraically expressed as

$$y(t) = f(y(t-1), y(t-2), \dots, y(t-n_y), u(t-1), u(t-2), \dots, u(t-n_u)) , \quad (2.4)$$

where t and n refer to time and number.

A few recent studies used the ML in the development of MPC controllers for energy efficiency and indoor environment optimization in buildings. Ferreira et al. [2.65] implemented an MPC controller with an ANN-based building model in a public building to control its HVAC system for optimizing indoor thermal comfort and energy consumption. However, experiments ran only for a few hours for each case and the energy consumption was not measured for evaluating the energy performance of the MPC. Most previous studies on MPC with an ML-based building model reported in the literature are based on simulations. Smarra et al. [2.66] developed an MPC controller using a random-forest-based building model, which was demonstrated by simulations to have comparable performance with respect to an MPC with a perfectly-known physics-based building model. Chen et al. [2.67] developed an MPC controller for hybrid ventilation buildings using an ANN-based building model. The MPC controller achieved better thermal comfort as compared to a rule-based controller in their simulations. Reynolds et al. [2.68] developed an MPC controller using an ANN-based building model for scheduling heating set points in a building. Their simulations show the MPC controller achieved 27% energy reduction as compared to conventional control. Afram et al. [2.63] developed an MPC controller for a residential building using an ANN-based building model and an energy-saving capacity of 6% - 73 % was found in their simulations. Experimental studies that could evaluate the performance of MPC with an ML-based building model covering a substantially long period are still lacking.

Due to its working principle, the accuracy of the building model in predicting the future evolution of building conditions is critically important to MPC of buildings. However, without the precise knowledge of the physics of the building, the construction of ML-based building

models rely heavily, often entirely, on historical building operation data, which poses major challenges to model accuracy. In many situations, the availability of high-quality building operation data is limited due to practical constraints such as construction project timeline, limitations in the capability of the original BAC system in data collection, etc. Besides, data collected by the original BAC system are building operation data under the control of the original BAC system. The data may not capture the building operation characteristics when it is controlled by MPC. The building model also requires continuous updating to capture the changes of some building physical characteristics over time due to changes in external factors, such as weather, or internal factors, such as internal furnishing and occupancy distribution, etc. However, most MPC systems using ML-based building models proposed in previous studies (e.g., [2.63] and [2.65] - [2.68]) do not have the automatic model update mechanism. Thus, a self-adaption mechanism that exploits online building operation data to update the ML-based building models continuously as the building is controlled by MPC in real-time is required to solve the challenges.

2.2.2.3 Human comfort model

MPC could make use of human comfort models including thermal comfort and visual comfort for optimising occupant well-being. For thermal comfort evaluation, the simplest way is to use indoor temperature as an index of indoor thermal comfort in the optimisation problem of MPC [2.70][2.71][2.72]. However, the actual indoor thermal comfort of occupants is determined by multiple factors including environmental factors (indoor air temperature, humidity, radiant temperature and air velocity) and individual factors (occupants' metabolic rate and clothing insulation). Thus, a better way to optimise indoor thermal comfort is to employ a comprehensive thermal comfort model, such as predicted mean vote (PMV) [2.73][2.74]. PMV considers both the environmental factors and individual factors by solving the heat balance of

the human body and the detailed evaluation method is described by Fanger [2.73]. PMV is adopted by many standards including ISO 7730 [2.74] and ASHRAE 55 [2.75]. The thermal sensation scales defined according to the PMV index are listed in Table 2.2.

Table 2.2 Thermal sensation scaled by PMV index [2.75]

PMV index	-3	-2	-1	0	1	2	3
Thermal sensation	Cold	Cool	Slightly cool	neutral	Slightly warm	Warm	Hot

The heat balance of the human body used in the PMV model is nonlinear and needs to be solved numerically, making it prohibitive for MPC to use the original PMV model directly for real-time optimization and control [2.72]. One approach to use the PMV thermal comfort model for MPC is to employ the thermal comfort zone, $(-0.5 \leq \text{PMV} \leq 0.5)$, in a psychometric chart [2.75][2.76], as the constraints in MPC, as shown in Figure 2.7. However, this approach can only manage indoor thermal comfort within the comfortable range instead of maintaining indoor thermal comfort close to thermal neutrality. Another approach is to simplify the PMV thermal comfort model for MPC. For instance, Cigler et al. [2.40] developed a linear PMV model using a linear approximation to construct an MPC controller for optimizing indoor thermal comfort. However, the indoor relative humidity (RH) which is one of the key factors of the PMV model is not modelled in the building model and is assumed to be fixed at 50%. Chen et al. [2.77] developed an MPC controller based on the PMV model for indoor thermal comfort optimization. However, the indoor mean radiant temperature and RH that are the key factors of the PMV are not modelled in the building model. The mean radiant temperature is assumed to be the same as the indoor air temperature and relative humidity is assumed to be known. Alamin et al. [2.78] developed an economic MPC controller for optimizing indoor PMV. However, the indoor PMV is evaluated based on indoor air temperature only. As thermal

comfort is affected by different factors including air temperature, humidity and mean radiant temperature, etc, it is necessary to include all of these variables in building models.

Figure 2.7 Thermal comfort zone in the psychrometric chart. Occupants' cloth insulation, indoor airspeed and occupants' metabolic rate are 0.5 clo, 0.1 m/s and 1.2 met, respectively [2.76].

Illuminance and discomfort glare probability (DGP) are the commonly used indices for evaluating visual comfort [2.79]. Illuminance is the ratio between the luminous flux incident on an infinitesimal surface. For an office environment, most standards [2.80][2.81] and studies [2.82][2.83][2.84] recommend a value of 500 lux as the lower acceptable threshold on the work plane. Many studies also recommend a value of 3000 lux as the upper acceptable threshold of the illuminance on the work plane [2.85][2.86].

DGP is a metric for evaluating the visual discomfort caused by glares. DGP was firstly introduced and validated by Wienold and Christoffersen [2.87][2.88]. DGP not only considers

the contrast ratio between the background, average luminance and glare source luminance, it also includes an evaluation of the level of illuminance perceived by the observer [2.89]. Based on the value of DGP, the glare could be rated by different classes as listed in Table 2.3.

Table 2.3 Rating of DGP [2.90]

DGP	< 0.35	0.35 - 0.40	0.4 - 0.45	> 0.45
Rating	Imperceptible	Perceptible	Disturbing	Intolerable

Few previous studies of MPC for BAC applications considered the optimization of visual comfort. Huchuk et al. [2.28] [2.29] developed an MPC controller for a roller blind of an office and the blind was regulated to prevent visual discomfort and reduce cooling/heating energy. Simulation results showed 35% reduction in electricity usage for space cooling and heating was achieved by the MPC controller. Lamano et al. [2.30] developed an MPC controller to optimize the operation of a Venetian blind in an office environment to optimize energy efficiency, indoor thermal comfort and visual comfort. The simulation results showed the MPC controller could achieve around 10% reduction of building electricity and maintained DGP below 0.35 throughout the year.

2.2.3 Optimisation problem

MPC solves an optimisation problem to achieve an objective function (minimising a cost function) in a prediction horizon while satisfying a set of constraints [2.91]. For BAC application, elements in an objective function including energy saving [2.70][2.71], peak load shifting [2.92][2.93][2.94], reducing set point tracking error [2.95][2.96][2.97], and improving indoor thermal comfort are commonly used in MPC [2.72][2.77][2.78][2.98]. Linear and quadratic representation of objective functions are mostly used in MPC. Linear cost functions are commonly used to minimise operation cost such as thermal energy and electricity in

buildings [2.99]. A typical representation of a linear objective function is shown in Equation (2.5), which minimises the control inputs of a controlled system such as cooling/heating power of a cooling/heating system. A linear programming optimiser is usually used to solve the optimisation problem in an MPC with a linear objective function and linear building model.

$$J = \text{Minimize}(\sum_{k=0}^N W_{u,t+k} \mathbf{u}_{t+k}) , \quad (2.5)$$

where J and W refer to objective and weighting factor, respectively. Subscript k is index variable.

However, in a case that there is mismatch between the building model in an MPC controller and the real response of the controlled building, the linear programming optimiser can exert ‘bang-bang’ control in which the control inputs generated by MPC change from maximum to minimum values in one control interval, resulting in waste energy [2.39]. A quadratic representation of the objective function, which is used in this thesis, is a possible alternative to avoid the problem [2.100]. A typical quadratic objective function is shown in Equation (2.6). The quadratic objective function incorporating a linear building model could be solved by a quadratic programming optimiser.

$$J = \text{Minimize}(\sum_{k=0}^N W_{u,t+k} (\mathbf{u}_{t+k})^2 + \sum_{k=0}^N W_{y,t} (\mathbf{y}_{t+k} - \mathbf{y}_{ref,t+k})^2) . \quad (2.6)$$

where subscript *ref* refers to reference.

The first term on the right-hand side of Equation (2.6) represents the cost of control inputs (e.g., cooling/heating power of a cooling/heating system). The second term on the right-hand side of

Equation (2.6) usually represents targeted room conditions such as room air temperature and indoor thermal comfort.

Constraints of the control inputs and outputs of the controlled system are considered in the optimisation of MPC. For BAC application, the constraints of the control inputs are determined by the capacities (e.g., cooling/heating capacity of a cooling/heating system) or change rates of the control inputs of the controlled system [2.101]. The constraints of outputs in buildings are indoor conditions such as room air temperature, indoor thermal comfort and indoor air quality [2.101]. Constraints could be classified into two types, hard constraints and soft constraints. Hard constraints are usually applied to variables that must be satisfied such as cooling/heating capacity of a cooling/heating system. Soft constraints are formulated using a slack variable that allows the variables exceeding the constraints for a certain amount. Soft constraints are usually applied to output variables of the controlled system such as room air temperature and indoor thermal comfort [2.99]. Several optimisation algorithms, including linear and nonlinear optimisation approaches, have been used for MPC. For a linear optimisation problem of MPC, linear programming [2.92] and quadratic programming [2.97] are commonly used. For a nonlinear optimisation problem of MPC, sequential quadratic programming [2.102], particle swarm optimisation [2.103] and genetic algorithm [2.104][2.105] are usually used.

The solution of the dynamic optimisation problem of MPC has high requirements for hardware (high-speed central processing unit and large memory) and software (optimisation libraries), which are significant barriers preventing the implementation of MPC in industry controllers such as programmable logic controller (PLC) or direct digital control (DDC). One solution to the problem is to use an explicit MPC, which calculates the explicit representation of the control laws in MPC using a piecewise affine (PWA) function [2.106]. However, these PWA control

laws could also be challenging to solve for MPC with many control variables such as large buildings with many systems [2.107].

Another approach is to develop an ML controller to approximate the control laws of MPC by supervised learning. The ML controller performs near-optimal control of buildings without the need to solve the optimisation problem. Thus, an ML controller could be much more computing-efficient than MPC, making it feasible to run in a PLC or DDC. May-Ostendorp et al. [2.108] developed an ML controller using classification and regression trees (CART) to extract the control laws of a water pump based on the offline solutions of an MPC controller. The ML controller was further experimentally implemented in an office and it was found capable of reproducing nearly all of the energy and comfort benefits of the MPC controller observed in simulations [2.109]. However, the control laws for the water pump extracted by the CART are the daily control profiles instead of real-time control signals. Thus, the controller is an open-loop and may not be applicable for fast-response buildings (e.g., lightweight buildings) and buildings with high-dynamic disturbances (e.g., dynamic weather conditions and internal loads). Another limitation is that the ML controller was trained using the simulation data of the MPC controller and the performance of the ML controller was also compared to the simulation results of the MPC controller, which may bring uncertainties in the development and the performance evaluation for the ML controller. Drgoňa et al. [2.107] [2.110] used the time-delay neural networks and regression trees to approximate the control laws of an MPC controller and developed an ML controller. The ML controller retained most of the performance of the MPC controller and significantly reduced the complexity and implementation cost of the control system. Klauco et al. [2.111] employed the regression trees to construct an ML controller learned from MPC control data and the control of the controller was found matching the MPC controller appropriately. However, the experimental evaluation

of the approach for real-time control in real buildings is still lacking in the literature. Thus, the feasibility and performance of the ML controller to approximate MPC for BAC applications need further experimental investigations.

2.2.4 MPC Performance

Numerous studies have demonstrated the energy saving potential of MPC for BAC applications through simulation and field-testing. By taking into consideration of disturbances such as weather conditions, occupancy behaviour, lighting load and plug load, MPC is capable of avoiding overcooling/heating to increase energy efficiency in buildings [2.112]. By using constraints of indoor conditions such as comfort range of indoor air temperature and thermal comfort, MPC enables buildings operating within safe regions while the energy consumption is minimised. Furthermore, when dynamic electricity price information is available and considered in MPC, dramatic reduction, generally around 30%, of peak load could be achieved [2.99]. Previous studies have demonstrated that of 10 – 30% reduction of energy consumption could be achieved by MPC for BAC [2.99].

Another major benefit of MPC for BAC is the improved indoor environment. By taking into account disturbances such as weather conditions and internal loads, MPC is able to improve steady-state responses, achieving less fluctuation of indoor conditions [2.70][2.113]. Besides, MPC is capable of exploiting a comprehensive thermal comfort model, such as PMV, which considers both environmental factors (e.g., indoor air temperature, humidity, radiant temperature and air velocity) and occupants' factors (e.g., metabolic rate and clothing insulation) for optimising indoor thermal comfort. Freire et al. [2.98] used the comfortable zone of PMV to decide the constraints for room air temperature and relative humidity in their MPC controller. The simulation results showed that the constraints were satisfied with 14% energy

saving. Álvarez et al. [2.72] used a nonlinear MPC controller to optimise occupants' sensation in a building using a PMV based thermal comfort model. The MPC controller was observed to maintain indoor PMV close to thermal neutrality, at most of the time. Ascione et al. [2.114] developed an MPC controller to optimise the operating cost of a heating system and a daily maximum predicted percentage of dissatisfied (PPD) in a building. The MPC controller achieved 8% reduction of PPD. The above-discussed studies employed the nonlinear thermal comfort models, making the optimisation nonlinear in MPC. Nonlinear MPC requires much more time to solve the optimisation problem as compared to linear MPC and makes it prohibitive to perform real-time control and optimisation for BAC applications. To avoid the complexity of nonlinear thermal comfort models, some studies simplified the thermal comfort models by linear approximation or statistical analysis. For instance, Cigler et al. [2.40] employed a linear approximated PMV model and then developed a linear MPC controller. The MPC controller achieved 10 - 15% additional energy saving, meanwhile, kept indoor thermal comfort within a comfortable zone at more time as compared to a conventional MPC controller without the PMV model. Alamin et al. [2.78] developed a transfer function model to evaluate indoor thermal comfort represented by PMV and an MPC controller employing the transfer function model. Chen et al. [2.77] developed an MPC controller employing a data-driven dynamic thermal sensation model to optimise occupants' thermal sensation due to the changes in indoor air temperature.

2.3 Research gaps and novelties of this study

2.3.1 Research gaps

Although numerous previous studies of MPC for BAC applications have been conducted, the applications of MPC to buildings in tropical Singapore are still rarely studied. Due to the hot and humid climate with high solar radiation, advanced building systems including separate

sensible and latent cooling (SSLC), automated lighting and automated shading are needed for buildings in tropical Singapore. However, previous studies only focused on the control of the single-coil ACMV system and a single building system as discussed in Section 2.2. Thus, further development of MPC is required to handle the dynamics of multiple cooling coils in the SSLC system and multiple building systems (ACMV, lighting and shading). The major research gaps are:

- i. The SSLC (e.g., ACB and DOAS) is an energy-efficient air-conditioning technology for tropical buildings and it requires a more sophisticated control than the conventional feedback control to handle the dynamics of multiple cooling coils. However, the application of MPC to SSLC air conditioning systems is seldom studied. Details are discussed in Section 2.2.1.
- ii. Most previous studies of MPC for BAC applications only focused on the control of a single system in buildings. The application of MPC to the coordinated control of multiple building services including ACMV, lighting and shading using MPC is rarely studied. Details are discussed in Section 2.2.1.

Besides the major research gaps list above, other research gaps also exist in the literature and need to be addressed for applying MPC to BAC, especially for the buildings in tropical Singapore. The other research gaps include:

- i. The physics-based building modelling is one popular approach to develop building dynamics models for MPC. However, in most MPC studies using the physics-based modelling approach, the focus had been on the prediction of indoor temperature while

the modelling of indoor humidity and mean radiant temperature is seldom covered. It is necessary to include humidity and mean radiant temperature in the building model MPC for thermal comfort optimization. Details are discussed in Section 2.2.2.1 and Section 2.2.2.3.

- ii. Most MPC systems using the ML-based building model in previous studies do not have the automatic model update mechanism to capture the changes of some building physical characteristics over time due to changes in external factors or internal factors. Thus, a self-adaption mechanism that exploits online building operation data to update the black-box building models continuously as the building is controlled by MPC in real-time is required to solve the challenges. Besides, experimental studies of MPC systems with ML-based building models are lacking in the literature. Details are discussed in Section 2.2.2.2.
- iii. The approach to approximate the control laws of MPC using ML is a promising solution to the issue that MPC requires high computing power. The ML controller learns from MPC and could reproduce the performance of MPC without solving the optimization problem. However, the experimental evaluation of the approach for real-time control in real buildings is still lacking in the literature. Details are discussed in Section 2.2.3.

2.3.2 Novelties of this study

The main contributions of this study focus on the investigation of the application of MPC to buildings in tropical Singapore and the filling in of the research gaps summarized in Section 2.3.1. The major novelties of this study include:

- i. The development of an MPC scheme to perform coordinated control of multiple cooling coils in SSLC air-conditioning systems including ACB and DOAS as well as the experimental evaluation of the control performance, as described in Chapter 4 and Chapter 5.
- ii. The development of an MPC scheme to perform coordinated control of multiple building systems including ACMV, lighting and shading to optimize energy efficiency, thermal comfort and visual comfort simultaneously as well as the experimental evaluation of the control performance, as described in Chapter 6.

Other novelties of this study include:

- i. The development of an approach, as described in Chapter 3, to constructing a linear physics-based building model that can predict multiple indoor conditions including room air temperature, humidity, mean radiant temperature and indoor PMV for constructing a linear MPC.
- ii. The development of an adaptive ML-based building modelling scheme that updates the building model regularly using online building operation data as well as the experimental evaluation of the control performance of MPC with an ML-based building model, as described in Chapter 7.
- iii. The experimental evaluation of an ML controller that could approximate the control laws of MPC without solving the optimization problem for ACMV control, as described in Chapter 8.

2.4 Summary

This section reviewed the previous studies of MPC for BAC applications, discussed the research gaps in the literature and summarized the novelties of this study. Conventional feedback control methods such as on/off and PID are widely used in BAC systems due to the simplicity in their control logic. However, the limitations due to the simple control logic make conventional feedback control cannot satisfy the energy efficiency demand of modern buildings. By contrast, MPC employs a building model for predicting and optimising future responses of a building. MPC for BAC applications has been demonstrated capable of achieving 10 – 30% energy, meanwhile, significantly improving indoor thermal comfort in previous studies. However, many research gaps exist in the literature including (1) the application of MPC to SSLC air-conditioning (e.g., ACB, DOAS) systems is seldom studied; (2) most physics-based building models for MPC in previous studies only focused on air temperature and excluded humidity and mean radiant temperature; (3) the application of MPC to coordinated control of multiple building systems (e.g., ACMV, lighting and shading) is seldom studied; (4) most ML-based building models for MPC in previous studies did not have the automatic model update mechanism to capture the changes of some building physical characteristics over time; (5) experimental evaluation of the approach to approximate the control laws of MPC using ML is lacking in the literature. The contributions and novelties of this study focused on filling in these gaps.

2.5 References

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Part II Modelling and Model Predictive Control Formulation

Chapter 3 A Model Predictive Control with Linear Building Thermal Model Incorporating Humidity and Thermal Comfort

3.1 Introduction

Developing a simplified building mathematical model has been a major challenge of MPC implementation for BAC applications [3.1]. Typically, MPC requires an appropriate building model for the prediction of future responses in order to optimise the control inputs of various systems (ACMV, lighting, etc.). Hence, the mathematical model of the building must be sufficiently accurate in predicting building dynamics and computationally efficient for real-time control and optimisation. Various building energy simulation tools such as EnergyPlus [3.2] and TRNSYS [3.3] can be used to construct and solve for the physical model of the building. However, these models and their accompanying solutions contain numerous nonlinearities that complicate and are prohibitive to real-time control and optimisation [3.1]. An alternative would be to develop simplified building physics-based models that are of medium to high fidelity and are computationally more efficient [3.1].

In many previous studies, the focus had been on the prediction of indoor temperature or cooling loads while latent loads and human thermal comfort are seldom covered [3.4]. In fact, it has been shown that latent loads can take up a significant portion of annual energy consumption (up to 60%) by ACMV systems in commercial buildings situated in the tropics [3.5]. Humidity and mean radiant temperature are also the key factors in the PMV thermal comfort index [3.6]. Therefore, in order to effectively achieve optimal building energy savings and indoor thermal comfort using MPC, it is necessary to include both the humidity, mean radiant temperature and thermal comfort index in the prediction model.

In this section, a mathematical building model, represented in state-space form is developed based on the BCA SkyLab test facility to predict indoor temperature, humidity, mean radiant temperature and thermal comfort. Building thermal mass is modelled using the RC network based on the as-built drawings. A linear approximation method is then used to linearise the ACMV and PMV models. The proposed building dynamics model is then calibrated and validated against experimental data obtained in the SkyLab test facility and the linearised PMV model is validated compared to the original PMV model. Finally, based on the proposed model, an MPC controller is proposed to control a typical FCU ACMV system of a virtual testbed in MATLAB/Simulink environment. Energy savings and thermal comfort improvement potentials of the proposed MPC controller are demonstrated through the simulations.

3.2 Mathematical modelling

3.2.1 Building dynamics

The building dynamics include the dynamics of indoor air, building structures (e.g., walls, floors, roofs) as well as building systems (e.g., ACMV, lighting). For a room space, the indoor air and ACMV system are considered as a complex open system with air-moisture mixture gas flow and vapour-water phase change. The ACMV system supplies the conditioned air (supply air) to the room space. Inside the room space, there are internal heat and moisture sources including human, lighting, and equipment. The room space also exchanges heat with the surroundings through the building's structures, as illustrated in Figure 3.1.

Figure 3.1 Heat and mass balance in a room space

In a typical ACMV system with FCU as shown in Figure 3.2, the fresh air mixes with the return air before entering the cooling coil in the FCU. Both the sensible and latent loads of the mixed air are dealt with by the cooling coil and part of the moisture in the mixed air stream will leave the ACMV system at the cooling coil due to the condensation.

Symbols $\dot{Q}$, $\dot{m}$, m , T and ψ refer to heat flow rate, mass flow rate, mass, temperature and humidity ratio. Subscripts *fa*, *ma*, *sa*, *cw* and *z* refer to fresh air, mixed air, supply air, chilled water and thermal zone

Figure 3.2 Schematic of a typical FCU ACMV system

Assuming no infiltration of outdoor air into room space, the moisture and heat balance of indoor air is described by Equations (3.1) and (3.2), respectively.

$$m_{air,z} \frac{d\psi_z}{dt} = \dot{m}_{moi,occ} + \dot{m}_{moi,sa}, \quad (3.1)$$

$$m_{air,z} C_{air} \frac{dT_z}{dt} = Q_{int,sen} + Q_{env} + Q_{sa}. \quad (3.2)$$

where Q is heat flow rate (W), $\dot{m}$ is mass flow rate (kg/s), m is mass (kg), ψ is humidity ratio (kg/kg) and T is temperature (K). In this thesis, all temperatures should be specified and evaluated using degree Kelvins. However, temperatures are displayed in degree Celsius, as it is easier to comprehend and appreciate. The subscript *int* refers to internal, *z* refers to thermal zone, *sen* refers to sensible, *sa* refers to supply air from ACMV, *moi* refers to moisture and *env* refers to envelop. $\dot{m}_{moi,occ}$ is the moisture gain from occupants and $\dot{m}_{sa}$ is moisture gain from the ACMV system by supply air. Q_{int} , Q_{sa} , and Q_{env} are internal sensible heat gain, heat brought by the ACMV system and heat gain from the building envelope.

3.2.1.1 Heat gain through walls

A thermal resistance-capacitance (RC) based modelling approach is adopted to represent the building thermal mass elements with various heat conduction and thermal storage. A second-order thermal RC model (two-node model), which has been adopted by many studies [3.7][3.8][3.9][3.10] and is demonstrated adequate for typical walls by Gouda et al. [3.7] and Fraisse et al. [3.9], is used to represent a building wall. Figure 3.3 shows the lumped parameter and RC representations of a building wall model. The wall is virtually split into two aggregates and only heat conduction in the normal direction is considered. In each of the aggregates, the temperature is assumed uniform. The RC model includes two thermal capacitances of the two

aggregates, three thermal conduction resistances of aggregates and two surface thermal resistances between surface and air (outer and inner surfaces). The same model treatment is applied to the roofs and the floors of a building. To reduce the errors caused by the simplification in the modelling, a model calibration procedure based on measured building operation data is conducted to refine the RC model. The calibrated RC model is also verified compared to the measured building data to make sure the model is accurate for predicting indoor conditions. The details of the model calibration and validation are shown in Section 3.4.3.

Figure 3.3 Model of a building wall

Based on the RC network representation, the state parameters representing the temperatures of the two aggregates can be derived as follows,

$$\frac{dT_1}{dt} = - \left[\frac{1}{C_{the,1}(R_{sur,o} + R_{sur,1})} + \frac{1}{C_{the,1}R_{1,2}} \right] T_1 + \frac{1}{C_{the,1}R_{1,2}} T_2 + \frac{1}{C_{the,1}(R_{sur,o} + R_{sur,1})} T_o + \frac{R_{sur,o}R_{sur,1}}{C_{the,1}(R_{sur,o} + R_{sur,1})} q_{sol}\alpha_{sur,o}, \quad (3.3)$$

$$\frac{dT_2}{dt} = - \left[\frac{1}{C_{the,2}(R_{sur,z} + R_{2,sur})} + \frac{1}{C_{the,2}R_{1,2}} \right] T_2 + \frac{1}{C_{the,2}R_{1,2}} T_1 + \frac{1}{C_{the,2}(R_{sur,z} + R_{2,sur})} T_z + \frac{R_{sur,z}R_{2,sur}}{C_{the,2}(R_{sur,z} + R_{2,sur})} \frac{q_{sol,tra}A_{win}}{A_{int}}. \quad (3.4)$$

where the symbols R , C , α and q refer to thermal resistance (K-m/W), thermal capacity (J/K), absorptance and heat flux density (W/m²), respectively. Subscripts *sur*, *o*, *l*, *the*, *sol*, *z*, *tra* and *win* refer to surface, outside, aggregate number, thermal, solar radiation, thermal zone, transmitted, and window, respectively. The last terms in Equations (3.3) and (3.4) represent the effect of the solar energy absorbed by exterior and interior surfaces.

The interior surface temperature can be modelled by,

$$T_{sur,z} = (T_2 R_{sur,z} + T_z R_{2,sur}) / (R_{2,sur} + R_{sur,z}) + R_{2,sur} R_{sur,z} q_{sol,tra} A_{win} / A_{env} (R_{2,sur} + R_{sur,z}). \quad (3.5)$$

Neglecting the effect of view factor, the mean radiant temperature T_{mr} can be calculated based on the temperature of all the interior surfaces,

$$T_{mr} = (T_{sur,z}^1 + T_{sur,z}^2 + \dots T_{sur,z}^n) / (A^1 + A^2 + \dots A^n). \quad (3.6)$$

$T_{sur,z}^n$ and A^n are the temperature of the surface and area of the interior surface n , respectively.

In the equations, the R and C of aggregates are determined by the materials' thermal properties.

The parameter R between surface and air is determined by convective and long-wave radiation heat transfer. The convection heat transfer can be described by a linear equation,

$$q_{conv} = h_{conv} (T_{sur} - T_{air}). \quad (3.7)$$

The convective heat transfer coefficient (W/K-m^2), h_{conv} , for the outer surface can be estimated by Equation (3.8) using average ambient velocity according to Palyvos [3.11]. The average ambient velocity here is assumed to be 2.2 m/s calculated based on the weather data of Singapore from International Weather for Energy Calculations [3.12].

$$h_{conv} = 5.8 + 3.94v_{air}. \quad (3.8)$$

h_{conv} for the inner surface can be assumed to be natural convection with constant values for different surfaces [3.13]. The values of h_{conv} for horizontal and vertical surfaces are of 4.0 and 3.1 W/K-m^2 , respectively, which are taken from Walton [3.13] directly.

The long-wave radiation heat transfer is calculated by a nonlinear equation,

$$q_{rad} = \varepsilon\sigma(T_{sur}^4 - T_{air}^4). \quad (3.9)$$

To obtain the constant parameter R in Equation (3.5), the radiation heat transfer equation is linearised as,

$$q_{rad} = \varepsilon\sigma(T_{sur} + T_{air})(T_{sur}^2 + T_{air}^2)(T_{sur} - T_{air}) = h_{rad}(T_{sur} - T_{air}), \quad (3.10)$$

The radiation heat transfer coefficient h_{rad} is considered constant since its variation is usually very small compared to its absolute value [3.14] in normal indoor conditions.

3.2.1.2 Heat gain from a double-glazed window

The heat gain from a window consisted of two components, (1) conduction heat gain due to the temperature difference between indoor and outdoor as well as (2) transmitted solar heat gain. The first component affects the indoor air directly while the second component was assumed to distribute on all the interior surfaces evenly. The latter is for simplicity, with the assumption that solar heat absorbed by any interior surface would quickly distribute to other interior surfaces by radiation.

A typical DGU window model is shown in Figure 3.4. The heat storage of the glass layers is assumed to have a negligible effect on room air temperature since the glass layers are thin [3.15]. Winkelmann [3.15] also suggested that the glass layers can be assumed to be opaque to long-wave radiation and it is valid for most glass products. Besides, the heat transfer coefficient of one glass layer is far greater than the surface convective/radiative heat transfer coefficient. Thus, the conductive thermal resistance of the glass layers can also be neglected.

Figure 3.4 Double-glazed window model and its RC representation

The model for heat gain through the window can be derived based on the RC model as

$$q_{win} = \tau_1 \tau_2 q_{sor} + \frac{[R_{sur,o} q_{sur,abs,1} + (R_{12} + R_{sur,o}) q_{sol,abs,2}]}{R_{sur,o} + R_{1,2} + R_{sur,z}} + (T_o - T_z) / (R_{sur,o} + R_{1,2} + R_{sur,z}). \quad (3.11)$$

The first two terms on the right-hand side of Equation (3.11) are solar heat gain terms and the third term is conduction heat gain. Parameter R for glass surface can be calculated in a similar way to the wall, as shown in Equation (3.10). The R for air gap can be modelled as [3.15],

$$q_{rad,1,2} = \frac{\sigma \varepsilon_1 \varepsilon_2}{1 - (1 - \varepsilon_1)(1 - \varepsilon_2)} (T_1^4 - T_2^4) = h_{rad} (T_1 - T_2), \quad (3.12)$$

$$R_{1,2} = R_{cond,gap} + 1/h_{rad}. \quad (3.13)$$

Subsequently, the solar heat gain coefficient (SHGC) of the window can be calculated as,

$$SHGC = [\tau_1 \tau_2 q_{sor} + [R_{sur,o} q_{sur,abs,1} + (R_{12} + R_{sur,o}) q_{sur,abs,2}] / (R_{sur,o} + R_{1,2} + R_{sur,z})] / q_{sol}. \quad (3.14)$$

3.2.1.3 Heat and moisture gain from ACMV system

For an FCU ACMV system, as shown in Figure 3.2, the supply air RH is assumed to be 100% when it is in operation, and the heat/mass transfer between the mixed air and the cooling coil can be described by

$$Q_{cw} = \dot{m}_{ma} (C_{air} + C_{vap} \psi_{ma}) (T_{ma} - T_{sa}) + \dot{m}_{ma} L_{vap} (\psi_{ma} - \psi_{sa}), \quad (3.15)$$

$$\psi_{sa} = 0.62198 p_{vap,sat} / (p_z - p_{vap,sat}), \quad (3.16)$$

$$p_{vap,sat} = e^{(77.345 + 0.0057T_z - 7235/T_z)/T_z^{8.2}}, \quad (3.17)$$

where the subscripts *ma*, *vap*, *sat* and *cw* refer to the mixed air, water vapor, saturation and chilled water, respectively. *L* refers to the specific latent heat (J/kg) of water condensation. The cooling power provided by the chilled water is enthalpy difference between return chilled water and supply chilled water.

The mass flow rate, temperature and humidity ratio of the mixed air can be modelled by

$$\dot{m}_{ma} = \dot{m}_{ra} + \dot{m}_{fa}, \quad (3.18)$$

$$T_{ma} = (H_{fa} + H_{ra})/[\dot{m}_{ma}(C_{air} + C_{vap}\psi_{ma})], \quad (3.19)$$

$$\psi_{ma} = (\dot{m}_{ra}\psi_{ra} + \dot{m}_{fa}\psi_{fa})/\dot{m}_{ma}. \quad (3.20)$$

Then the moisture gain from supply air can be modelled by

$$\dot{m}_{moi,sa} = \dot{m}_{sa}(\psi_{sa} - \psi_{ra}). \quad (3.21)$$

The heat gain from supply air is modelled by

$$Q_{sa} = \dot{m}_{sa}(C_{air} + C_{vap}\psi_{sa})T_{sa} - \dot{m}_{sa}(C_{air} + C_{vap}\psi_{ra})T_{ra}. \quad (3.22)$$

The nonlinear Equations (3.16) and (3.17) is replaced by a linear equation

$$\psi_{sa} = 7.014 \times 10^{-4} T_{sa} - 0.1913 . \quad (3.23)$$

Equation (3.23) is a linear correlation of air temperature and saturated humidity ratio fitted based on the data generated by Equations (3.16) and (3.17) using the linear regression method. Equation (3.23) is compared to the data generated by Equations (3.15) and (3.16) as shown in Figure 3.5. Figure 3.5 shows that the linear approximation is in good agreement with results from the nonlinear equations. Equation (3.23) is valid in a temperature range of 283.15 K – 293.15 K that covers the typical range of supply air temperatures.

Figure 3.5 Comparison of nonlinear equations and linear equation

Given that the mass flow rate of water vapor is small as compared to air, the sensible enthalpy of water vapor is assumed negligible. With this assumption, Equations (3.15) to (3.22) can be simplified to

$$\begin{aligned} \dot{m}_{moi,sa} = & 2.578 \times 10^{-4} \dot{m}_{fa} T_{fa} + 2.578 \times 10^{-4} \dot{m}_{ra} T_{ra} - 2.565 \times 10^7 Q_{cw} + \\ & 0.6325 \dot{m}_{fa} \psi_{fa} - (\dot{m}_{fa} + 0.3675 \dot{m}_{ra}) \psi_{ra} - 0.07031 \dot{m}_{fa} - 0.07031 \dot{m}_{ra}, \end{aligned} \quad (3.24)$$

and,

$$Q_{sa} = 369.4\dot{m}_{fa}T_{fa} - (1005\dot{m}_{fa} + 635.6\dot{m}_{ra})T_{ra} - 0.3675Q_{cc} + 9.062 \times 10^5(\dot{m}_{fa}\psi_{fa} + \dot{m}_{ra}\psi_{ra}) + 1.734 \times 10^5\dot{m}_{fa} + 1.734 \times 10^5\dot{m}_{ra}, \quad (3.25)$$

According to the assumptions made above, the equations are valid under the conditions of $RH_{sa} = 100\%$, $283.15K < T_{sa} < 293.15K$. When the supply and fresh air flow rates are constant, Equations (3.24) and (3.25) become linear.

3.2.2 Thermal comfort

Two popular methods to evaluate human thermal sensation in buildings could be found in literature including the PMV model proposed by Fanger [3.6] and the adaptive comfort model proposed by De Dear [3.16]. The main difference between the two models is that the adaptive comfort model considers the effects of outdoor climate on indoor comfort whereas the PMV model does not. However, De Dear [3.17] suggests that the PMV model has good prediction performance for conditioned buildings, whereas the adaptive comfort model is more applicable to naturally ventilated buildings. Thus, the PMV model is used in this study for buildings with air-conditioning. The PMV model is based on the energy balance of the human body with its surrounding environment [3.18][3.19][3.21]. The PMV index has six key parameters including metabolic rate, clothing insulation, air temperature, mean radiant temperature, air velocity and air relative humidity and is adopted by comfort standards ISO 7730 [3.18] and ASHRAE Standard 55 [3.21]. The PMV index is calculated by

$$PMV = (0.303e^{-0.036M} + 0.028)Q_{diff}. \quad (3.26)$$

The difference between the internal heat production and loss, Q_{diff} , that occurs in a human body is calculated by

$$Q_{diff} = M - Q_{work} - Q_{res} - Q_{sens} - Q_{evap}, \quad (3.27)$$

$$Q_{res} = 0.0014M(307.15 - T_{air}) + 1.72 * 10^{-5}M(5867 - p_{vap}), \quad (3.28)$$

$$Q_{sens} = 39.6 * 10^{-9}f_{clo}(T_{clo}^4 - T_{mr}^4) + f_{clo}h_{conv}(T_{clo} - T_{air}), \quad (3.29)$$

$$Q_{evap} = 0.42(M - Q_{work} - 58.15) + 3 * 10^{-3}[5733 - 6.99(M - Q_{work}) - p_{vap}]. \quad (3.30)$$

The cloth surface temperature can be estimated by

$$T_{clo} = T_{skin} - R_{clo}[f_{clo}h_{conv}(T_{clo} - T_{air})] - Ins_{clo}[39.6 * 10^{-9}f_{clo}(T_{clo}^4 - T_{mr}^4)] . \quad (3.31)$$

In Equations (3.26) to (3.31), M is the metabolic rate of a human being (W), p is air pressure (Pa), f_{clo} is clothing factor, and Ins_{clo} is clothing insulation (1 clo = 0.155 m²-K/W). The subscripts *clo*, *mr*, *vap*, *sens*, *evap*, *res*, *skin* and *work* refer to clothing, mean radiant, water vapour, sensible, evaporation from occupant skin, respiration of occupant, skin surface, and external work, respectively.

There are two nonlinear items, radiative heat transfer $39.6 \times 10^{-9}f_{clo}(T_{clo}^4 - T_{mr}^4)$ and water vapour pressure, p_{vap} , in the PMV model. The radiative heat transfer term can be linearised by,

$$\begin{aligned}
Q_{rad} &= 39.6 \times 10^{-9} f_{clo} [(T_{clo})^4 - (T_{mr})^4] \\
&= 39.6 \times 10^{-9} f_{clo} (T_{clo} + T_{mr})(T_{clo}^2 + T_{mr}^2)(T_{clo} - T_{mr}) \\
&= h_{rad} f_{clo} (T_{clo} - T_{mr}).
\end{aligned} \tag{3.32}$$

The radiant heat transfer coefficient h_{rad} could be assumed constant as the variations of cloth temperature and mean radiant temperature are relatively small compared to their absolute values [3.14]. Then the cloth surface temperature and sensible heat loss can be simplified and re-written as

$$T_{clo} = [T_{skin} + R_{clo} f_{clo} (h_{conv} T_{air} + h_{rad} T_{mr})] / [1 + In_{s_{clo}} f_{clo} (h_{conv} + h_{rad})], \tag{3.33}$$

$$Q_{sens} = f_{clo} h_{rad} (T_{clo} - T_{mr}) + f_{clo} h_{conv} (T_{clo} - T_{air}). \tag{3.34}$$

The water vapour pressure can also be calculated by the following equation, for air temperatures within 293.15 K to 303.15 K covering the range of typical room temperatures

$$p_{vap} = \psi_z p_z / (\psi_z + 0.622) \cong 1.598 \times 10^5 \psi_z. \tag{3.35}$$

Then the heat loss of respiratory heat and evaporation can be simplified and re-written as

$$Q_{res} = 0.0014M(307.15 - T_{air}) + 1.72 \times 10^{-5}M(5867 - 1.598 \times 10^5 \psi_z), \tag{3.36}$$

$$\begin{aligned}
Q_{evap} &= 0.42(M - Q_{work} - 58.15) + 3 \times 10^{-3} [5733 - 6.99(M - Q_{work}) - \\
&\quad 1.598 \times 10^5 \psi_z].
\end{aligned} \tag{3.37}$$

In a scenario where the cloth factor, the metabolic rate of the occupants, external work of the occupants and room pressure can be assumed constant, likely so in a typical office environment, Equations (3.26), (3.33), (3.35), (3.36) and (3.37) become linear. The PMV equation can be reduced to

$$PMV = \left[\frac{(0.6835h_{conv} + 0.005136h_{rad} + 0.06025)T_{air} + 0.6784h_{rad}T_{mr} + (35.71h_{conv} + 35.71h_{rad} + 418.9)\psi_z + 7.308 - 207.6h_{rad} - 207.6h_{conv}}{(h_{conv} + h_{rad} + 11.73)} \right] \quad (3.38)$$

The convective heat transfer coefficient can be assigned a constant value when there is no significant variation of air velocity and it can be determined by,

$$h_{conv} = \begin{cases} 2.38(T_{clo} - T_{air})^{0.25}, & 2.38(T_{clo} - T_{air})^{0.25} > 12.1v_{air}^{0.5} \\ 12.1v_{air}^{0.5}, & 2.38(T_{clo} - T_{air})^{0.25} < 12.1v_{air}^{0.5} \end{cases} \quad (3.39)$$

Equation (3.39) is from ISO 7730 [3.18]. The upper and lower terms on the right-hand-side of Equation (3.39) are the equations to calculate the heat transfer coefficients of natural convection and forced convection, respectively.

Thus, Equation (3.38) could be re-written as

$$PMV = c_1T_z + c_2T_{mr} + c_3\psi_z - c_0, \quad (3.40)$$

where c refers to coefficient.

3.2.3 State-space representation

The linear building model developed in this chapter including sub-models of indoor air [Equation (2.1) and (2.2)], building wall/floor/roof [Equations (3.3) to (3.6)], window

[Equation (3.11)], ACMV system [Equations (3.24) and (3.25)] and PMV [Equation (3.40)] can be written as a state-space model (SSM) as described by Equations (3.41) and (3.42). The state-space representation is commonly used in control system development and it is used in the development of the MPC formulation in this thesis.

$$dx_i/dt = \sum_{j=1}^{n_x} \mathbf{A}_{i,j} x_j + \sum_{k=1}^{n_u} \mathbf{B}_{i,k} u_k. \quad (3.41)$$

In Equation (3.41), the states (x) include indoor air temperature, humidity ratio as well as the aggregate temperature of building envelopes. The inputs (u) consist of the weather conditions, internal gains and ACMV system control variables.

The output parameters, indoor air temperature, indoor humidity ratio and PMV, are calculated based on the input (u) and states (x) as shown in Equation (3.42).

$$\mathbf{y}_l = \sum_{j=1}^{n_x} \mathbf{C}_{l,j} x_j + \sum_{k=1}^{n_u} \mathbf{D}_{l,k} u_k. \quad (3.42)$$

The input, state and output vectors, and matrices $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$ and $\mathbf{D}$ are summarised in Table 3.1. Since the outputs T_z , and ψ_z are also state parameters, there is no feedthrough from inputs. For the output PMV [calculated by Equation (3.40)], it requires feedthrough from measured inputs parameters T_{fa} , Q_{win} and $CONS$. Thus, the developed SSM is adequate for building MPC controllers.

Table 3.1 Outputs, inputs and states of SSM

Inputs	Description	States	Description	Outputs	Description
T_{fa}	Fresh air temperature (K)	T_{lm}	Temperature of indoor thermal mass (K)	T_z	Room air temperature (K)
ψ_{fa}	Fresh air humidity ratio(kg/kg)	T_z	Room air temperature (K)	ψ_z	Indoor humidity ratio(kg/kg)
Q_{cw}	Cooling power of chilled water (W)	ψ_z	Indoor humidity ratio(kg/kg)	PMV	Thermal comfort index
$Q_{int,sen}$	Internal sensible heat gain (W)	$T_{ew,1}$	Temperature of exterior wall aggregate 1 (K)		
$Q_{int,lat}$	Internal latent heat gain (W)	$T_{ew,2}$	Temperature of exterior wall aggregate 2 (K)		
Q_{win}	Heat gain from window-blind system (W)	$T_{iw,1}$	Temperature of interior wall aggregate 1 (K)		
$q_{sor,ew}$	Incident solar irradiance on outer surface of exterior wall (W/m ²)	$T_{iw,2}$	Temperature of interior wall aggregate 2 (K)		
$q_{sor,roof}$	Incident solar irradiance on outer surface of roof (W/m ²)	$T_{flo,1}$	Temperature of floor aggregate 1 (K)		
$CONS$	Constant 1	$T_{flo,2}$	Temperature of floor aggregate 2 (K)		
		$T_{roof,1}$	Temperature of roof aggregate 1 (K)		
		$T_{roof,2}$	Temperature of roof aggregate 2 (K)		

3.3 MPC formulation

Figure 3.6 shows the schematic of an MPC controller, which generates the optimal cooling power (Q_{cw}). The optimal cooling power is sent to the ACMV system in buildings to achieve optimised thermal comfort and energy saving. The objective function of the MPC controller is defined by

$$J = \text{Minimize}(\sum_{k=0}^N \hat{Q}_{t+k|t}^2 + \sum_{k=0}^N (W_{PMV} \widehat{PMV}_{t+k|t})^2 + \sum_{k=0}^N W_{\epsilon} (\epsilon_{t+k|t})^2). \quad (3.43)$$

The objective function seeks to minimise the cooling power as represented by the first term on the right-hand side of Equation (3.43). The PMV index deviation from thermal neutrality is represented by the second term. In Equation (3.43), W_{PMV} and W_{ϵ} are weighting factor of the significance of indoor thermal comfort and constraint violation penalty weighting factor, respectively. As the electricity tariff in Singapore for low-tension supplies is constant within a day [3.20] and it applies to the test buildings used in this study, the demand response is not considered in Equation (3.43). However, in buildings that have dynamic energy prices in a day, the energy price could be added as a weighting factor for the first term on the right-hand side of Equation (3.43). Then the objectives of Equation (3.43) become minimizing the energy bill and the deviation of the PMV index from thermal neutrality during the prediction horizon.

The normalized cooling power and PMV index, $\hat{Q}$ and $\widehat{PMV}$ are defined as

$$\hat{Q} = Q / (Q_{max} - Q_{min}), \quad (3.44)$$

and

$$\widehat{PMV} = PMV / (PMV_{max} - PMV_{min}). \quad (3.45)$$

PMV_{max} and PMV_{min} are the upper and lower limits of the PMV index. Q_{max} and Q_{min} are the upper and lower limits of cooling capacity for the ACMV system. Specifically, the constraints of PMV index are set $-0.5 \leq PMV \leq 0.5$ for general thermal comfort, according to ASHRAE Standard 55 [3.21] The room air temperature is not constrained since the constraints of PMV already ensure the indoor thermal comfort. To avoid non-solution in the optimisation routine, soft constraints are adopted to allow the PMV to exceed the constraints within a certain tolerance range. The tolerance range is defined by as

$$\widehat{PMV}_{min} - \epsilon \cdot ECR_{min} < \widehat{PMV} < \widehat{PMV}_{max} + \epsilon \cdot ECR_{max}. \quad (3.46)$$

Equal Concern for the Relaxation (ECR) is defined by Bemporad et al. [3.22]. The MPC controller seeks to compromise between the soft constraints and the objective function to solve the optimal slack variable. If the optimal slack variable ϵ is 0, the MPC controller will not violate the constraints. The constraint violation penalty weighting factor and ECR are set at 100000 and 1. The combination represents small allowable violations according to Bemporad et al. [3.22]. The MPC formulation is developed in MATLAB/Simulink platform using the Model Predictive Control Toolbox [3.22].

Figure 3.6 Schematic of a MPC controller

3.4 Case study

3.4.1 Test building

The test building is the Test Cell of the BCA SkyLab located in the BCA Academy in Singapore. BCA SkyLab has two side-by-side, identically equipped experimental cells with full-height window façade on one side, as shown in Figure 3.7. The two cells are furnished to mimic the interior of a typical office environment. The Test Cell is used to develop the dynamic model of the building with the properties of the envelope summarised in Table 3.2. The model considers the partition walls between the cells and the control room to be adiabatic on the assumption that the temperature differences between these three compartments are negligible.

(a)

(b)

Figure 3.7 (a) Exterior of BCA SkyLab. (b) Schematic drawing of BCA SkyLab

The internal heat load in the Test Cell is physically simulated by four heating dummies and two humidifying devices, as shown in Figure 3.8 and summarised in Table 3.3. There are four typical office workstations in the cell. Each heating dummy, housing a light bulb of 75 W inside, is fabricated according to EN 14240:2004 [3.23] to represent sensible heat load from human occupants, following 2009 ASHRAE Handbook-Fundamentals [3.24] for an office worker with moderating duties. A heating dummy is put at the seating position of each workstation. The sensible heat from plug load is set at 180 W per workstation following the recommended load factor for an office space of medium/heavy load density in 2009 ASHRAE Handbook-Fundamentals [3.24]. Out of the 180 W, 60 W comes from under the desk. The remaining 120 W of sensible heat is placed on top of the desks to represent other office equipment such as monitors and printers. The plug loads are simulated by putting light bulbs with the corresponding wattage in empty desktop computer casings. Moisture, equivalent to a total of

220 W latent heat, is generated by the two humidifying devices to simulate the latent load of four occupants.

Figure 3.8 Internal setup of Test Cell

3.4.2 ACMV system

A fan coil unit (FCU) and an active chilled beam (ACB) ACMV systems are installed in the Test Cell. However, the case study in this section is based on the FCU system of Test Cell as shown in Figure 3.9. The FCU operates at constant fan speed (air volume), as shown in Table 3.3, and is controlled by a thermostat that is linked to the actuator that regulates the chilled water flow rate through the cooling coil in the FCU. The thermostat-controlled chilled water flow rate according to a room temperature set point that is determined by a PID controller. The conditioned air is then supplied to the cell through four 4-way spread type ceiling air diffusers and subsequently returned through the six slot type diffusers on the ceiling.

Figure 3.9 Schematic of the FCU ACMV system in SkyLab

Table 3.2 Building envelope properties of BCA SkyLab

Envelop	External wall	Internal wall	Roof	Floor	Window
Layers	<ul style="list-style-type: none"> Aluminium composite panel Air gap Fiber cement board Gypsum plasterboard Rockwool insulation Plasterboard Rockwool insulation Plasterboard Rockwool insulation Gypsum plasterboard 	<ul style="list-style-type: none"> Gypsum plasterboard Rockwool insulation Plasterboard Rockwool insulation Plasterboard Rockwool insulation Gypsum plasterboard 	<ul style="list-style-type: none"> Screed board Aluminium composite panel Air gap Aluminium tile 	<ul style="list-style-type: none"> Rotating platform Air gap Closed cell insulation Air gap Floor steel panel Finishes 	<ul style="list-style-type: none"> Low E glass Air gap Clear glass
U value	0.22 W/m ² K	0.2 W/m ² K	0.245 W/m ² K	0.25 W/m ² K	1.56 W/m ² K

Table 3.3 Operation schedule of the BCA SkyLab Test Cell

Parameter	Value
Occupancy rate	0.092 person/m ² floor area
Internal heat loads	
• Equipment	16 W/m ² floor area
• People (Sensible heat)	75 W/person
• People (Latent heat)	55 W/person
• Maximum lighting	8.22 W/m ² floor area
Conditioned air supply flow rate of FCU	539.4 L/s
Fresh air supply flow rate of FCU	26.2 L/s
Office hours	9 am – 6 pm of weekday

3.4.3 Model calibration and validation

3.4.3.1 Thermal dynamics model

The building dynamics model of SkyLab Test Cell described in Section 3.2.1 is further calibrated and refined using measurement data obtained in the test building. Ten days (10th to 19th October 2017) worth of experiments were conducted to measure the room temperature and humidity responses to different conditions, as shown in Figure 3.10 and Figure 3.11. Subsequently, the accuracy of the calibrated model was validated against the experimental data.

The test conditions in the test building are shown in Table 3.4. From 10th to 13th October, the ACMV system and internal loads were running at their designed operation conditions, as shown in Table 3.3. The data obtained in these four days were used for model calibration. From 14th to 19th October, the data obtained in this period were used for model validation. Within this period, two days (16th and 17th) were operated in the same way as that in the calibration period. Another three days (14th, 15th, 18th) were operated with both the ACMV system and internal loads switched off to obtain the free responses of room air temperature and humidity to outdoor weather conditions. One day (19th) had the ACMV system on during office hours

but without internal loads. This experimental arrangement allows validation under different sets of conditions.

Table 3.4 Experimental conditions in BCA SkyLab for model calibration and validation

Date in October	10	11	12	13	14	15	16	17	18	19
Purpose	Model calibration				Model validation					
ACMV system	On	On	On	On	Off	Off	On	On	Off	On
Internal loads	On	On	On	On	Off	Off	On	On	Off	Off

Weather, room conditions, and ACMV system parameters were measured in the test building, as summarised in Table 3.5. The locations of these sensors are indicated in Figure 3.8 and Figure 3.9. Sensor readings were recorded at 5-second intervals and stored at one-minute intervals in SkyLab BMS. The variables of the air loop (dry bulb temperature, humidity and flow rates), the chilled water loop (temperature, flow rate) and the weather conditions (outdoor air temperature, humidity and solar radiations) were measured and used as inputs for the building dynamics model. The room conditions including air temperature and humidity were measured as the benchmark for subsequent model calibration and validation.

The parameters R and C in the thermal RC model of walls, floors and roofs are the key factors that affect the simulation performance of the building dynamics. Thus, the R and C parameters are tuned in this calibration procedure. The R and C values of the walls, floors and roofs can be calculated by the thermal properties of the materials as the initial values. Other indoor thermal masses such as furniture, ducts, etc. are represented by a 1R1C node which is only connected to room air temperature node. The R and C values are assigned an estimated value and bounded between 0 and $+\infty$. The Trust-Region-Reflective Least Squares optimisation

method [3.25] is then employed to tune the R and C parameters in MATLAB environment. The objective is to minimise the sum squared error of room temperature described by

$$J = \text{Minimize}(\sum_{k=0}^N (T_{z,sim} - T_{z,mea})^2). \quad (3.47)$$

$T_{z,sim}$ and $T_{z,mea}$ refer to the simulated room air temperature by the building dynamics model and the measured room air temperature, respectively.

The simulated room air temperature (using the calibrated building dynamics model) and the measured room air temperature are compared as shown in Figure 3.11 (a) and good agreement is observed between the simulated and measured room air temperatures. The distribution of the absolute errors of the room air temperature prediction during office hours is shown in Figure 3.12 (a). 75% of absolute errors of the room air temperature prediction during the office hours of validation days are less than 0.84 °C and the median absolute error is 0.49°C, suggesting high accuracy of the calibrated building dynamics model for indoor air temperature prediction. The mean absolute percentage errors (MAPE) of room air temperature during the office hours of the calibration days and validation days are 1.07% and 2.28%, respectively.

The indoor humidity ratio response of the calibrated building dynamics model is also verified against the measured data as shown in Figure 3.11 (b) and Figure 3.12 (b). Figure 3.11 (b) shows a good agreement between the simulated and measured humidity ratios during office hours. Figure 3.11 (b) shows that 75% of absolute errors of the indoor humidity ratio prediction during the office hours of validation days are less than 7.56×10^{-4} kg/kg and the median absolute error is 4.98×10^{-4} kg/kg, suggesting high accuracy of the calibrated building dynamics model for indoor humidity prediction. The mean absolute MAPEs of room air

temperature during the office hours of the calibration days and validation days are 2.88 % and 4.59 %, respectively.

Figure 3.11 shows that the prediction performance of the calibrated building dynamics model, especially for indoor humidity prediction, during non-office hours is worse than that during office hours. This is due to the assumption that no infiltration of outdoor air into room space made in the building modelling as described in Section 3.2.1. The assumption is valid during office hours as the ACMV system supplies fresh air into the room space and keeps the indoor air pressure positive relative to outdoor. However, the mismatch during non-office hours does not affect the control performance of the MPC system for building systems as the MPC system is only operating during office hours and is off during non-office hours. When the MPC system is switched on in the morning, the state variables (e.g., room air temperature and humidity ratio) of the building model are initialised by the measured room conditions that are fed back to the MPC system.

(a)

(b)

Figure 3.10 Test conditions for model calibration and validation

(a)

(b)

Figure 3.11 Comparison of simulated (a) room air temperature and (b) humidity ratio with measured data

(a)

(b)

Figure 3.12 Statistical distributions of the absolute errors of the simulated (a) indoor air temperature and (b) indoor humidity ratio during office hours against the measured data.

3.4.3.2 Thermal comfort model

For the office environment and summer season, the cloth insulation and the metabolic rate per occupant are assumed to be 0.5 clo and 1.2 met, respectively. In SkyLab Test Cell, the mean velocity of 0.136 m/s measured by the air velocity sensor as indicated in Figure 3.7 is adopted as the representative air velocity in the room space. Using the values of cloth insulation,

metabolic rate and air velocity, the parameters c_0 , c_1 , c_2 and c_3 in the linearized PMV model [Equation (3.40)] are estimated to be 88.335, 0.153, 0.142 and 35.707 respectively.

The proposed linear PMV model is verified by comparing its predictions to the original PMV model that is nonlinear using a set of inputs data. The data have 2000 sets of input variables and each set includes six variables, i.e., room air temperature, mean radiant temperature, indoor RH, indoor air velocity, occupant's metabolic rate and cloth insulation. The room air temperature, mean radiant temperature and indoor RH are generated randomly within ranges of (294.15 K, 301.15 K), (294.15 K, 301.15 K) and (40%, 90%), respectively. The ranges cover typical room conditions of SkyLab Test Cell when the air-conditioning is on. The indoor air velocity, occupant's metabolic rate and cloth insulation are assumed to be constant at 0.136 m/s, 1.2 met and 0.5 clo, respectively.

Figure 3.13 shows the comparison of the prediction results of the linear and original PMV models using the inputs data. Figure 3.13 (a) shows that the PMV results predicted by the linear PMV model distribute close to the PMV results predicted by the original PMV model. The R^2 of the PMV results predicted of the linear PMV model compared to the original PMV model is 0.9998, suggesting good agreement between the linear and original PMV models. Figure 3.13 (b) shows the absolute errors between the PMV results predicted by the two models. It is observed that the absolute errors are within (0, 0.026) and the median absolute error is 0.008, suggesting high accuracy of the linear PMV model for predicting indoor thermal comfort.

(a)

(b)

Figure 3.13 Comparison of the prediction results of the linear and original PMV models. (a) predicted PMV, (b) absolute errors

The matrices A , B , C and D of the SSM for SkyLab Test Cell are shown in Table A.1 to Table A.4, respectively. To test the implementation and performance of the proposed MPC controller, a nonlinear model with 97 states of BCA SkyLab was built in MATLAB/Simulink to represent the true building as a virtual testbed. The virtual testbed includes all the three rooms of BCA SkyLab, the interactions between different rooms as well as air leakage. In contrast to the SSM,

the nonlinear virtual testbed model was solved by finite difference method (FDM) to obtain the heat conduction in the envelope and theoretical nonlinear equations are used to represent the ACMV system and thermal comfort. The simulation of the nonlinear virtual testbed is solved by the solver of MATLAB/Simulink using the Euler method [3.26].

Table 3.5 Sensors installed in BCA SkyLab Test Cell

Category	Sensors	Brand	Model	Range	Resolution	Accuracy
Weather conditions	Global and Diffuse Irradiance sensor	AT Delta-T Devices	SPN1 & SPN1/BP	0 - 2000 W/m ²	0.6 W/m ²	10 W/m ²
	Outdoor air RH	Eyc tech	THS 307	0 - 100%	0.10%	1.50%
	Outdoor air dry bulb temp	Kimo	TH210	-20 – 80°C	0.1°C	0.25°C
Room conditions	Interior globe temperature sensor	Kimo	TM 110	-20 - 80°C	0.1°C	0.5°C
	Interior dry bulb temps	Precon	ST-S3EW-XPA	-40 - 105°C	0.1°C	0.2°C
	Interior relative humidity	Vaisala	HMW90	0 - 100%	0.10%	1.70%
	Omnidirectional air velocity sensor	Swema	Swema 03	0.05 - 10 m/s	-	0.03
ACMV	In Line Electromagnetic Flow Meter	ABB	Water Master Series	0 - 20 m ³ /h	-	0.20%
	Duct Temperature Sensor	ACI	A/AN-D	-40 -150°C	0.1°C	0.2
	Air Flow Rate Sensor	ACI	ESF-35-2	0 – 16 m/s	-	5%
	Normal Type Immersion Temperature Sensor	ACI	A/AN-I	-40 -150°C	0.1°C	0.2°C

3.4.4 Simulation test of the developed MPC

3.4.4.1 Simulation setup

Three simulation scenarios are considered in this study:

- Scenario 1: ON/OFF control of FCU cooling power, representing conventional control method. The cooling power by FCU is maximum (ON) when the room air temperature reaches 25°C and reduced to 0 W (OFF) when the room air temperature decreases to 23°C. This range of room air temperature is set according to the recommended comfort temperature in Singapore Standard 554 [3.27].
- Scenario 2: MPC control with a low weighting factor (W_{PMV}) of 1 is used in the objective function making the energy saving term to dominate in the optimisation (or “energy-saving-biased”).
- Scenario 3: MPC control with a high weighting factor of 4 is used in the objective function making the thermal comfort term to dominate in the optimisation (or “thermal-comfort-biased”).

During office hours (9 am to 6 pm, Monday to Friday). The fan in FCU is switched on to provide the design supply air and fresh air flow rates, as described in Table 3.3. The fractions of lighting and equipment load with respect to their respective full load are 1 (representing switched on). During non-office hours, the blinds are set at the open position. FCU fan, lighting and equipment are switched off. The weather data of Singapore from International Weather for Energy Calculations [3.12] are used to represent a typical year (year 1999). Simulations of all three scenarios are conducted for January, which is during the monsoon season of Singapore when the weather conditions can exhibit rapid changes. The simulation studies are performed

in MATLAB/Simulink which is installed in a computer with Intel(R) Core(TM) i7-7500U (2.7 - 2.9 GHz) CPU and 24 GB memory. The control interval and prediction horizon for the MPC controllers are 5 minutes and 10 control intervals, respectively.

3.4.4.2 Simulation results

The running time per optimisation in the MPC controller is 0.082 s for Scenario 2 and 0.077 s for Scenario 3. Each optimisation included solving the SSM to obtain the optimal control signal. The running time is very small compared to the control interval (300 s). This result indicates that the MPC controller developed in this study is computationally efficient for real-time BAC applications.

Figure 3.14 presents the simulation results (the indoor PMV, air temperature and normalized total cooling power supplied by FCU) of the three scenarios of a typical day (2nd January) in the simulation period. Looking at the results for office hours, the PMV, room air temperature and cooling power of the MPC scenarios (Scenarios 2 & 3) have much less variations than Scenario 1 with ON/OFF control. It indicates that possible disturbance to occupants due to variation of indoor air condition was much better controlled by MPC than the conventional on/off type control. The PMV of Scenarios 2 and 3 always approach 0.5 and 0, respectively (with certain tolerance due to soft constraints). Since the MPC controller is a multiple objectives controller, the controller always seek to compromise between minimising energy consumption and minimising PMV deviation from 0 depending on the preset weighting factor. For Scenario 2, the MPC controller always seeks for least energy consumption while PMV is still within the tolerance from the upper limit, during office hours. For Scenario 3, the PMV is kept around 0 during office hours, indicating the best thermal comfort out of the three scenarios. For Scenario 1, the PMV and room air temperature exhibit fluctuating patterns during office

hours because of the fluctuation of cooling power due to the ON/OFF actions. The ACMV system and internal loads are off during non-office hours.

Figure 3.14 Indoor PMV, room air temperature and normalized cooling power supplied by FCU results of three scenarios on 2 January

The PMV and normalized cooling power distributions during office hours in the month of January are plotted in box-and-whisker plots and histograms, as shown in Figure 3.15 and Figure 3.16, respectively. Figure 3.15 exhibits the outlier, maximum, 3rd quartile, median, mean, 1st quartile and minimum values of the PMV and normalized cooling power and Figure 3.16 shows the percentage of time of PMV, and normalized cooling power at indicated values during office hours. The daily PMV MAD from 0 and daily mean normalized cooling power during office hours are also plotted in Figure 3.17 for workdays.

(a)

(b)

Figure 3.15 Indoor (a) PMV and (b) normalized cooling power distributions of three scenarios during January

(a)

(b)

Figure 3.16 Percentage of time indoor PMV (a) and normalised cooling power (b) are at the indicated values during office hours of January

(a)

(b)

Figure 3.17 (a) Daily MAD of PMV from 0, and, (b) daily mean normalized cooling power during office hours of workdays in January

Figure 3.15 (a) shows that more than three quarters ($> 75\%$) of the office hours are having negative PMV values in Scenario 1. It indicates that the ON/OFF control could over-cool the room and lead to extra energy consumption for the majority of the time. This echoes Figure 3.16 (b) that the normalized cooling power is running at maximum in nearly 80% of the time during office hours and Figure 3.17 (b) that the normalized cooling power is always the largest

among the three scenarios. Table 11 shows that Scenario 2 consumes least cooling energy among the three scenarios but the mean PMV index is the highest, slightly beyond the upper limit of 0.5. However, Scenario 2 achieves the most stable indoor environment as indicated by having the lowest standard deviation of PMV during office hour of 0.092 among the three scenarios. The stable indoor environment can improve human thermal comfort according to ASHRAE Standard 55-2013 [3.21]. The overall energy savings for Scenario 2 compared to Scenario 1 is 19.4%. Scenario 3 achieves the best thermal comfort among the three scenarios, with near 0 median PMV. Over 90% of the office hours are having PMV values within -0.09 to 0.12 and the daily mean PMV deviation from 0 during office hours is below 0.1 in 20 workdays out of the total 21 workdays, which indicates that the indoor environment is very close to thermal neutrality. With this high level of thermal comfort, Scenario 3 still achieves 6% of energy savings compared to Scenario 1, as shown in Table 3.6. The energy savings are estimated based on the electricity consumption calculated using an assumed chiller COP of 5.86 from the specification of the chiller used in BCA SkyLab.

Table 3.6 Summary of simulation results of January using Singapore weather data

Scenario	Electric energy consumption (kWh)	Electric energy saving (%)	SD of normalized cooling power (kW)	MAD of PMV from 0	SD of PMV
1	100.70	-	0.412	0.173	0.190
2	81.15	19.4	0.070	0.556	0.092
3	94.71	6.0	0.052	0.065	0.136

3.5 Summary

This section proposed an approach to construct an SSM, which can be used to predict indoor temperature, humidity and thermal comfort for indoor environment control with MPC. The RC model was adopted to represent the thermodynamics in the building. The heat transfer and

dehumidification processes in the ACMV system and PMV index calculation model were linearised by linear approximation of the nonlinear items in the theoretical models. The method allows the development of SSM based on as-built drawing with physical meaning directly, instead of training a black or grey model by measuring a large number of input/output data. A simplified SSM having 11 states based on the Test Cell of the BCA SkyLab testing facility was developed using as-built drawing data. The SSM was calibrated and validated with experimental data obtained in BCA SkyLab.

An MPC controller was developed with two objectives: 1) minimise the total cooling energy consumption of FCU; 2) minimise the deviation of PMV index from 0 to achieve the best thermal comfort. Simulations were conducted for three scenarios including an ON/OFF scenario representing conventional control and two MPC control scenarios with one in energy-saving-biased setting and another one in the thermal-comfort-biased setting. The simulations tested the proposed SSM in a nonlinear virtual test bed having 97 states in the MATLAB/Simulink environment. The proposed SSM was shown to be suitable for real-time indoor environment control with MPC. The proposed MPC controller using the simplified SSM requires less than 0.1 s for solving the optimisation problem, suggesting that the controller is suitable for real-time BAC applications. By operating the thermal-comfort-biased setting, the MPC controller can maintain excellent thermal comfort at close to thermal neutrality while still able to achieve 6% energy savings as compared to the conventional on/off control. Switching to the energy-saving-biased setting, the MPC controller pushed the energy savings to 19.4% while keeping the PMV value at around 0.5 that is at the upper bound of the comfortable range.

3.6 References

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Part III Model Predictive Control for Air- Conditioning and Mechanical Ventilation Control

Chapter 4 Model Predictive Control of an Active Chilled Beam Air-Conditioning System

4.1 Introduction

Typical ACMV systems employ a single cooling coil to provide both sensible cooling and dehumidification to the air that is supplying to the indoor space. To handle the latent load, chilled water temperature as low as 4 - 7°C [4.1] is used, limiting the thermodynamic efficiency of chillers [4.2][4.3][4.4]. In addition, conventional ACMV systems with one cooling coil could not effectively accommodate the variability in sensible heat ratio in buildings, resulting in uncomfortable indoor humidity [4.5]. As a potential solution to these issues, using separate cooling coils for sensible and latent loads could provide extra flexibility, compared to single-coil systems, to achieve better thermodynamic efficiency and adjustability for different sensible heat ratio. Such kind of a system is often referred to as separate sensible and latent cooling (SSLC) system.

Active chilled beam (ACB) system as an energy-efficient SSLC air-conditioning technology is gaining popularity worldwide [4.1][4.6][4.7][4.8]. Many studies have suggested that ACB can save up to 30% of energy [4.1][4.9][4.10][4.11], compared to typical conventional air-conditioning systems, such as FCU. ACB typically consists of a (1) primary cooling coil in the primary air-handling unit (PAU) to deal with all the latent load and part of the sensible load and (2) a cooling coil in ceiling-mounted chilled beam terminal to deal with the remaining part of the sensible load, as shown in Figure 4.1. This arrangement essentially splits part of the sensible load from the primary cooling coil to the cooling coils in the chilled beam terminals, instead of dealing with all the heat loads (latent and sensible) in the same coil as typically found in FCU/AHU systems. The primary air is then supplied into the chilled beam terminal through nozzles and produces a pressure degradation (relative to room space) at the outlets of the

nozzles. The pressure degradation is due to the increase of airspeed and dynamic pressure of the primary air as it flows through the nozzles according to the Bernoulli's principle. The pressure degradation of primary air results in a low pressure in the chilled beam chambers that induces room air to pass through the cooling coil and mix with the primary air. Such a feature of ACB systems leads to less airflow provision by a fan, and thus, consumes less fan energy compared to conventional FCU systems. The chilled beam cooling coil uses higher chilled water temperature ($13 - 17^{\circ}\text{C}$) than that typically found in FCU systems ($4 - 7^{\circ}\text{C}$) [4.1], allowing chillers to operate at higher thermal efficiency.

Figure 4.1 Schematic of a typical ACB system

A major challenge of ACB systems is that sophisticated control is needed to avoid condensation at the chilled beam cooling coil. The smaller supply airflow rate (a major energy-saving feature) of ACB systems also results in slower responses to dynamic heat loads, which leads to considerable degradation in energy and thermal comfort performance of ACB systems [4.11][4.12]. The separation of the partial sensible load to the cooling coils in the chilled beam terminals provides an extra potential for zonal control. These unique features of ACB systems require new control strategies and algorithms to better utilise the energy-saving potential of

ACB systems. Compared to conventional control, MPC has advantages in handling the dynamic conditions of buildings by optimising the future control strategies based on forwarding prediction, making MPC a potential solution to the control needs of ACB systems.

This chapter experimentally investigates the control performance of an MPC controller for an ACB system further developed from the linear SSM developed in Chapter 3 in terms of energy and thermal comfort. The MPC controller developed in Chapter 3 is employed to control an FCU system. Experiments were conducted in the BCA SkyLab test facility. The control performance of the MPC controllers is compared to a conventional BMS employing a PID control strategy.

4.2 Methodology

4.2.1 Test building

Experiments were conducted in the BCA SkyLab test facility as described in Section 3.4.1. SkyLab is equipped with a conventional BMS with a PID-based control algorithm to control the various building systems (ACMV, lighting, shading, etc.). An MPC system is developed and implemented in the Test Cell as an additional controller. The Test Cell can switch between the original BMS and the MPC system depending on experimental needs.

The window façade in the Reference Cell is composed of double glazed units (DGU) with Low-e coating. The Low-e coating is titanium nitride with a thickness of 300nm. The emissivity of the Low-e coating is 0.07 and its reflectivity for infrared light is 0.93. The visible light transmission (VLT), solar heat gain coefficient (SHGC), and U-value of the Low-e DGU are 63%, 0.27 and 1.55 W/m²K, respectively. The window façade in the Test Cell DGU with EC coating. In all the experiments of this chapter, the tint level of the EC glazing was kept

constant at 38% such that its SHGC was matching with that of the Low-e glazing in the Reference Cell. Venetian blinds are installed behind the window façades but the blinds were all drawn up during the experiments described in this chapter.

4.2.2 ACMV systems

4.2.2.1 FCU system

Each of the two experimental cells has an FCU ACMV system consisting of an FCU that is composed of a cooling coil and a CAV fan, as illustrated in Figure 3.9 in Chapter 3. More details of the FCU ACMV system are described in Section 3.4.1.

4.2.2.2 ACB system

In addition to the conventional FCU system, an ACB system, as shown in Figure 4.2, is also installed in Test Cell as an alternative. The ACB system consists of a PAU that supplies pre-cooled primary air to the six chilled beams installed on the false ceiling of Test Cell, as shown in Figure 4.3. Each chilled beam has dimensions of 119 mm (width) $\times$ 594 mm (depth) $\times$ 220 mm (height). The induction ratio (induced airflow rate/primary airflow rate) of the chilled beam is 3.04 at the operation condition of the experiments.

Figure 4.2 Schematic drawings of the ACB system in BCA Test Cell

Figure 4.3 Setup of Test Cell and Reference Cell of SkyLab

The chilled water flow rate through the PAU cooling coil is regulated by a thermostat-controlled valve (WV 2 in Figure 4.2), which controls the pre-cooled air off-coil temperature to the set point of 16°C. The PAU supplies pre-cooled primary air at 147 L/s. As the pre-cooled primary air reaches the chilled beam, it mixes with the induced air. The sensible load in the induced air is removed by the chilled beam cooling coils. The induced air then mixes with the primary air and the mixed air is then supplied to the room space.

In contrast to the conventional FCU system, the room space of the Test Cell is divided into three virtual thermal zones in the ACB system. The control of the six chilled beams is divided into three groups (two chilled beams each). Each group serves a virtual thermal zone, as shown in Figure 4.3. The cooling coils of chilled beams in each group are controlled by a modulating chilled water valve (WV 4 – 6 in Figure 4.2), which is controlled by a thermostat installed in each thermal zone. The room temperature set point is at 24°C in all the three thermostats. The

locations of these three additional thermostats are shown in Figure 4.3. The three zones are controlled individually to eliminate temperature gradient caused by non-uniform heat load distribution across the three zones (e.g., thermal zone 3 is subjected to more heat gain from the window façade than other zones). The chilled water supply temperature in the chilled beam loop is set at 17°C, which is controlled by a modulating valve (WV3 in Figure 4.2) in the main chilled water loop. Heat exchange between the chilled beam loop and the main chilled water loop is through a plate heat exchanger (Alfa Lova M3-FG) with a heat transfer capacity of 5 kW. The water flowrate capacities for the chilled beam loop and main chilled water loop are 0.45 and 0.22 L/s, respectively. The heat exchanger has ten plates made of Ti and each plate is 0.6-mm-thick with an area of 0.3 m². The chilled water supply temperature in the chilled beam loop is set at 17°C that is higher than the dew point temperature of the induced air (room air) to prevent condensation. The chilled water pump in the chilled beam loop (WP 1 in Figure 4.2) is regulated according to the status of the chilled beams according to the control logic shown in Table 4.1

Table 4.1 Control logic of ACB in original SkyLab BMS

Status of chilled water valves (WV4 – WV6)	Pump speed (WP1)
All three valves closed	0%
Two valves closed and one valve open	33%
One valve closed and two valves open	66%
All three valves open	100%

4.2.2.3 Instrumentation

The test facility is equipped with a vast network of sensors to monitor the operation of various systems. Air humidity, globe temperature and air velocity sensors, which facilitate the measurement of PMV, are installed in both cells. Sensors for monitoring ACMV system parameters (temperatures, humidity and flow rates in the air loop) and weather conditions

(humidity, temperature and solar radiation) are installed as indicated in Figure 4.2. Chilled water flow rates were monitored by electromagnetic flow meters. Chilled water temperatures (supply and return) were monitored by immersion temperature sensors installed in the chilled water pipes. Indoor PMV is calculated based on measured indoor globe temperature, air temperature, humidity and air velocity as well as the assumed constant cloth insulation level of 0.5 clo and metabolic level of 1.2 met per occupant. Power meters (PowerLogic IEM 3155) were installed to monitor the lighting, plug load, fan power and pump power individually, as shown in Figure 4.2 and Figure 4.3. More details of the sensors are described in Chapter 3.

4.2.3 Modelling

The model of SkyLab Test Cell with the FCU system is the same as that developed in Chapter 3. For the ACB system, additional chilled beams are modelled. In the ACB system, the chilled beam cooling coils only deal with the sensible load and no condensation is allowed. The water condensation in the chilled beam coils is avoided by keeping the temperature of the chilled water supplied into the chilled beams higher than the dew point temperature of the induced air. More details are described in Section 4.2.2.2.

As there is no water condensation in the chilled beam cooling coils, the cooling power from the chilled beams acts as a sensible heat sink to the room space. As the working principle of the PAU in the ACB system is essentially the same as the FCU. The linear FCU model [Equations (3.24) and (3.25) in Chapter 3] developed in Chapter 3 could be applied to the PAU. Adding the cooling power of the chilled beams into the PAU model, the moisture and heat gain from the ACB system (a PAU and 6 chilled beams) could be modelled as

$$\begin{aligned} \dot{m}_{moi,sa} = & 2.58 \times 10^{-4} \dot{m}_{fa} T_{fa} + 2.58 \times 10^{-4} \dot{m}_{ra} T_{ra} - 2.57 \times 10^7 Q_{cw,PAU} + \\ & 0.633 \dot{m}_{fa} \psi_{fa} - (\dot{m}_{fa} + 0.368 \dot{m}_{ra}) \psi_{ra} - 0.0703 \dot{m}_{fa} - 0.0703 \dot{m}_{ra}, \end{aligned} \quad (4.1)$$

and

$$\begin{aligned} Q_{sa} = & 369.4 \dot{m}_{fa} T_{fa} - (1005 \dot{m}_{fa} + 635.6 \dot{m}_{ra}) T_{ra} - 0.368 Q_{cw,PAU} + \sum_1^6 Q_{cw,CB,i} + 9.062 \times \\ & 10^5 (\dot{m}_{fa} \psi_{fa} + \dot{m}_{ra} \psi_{ra}) + 1.734 \times 10^5 \dot{m}_{fa} + 1.734 \times 10^5 \dot{m}_{ra}. \end{aligned} \quad (4.2)$$

Comparing to the linearized FCU model [Equations (3.24) and (3.25)] developed in Chapter 3, the ACB system models have additional heat sink terms ($\sum_1^6 Q_{cw,CB,i}$) representing the six chilled beams in Equation (4.3)

Based on the models of walls, roofs, floors, room air and PMV developed in Chapter 3, and the ACB model [Equations (4.1) and (4.2)], an SSM for constructing the MPC controller for ACB system is developed. The descriptions of the inputs, states and outputs are listed in Table 4.2 and the matrices **A**, **B**, **C** and **D** are given in Table A.5 to Table A.8.

4.2.4 Model validation

The building dynamics model of SkyLab Test Cell with the ACB system is also verified against the measured data. Seven days (15th - 21st January 2018) worth of experiments were conducted to measure the room temperature and humidity in SkyLab Test Cell responding to different conditions, as shown in Figure 4.4 and Figure 4.5. The first five days are workdays and the remaining two days are weekends. The ACMV system (ACB), lighting system and simulators of internal loads of SkyLab Test Cell were switched on during the office hours and were switched off during the remaining time according to the design conditions described in Table 3.3 and Section 4.2.2.2. The weather conditions, ACMV variables and room conditions are measured by the sensors listed in Table 3.5 and stored in SkyLab BMS at 1-minute intervals.

(a)

(b)

Figure 4.4 Test conditions for the model validation. (a) Measured solar irradiances and (b) measured cooling powers

The room air temperature and humidity ratio simulated by the building dynamics model are compared to the measured data as shown in Figure 4.5. It is observed that the simulated room air temperature and humidity ratio during office hours have good agreements with the measured data. The prediction performance of the building dynamics model during non-office hours, especially for indoor humidity ratio prediction, is worse than that during office hours. However, it does not affect the control performance of the MPC system as the MPC system only operates during office hours. The detailed discussion is described in Section 3.4.3.1. Figure 4.6 shows

the distributions of the absolute errors of the simulated room air temperature and indoor humidity ratio against the measured data. The median absolute errors of the simulated room air temperature and indoor humidity ratio are 0.32°C and $2.06 \times 10^{-4} \text{ kg/kg}$, respectively, suggesting high accuracy of the building dynamics model for predicting room air temperature and indoor humidity ratio in SkyLab Test Cell with the ACB system. The MAPEs of the simulated room air temperature and indoor humidity ratio during office hours are 1.65% and 3.18%, respectively.

(a)

(b)

Figure 4.5 Comparison of the simulated (a) room air temperature and (b) humidity ratio during hour office hours with the measured data

Figure 4.6 Statistical distributions of the absolute errors of the simulated (a) indoor air temperature and (b) indoor humidity ratio against the measured data.

4.2.5 MPC control system

Two MPC controllers are employed for the FCU and ACB ACMV systems, respectively. The MPC controller for the FCU ACMV system is the same as that developed in Chapter 3. The objective function of the MPC controller for the ACB system is to minimise the cooling power of the PAU, the chilled beams and to optimise indoor thermal comfort (minimising the deviation of PMV from 0). The objective function, J , is expressed as,

$$J = \text{Minimize}(\sum_{i=0}^M \sum_{k=0}^N \hat{Q}_{i,t+k|t}^2 + \sum_{k=0}^N (W_{PMV} \widehat{PMV}_{t+k|t})^2 + \sum_{k=0}^N W_{\epsilon} (\epsilon_{t+k|t})^2), \quad (4.3)$$

Symbol M refers to the total number of cooling coils in the ACMV system. The constraints of the MPC for ACB ACMV system are the same as the MPC for FCU ACMV system. This W factor, control interval and prediction horizon for both MPC controllers are 1, 5 minutes and 12 control intervals, respectively.

Table 4.2 Description of inputs, states, outputs of the SSM for SkyLab Test Cell with ACB ACMV system

Inputs	Description	States	Description	Outputs	Description
T_{fa}	Fresh air temperature (K)	T_{tm}	Temperature of indoor thermal mass (K)	T_z	Room air temperature (K)
ψ_{fa}	Fresh air humidity ratio(kg/kg)	T_z	Room air temperature (K)	ψ_z	Indoor humidity ratio(kg/kg)
T_c	Control room temp (K)	ψ_z	Indoor humidity ratio(kg/kg)	PMV	Thermal comfort index
$Q_{cw,PAU}$	Cooling power of FCU (W)	$T_{ew,1}$	Temperature of exterior wall aggregate 1(K)		
$Q_{inte,sen}$	Internal sensible heat gain (W)	$T_{ew,2}$	Temperature of exterior wall aggregate 2(K)		
$Q_{cw,ACB}$	Cooling power of ACB (W)	$T_{iw,1}$	Temperature of interior wall aggregate 1(K)		
Q_{lig}	Lighting power (W)	$T_{iw,2}$	Temperature of interior wall aggregate 2(K)		
$Q_{inte,lat}$	Internal latent heat gain (W)	$T_{flo,1}$	Temperature of floor aggregate 1(K)		
Q_{win}	Heat gain from window façade (W)	$T_{flo,2}$	Temperature of floor aggregate 2(K)		
$q_{sor,ew}$	Incident solar irradiance on outer surface of exterior wall (W/m ²)	$T_{roof,1}$	Temperature of roof aggregate 1(K)		
$q_{sor,roof}$	Incident solar irradiance on outer surface of roof (W/m ²)	$T_{roof,2}$	Temperature of roof aggregate 2 (K)		
$CONS$	Constant 1 (input for the constant term in linearised PMV model)				

4.2.6 Control system architecture

The control system architecture in SkyLab is illustrated in Figure 4.7. The set points (24°C for room space of both cells and 16°C for primary air of ACB system in Test Cell) are defined in the original SkyLab BMS system and passed to the thermostats installed in the two cells (four in Test Cell and one in Reference Cell as shown in Figure 4.3. The pump speed control signal is given from the original SkyLab BMS according to the status of WV 4 – 6 as described by Table 4.3.

Figure 4.7 Integration between the MPC system and the BCA SkyLab test facility

In Test Cell, the additional MPC system is integrated with the original SkyLab BMS and hardware, as shown in Figure 4.7. The MPC algorithm is developed in MATLAB/Simulink environment and has a hierarchical structure consisting of two levels of controllers, the MPC (high-level supervisory controller) and the PID controllers (low-level controller). An Open Platform Communications (OPC) interface is developed to enable the communication between

the MPC system and the original SkyLab BMS. An input/output (I/O) device (National Instruments, cDAQ-9189) is installed to deliver the control signals from the MPC system to the ACMV systems in the Test Cell. A manual switch is installed to allow switching between the original SkyLab BMS and the MPC system for the Test Cell control. When the control of the ACMV systems is switched to the MPC system, the controllers highlighted by red rectangles in Figure 3.9 and Figure 4.2 are switched to be controlled by MPC and the controller in black rectangles (shown in Figure 3.9 and Figure 4.2) remains with the original control. The MPC controller fetches measured room and weather conditions from the SkyLab BMS through the OPC interface at 5-second intervals. Based on the measurements, the MPC controller generates the optimal cooling power set points (at 5 minutes interval) for the ACMV systems and sends it to the low-level PID controllers.

Table 4.3 Control logic of ACB in the MPC system

$T_{z,1} - T_{z,3}^*$	$T_{z,2} - T_{z,3}^*$	Status of WV 4	Status of WV 5	Status of WV 6
$> 0.2^{\circ}\text{C}$	$> 0.2^{\circ}\text{C}$	100%	100%	100%
$> 0.2^{\circ}\text{C}$	$< 0.2^{\circ}\text{C}$	100%	50%	100%
$< 0.2^{\circ}\text{C}$	$< 0.2^{\circ}\text{C}$	50%	50%	50%
$< 0.2^{\circ}\text{C}$	$> 0.2^{\circ}\text{C}$	50%	100%	100%

* $T_{z,1}$, $T_{z,2}$, $T_{z,3}$ refer to air temperature in thermal zone 1 – 3.

When the MPC system is controlling the conventional FCU system, the cooling power set point of the FCU generated by the MPC controller is converted to the chilled water valve opening signal by the low-level PID controller and is sent to WV1 at 5-second intervals through the I/O device. When the MPC system is controlling the ACB system, the MPC controller generates two separate cooling power set points for the PAU and the chilled beams. The two cooling power set points are converted into valve opening and pump speed for the PAU and the chilled beams, respectively, by the low-level PID controllers. The MPC system also takes over the

control of WV 4 – 6 from the zonal thermostats, using a control logic shown in Table 4.3. The valve-opening signals are delivered to WV 2 and WV 4 - 6 through the I/O device. The pump speed signal is delivered to WP 1 through the OPC interface and the original SkyLab BMS.

4.2.7 Experimental arrangements

The performance of the MPC system was evaluated under two test settings: Setting 1) Conventional FCU with original BMS vs. Conventional FCU with MPC, and Setting 2) Conventional FCU with original BMS vs. ACB with MPC. Setting 1 evaluated the performance of the MPC system as compared to the original BMS when both cells were using the same conventional FCU system. Setting 2 evaluated the performance of the MPC-controlled ACB system (the ‘advanced’ system) as compared to the conventional FCU system controlled by the original BMS (the ‘reference’ system). Each setting consists of a baseline test and an MPC test. In the baseline tests, both cells’ ACMV systems were controlled by the original BMS. The baseline tests measured the baseline energy performance differences between the two cells caused by various uncertainties (e.g., sensor errors, air leakage and ACMV system structure differences, etc.) were measured. In the MPC tests, the ACMV control in the Test Cell was switched to the MPC system whereas the Reference Cell remained using the original BMS. Table 4.4 summarises the schedule of tests. The same amount of internal heat load was applied in each cell in all tests. Both experimental cells were exposed to the same weather conditions in each test, due to their side-by-side arrangement. All the tests were conducted during Mar – Apr 2018. Each test ran for 2 days (from 9 am – 6 pm per day covering typical office hours) of similar sky conditions, as evaluated by Sky Clearness Index (K_t) which is the ratio of the global horizontal irradiance to the extra-terrestrial irradiance [4.13]. K_t is classified into clear ($K_t \geq 0.65$), intermediate ($0.2 \leq K_t < 0.65$) and overcast ($K_t < 0.2$) sky [4.14].

Table 4.4 Test schedules of MPC for ACMV systems in SkyLab

Test setting	Cell	ACMV system	Control System	Kt
1 (Baseline)	Test Cell	Conventional FCU	BMS*	Day 1: 0.37
	Ref. Cell	Conventional FCU	BMS	Day 2: 0.30
1 (MPC)	Test Cell	Conventional FCU	MPC	Day 1: 0.41
	Ref. Cell	Conventional FCU	BMS	Day 2: 0.47
2 (Baseline)	Test Cell	ACB	BMS*	Day 1: 0.46
	Ref. Cell	Conventional FCU	BMS	Day 2: 0.48
2 (MPC)	Test Cell	ACB	BMS	Day 1: 0.31
	Ref. Cell	Conventional FCU	MPC	Day 2: 0.36

*Original BMS with PID control algorithm in the BCA SkyLab

4.3 Test Results

4.3.1 Baseline tests

Figure 4.8 shows the breakdown of average daily (average of two days) electricity consumption by the ACMV systems in the two baseline tests. In the conventional FCU system, the electricity is consumed by cooling, the fresh air fan and the supply air fan in the FCU. In the ACB system, the electricity is consumed by cooling, the fresh air fan, and the supply air fan in the PAU and the chilled water pump in the chilled beam loop. The electricity consumption of cooling is estimated based on the COP of the chiller ($COP = 5.87$) serving SkyLab. Figure 4.8 (a) shows that when the two cells were both using the conventional FCU system with the original BMS control, the discrepancy in total electricity consumption by the ACMV system between the two cells was about 2.5% (Test Cell < Reference Cell). When the Test Cell was switched to the ACB system, the discrepancy in total electricity consumption by the ACMV system between the two cells was about 2.3% (Test Cell > Reference Cell). The results indicate the level of experimental error due to discrepancies between the two cells.

(a)

(b)

Figure 4.8 Average daily electricity consumption by the ACMV system (a) Test Setting 1(baseline), (b) Test Setting 2 (baseline)

4.3.2 MPC for conventional FCU system

Figure 4.9 shows the time profiles of measured room air temperature and indoor PMV results of Test Setting 1 (MPC test) Day 1. The weather conditions of this day are plotted in Figure 4.10. Figure 4.9 shows that the MPC system maintained stable room air temperature and PMV throughout most of the day despite the outdoor weather disturbances, indicating the ability of

the MPC system in stabilising the indoor conditions. The MPC system maintained the PMV close to, but still below, the upper limit of thermal comfort requirement (0.5). The multiple-objectives defined in the MPC objective function makes the MPC controller to always seek the optimal trade-off between energy consumption and indoor thermal comfort by minimising the cooling power and PMV deviation, subjected to thermal comfort constraints ($-0.5 \leq \text{PMV} \leq 0.5$). In contrast, the indoor air temperature and PMV in the Reference Cell exhibit highly fluctuating patterns due to the reactive (PID) control logic used in the original BMS. At some time periods, such as during 10 am to 11 am, PMV in the Reference Cell went lower than the lower thermal comfort limit (-0.5), suggesting that there could be over-cooling during those periods, leading to excessive cooling energy consumption and uncomfortable situations. Similar observations are found on Day 2.

(a)

(b)

Figure 4.9 Measured (a) indoor air temperature and (b) indoor PMV in Test Setting 1 (MPC test) day 1.

(a)

(b)

Figure 4.10 Measured (a) outdoor air temperature and RH, and (b) Global irradiance and Sky clearness index on Day 1 of Test Setting 1 (MPC test)

The different control characteristics between the original BMS and the MPC systems are revealed in Figure 4.11, which presents the time profiles of chilled water valve (WV1) opening and cooling power (electrical) on Test Setting 1 (MPC test) Day 1. The cooling power is deduced based on the flow rate, the temperature difference between return and supply chilled water measured at the FCU cooling coil as well as a chiller COP of 5.87. Figure 4.11 (a) shows that the chilled water valve opening fluctuated largely when it was controlled by the original BMS, indicating the characteristics of the reactive (PID) control logic. It suggests that the large fluctuating patterns of room air temperature and PMV in the Reference Cell could mainly be attributed to the control characteristics of the original BMS. In contrast, the chilled water valve opening in the MPC system shows small fluctuations around 20% but at a much higher frequency of modulation compared to the original BMS. Such control characteristics of the MPC system contributed to the stable room air temperature and PMV in the Test Cell. The different control characteristics of the original BMS and the MPS system gave rise to the different fluctuation patterns of cooling power shown in Figure 4.11 (b). The cooling power in

the original BMS varied largely between 0 – 1.4 kW whereas in the MPC system the cooling power showed small variations between 0.4 – 0.8 kW for most of the day. The results suggest that the MPC system required a much smaller range of control motions to reach the control targets compared to the original BMS, despite the fact that the room space was subjected to disturbances (changes in outdoor weather conditions as shown in Figure 4.10. This could be attributed to the prediction capability of the MPC system that optimised control actions, based on forwarding prediction, in real-time.

(a)

(b)

Figure 4.11 ACMV system parameters on Day 1 of Test Setting 1 (MPC test), (a) Water valve (WV 1) opening, (b) Cooling power

Figure 4.12 summarises the distribution of cooling power and indoor PMV in the two-day-long Test Setting 1 (MPC test). Figure 4.12 echoes the observations from Figure 4.9 and Figure 4.11 that the cooling power and indoor PMV have much less variations when the MPC system was used, compared to the original BMS. The median cooling power is 0.57 kW for MPC but it increases to 0.72 kW for original BMS, indicating that the MPC system ran the ACMV system at lower cooling power than the original BMS for most of the time. Figure 4.12 (b) shows that the median indoor PMV for MPC is 0.42 whereas, for original BMS, it is -0.32. When the original BMS was used, the majority of the time (over 95 percentile) was having negative indoor PMV, in which 9% of the time was too cool ($PMV < -0.5$), suggesting the occurrence of overcooling and excessive cooling energy consumption. Similar to the observations in Figure 4.9 (b), the MPC system kept the indoor PMV close to the upper limit of the comfortable range ($PMV < 0.5$) with a narrow distribution (0.39 to 0.44 interquartile range) fulfilling the thermal comfort criteria ($-0.5 \leq PMV \leq 0.5$) at all time. This resulted in a much more stable indoor thermal comfort environment with less cooling energy consumption compared to the original BMS.

(a)

(b)

Figure 4.12 Distributions of (a) cooling power and (b) PMV of Test Setting 1 (MPC test)

The average daily electricity consumed by ACMV systems of MPC and SkyLab BMS control in Test 1 is presented in Figure 4.13. MPC saved 14.7% in electricity consumed by the ACMV system compared to the original BMS. Since the fans in both cells' ACMV systems were operating at the same constant levels, the difference in fan energy consumption between MPC and original BMS control is negligible. The savings by MPC were entirely derived from cooling energy savings.

Figure 4.13 Electricity consumption by ACMV systems of Test Setting 1 (MPC test)

4.3.3 MPC for ACB system

Figure 4.14 shows the time profiles of measured room air temperature and indoor PMV results on Day 1 of Test Setting 2 (MPC test). Similar to the observations in Test Setting 1, the MPC-controlled ACB system also maintained stable room air temperature and PMV throughout most of the day despite the outdoor weather disturbances. MPC system maintained the PMV close to, but still below, the upper limit (0.5) of thermal comfort requirement. The time profiles of weather conditions of the day are plotted in Figure 4.15.

(a)

(b)

Figure 4.14 Room conditions on Day 1 of Test Setting 2 (MPC test). (a) indoor air temperature, (b) indoor PMV

(a)

(b)

Figure 4.15 Measured (a) outdoor air temperature and RH, and (b) Global irradiance and Sky clearness on Day 1 of Test Setting 2 (MPC test)

The distribution of indoor PMV in the 2-day-long Test Setting 2 (MPC test) is summarised in Figure 4.16, which echoes the observations from Figure 4.14 that MPC maintained stable room conditions. The median indoor PMV for MPC-controlled ACB is 0.35 whereas for original-BMS-controlled conventional FCU, it is -0.30. The MPC-controlled ACB system kept the indoor PMV close to the upper limit of the positive comfort zone ($PMV < 0.5$) with a narrow distribution range (0.30 to 0.39 interquartile range), fulfilling the thermal comfort criteria (-0.5

$< PMV < 0.5$) at all time. The average daily electricity consumed by the two ACMV systems in Test Setting 2 (MPC test) are presented in Figure 4.17. Compared to the BMS-controlled FCU system, the average daily electricity consumption of the MPC-controlled ACB system is 20% less.

Figure 4.16 Distributions of PMV of Test Setting 2 (MPC test)

Figure 4.17 Electricity energy consumption by ACMV systems of Test Setting 2 (MPC test)

4.4 Discussion

The performance of the MPC in controlling the ACB system is compared to the original BMS by extracting the results from Test Setting 2. Figure 4.18 compares the distributions of indoor PMV measured in Test Cell during Test Setting 2 (MPC test) with that measured in Test Cell during Test Setting 2 (Baseline). It shows that the MPC controller was able to take advantage of the comfortable PMV range ($-0.5 < \text{PMV} < 0.5$) by keeping the indoor PMV close to the upper limit (0.5) using the optimisation algorithm described in Chapter 3. The original BMS followed the control logics as described in Section 4.2.2, which regulated the primary air temperature and room air temperature around 16°C and 24°C , respectively. Figure 4.19 shows the energy performance of the ACB system controlled by these two controllers. Compared to the original BMS, the MPC-controlled ACB system consumes 19.6% less on average daily electricity. The savings mainly come from reduced cooling and chilled water pump energy consumptions. The MPC controller achieved such energy savings while keeping the indoor PMV within the thermal comfort criteria at all time.

Figure 4.18 Distributions of indoor PMV with ACB: MPC-controlled ACB - Test setting 2 (MPC test), BMS-controlled ACB - Test Setting 2 (Baseline)

Figure 4.19 Electricity consumption by ACMV systems: MPC-controlled ACB - Test setting 2 (MPC test), BMS-controlled ACB - Test Setting 2 (Baseline)

4.5 Summary

This chapter implemented a control system based on an MPC algorithm for ACMV system control developed in Chapter 3. The MPC algorithm optimises both the cooling energy and indoor thermal comfort. Experiments were conducted in the BCA SkyLab test facility to evaluate the performance of the MPC system in controlling a conventional FCU system and an ACB system, as compared to the more typical BMS employing PID control logic. The experiments ran under the tropical climate of Singapore. The internal heat loads and furnishings of the test facility mimicked a typical office environment. Compared to the BMS, the MPC system achieved 14.7% electricity savings when it was used to control the conventional FCU system and 20% when it was used to control the ACB system. The MPC system achieved such energy savings while enhancing indoor thermal comfort. Indoor thermal conditions (air temperature, PMV) were maintained stable by the MPC system whereas large variation of thermal conditions was found when the BMS was used. Indoor PMV was maintained within the thermal comfort limit ($-0.5 < \text{PMV} < 0.5$) at all time in both ACMV systems when the MPC

system was used. In contrast, the indoor PMV became too cool for about 9% of the time when the BMS was controlling the FCU system.

4.6 References

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Chapter 5 Model Predictive Control for an Air-Conditioning System with Dedicated Outdoor Air System

5.1 Introduction

In addition to the ACB system studied in Chapter 4, another popular approach of implementing SSLC is to add an extra cooling coil dedicated to outdoor air conditioning, or dedicated outdoor air system (DOAS) [5.1][5.2][5.3][5.4]. The cooling coil in DOAS uses low-temperature chilled water for handling the latent ventilation load and parts of the sensible building load. The SSLC system assisted by DOAS (or DOAS air-conditioning system) consists of another secondary cooling coil that uses higher-temperature chilled water to deal with the remaining sensible load. Compared to conventional single-coil systems such as FCU and AHU, DOAS air-conditioning systems have advantages of improved indoor thermal comfort, better control of indoor humidity and energy efficiency [5.2][5.5][5.6][5.7][5.8][5.9]. However, a control scheme much more sophisticated than those found in single-coil systems (such as FCU and AHU) is needed to operate DOAS air-conditioning systems to fulfill their potential in terms of energy efficiency and thermal comfort [5.10][5.11]. In a DOAS air-conditioning system, control of the two cooling coils is inter-dependent as sensible load in a building is handled by both cooling coils. The complexity of simultaneous control and dynamics of the two coils in DOAS air-conditioning systems makes the control of DOAS air-conditioning systems more challenging as compared to conventional single-coil systems.

The reactive control in current BAC systems is a non-integrated control approach and typically for SISO systems. As a result, it is not able to coordinate between multiple systems, such as two cooling coils in the DOAS air-conditioning systems [5.10][5.12]. However, MPC can optimise and obtain the best control strategies for multiple systems (e.g. two cooling coils in DOAS air-conditioning systems) in a coordinated way through minimising a multi-objective

cost function. Thus, MPC is a potential approach to fulfill the full potential of the DOAS air-conditioning system in terms of energy use and thermal comfort.

In this chapter, an MPC system is developed for a test building equipped with an AHU system. The test building is a lecture theatre (LT3) on the campus of NTU in Singapore. The original AHU is of conventional single-coil setup, which is later modified to a DOAS air-conditioning setup for comparative study. A linear building model that accounts for building dynamics, thermal comfort and ACMV system is employed in the MPC system. The control performance of the MPC system is compared to a BMS that is based on a PID strategy.

5.2 Methodology

5.2.1 Test building

Experiments were conducted in LT3 in the north academic complex on the campus of NTU, as shown in Figure 5.1. The walls of the test room (LT3) are of 0.2-m-thick reinforced concrete and the external surfaces are exposed to outdoor air, as shown in Figure 5.2. The wall surface area is 204 m². The roof and floor of the test room are composed of 0.4-m-thick reinforced concrete. The total floor area of the test room is 255 m². The test room has four entrances/exits and each entrance/exit has two doors at both ends, preventing the air leakage through the opening of the doors.

The test room is fitted with 240 seats, divided into three columns (left, middle and right) as shown in Figure 5.3. A total of 151 lamps are fitted on the ceiling, each rated at 30 W, providing a lighting power density of 17.8 W/m² of floor area. The heat gain from occupants and lighting forms the bulk of the internal load.

Figure 5.1 A view of the north academic complex and the location of the test room (LT3) at level 2, NTU Yuan Garden Campus

Figure 5.2 Internal setup in the test room

Figure 5.3 Internal view of the test room

5.2.2 ACMV system

The test room is originally air-conditioned by a single-coil VAV AHU (DAIKIN, DDMI-0717-H) as shown in Figure 5.4. The volume air flow rate is regulated within a range of 8,000 – 15,000 m³/h by a VSD fan that varies between 25 – 45 Hz, according to a temperature set-point of 24°C in the return air. The supply air is distributed into the room space through 24 diffusers and the room air returns to the AHU through 18 return air grilles, as shown in Figure 4.3. Fresh air flowrate is regulated by a motorized FAD according to a CO₂ concentration set point of 900 ppm in the return air. The RAD is kept 100% open when the CO₂ concentration in return air is below 1000 ppm and is regulated to 50% open when the CO₂ concentration goes beyond 1000 ppm. Chilled water flow rate through the cooling coil is regulated by a two-way motorized water valve (WV1 in Figure 5.4) according to the temperature set point of supply air, defined in Equation (5.1)

$$T_{sa,sp} = 288.15 - (T_{ra} - T_{ra,sp}) . \quad (5.1)$$

The chilled water for the ACMV system is provided by a central chiller plant in the test building, which has an average COP of 5.39. The average temperature of the chilled water entering the cooling coil in AHU is 8.5°C.

Figure 5.4 The original ACMV system in the test room

In the later stage of the study, the ACMV system was modified by adding a DOAS between the FAD and fresh air inlet, as shown in Figure 5.5. The original cooling coil in AHU acts as a secondary cooling coil for dealing with the remaining sensible load. Chilled water flowrate through the water loop of the DOAS was regulated by a two-way motorized valve (WV2 in Figure 5.5). Since there is no separate higher-temperature chiller in the main chiller plant of the test building, the water loop of the secondary cooling coil was modified such that the chilled water supply temperature could be raised. A constant-speed water pump (ELEMO, YE3-90L-2) and two three-way motorized valves (WV3 and WV4 in Figure 5.5) were installed, which regulated the mixing of chilled water from the chiller plant and recirculated chilled water from the secondary cooling coil. The mixed chilled water with a higher temperature of 11°C was supplied into the secondary cooling coil.

Figure 5.5 The modified DOAS air-conditioning ACMV system in the test room

5.2.3 Instrumentation

A set of sensors were installed for the implementation of the MPC system and monitoring of its control performance. These include 12 temperature-humidity-pressure-lux (THPL) sensors in the room space, as shown in Figure 5.2 and Figure 5.3, as well as globe temperature and air velocity sensors at the seating level at the middle of the test room. The air temperature, globe temperature, RH and air velocity measured by the above-mentioned sensors are used to calculate PMV in the test room. Other variables for PMV calculation including metabolic rate and clothing insulation are assumed to be constant at 1.2 met and 0.5 clo per occupant, respectively. Sensors for monitoring air variables in the ACMV system including combined temperature-RH, flowrate and CO₂ concentration were installed as shown in Figure 5.5. As the occupancy load is highly dynamic, continuous counting of occupants is required for real-time control and optimisation of the MPC system. The real-time CO₂ readings in the ACMV system are used to estimate the occupancy count inside the room space as one of the inputs of the MPC system for real-time control. The details of the estimation of occupancy count are described in Section 5.2.5. A combined temperature-RH sensor was installed outside of the test room to

measure outdoor conditions. Two thermal energy meters (Contrec 212) were installed in the water loop to monitor the cooling powers supplied to DOAS and AHU, respectively. A power meter (Siemens PAC3200) was installed to measure the electric powers of the CSD pump and VSD fan. Detailed specifications of the above-mentioned sensors are summarised in Table 5.1.

Table 5.1 Specifications of sensors installed in the test room

Location	Sensor	Variables	Brand	Model	Range	Accuracy
Room space	THPL	Temperature	EDS	MN-ENV-THPL	-20 – 85°C	± 0.25°
		RH	EDS	MN-ENV-THPL	0 – 100%	± 3%
	Globe temp	Temperature	Delta OHM	TP3276.2	-10...+100°C	1/3 DIN [#]
	Air velocity	Velocity	SIEMENS	QVM62.1	0-15 m/s	± (0.2 m/s + 3% of reading)
ACMV	Power meter	Voltage	SIEMENS	PAC3200	3 – 400 V AC	± 0.3%
		Current	SIEMENS	PAC3200	0 – x* A	± 0.2%
	Combined temp. & RH	Temperature	Schneider	SHD 101	-10 – 60°C	± 0.2°C
		RH	Schneider	SHD 101	0 – 95%	± 2%
	CO ₂	CO ₂	Veris Industries	CD Series	0 – 2000 ppm	± 20 ppm
	Thermal energy meter	Heat flux	Contrec	212	-	-
		Flowrate	ABB	WaterMaster Series	0-20 m ² /h	0.2%
		Temperature	ABB	TSC420	-50 – 300°C	± 0.15°C
Outdoor	Combined temp & RH	Temperature	Delta OHM	HP3217.2R	-40 – 100°C	1/3 DIN
		RH	Delta OHM	HP3217.2R	0 – 100% RH	± 2% RH

*refer to current reading of voltage in the power meter

Refer to accuracy class B defined in Ref. [5.13]

5.2.4 Modelling

In the test room, heat gain includes internal heat gain (occupancy load and lighting load), heat exchange with building thermal mass (e.g., walls, roof and floor) and thermal energy from the ACMV system. A thermal RC model is developed to describe the heat transfer in the room space, as shown in Figure 5.6. The RC model has thermal nodes representing the temperatures of interior thermal mass (building structures without surfaces exposed to outdoor air such as roof and floor of the test room), exterior thermal mass (building structures with surfaces exposed to outdoor air such as walls of the test room) and air in the room space. Other thermal masses such as furnishings and installation are not modelled in the thermal RC model, as the dimensions and property information are not available. However, a model calibration procedure based on measured building data is conducted to refine the thermal RC model and details are described in Section 5.2.5. No heat exchange between the test room and the adjacent rooms through the floor/roof is assumed.

Figure 5.6 RC thermal model of the test room

The equivalent thermal resistance and capacitance of the exterior thermal mass are calculated by Equations (5.2) and (5.3), respectively.

$$R_{em} = 1 / \left(\frac{1}{R_1} + \frac{1}{R_2} \dots \frac{1}{R_n} \right), \quad (5.2)$$

$$C_{em} = C_{em,1} + C_{em,2} + \dots C_{em,n}. \quad (5.3)$$

In Equation (5.2) and (5.3), subscripts n and em , refer to the number and exterior thermal mass, respectively. Equations (5.2) and (5.3) can also be applied for the calculation of equivalent thermal resistance and capacitance for the interior thermal mass of the test room.

The thermal RC network in Figure 5.6 could be described by

$$C_z \dot{T}_z = Q_{int} + Q_{sa} + \frac{T_{is,em} - T_z}{R_{is,em}} + \frac{T_{is,im} - T_z}{R_{is,im}}, \quad (5.4)$$

$$C_{iw} \dot{T}_{im} = \frac{T_{is,im} - T_{im}}{0.5R_{cond,im}}, \quad (5.5)$$

$$C_{ew} \dot{T}_{em} = \frac{T_{is,em} + T_{is,em} - 2T_{em}}{0.5R_{cond,em}}. \quad (5.6)$$

$$\frac{T_{is,em} - T_z}{R_{is,em}} + \frac{T_{is,em} - T_{em}}{0.5R_{cond,em}} = 0. \quad (5.7)$$

In Equations (5.4) - (5.7), subscripts is , es , im refer to surface exposed to room air, surface exposed to outdoor air and interior mass, respectively. The surface resistances of the inner and outer surfaces of walls/roofs/floors are assumed to be constant at 0.12 and 0.044 (m²-K)/W, respectively. The values of the surface resistances are taken from 2009 ASHRAE Handbook: Fundamentals [5.14] directly. The values are for the summer season with the assumption that

the surfaces of the walls/roofs/floors are non-reflective and convective heat exchange between inner surfaces and room air is the natural convection.

The dynamics of humidity ratio in the room space [Equation (3.1)] and linear PMV calculation model [Equation (3.40)] developed in Chapter 3 are employed for the test room. For Equations (5.4) and (3.1), no air infiltration (via cracks of envelopes or opening of doors) from outdoor to indoor is assumed when the ACMV system is on as it supplies fresh air and pressurizes the room space. In addition, the changeover of students for different lecture courses only happens for short times before or after classes. Thus, the effect of the changeover of students on room conditions is neglected. The room air leaves from indoor to outdoor through exfiltration and the flowrate is assumed the same as the fresh air to maintain indoor air mass balance.

When the ACMV system of the test room operates conventionally (DOAS off and AHU on), RH of the air from the cooling coil of AHU is assumed at 100%. Heat and moisture gain from the conventional AHU system can be calculated by Equations (3.24) and (3.25) developed in Chapter 3.

When the ACMV system for the testbed operates in a way of SSLC (both AHU and DOAS are on), the cooling coil in AHU acts as a secondary cooling coil for separate sensible and latent cooling. RH of the air from the cooling coil of DOAS is assumed to be 100%. It is also assumed that no water condensation in the secondary cooling coil which is achieved by maintaining the chilled water supply temperature to the secondary cooling coil higher than the dew point of the air from the secondary cooling coil. Thus, the secondary cooling coil in the DOAS air-conditioning system acts as a sensible heat sink to the room space. Incorporating with the linear

ACMV model for FCU/AHU developed in Chapter 3, moisture and heat gain from the DOAS air-conditioning system is modelled based on Equations (3.24) and (3.25)

$$\dot{m}_{moi,sa} = 2.58 \times 10^{-4} \dot{m}_{fa} T_{fa} - 2.57 \times 10^7 Q_{cw,DOAS} + 0.633 \dot{m}_{fa} \psi_{fa} - \dot{m}_{fa} \psi_{ra} - 0.0703 \dot{m}_{fa}, \quad (5.8)$$

and

$$Q_{sa} = 369.4 \dot{m}_{fa} T_{fa} - 1005 \dot{m}_{fa} T_{ra} - 0.368 Q_{cw,DOAS} - Q_{cc,AHU} + 9.062 \times 10^5 \times \dot{m}_{fa} \psi_{fa} + 1.734 \times 10^5 \dot{m}_{fa}. \quad (5.9)$$

In Equations (3.24), (3.25), (5.8) and (5.9), variables $\dot{m}_{fa}$ and $\dot{m}_{ra}$ are time-varying variables for the ACMV system in the test room. In real-time control, the ACMV model can be adapted at each time step with measured flowrates of fresh air and return air. Thus, MPC employing the adaptive ACMV model is also reformulated at each time step based on the updated ACMV model.

The indoor thermal comfort could be calculated using the linear PMV model as described by Equation (3.40). The cloth insulation and metabolic rate per occupant in LT3 are assumed to be constant at 0.5 clo and 1.2 met, respectively.

5.2.5 Model calibration and validation

To reduce prediction errors due to uncertainties in the building dynamics model described by in Section 5.2.4, it was calibrated and refined using measured data of LT3. The uncertainties can result from undefined properties of building structure and simplification that is assumed in the modelling.

A total of fourteen days of measured data in the test room are collected for model calibration and verification. The data were measured by the sensors described in Table 5.1 and stored at 5-min intervals. Measured data of the first eight days were used to calibrate the parameters of the thermal RC model described by Equations (5.4) - (5.6). The calibrated building dynamics model was then verified by comparing predicted results and the measured data of the remaining six days. Figure 5.7 and Figure 5.8 show the weather, AMCV and room conditions during the measurement period. Lighting power in the test room is assumed to be 100% when the ACMV system is on and 0% when ACMV is off. The ACMV was operating in the AHU setting (AHU is on and the DOAS is off) and was controlled by the original BMS. The number of occupants is estimated based on the steady-state CO₂ balance in the room space using measured supply air flow rate and CO₂ concentration in return and supply air,

$$n_{occ} = G_{sa}(conc_{ra} - conc_{sa})/S, \quad (5.10)$$

where G , Num , C and S refer to volume flow rate (m³/s), number of occupants, CO₂ concentration (m³/m³) and CO₂ generation rate per person (m³/s).

(a)

(b)

Figure 5.7 Measured ACMV and outdoor conditions for model calibration and verification.

(a) Cooling power and estimated number of indoor occupants, (b) outdoor air temperature and humidity.

Given that uncertainties in the building dynamics model are the R and C parameters of thermal RC network, they are tuned in the calibration to minimise the error sum of squares (SSE) of room air temperature between measurements and that predicted by the thermal RC model using the same algorithm (Trust-Region-Reflective Least Squares) as that in Chapter 3.

Figure 5.8 shows the comparison of room air temperature simulated by the thermal dynamics model and the measured data in LT3 during both calibration and verification periods. The time profile results of the simulated and measured room air temperatures are plotted in Figure 5.8 (a). The absolute errors of the simulated room air temperature during both calibration and validation periods are shown in Figure 5.8 (b). The median errors of the simulated room air temperature are 0.3°C and 0.55°C during the calibration and validation periods, respectively. The MAPEs are 2% and 2.5% during the calibration and verification periods, respectively, suggesting good agreement between the simulated and measured room temperatures. The room humidity ratio predicted by Equation (3.1) also has good agreement with measured room humidity ratio when the ACMV was on and the MAPE is 7%.

(a)

(b)

Figure 5.8 Comparison of the simulated and measured room air temperatures. (a) Time profile plot, (b) absolute errors

The building dynamics model of LT3 with the DOAS air-conditioning system is also verified by comparing to the measured data. The data were measured during 29th January 2019 – 4th February 2019. The ACMV was operating in the SSLC setting (both the AHU and DOAS are on). The test conditions for verifying the building dynamics model with DOAS air-conditioning system are shown in Figure 5.9.

(a)

(b)

(c)

Figure 5.9 Measured ACMV and outdoor conditions for model verification. (a) The cooling power of AHU and DOAS, (b) the estimated number of occupants, (c) outdoor air temperature and humidity.

Figure 5.10 shows the comparison of the simulated room air temperature by the building dynamics model against the measured data. The time profile results of the simulated and measured room air temperatures are plotted in Figure 5.10 (a). The absolute errors of the simulated room air temperature are shown in Figure 5.10 (b). The median error of the simulated room air temperature is 0.28°C , suggesting a good prediction performance of the building

dynamics model. The MAPE of the simulated room air temperature is 1.2%. The prediction performance of indoor humidity ratio by the building dynamics model is as compared to the measured data and the MAPE of the simulated indoor humidity ratio when the ACMV was on is 8%.

(a)

(b)

Figure 5.10 Comparison of the simulated and measured room air temperatures. (a) Time profile plot, (b) absolute errors

The model of LT3 described in Section 5.2.4 is written in an SSM. The description of the inputs, states and outputs of the SSM is listed in Table 5.2. For each of the two studied ACMV systems (original single-coil AHU and DOAS air-conditioning), an SSM for building model is created. Matrices **A**, **B**, **C** and **D** of SSMs for the original AHU system and the DOAS air-conditioning system are shown in the Appendix, Tables A.9 – A.16. The two SSMs are linear with time-varying parameters ($\dot{m}_{fa}$ and $\dot{m}_{ra}$).

Table 5.2 Description of inputs, states and outputs for SSM

Inputs	Description	States	Description	Outputs	Description
$Q_{cw,AHU}$	Total cooling power provided by AHU (W)	T_z	Room air temperature (K)	T_z	Room air temperature (K)
$Q_{cw,DOAS}^*$	Total cooling power provided by DOAS (W)	T_{im}	Temperature of interior thermal mass (K)	ψ_Z	Indoor humidity ratio (kg/kg)
T_{fa}	Fresh air temperature (K)	T_{em}	Temperature of exterior thermal mass (K)	PMV	Indoor PMV
ψ_{fa}	Fresh air humidity ratio (kg/kg)	ψ_Z	Indoor humidity ratio (kg/kg)	T_{mr}	Mean radiant temperature (K)
T_{oa}	Outdoor air temperature (K)				
Q_{int}	Internal heat gain (W)				
$\dot{m}_{moi,int}$	Internal moisture gain (kg/s)				
$CONS$	Constant 1 (feedthrough to output PMV)				

*Input of cooling power provided by DOAS only applies to SSM with DOAS air-conditioning system. It is excluded for building SSM with original AHU system.

5.2.6 MPC controllers

Two MPC controllers were developed for controlling the original AHU system and DOAS air-conditioning system, respectively. The MPC controller for original AHU (MPC-AHU) controls the original AHU to deal with both sensible and latent loads by a single cooling coil. The MPC controller for DOAS air-conditioning system (MPC-SSLC) controls the DOAS to deal with the latent load and a fraction of the sensible load and the AHU to deal with the remaining sensible load. The two MPC controllers share the same overall structure, as shown in Figure 5.11, consisting of an optimisation solver, SSM, constraints and a cost function. With inputs of measured disturbances, MPC optimises control signals to the ACMV system of the test room. State parameters in SSM are updated at each control interval to compensate for the model error of SSM and avoid the accumulation of prediction error in the MPC controller. The feedback of state parameters is estimated by a Kalman filter based on the difference between SSM predicted and measured room conditions. Measured flowrates of fresh and return air are fed back to MPC to update the ACMV model in SSM.

Figure 5.11 Schematic of the MPC for the test room

5.2.6.1 MPC controller for conventional AHU

The MPC formulation developed in Chapter 3 for the FCU in SkyLab is applied to the single-coil AHU of this test room. The SSM of MPC-AHU is described in Table 5.2 and Table A.9 to

Table A.12. However, additional constraints of indoor humidity ratio are added to the MPC controller.

A maximum indoor relative humidity of 65%, recommended by ASHRAE Standard 62.1 [5.17], is used to calculate the upper bound of indoor humidity ratio,

$$\psi_{z,max} = 0.00075T_z - 0.005915. \quad (5.11)$$

Equation (5.11) is a linear correlation of air humidity ratio and air temperature for a fixed air relative humidity of 65%, which is fitted based on data generated by psychrometrics [5.14]. Equation (5.11) is valid in a temperature range of 22 – 27°C, which covers the typical range of room air temperature. The approximated results by Equation (5.11) which are compared to the data generated by psychrometrics are shown in Figure 5.12 and good agreement is observed. Thus, the constraints for the MPC controller are

$$0 \leq \psi_z \leq \psi_{z,max} . \quad (5.12)$$

The constraints of humidity ratio are softened by a slack variable and more details about the slack variable are described in Chapter 3.

Figure 5.12. Comparison of linear equation and data generated by psychrometrics

5.2.6.2 MPC controller for DOAS air-conditioning system

The objective function of MPC-SSLC aims at minimising the cooling energy consumed by cooling coils in both AHU and DOAS, and achieving the best indoor thermal comfort

$$J = \text{Minimize}(\sum_{k=0}^N \hat{Q}_{AHU,t+k|t}^2 \sum_{k=0}^N \hat{Q}_{DOAU,t+k|t}^2 + \sum_{k=0}^N (W_{PMV} \widehat{PMV}_{t+k|t})^2 + \sum_{k=0}^N W_{\epsilon} (\epsilon_{t+k|t})^2). \quad (5.13)$$

The objective function, Equation (5.13), holds for SSM for the DOAS air-conditioning system described in Table 5.2 and Table A.13 to Table A.16 in the Appendix, constraints for cooling power of cooling coils in both AHU and DOAS, and constraints for indoor PMV index. The constraints for cooling power of AHU and DOAS are the cooling capacities of the cooling coils in AHU and DOAS, respectively. The constraints of indoor PMV index and indoor humidity ratio are the same as that of MPC-AHU. A control interval of 2 minutes is applied to the MPC controllers, which enables the MPC controllers to deal with the dynamic occupancy level in the lecture theatre. The prediction horizon of the MPC controllers is 30 control intervals (60-mins), which covers the response time of the thermal conditions in the lecture theatre (e.g.,

around 30 minutes for indoor PMV to be cooled down to the best thermal comfort during morning start-up of ACMV).

5.2.7 Control system architecture

The control system for the test room is illustrated in Figure 5.13. In parallel to the original BMS, an additional MPC system is added. A manual switch is installed to allow switching between the original BMS and the new MPC system for controlling the ACMV system. When the ACMV is running in the AHU setting (AHU is on, DOAS is off), the two-way motorized valve (WV1), VSD fan and FAD, as shown in Figure 5.4 and Figure 5.5, are controlled by the selected control system. If the original BMS is controlling (BMS-AHU), the BMS controls the AHU according to the strategies described in Section 5.2.2. If the MPC is controlling (MPC-AHU), the MPC server generates optimal cooling power set-point for the AHU and passes the set-point to a local controller (Schneider AS-P) through Modbus TCP/IP. The local controller regulates the various actuators according to the logic summarised in Table 5.3.

Table 5.3 Control logic in the local controller for MPC-AHU

Actuator	Control parameter	Set point
WV1	Cooling power	Send from MPC
VSD fan	Supply air temperature	15°C
FAD	CO ₂ level in return air (fine)	900 ppm
RAD	CO ₂ level in return air (coarse)	1000 ppm

Figure 5.13 Architecture of MPC system for the test room

When the ACMV system is running in the SSLC setting (both AHU and DOAS are on), all the actuators in the ACMV system are controlled by MPC (MPC-SSLC). MPC-SSLC generates optimal cooling power set-points for both the DOAS and AHU. The two cooling power set-points are passed to the local controller, which then regulates the actuators according to the logic summarised in Table 5.4. The dew point temperature of the mixed air is constantly monitored based on the measured air temperature and RH at return air and off-coil of DOAS. The supply air temperature is controlled to be 1°C higher than the dew point of mixed air so that there is no latent load in the secondary coil.

Table 5.4 Control logic in the local controller for MPC-SSLC

Actuator	Control parameter	Set point
WV1	Cooling power of secondary coil	Send from MPC
WV2	Cooling power of DOAS coil	Send from MPC
WV3 & WV4 & Pump	Chilled water supply temperature to the secondary coil	11°C
VSD fan	Supply air temperature	1°C + dew point of mixed air
FAD	CO ₂ level in return air (fine)	900 ppm
RAD	CO ₂ level in return air (coarse)	1000 ppm

Readings from sensors in the ACMV system, room space (except for the THPL sensors) and outdoors are fed through the local controller to the MPC system at 5-second intervals. THPL sensor readings are passed to the MPC controller directly through the internet. The MPC controller stores all the measured data on the MPC server. Unless otherwise stated, data storage occurs every 5 minutes. The stored data are used for subsequent analysis of system performance.

5.2.8 Experiment arrangement

The weekly lecture class schedule in the test room during the test period is listed in Table 5.5. There are 240 seats in the test room for students and the actual number of students in the test room is estimated by Equation (5.10). Equation (5.10) is executed in the controller server automatically and continuously to provide real-time occupancy count for the MPC system during the test period. There are 40 hours of classes per week and the schedule repeats weekly for the test period. The internal loads (occupancy and lighting load) during class time are assumed to be the same for every week. The ACMV system is switched on 30 minutes before and switched off immediately after each class. However, if the time gap between the end of a class and the start of the next class is shorter than 60 minutes, the ACMV system is kept on during the time gap. Lighting power is assumed to be 100% when the ACMV system is on and 0% when it is off. Three settings 1) BMS-AHU, 2) MPC-AHU and 3) MPC-SSLC are

conducted in the test room during January – March of 2019. The test for each setting ran for two weeks.

Table 5.5 Class schedule in the test room

	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00
Monday													
Tuesday													
Wednesday													
Thursday													
Friday													

5.3 Test results

Figure 5.14 shows the time series of the measured indoor PMV, room air temperature, RH and cooling power under the three settings (BMS-AHU, MPC-AHU and MPC-SSLC) on a Tuesday, which is the busiest day of the week in terms of the class schedule. As shown in Figure 5.14 (a), indoor PMV was maintained close to the best thermal comfort ($PMV = 0$) during most of the class time in the two MPC settings. This could be attributed to the thermal comfort model, described by Equation (3.40), for thermal comfort optimisation in both MPC controllers. In contrast, BMS-AHU kept the indoor PMV at the cool side ($PMV < 0$) of thermal comfort for most of the class time, indicating excessive cooling of the room space due to the tracking of a single temperature set-point. Figure 5.14 (b) and (c) illustrate that BMS-AHU maintained lower room air temperature and RH as compared to the MPC settings, echoing the trend for PMV observed in Figure 5.14 (a). Figure 5.14 (d) shows that BMS-AHU uses higher cooling power than the two MPC settings for most of the time, suggesting that BMS-AHU could consume a higher amount of cooling energy than the two MPC settings.

(a)

(b)

(c)

(d)

Figure 5.14 Time profile of measured variables in test bed on Tuesday. (a) indoor PMV, (b) room air temperature, (c) room air RH, (d) cooling power of ACMV system.

The statistical distributions of the measured indoor PMV, room air temperature and RH, as well as cooling power during class time for the three settings in the test period are shown in Figure 5.15 as box plots. Figure 5.15 (a) shows that the median indoor PMV for BMS-AHU, MPC-AHU and MPC-SSLC are -0.23, -0.09 and -0.02, respectively. This suggests that MPC-SSLC maintains the best indoor thermal comfort among the three settings whereas BMS-AHU is the worst. Both MPC settings kept indoor PMV within the comfortable zone ($-0.5 \leq \text{PMV} \leq 0.5$) during all the class time whereas indoor PMV went below -0.5 (overcooling) occasionally in BMS-AHU setting. Figure 5.15 (b) shows that BMS-AHU chases the indoor air temperature set point of 24°C whereas the MPC settings kept the indoor air temperature at around 24.7°C, which is decided by the objective of achieving best thermal comfort in both MPC controllers. However, the indoor temperature distribution for MPC-SSLC is much narrower than that observed in MPC-AHU, indicating that SSLC is more capable of maintaining stable room temperature than the single-coil AHU. Figure 5.15 (c) shows that MPC-SSLC kept room air RH under the upper bound (65%) at all class time whereas the room air RH in the MPC-AHU setting goes beyond the upper limit occasionally. MPC-SSLC also maintains more stable room RH than MPC-AHU. Figure 5.15 (d) shows that the average cooling power in the BMS-AHU setting during class time is the highest among the three settings, which echoes the observation in Figure 5.14. Figure 5.15 suggests that MPC-SSLC outperforms the other two settings in terms of reducing cooling power and maintaining thermal comfort. BMS-AHU has the worst performance among the three settings.

(a)

(b)

(c)

(d)

Figure 5.15 Statistical distributions of measured variables in test bed in the whole test period
(a) indoor PMV, (b) room air temperature, (c) room air RH, (d) cooling power of ACMV system

Figure 5.16 shows the average weekly ACMV electricity consumption for each setting. The values shown in Figure 5.16 are averaged over the two-week test period in each setting. ACMV electricity consumption consists of the consumption by chiller, fan and pump (in the case of MPC-SSLC). The chiller electricity consumption is estimated based on the measured cooling energy and a COP value of 5.39 for the central chiller plant serving the test building. Electricity consumption by the fan and pump are measured by the electric power meters as described in Table 5.1. The MPC settings produce 16 – 18% energy saving as compared to BMS-AHU. Among the two MPC settings, MPC-SSLC consumes slightly less chiller energy than MPC-AHU but MPC-SSLC consumes extra fan and pump energy. The extra fan energy in SSLC is mainly due to the higher airflow volume needed to compensate for the raised supply air temperature to avoid condensation in the secondary cooling coil. The extra pump energy in SSLC is because of the need to recirculate chilled water in the secondary coil loop to achieve raised chilled water supply temperature, due to the lack of a separate higher temperature chiller

in the test building. These extra consumptions lead to less energy saving by MPC-SSLC than MPC-AHU.

Figure 5.16 Average weekly ACMV electricity consumption

If the SSLC system is implemented in a building with separate chillers for the DOAS and secondary coil, the thermal efficiency of the higher-temperature chiller that provides chilled water for the secondary cooling coil could be higher and the extra pump energy consumption could be eliminated. An adjusted average weekly ACMV electricity consumption of MPC-SSLC based on this fictitious scenario is estimated as shown in Figure 5.16 (MPC-SSLC_{adj}). Assuming chiller efficiency is increased by 2%/°C rise in chilled water supply temperature [5.18][5.19], the COP of the higher-temperature chiller producing chilled water of 11°C for the secondary coil is estimated to be 5.66. Applying the estimated COP value to the secondary coil and removing the pump energy consumption, MPC-SSLC_{adj} is estimated to have 20% energy saving as compared to BMS-AHU.

5.4 Summary

This chapter proposed an MPC system for the control of conventional single-coil AHU and DOAS air-conditioning ACMV systems. The MPC system employs a linear SSM, which consists of sub-models of thermal RC, PMV and ACMV, for forwarding prediction of building responses. A real-time optimisation scheme with a multi-objective cost function is implemented, which optimises both cooling energy efficiency and indoor thermal comfort while maintaining indoor PMV and RH within the required ranges. The proposed MPC system was developed and experimentally implemented in a lecture theatre on the campus of NTU as a test building. The control performance of the MPC system for the single-coil AHU and DOAS air-conditioning systems was compared to a conventional reactive control based BMS. The MPC system achieved 18% and 16% electricity savings for the single-coil AHU and DOAS air-conditioning systems, respectively, as compared to the BMS. The slightly lower energy saving by the DOAS air-conditioning system is mainly caused by the lack of a separate higher-temperature chiller in the test building. If the system is implemented in a building equipped with a separate higher-temperature chiller, it is estimated that the MPC-controlled DOAS air-conditioning system can achieve 20% energy savings compared to the conventional BMS-controlled AHU system. The MPC system significantly improved indoor thermal comfort by maintaining indoor PMV stably close to thermal neutrality ($PMV = 0$), as compared to the BMS which kept indoor thermal comfort at the cool side ($PMV < 0$) with large variations for most of the time. Compared to the single-coil AHU, DOAS air-conditioning has better control capability for the MPC system to achieve a better indoor environment in terms of indoor thermal comfort and RH.

5.5 References

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Part IV Model Predictive Control for Coordinated Building Systems Control

Chapter 6 Model Predictive Control for Coordinated Air-Conditioning, Lighting and Shading Control

6.1 Introduction

Studies suggest that current building systems are not operating as efficiently as they could be [6.1]. ACMV and lighting systems controlled by current BAC systems have the potentials of energy efficiency improvement for around 20% [6.2] and up to 60% [6.3][6.4], respectively, through upgrading the control scheme. Besides, the heat load from windows in current buildings results in large cooling demand, accounting for around 30% of cooling energy consumption [6.5][6.6]. Some technologies such as advanced ACMV system (e.g., ACB), automated lighting (e.g., scheduled lighting and occupancy/daylight-sensor-based lighting) and shading technologies (e.g., blinds and tinted glasses) have been used in buildings to improve the energy efficiency. However, these building systems, including ACMV, lighting and shading systems in current buildings are under their own control without coordination [6.7][6.8][6.9] due to the limitations of current BAC systems, which could cause energy-inefficiency in buildings.

This chapter develops an MPC system for coordinated ACMV, shading and lighting control in buildings. A linear SSM, capturing building dynamics and indoor thermal comfort, developed in Chapter 3 and Chapter 4 is employed to optimise energy efficiency and indoor thermal comfort in buildings. Models for predicting lighting power and indoor visual comfort are developed in this chapter based on measured building operation data for optimising lighting power, heat gain from the window and indoor visual comfort. The models are used to construct an MPC system to perform coordinated control of ACMV, lighting and shading systems. The MPC system is implemented in the BCA SkyLab test facility. The performance of the MPC system is compared to the original BMS of SkyLab, which is based on a PID strategy.

6.2 Methodology

6.2.1 Test building

These experiments were implemented in BCA SkyLab. The information of SkyLab including ACMV system, sensor network, heat load setup, and envelope of BCA SkyLab was described in Chapter 3 and Chapter 4. More details of shading and lighting systems are described in this chapter.

6.2.2 Windows

The DGU of the window in Test Cell is composed of an EC coating glass layer (12 mm thickness), an air gap (15 mm thickness) and a Low-e coating glass layer (6 mm thickness) from outdoor to indoor, as shown in Figure 6.1 (a). The colour of the EC coating is adjustable between fully clear (0% tint level) and fully dark (100% tint level) to modulate the heat gain and daylight penetration through the window. The response for the EC coating tinting from fully clear to fully dark takes 3 minutes. The properties of VLT, SHGC and U-value of the EC DGUs as shown in Table 6.1. The tint level of the window in Test Cell (EC window) is controlled by a cloud server, which accepts external control signals (control signals generated by the MPC system in this study). In this study, all eight EC DGU panels are maintained at the same tint level. The DGUs of the window in Reference Cell consist of a Low-e coating glass layer (6 mm thickness), an air gap (12 mm thickness) and a clear glass (6 mm thickness) layer from outdoor to indoor, as shown in Figure 6.1 (b). The Low-e coating is titanium nitride with thickness of 300nm. The emissivity of the Low-e coating is 0.07 and its reflectivity for infrared light is 0.93. The visible light transmission (VLT), solar heat gain coefficient (SHGC), and U-value of the Low-e DGU are 63%, 0.27 and 1.55 W/m²K, respectively. Blind systems are fitted right after the inner surface of the windows in both cells but retracted during experiments.

Figure 6.1 Schematic of DGUs in SkyLab. (a) EC window in Test Cell, (b) Low-e window in Reference Cell

Table 6.1 Properties of EC window in Test Cell of SkyLab*

Tint level (%)	0	17	29	38	47	55	63	70	79	87
VLT (%)	63.6	56.4	49.3	42.8	36.2	30.2	24.1	18.7	13.2	7.6
SHGC (%)	44.2	38.6	33.0	28.4	23.8	20.1	16.4	13.6	10.7	8.2
U-value (W/m ² K)	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3

*The properties data of the EC window are from the manufacturer.

6.2.3 Lighting system

Both Test Cell and Reference Cell are fitted with eight lighting fixtures, T5 fluorescent lamp (PHILIPS TBS460 3×TL5-14W HFS D6), on the false ceiling as shown in Figure 6.2 and Figure 6.3. Each lighting fixture is 0.6 m in length and 0.6 m in width. Two alternative modes, constant and automated dimming based on daylight (controlled by DALI dimming algorithm), are available for both cells. The two modes of the lighting system for the two cells could be switched in SkyLab BMS. When the lighting system is under automated dimming mode, a light regulates the power of the lights according to the illuminance measured by a daylight sensor,

which is facing the exterior window, as shown in Figure 6.3. The control logic (correlation between power and reading of the daylight sensor for different lights) in the automated dimming system was identified by Lamano et al. [6.10]. When the lighting system is under the constant mode, the lights are on and at the maximum power. The maximum lighting power is 8.33 W/m² of floor area for each cell.

Figure 6.2 Top view of BCA SkyLab

Note: Each thermal zone has two chilled beam units

Figure 6.3 Schematic of ACMV, lighting and shading systems in SkyLab Test Cell.

6.2.4 Instrumentation

The sensor network for monitoring the ACMV system variables, indoor thermal conditions and weather conditions was described in Chapter 3. Additional sensors are installed in SkyLab for controlling and monitoring the indoor visual conditions.

Each cell of SkyLab is equipped with an HDR imaging system to measure the indoor glare condition, as shown in Figure 6.2. The core component of the imaging system is an HDR camera (Canon 70D), which has a fisheye lens (Sigma 8 mm F/3.5 EX DC) for 180° circular imagery. The camera-lens set is facing, 3 metres away, window façade and mounted on a tripod at standing height level (1.7 m) due to the fact that higher glare at this level is more frequent than seating level (1.1 m) during previous tests [6.11]. A photometric sensor (LICOR LI-210R, accuracy $\pm 5\%$) is mounted on top of the camera, facing the window facade. Data from the photometric sensor are transferred to a server for data processing through a DAQ module (LabJack U3-HV). Bracketed pictures are taken automatically at 5-minute intervals using *hdrcaposx* software [6.12] during office hours. A software tool, *hdrgen* [6.12], is used to convert the LDR images to an HDR image. The photometric sensor data are used for vignetting correction of the lens and images calibration with *RADIANCE* software [6.13]. Finally, the discomfort glare metrics, DGP, is evaluated based on the HDR images with *evalglare* software [6.14]. The images, DGP data and illuminance data are stored in the server.

In each cell, indoor horizontal illuminance level at working plane height and vertical illuminance level right behind window façade are measured by seven and one illuminance sensors, respectively. The four illuminance sensors in lighting zone 1 and 2 have a measurement range of 0 - 10,000 lux (KIMO LR-110 PN, accuracy $\pm 3\%$ of reading) and the

rest four have a measurement range of 0 - 150,000 lux (REINHARDT light intensity sensor, accuracy $\pm 6\%$ of reading).

6.2.5 Building modelling

A linear SSM of SkyLab capturing building dynamics and thermal comfort were developed in Chapter 3 and Chapter 4. This chapter employs the SSM for optimising indoor thermal comfort and ACMV energy consumption. To optimise indoor visual comfort, lighting power and heat gain from windows, models to predict indoor illuminance and lighting power are developed.

6.2.5.1 Daylight model

Indoor light conditions of SkyLab Test Cell during daytime are mainly determined by daylight penetration from the window façade. Since the daylight incidence on the window façade is not measured in SkyLab, it is calculated based on luminous efficacy with inputs of the measured solar radiation in this study. Luminous efficacy describes the capacity of a light source to produce visible light [6.15]. For daylight produced by solar radiation, luminous efficacy is the ratio of daylight illuminance to solar irradiance,

$$LE = E_{dl}/I_{sol} , \quad (6.1)$$

where symbols LE , E and I refer to luminous efficacy, illuminance (lux) and irradiance (W/m^2). Subscripts dl refers to daylight.

For a surface exposed to outdoor space, such as the window façade of SkyLab Test Cell, the incident solar irradiance consists of diffuse irradiance ($I_{dif,inc}$), direct irradiance ($I_{dir,inc}$) and irradiance reflected by ground ($I_{gro,inc}$) [6.16] [6.17].

The incident diffuse irradiance on the surface can be calculated by the method of Perez et al. [6.16] as follow,

$$I_{dif,inc} = I_{dif}c_{hb}\sin\theta_{tilt} + I_{dif}(1 - c_{cb})(1 + \cos\theta_{tilt})/2 + I_{dif}c_{cb}\max(0, \cos\theta_{inc})/\max(0.087, \cos\theta_{zen}), \quad (6.2)$$

where symbols c and θ refer to coefficient and angle. Subscripts hb , cb , inc , dif , zen and $tilt$ refer to horizon brightening, circumsolar brightening, incident, diffuse, solar zenith and tilt of the surface. The circumsolar brightening coefficient c_{cb} and horizon brightening coefficient c_{hb} are defined by Perez et al. [6.16] as follows

$$c_{cb} = f_{11} + f_{12}f_{sb} + f_{13}\theta_{zen}, \quad (6.3)$$

$$c_{hb} = f_{21} + f_{22}f_{sb} + f_{23}\theta_{zen}. \quad (6.4)$$

The values of the factors in Equation (6.3) and (6.4) could be found in a lookup table provided by Perez et al. [6.16] according to sky conditions.

The incident direct solar irradiance on the surface can be calculated using the incident angle of solar beam to the surface

$$I_{dir,inc} = I_{dir}\cos\theta_{inc}. \quad (6.5)$$

In SkyLab, a solar radiation sensor is installed on the rooftop as shown in Figure 4.2 in Chapter 4, which is able to measure global horizontal irradiance I_{glo} and diffuse horizontal irradiance I_{dif} . The solar direct irradiance can be evaluated based on the measured I_{glo} and I_{dif}

$$I_{dir} = (I_{glo} - I_{dif})/\sin\theta_{alti}. \quad (6.6)$$

Thus, illuminances produced by the incident direct irradiance, incident diffuse irradiance and illuminance produced by ground reflected irradiance on the surface could be calculated by

$$E_{dir,inc} = LE_{dir}I_{dir,inc}, \quad (6.7)$$

$$E_{dif,inc} = LE_{dif}I_{dif,inc}, \quad (6.8)$$

$$E_{gro,inc} = r_{gro}LE_{glo}I_{glo}(1 - \cos\theta_{tilt})/2, \quad (6.9)$$

where symbol r refers to reflectivity of visual light, subscript gro refers to ground. Luminous efficacies for direct and diffuse irradiance are calculated by [6.16]

$$LE_{glo} = c_{1,glo} + c_{2,glo}PWC + c_{3,glo}\cos\theta_{zen} + c_{4,glo}Ln^{fc_{sb}} \quad (6.10)$$

$$LE_{dif} = c_{1,dif} + c_{2,dif}PWC + c_{3,dif}\cos\theta_{zen} + c_{4,dif}Ln^{fc_{sb}}, \quad (6.11)$$

$$LE_{dir} = \max[0, c_{1,dir} + c_{2,dir}PWC + c_{3,dir}\exp(5.37\theta_{zen} - 5) + c_{4,dir}fc_{sb}], \quad (6.12)$$

Coefficients c_1 , c_2 , c_3 and c_4 and factor fc_{sb} and (6.4) could be found in a lookup table provided by Perez et al. [6.16] according to sky conditions.

The illuminance transmitted by the EC window (vertical illuminance level right after the inner surface of the EC window) in SkyLab Test Cell could be calculated by,

$$E_{tra} = VLT * E_{dir,inc} + VLT * E_{dif,inc} + VLT * E_{gro,inc} , \quad (6.13)$$

where VLT refers to visible light transmittance.

6.2.5.2 Visual comfort prediction model

The main target of shading optimisation in the MPC system for SkyLab Test Cell in this study is to prevent visual discomfort caused by excessive daylight penetration. The minimum indoor illumination conditions are controlled by the lighting controller in SkyLab. The lower threshold of illuminance at the work plane is 500 lux [6.18][6.19]. 3000 lux is selected as the upper threshold of the acceptable illuminance at the work plane [6.19][6.20]. The upper threshold of indoor DGP is 0.35, which means imperceptible glare when the upper threshold is fulfilled according to Ref. [6.21]. However, previous tests Zhou et al. [6.22] found that when the horizontal illuminance at the work plane was lower than 3000 lux, the indoor DGP was always below 0.35. Thus, the upper threshold illuminance at a work plane of 3000 lux is used as the constraint for indoor visual comfort optimisation. Therefore, the correlation of the maximum illuminance level at work plane (in lighting zone 4 as shown in Figure 6.2) and daylight penetration in SkyLab Test Cell needs to be modelled.

An experiment was conducted in SkyLab Test Cell to generate measured data to train a data-driven model for predicting maximum illuminance at work plane. The measurement was conducted during 30/January/2018 - 8/February/2018. Maximum indoor illuminance at work plane was measured by the horizontal illuminance sensor in lighting zone 4, as shown in Figure 6.2. The transmitted illuminance of the EC window was measured by the vertical illuminance sensor, as shown in Figure 6.2. The measured illuminance data was recorded by SkyLab BMS at 1-min intervals. The window façade was facing north during 30/January/2018 - 1/February/2018 and west during 2/February/2018 – 8/February/2018 to capture different solar incidence conditions. The lighting system in Test Cell was at automated dimming mode during the measurement period.

Based on the measured data, the correlation of the maximum illuminance at work plane and transmitted illuminance of the EC window was fitted using linear regression as shown in Figure 6.4. Figure 6.5 shows the comparison of the maximum illuminance at work plane estimated by the fitted correlation (E_{est}) as compared to the measured data (E_{mea}). It shows that 90% of the estimated values are within ($E_{mea} - 235$ lux, $E_{mea} + 234$ lux). The R^2 of the fitting is 0.95, suggesting that the fitted model is good for predicting the maximum illuminance on the work plane. The maximum illuminance at work plane could be estimated based on measured solar radiation, tint level of the EC window, Equations (6.1) - (6.13), Table 6.1 and the fitted model as described by Figure 6.4.

Figure 6.4 Fitted correlation of illuminance at work plane and transmitted vertical illuminance from the EC window

Figure 6.5 Comparison of the measured and estimated maximum illuminances at work plane

6.2.5.3 Lighting power prediction model

To predict the lighting power regulated by the lighting controller (automated dimming mode), the correlation of illuminance sensed by the daylight sensor and the measured transmitted illuminance of the window is also fitted, as described by Equation (6.14), based on the same experimental data as described in Section 6.2.5.2. The comparison of illuminance sensed by

the daylight sensor and the transmitted vertical illuminance from the window is shown in Figure 6.6. The 95th and 5th percentiles of the errors between the estimated illuminance (E_{est}) and the measured illuminance (E_{mea}) are 127 lux and -167 lux, respectively. It means 90% of the estimated illuminances are within ($E_{mea} - 167$ lux, $E_{mea} + 127$ lux). The R^2 of the measured illuminance versus the estimated illuminance is 0.9. Thus, Equation (6.14) is considered good to estimate the illuminance sensed by the daylight sensor.

$$E_{dls} = -6.88 * 10^{-6} E_{tra,dif} E_{tra,gro} - 0.135 \cos \theta_{inc} E_{tra,gro} + 0.474 \cos \theta_{inc} E_{tra,dif} + 0.113 * E_{tra,gro} + 0.0467 * E_{tra,dif} - 41.4 * \cos \theta_{inc} + 9.5. \quad (6.14)$$

$E_{tra,dir}$, $E_{tra,dif}$ and $E_{tra,gro}$ refer to the three terms at the right-hand side of Equation (6.13). Thus, the lighting powers of the four lighting zones in SkyLab Test Cell could be estimated based on measured solar radiation, shading level of the EC window, Equations (6.1) - (6.14), Table 6.1 and control logic of the automated dimming system (correlation between the measurement in daylight sensor and the lighting power) modelled by Lamano et al. [6.10].

Figure 6.6 Comparison of measured illuminance and estimated illuminance sensed by the daylight sensor

6.2.6 Control system

Figure 6.7 shows the MPC system for coupling of ACMV, shading and lighting control in Test Cell. The MPC system controls the ACMV and shading systems coordinating with the existing lighting controller. The same MPC algorithm [Equation (4.3)] for the ACB system developed in Chapter 4 is employed in this MPC system for controlling the ACB system. The objective function of the shading control is described by Equation (6.15), which aims to minimise the electricity consumed by the lighting as well as the electricity consumed by the chiller to deal with the heat gain from the lighting and windows.

$$J = \text{Minimize}((EP_{lig} + EP_{lig}/COP + Q_{win}/COP), \quad (6.15)$$

where symbols EP and COP refer to electric power and coefficient of performance of a chiller. Subscripts lig and win refer to lighting and window. The objective function is subjected to the constraints,

$$500 \text{ lux} \leq E_{wp} \leq 3000 \text{ lux}. \quad (6.16)$$

Although the MPC system uses two objective functions for the shading control and ACB control, the optimization problems of the shading control, the ACB control and the automated dimming are coupled as shown in Figure 6.7. The coupling includes (1), the ACB optimizer receives the estimated heat gain from the window and lighting based on the solved optimal shading level from the shading optimizer as the inputs to optimize indoor thermal comfort and cooling energy; (2) the automated dimming logic and the COP of the chiller are included in the optimization problem of the shading control as described in Equation (6.15) for optimizing

visual comfort, electricity consumed by the light and electricity consumed by the chiller; (3) the room air temperature regulated by the ACB optimizer is measured and passed to the optimizer of the shading control to for optimizing the electricity consumed by the chiller.

The shading optimizer is a static optimiser that searches the optimal shading level of the EC window to minimize the objective function [Equation (6.16)] with the inputs of measured solar radiation, outdoor air temperature and room air temperature using the bisection algorithm. Once the optimal shading levels are determined, the heat gains from the EC window and lights in a prediction horizon are estimated and passed to the ACB optimizer, which is a dynamic optimizer. Based on the inputs of weather conditions, estimated heat gain from the EC window and lights, the ACB optimizer generates the optimal control decisions for the ACB system using quadratic programming.

The use of two different objective functions for shading and ACB control in the coupled way instead of using one objective function for both shading and ACB control is due to (1) the indoor light conditions respond to lighting and daylighting instantly without time delay (time-independent), the optimization problem of shading control could be solved by a static optimizer instead of the dynamic optimizer for ACB control; (2) the visual comfort and lighting power prediction models are nonlinear. If incorporating the thermal comfort term in the objective function of the shading control, the optimization problem becomes dynamic and nonlinear, making it not suitable for real-time optimization and control. If combining the objective functions of shading and ACB control as one objective function, the whole MPC system will be nonlinear and is not suitable for real-time optimization and control; (3) as the indoor thermal comfort is mainly regulated by the ACMV system rather than the shading system, the thermal comfort term is not included in the objective function for shading control.

Figure 6.7 Coupling of ACMV control, shading control and automated dimming in the MPC system

The control systems of SkyLab are illustrated in Figure 6.8. Room air temperature set points for both cells, primary air temperature set point for the ACB system and lighting mode for both cells are defined in the original SkyLab BMS. SkyLab BMS sends the temperature set points and lighting mode to the thermostats (four thermostats in Test Cell and one thermostat in Reference Cell) and the lighting controller respectively. SkyLab also sends the control signal to the water pump (WP1) of the ACB system directly. A cloud server (HALIO) sends the tint level set point to the EC window through the internet. The MPC system is installed as an additional control for Test Cell. The integration of the MPC system with SkyLab BMS and ACMV systems was described in Chapter 4. The MPC system is also integrated with the cloud sever. The MPC system sends tint level set point to the cloud server through an interface (API). The cloud server delivers the control signals to the EC window. The tint level set point is applied to all the eight EC DGU panels.

Figure 6.8 Integration between the MPC system and the BCA SkyLab test facility

6.3 Test results

The experiment arrangements including two tests are listed in Table 6.2. The ACB system and EC window in Test Cell were controlled by the MPC system and the lighting in Test Cell was at automated dimming mode in both tests. The FCU system in Reference Cell was controlled by SkyLab BMS in both tests. The lighting in Reference Cell was at automated dimming mode in Test 1 and constant mode in Test 2 to represent two typical office setups. Each test ran during office hours (9 am to 6 pm) and repeated for two workdays with similar sky conditions as evaluated by Sky Clearness Index.

In Chapter 4, it is observed that the discrepancy in total electricity consumption by ACMV system between the two cells (ACB system in Test Cell and FCU system in Reference Cell) was about 2.3%, which is an indication on the level of experimental error due to discrepancies between the two cells for the experiments in this chapter.

Table 6.2 Arrangement of test for the developed MPC system in SkyLab

Test	Cell	ACMV system	ACMV Control Strategy	Window	Shading control	Lighting mode	Sky clearness index
1	Test Cell	ACB	MPC system	EC	MPC system	Automated dimming	Day 1: 0.28
	Ref. Cell	FCU	SkyLab BMS	Low-e	-	Automated dimming	Day 2: 0.41
2	Test Cell	ACB	MPC system	EC	MPC system	Automated dimming	Day 1:0.36
	Ref. Cell	FCU	SkyLab BMS	Low-e	-	Constant	Day 2:0.22

Figure 6.9 shows the time profiles of the measured indoor air temperature and indoor PMV in both cells on Day 1 of Test 1. The MPC system achieved very stable indoor air temperature and indoor PMV in Test Cell throughout the office hours on the day. The MPC system maintained indoor PMV close to but below the upper bound of indoor thermal comfort ($PMV = 0.5$) during the most time. In contrast, indoor conditions (indoor air temperature and indoor PMV) of Reference Cell controlled by SkyLab BMS was highly fluctuating throughout the office hours on the day due to the reactive control strategy used in SkyLab BMS. Indoor PMV in Reference Cell was lower than the lower PMV bound ($PMV = -0.5$) during 10:00 am to 11:00 pm, which indicates thermal discomfort happened and excessive cooling was supplied into the room space.

(a)

(b)

Figure 6.9 Indoor air temperature (a) and PMV (b) in both two cells of SkyLab on Day 1 of Test 1

Figure 6.10 shows the measured indoor DGP and illuminance at work plane in both cells on Day 1 of Test 1. In Reference Cell, indoor DGP was beyond the upper bound ($DGP = 0.35$) during 12.50 pm - 13.50 pm and the maximum illuminance at work plane (lighting zone 4) was beyond the upper bound (3000 lux) during 12.30 pm – 15.30 pm, which indicates visual discomfort could happen in Reference Cell during the periods. In contrast, the MPC system regulated the EC window to darken the EC DGU panels at 12:30 pm to reduce the daylight penetration to prevent uncomfortable indoor illuminance and DGP in Test Cell, as shown in Figure 6.11. Similar observations of indoor thermal and visual conditions were found in the rest days of Tests 1 and 2.

(a)

(b)

Figure 6.10 Measured indoor (a) DGP and (b) illuminance on Day 1 of Test 1

Figure 6.11 Tint level of EC window on Day 1 of Test 1

In Test 1, lighting systems of both cells operated at automated dimming mode and the lighting powers were regulated according to readings in daylight sensors. Figure 6.12 and Figure 6.13 show the daylight sensor readings and zonal lighting powers on Day 1 of Test 1, respectively. When outdoor solar radiation was low (10 am - 12 am, 16 pm - 18 pm), the EC window was fully clear (at 0% tint level) according to the solutions of optimising the trade-off [Equation (6.15)] between lighting power and heat gain from the EC window, as shown in Figure 6.11. Thus, daylight sensor readings and lighting powers in the two cells were close during the period, as shown in Figure 6.12 and Figure 6.13. When global solar radiation is high (12 am to 16 pm), the MPC system regulated EC window to reduce daylight penetration, and thus, daylight sensor readings and lighting powers in Test Cell were lower than that of Reference Cell. This indicates that partial electric energy saving potential of lighting in Test Cell is sacrificed to maintain comfortable indoor visual comfort.

Figure 6.12 Daylight sensor readings on Day 1 of test 1 in both cells

(a)

(b)

Figure 6.13 Lighting power on Day 1 of test 1. (a) Reference Cell, (2) Test Cell

Figure 6.14 shows the distributions of indoor PMV, maximum illuminance at work plane and indoor DGP of the two tests. Figure 6.14 (a) shows that indoor PMV in Test Cell is within comfortable thermal comfort range ($-0.5 < \text{PMV} < 0.5$) during more than 95% of the test period and close to the upper bound ($\text{PMV} = 0.5$) of the thermal comfort range, echoing with the observations in Figure 6.9 (b). The measured indoor PMV in Reference Cell is negative during the most time of the test period, which indicates excessive cooling energy was consumed by Reference Cell. Figure 6.14 (b) shows the maximum illuminance of work plane in Reference Cell is above the upper bound (3000 lux) during around 20% of the test period. In contrast, the maximum illuminance of work plane in Test Cell is below the upper bound (3000 lux) during all the test period. Figure 6.14 (c) shows that the measured indoor DGP in Test Cell is less than 0.35 during the entire test period. For Reference Cell, indoor DGP was maintained lower than 0.35 at 95.6% time of the test period.

(a)

(b)

(c)

Figure 6.14 Distributions of measured (a) indoor PMV, (b) maximum illuminance at work plane and (c) indoor DGP during all the test days

The electricity consumption results of the two tests are shown in Figure 6.15. For Reference Cell, electricity consumption is by cooling, fresh air fan, supply air fan and lighting. For Test Cell, electricity consumption is by cooling, fresh air fan, supply air fan, lighting, water pump and EC window. The electricity consumption due to cooling is estimated based on a COP of the chiller (COP = 5.87) serving SkyLab. Figure 6.15 (a) shows that Test Cell consumed 15.1% less building electricity energy than Reference Cell in Test 1. The energy saving is mainly from ACMV which consumed 22.7% less electricity as compared to that in Reference Cell. However, the lighting electricity consumed by Test Cell is slightly higher than Reference Cell due to less daylight penetration in Test Cell to prevent indoor visual discomfort. In Test 2, Test Cell consumes 20.3% less building electricity than Reference Cell. The energy saving is mainly from ACMV and automated dimming which consumed 21.4% and 23.4% less electricity than that in Reference Cell, respectively.

(a)

(b)

Figure 6.15 Energy performance comparison of the two cells. (a) Test 1, (b) Test 2

In Chapter 4, the MPC system was also used to perform individualized ACB control (Test Setting 2 in Table 4.4). Thus, the performance of the MPC system for coordinated control of ACB, shading (EC window) and automated dimming systems (Test 2 in Table 6.2) could be compared to the performance of the MPC for individualized ACB control. However, there is no case that only the shading system is controlled by the MPC system. Thus, the performance of the MPC system for individualized shading control has to be estimated using the two cases (Test Setting 2 in Table 4.4 and Test 2 in Table 6.2) described above. This is one of the limitations of the study.

Figure 6.16 shows the energy performance comparison of BMS controlled ACB ('BMS-ACB'), MPC for individualized ACB control ('MPC-ACB') and MPC for coordinated building systems (ACMV, lighting and shading) control ('MPC-Coordinated Control'). For the MPC-ACB and BMS-ACB cases, the EC window is at a constant tint level of 38% so that the EC window has the same SHGC as the Low-e window in Reference Cell and lighting was at the constant mode. The data of the MPC-ACB and BMS-ACB cases are from the tests described

in Chapter 4 and the electricity consumed by the EC window of the two cases is excluded. Figure 6.16 shows that the energy savings of MPC-ACB and MPC-Coordinated Control are 14.9 % and 21.4%, respectively, as compared to BMS-ACB. Thus, it is estimated that the shading control with the MPC system could save building energy by 6.5% as compared to no shading. The thermal comfort performance comparison of BMS-ACB, MPC-ACB and MPC-Coordinated Control is shown in Figure 6.17. It is observed that both MPC-ACB and MPC-Coordinated Control were able to take advantage of the comfortable PMV range ($-0.5 < PMV < 0.5$) by keeping the indoor PMV close to the upper limit (0.5) to minimise the cooling energy consumption.

Figure 6.16 Energy performance comparison of BMS-ACB, MPC-ACB and MPC-Coordinated Control

Figure 6.17 Thermal comfort performance comparison of BMS-ACB, MPC-ACB and MPC-Coordinated Control

6.4 Summary

A scheme to couple ACMV, shading and lighting systems for coordinated control using MPC is proposed in this chapter. An MPC system controlling ACMV and shading system incorporating an automated lighting controller is developed to optimise building energy efficiency and occupant's comfort (visual comfort and thermal comfort). The MPC system was implemented in the SkyLab test facility for evaluating the control performance. Based on the test results, it is found that:

- The developed MPC system was able to achieve 15.1 – 20.3% building electricity saving as compared to the original SkyLab BMS,

- The developed MPC system greatly improved indoor thermal comfort as compared to the original SkyLab BMS, maintaining PMV within the acceptable range (-0.5, 0.5) at 96.3% test period,
- The developed MPC system greatly improved indoor visual comfort by regulating the tint level of the EC window as compared to the conventional Low-e window, maintaining the maximum illuminance at work plane less than 3000 lux and indoor DGP less than 0.35 at the entire test period.
- Compared to MPC for ACB control only, MPC for coordinated building services control achieved 9% reduction in building electricity consumption.

6.5 References

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Part V Merging Model Predictive Control and Machine Learning for Building Control

Chapter 7 Model Predictive Control with Adaptive Machine Learning based Building Model

7.1 Introduction

The machine learning (ML) technique is another advanced technology that has gained increasing attention for BAC [7.1] application, especially for building modelling. The conventional physics-based building modelling approach as described in Chapter 3 for MPC takes heat and mass transfers in buildings into account, which requires high levels of expertise in building physics and detailed building information (e.g. thermal capacitance and thermal conductance of building thermal mass) to do. This modelling approach demands a large amount of effort in model construction, especially for large, complex buildings [7.2][7.3]. In contrast, ML is a data-driven modelling approach that constructs a model merely based on data, which means an ML-based building model could predict building dynamics without knowing the physics and information of the building [7.4]. ML has been applied to predict the indoor environment [7.5], energy consumption [7.6], occupancy behaviour [7.7][7.8], and weather conditions [7.9] for buildings. Thus, the ML-based building modelling approach could be a promising solution to constructing MPC for large buildings.

Although some recent studies have applied the ML technique to MPC for energy efficiency and indoor environment optimization in buildings, experimental studies that could evaluate the performance of MPC with an ML-based building model covering a substantially long period are still lacking as discussed in Section 2.2.2.2.

Due to its working principle, the accuracy of the building model in predicting the future evolution of building conditions is critically important to MPC of buildings. However, without the precise knowledge of the physics of the building, the construction of ML-based building

models relies heavily, often entirely, on historical building operation data, which poses major challenges to model accuracy. In many situations, the availability of high-quality building operation data is limited due to practical constraints such as construction project timeline, limitations in the capability of the original BAC system in data collection, etc. Besides, data collected by the original BAC system are building operation data under the control of the original BAC system. The data may not capture the building operation characteristics when it is controlled by MPC. The building model also requires continuous updating to capture the changes of some building physical characteristics over time due to changes in external factors, such as weather, or internal factors, such as internal furnishing and occupancy distribution, etc. However, most ML-based MPC systems proposed in previous studies do not have the automatic model update mechanism. A solution to these challenges is to develop a self-adaptive ML-based building model that exploits online building operation data to update the building model continuously as the building is controlled by MPC in real-time.

In this Chapter, an MPC system using a self-adaptive ML-based building model is developed and its control performance is experimentally investigated. The MPC system is implemented in an office of the Research Techno Plaza (RTP) building on the campus of NTU. The energy and thermal comfort performance of the MPC system is evaluated and compared to the original thermostat that is based on PID control.

7.2 Methodology

Figure 7.1 gives an overview of the methodology adopted by this study. Historical building operation data of the test building controlled by its original BMS are collected offline into a database. The historical building operation data are used to construct and train an initial building model using ANN, which is chosen due to its high accuracy to model nonlinear

systems [7.10]. The ANN-based initial building model is then used to formulate an initial MPC controller. The initial MPC controller is integrated into the test building and replaces the original BMS to perform real-time control of the test building, which generates a new set of online building operation data. This new data set is collected and fed back to the database at each control interval for adaptation of the ANN-based building model periodically at a time interval ('model adaption interval'). Once the ANN-based building model is updated by adaptation, a new MPC controller is formulated automatically using the updated model and performs real-time control during the next model adaption cycle. Finally, the control performance of the MPC controller is evaluated by comparing to historical building operation data.

Figure 7.1 Schematic view of the overall methodology

7.2.1 Test building

Experiments were carried out in an office at level 3 of the RTP building on the campus of NTU, as shown in Figure 7.2. The floor area of the office is 46 m² and the floor-to-ceiling height is 3 m. The office is surrounded by adjacent air-conditioned spaces including offices, corridor and atrium. Thus, outdoor thermal effect on indoor conditions of the office is neglected. Partition wall 1 and 2 are 0.1 m thick and each is fitted with four internal windows (1.8 m W × 1.2 m H). Partition wall 3 has an entrance (1.4 m W × 2.2 m H) and is fitted with a window (1.4 m

$W \times 1.2 \text{ m H}$) at each side of the entrance. The structural wall adjacent to the atrium is 0.23 m thick and is fitted with a window ($2.7 \text{ m W} \times 3.5 \text{ m H}$).

The office has eleven desks arranged along the walls and a meeting table at the middle, as shown in Figure 7.2. Internal lighting is provided by eight $0.6 \text{ m} \times 0.6 \text{ m}$ lighting fixtures with light-emitting-diode (LED) lamps fitted on the ceiling. Each light fixture draws 40 W of lighting power. The lights are controlled by a manual switch.

Figure 7.2 RTP building and experimental setup of the office

7.2.2 ACMV system

Air conditioning to the office is provided by a ceiling-mounted variable air volume (VAV) box with a maximum airflow capacity of 1320 m³/h. The VAV box supplies conditioned air through three 4-way spread type ceiling diffusers with dimensions of 0.6 m × 0.6 m. The conditioned air to the VAV box is supplied from an FCU mounted outside of the office. The FCU also serves a few other adjacent offices, simultaneously. Room air is returned through a liner grille and finally to the FCU through the ceiling air plenum, as shown in Figure 7.2. The supply air flowrate was regulated by an air damper in the VAV box, which was originally controlled by a thermostat with a room temperature set point of 23°C. Supply air temperature is not controllable by the thermostat but it varies between 16 – 22°C during the test period based on measurement. The pre-set control parameters in the original thermostat are not being adjusted so to preserve the original control characteristics of the thermostat. The MPC system is implemented as an add-on alternative control for the VAV box. The control of the VAV box could switch between the original thermostat control and the MPC system. Air conditioning is on from 8 am to 6 pm, Monday to Friday and is switched off during the remaining time of the week.

7.2.3 Instrumentation

Additional sensors are installed in the room space and ACMV system, as shown in Figure 7.2, for the implementation of the MPC system and to monitor the performance of the two control systems (original thermostat and MPC). A combined air temperature- RH sensor and an airflow sensor are installed in the supply air duct leading to the VAV box for real-time monitoring of cooling power supplied to the office. Another combined air temperature-RH sensor is installed on the meeting table for real-time monitoring of room conditions. A thermal comfort measurement device that consists of sensors for measuring air temperature, RH, air velocity

and globe temperature and a data logger is installed near the meeting table for monitoring of thermal comfort in the room space. The specifications of these additional sensors are listed in Table 7.1.

Table 7.1 Specifications of the sensors installed in the test room and ACMV system

Sensors	Brand	Model	Resolution	Range	Accuracy
Combined air temperature - RH	REGIN	HTDT10-420	0.1°C	-40 to +60°C	± 0.01°C
			0.1% RH	0 to 100% RH	± 2% RH
Air flow rate	SIEMENS	QVM62.1	0.1 m/s	0 to 10 m/s	± 0.2 m/s
Thermal comfort measurement device	Delta OHM	-	-	-	-
• <i>Data logger</i>		HD32.3	-	-	-
• <i>Combined air temperature - RH</i>		HP3217.2R	0.1°C	-40 to +100°C	1/3 DIN*
			0.1% RH	0 to 100% RH	± 1.5% RH
• <i>Globe temperature</i>		TP3276.2	0.1°C	-10 to +100°C	1/3 DIN
• <i>Air velocity</i>		AP3203.2	0.1 m/s	0.1 to 1 m/s	± 0.2 m/s

7.2.4 Building modelling

To achieve optimal energy efficiency and thermal comfort, the building model should be able to capture the dynamics of building physics and to estimate indoor thermal comfort. Thus, the building model includes two sub-models: (1) a building dynamics model that predicts indoor conditions such as air temperature, humidity and globe temperature with inputs of internal loads, weather conditions and cooling power of ACMV systems and, (2) a thermal comfort model to estimate indoor thermal comfort index with inputs of indoor conditions.

A dynamic ANN for time series prediction is needed to capture the time-dependent nature of building dynamics [7.11]. An ANN with the dynamic recurrent nonlinear autoregressive exogenous (NARX) architecture, is employed here. The internal architecture of the NARX ANN is a feedforward multi-layer perceptron (MLP) ANN, which is an ANN structure for modelling continuous linear/nonlinear systems [7.11]. The NARX ANN architecture has three layers including input, hidden and output layers. It is constructed based on the MLP ANN by adding a feedback loop and time delays. A NARX ANN model could be expressed by a nonlinear function as

$$y(t) = f(y(t-1), y(t-2), \dots, y(t-d_y), u(t-1), u(t-2), \dots, u(t-d_u)) , \quad (7.1)$$

where symbols f , y , u , t and d refer to function, output, input, time and number of time steps delayed. A sigmoidal activation function that is commonly used in MLP ANN is employed here. The model parameters including weights and biases are identified by supervised learning using measured building operation data. The number of neurons in the hidden layer of the NARX ANN is selected by trial and error method [7.12].

In this chapter, two ANN models including a building dynamics model for predicting room air temperature and a thermal comfort model for predicting indoor PMV of the office are developed, as illustrated in Figure 7.3. The ANN-based building dynamics model is based on the NARX structure. The inputs of the building dynamics model for room air temperature (T_z) prediction includes cooling power (Q_{sa}) provided by supply air, hour of day (hod), operation status of ACMV (1-on, 0-off) and the feedback of room temperature. The building dynamics model could be expressed as

$$T_z(t + 1) = f(Q_{sa}(t), hod(t), os(t), T_z(t)) , \quad (7.2)$$

where T , Q , hod , os , and t refer to temperature ($^{\circ}\text{C}$), heat flow rate (W), hour of day, operation status of ACMV (1 for on, 0 for off) and time (s). Subscripts z and sa refer to thermal zone and supply air.

The room air temperature is measured by the combined air temperature - RH sensor installed on the meeting table. The cooling power provided by supply air from the VAV box is calculated using the measurements of supply air temperature, room air temperature and supply air flowrate, as expressed by

$$Q_{sa} = \dot{m}_{sa}(T_z - T_{sa}), \quad (7.3)$$

where $\dot{m}$ refers to mass flow rate (kg/s), based on the assumption that room air is well mixed in the office. Since the air-conditioning of the office only involves the airside (VAV box), the measurement of latent cooling power is highly sensitive to the measurement error of RH in the supply/return air. The modelling of the ACMV system is based only on the sensible load for

this testbed. Thus, indoor RH is not predicted by the building dynamics model but is measured and assumed constant at the measured value during a prediction horizon for indoor PMV prediction.

The thermal comfort model for indoor PMV prediction is an MLP based feedforward ANN without feedback. The feedforward neural network model could be expressed by

$$PMV = f(T_z, RH_z) . \quad (7.4)$$

The model is trained by providing measured room air temperature and RH data as input and measured indoor PMV data by the thermal comfort measurement device as output. The metabolic rate per occupant for PMV calculation in the office is assumed constant at 1.2 met for common office work. Cloth insulation is also assumed constant at 0.57 clo of the occupants wearing trousers and short-sleeve shirts in the office.

(a)

Figure 7.3 ANN models for (a) room air temperature prediction and (b) indoor PMV prediction

The historical building operation data for training of the initial ANN models were measured for one-month-long when the office was under the original thermostat control. The measured data are acquired by an I/O device (National Instruments cDAQ-9189) in real-time at 5-second intervals and stored in the database at 5-minute intervals, except that the measured indoor PMV is stored in the data logger of the PMV measurement device at 5-minute intervals. The historical building operation data and indoor PMV data are divided into three subsets randomly picked along the timeline. 70% of the data are used for model training, 15% for model validation and refinement, the remaining 15% are used for testing. The two neural network models are trained using the Levenberg-Marquardt (LM) algorithm in MATLAB deep learning toolbox. Two neurons are selected for the hidden layer in this study for both building dynamics model and thermal comfort model based on trial and error. The R-values of training, validation and testing of the initial building dynamics model are 0.995, 0.995 and 0.996, respectively and 0.998, 0.998 and 0.998, respectively, for the thermal comfort model. The building dynamics model will be further updated continuously when the MPC is controlling the office using the online building operation data whereas the thermal comfort model remains unchanged.

7.2.5 MPC formulation

The objectives of the MPC controller, as described by Equation (7.5), are to minimize the cooling energy consumed by the ACMV system and to optimize indoor thermal comfort in terms of the PMV index.

$$J = \text{Minimize}(\sum_{k=1}^N \hat{Q}_{t+k|t}^2 + \sum_{k=1}^N [W_{PMV}(\widehat{PMV}_{t+k|t} - \widehat{PMV}_{ref})]^2 + W_{\varepsilon}\varepsilon_{t+k|t}), \quad (7.5)$$

where symbols J , $\hat{Q}$, $\widehat{PMV}$, W , N , and ε refer to objective, normalized cooling power, normalized PMV index, penalty factor, prediction horizon, and slack variable. Subscripts *ref* and k refer to reference and index of time steps. Particularly, the three terms on the right-hand-side refer to the costs of cooling energy consumption, thermal discomfort and constraint violation, respectively. The normalized cooling power, $\hat{Q}$, is the ratio of instantaneous cooling power over the cooling capacity of the ACMV system, defined as

$$\hat{Q} = Q/Q_{max}. \quad (7.6)$$

The normalized PMV index, $\widehat{PMV}$, is the ratio of measured indoor PMV over the comfortable range of PMV, defined as

$$\widehat{PMV} = PMV/(PMV_{max} - PMV_{min}). \quad (7.7)$$

The constraints of cooling power provided by ACMV systems are $(0, Q_{max})$ and the constraints of indoor PMV are $(-0.5, 0.5)$, which are the comfortable thermal comfort range [7.13].

The penalty factor, W_{PMV} , is set at 4 which gives a high weightage to the thermal comfort term compared to other terms in Equation (7.5). With this setting, the MPC controller puts emphasis on keeping indoor PMV close to thermal neutrality ($PMV = 0$) as it seeks to minimize cooling energy consumption. The control interval and prediction horizon are 5-min and 12 control intervals, respectively.

As the NARX ANN-based building dynamics model is nonlinear, a nonlinear optimizer is needed to solve the nonlinear optimization problem of the MPC. Several global optimization approaches such as genetic algorithm (GA) [7.14], particle swarm optimization (PSO) [7.15] and firefly algorithm (FA) [7.16] as well as gradient-based approaches such as interior-point method [7.17] and subsequent quadratic programming (SQP) [7.18] have been used to solve the nonlinear optimization problems in BAC applications. The global optimization approaches have good performance in finding global optima as compared to the gradient-based approaches. However, these global optimization approaches are computationally intractable for real-time optimization in a dynamic system since solutions would need to be reached within a short control interval [7.19]. Gradient-based approaches could have much faster convergence than global optimization approaches [7.11] but are susceptible to yielding local optimal, instead of global, with inappropriate initial guesses of solutions. In order to address the challenges facing the two types of approaches, this study proposes a hybrid optimization approach combining the exhaustive search method (ESM) and SQP to solve the nonlinear optimization problem of the MPC. The concept behind the hybrid optimization approach is that coarse global optimal solutions in the prediction horizon are first searched using ESM without iterations. The coarse solutions are then passed to the SQP optimizer as initial guesses. The SQP optimizer then searches the final optimal solutions around the initial guesses by numerical computation. This

approach speeds up the convergence and reduces the possibility of landing in local optimal solutions, as compared to common approaches of using fixed or random initial guesses.

Since the solution of cooling power is constrained within the range $(0, Q_{max})$, the solution in a time step could be discretized into a series of candidates $(Q_1, Q_2, \dots, Q_m)$, where $Q_1 = 0$ and $Q_m = Q_{max}$, for ESM based optimization. The control horizon is set as 2 control intervals [7.20] here, which means that all solutions after time $t + 2$ (i.e., $Q(t+3), \dots, Q(t+N)$) are set to be the same as $Q(t+2)$. Using a short control horizon reduces computation demand by limiting the size of the search space of the ESM optimization problem to m^2 and helps in achieving internal stability in the MPC controller [7.20]. The variable m is given a value of 10 which gives computationally tractable optimization problems (100 solution candidates) for the ESM optimizer without making the initial guesses too coarse. The ESM optimizer searches the optimal solutions by comparing the costs [Equation (7.5)] of all the candidates and passes the optimal solutions to the SQP optimizer as the initial guesses. This study employs the MATLAB environment [7.20] to solve the hybrid optimization problem.

7.2.6 Control system

The proposed MPC system consists of an MPC controller, a model adaptation module and a local controller, as illustrated in Figure 7.4. The MPC system is initialized using measured historical building operation data. As the MPC system controls the building, the MPC controller generates optimal solutions (cooling power of the ACMV system) in the prediction horizon and passes the solutions of the first control interval to the local controller. The local controller is based on the PID scheme and tracks the optimal cooling power by regulating the actuators in the ACMV system. The online building operation data, including the cooling power control signal generated by the MPC controller, measured disturbances and room

conditions, as shown in Figure 7.4, are stored in the database of the model adaptation module at 5-minute intervals. The model adaptation module updates the building dynamics model by supervised learning using the building operation data stored in the database. The frequency of the model adaptation is controlled by a timer in the module. This MPC system uses a model adaptation time interval of 24 hours, covering a full diurnal operation cycle of test buildings. This model adaptation time interval allows the accumulation of building operation data to a volume that could cause significant changes in the building dynamics model in model adaptation. The MPC system is implemented in a control sever with a CPU of Intel Core i5-3317U @ 1.70GHz and 4G RAM.

Figure 7.4 A schematic drawing showing the architecture of the proposed MPC system

7.2.7 Experiment arrangement

Two test cases including the VAV box is (1) controlled by the original thermostat ('thermostat' case), and (2) controlled by the MPC system ('MPC' case), were conducted. The thermostat case is the baseline case evaluating the control performance of the MPC system. The thermostat control is based on a PID control scheme that is widely used in current buildings. Therefore, it is considered as a representative of the control system in current buildings. Each test case ran

for a continuous period that contains 20 workdays (December 2018 – January 2019 for thermostat case and February 2019 – March 2019 for MPC case). Besides the purpose of revealing the control performance of the thermostat, the building operation data measured during the thermostat case are also used to construct the initial ML-based building dynamics and thermal comfort models for the MPC controller.

7.3 Test results

7.3.1 Performance of MPC system

The solving time per optimization of the ML-AMPC controller in the control server is 2.5 s, which is much smaller than the control interval of 300 s of the proposed MPC. This suggests that the developed MPC system is suitable for real-time optimization and control for BAC applications.

Figure 7.4 shows the statistical distributions of indoor PMV and room air temperature measured during the office hours of the test period. The result is plotted in daily time series. The range from 5th percentile to 95th percentile as well as the median values are shown. Figure 7.4 (a) shows that the median PMV was maintained very close to 0 (thermal neutrality) when MPC was used whereas the original thermostat control kept the median PMV negative at most of the time, suggesting better indoor thermal comfort achieved by the MPC as compared to the thermostat. During the morning start-up period (0800 – 0930 hrs), the thermostat control overcooled the office. This might be attributed to the reactive nature of the thermostat control, which allowed the morning cooling to overshoot. In contrast, the MPC cooled down the office smoothly to reach the desired comfort level without overshooting during the morning start-up period. The predictive capability of the MPC might have prevented overshooting of cooling, bringing advantages in energy efficiency and occupant comfort. In addition, the distribution

range of PMV is much narrower with the MPC than that with the thermostat. It suggests that occupants were subjected to much less fluctuation of thermal sensation during the day with MPC than they were with thermostat control. The corresponding statistical distributions of the measured indoor air temperature are shown in Figure 7.4 (c) and (d). It echoes the observations from Figure 7.4 (a) and (b).

The distributions of indoor PMV, room air temperature measured during the office hours of the test period are also plotted as box-and-whisker diagrams in Figure 7.6. It shows that the median indoor PMV of the thermostat case is -0.09 with an interquartile range of (0.00, -0.20). In comparison, the median indoor PMV of the MPC case is 0.05 with a much narrower interquartile range of (0.01, 0.09). It suggests that the MPC provided better thermal comfort to the office by maintaining the PMV closer to thermal neutrality for most of the time than the thermostat control did. The MPC also reduced fluctuation of thermal sensation during office hours, compared to the thermostat.

(a)

(b)

(c)

(d)

Figure 7.5 Statistical distributions of indoor conditions measured during office hours of the test period. (a) & (b) Indoor PMV distribution. (c) & (d) Room air temperature distribution.

(a)

(b)

Figure 7.6 Box-and-whisker plot of (a) indoor PMV and (b) room air temperature measured during office hours of the test period

Figure 7.7 shows the statistical distribution of measured cooling power in the two cases. The cooling power here refers to the sensible cooling power provided by the supply air from the VAV box to the office. The average cooling power reduces from 1.88 kW in the thermostat case to 0.78 kW in the MPC case, indicating that the MPC case consumed 58.5% less cooling energy than the thermostat case did. This energy saving is achieved by taking advantage of thermal comfort knowledge and model-based optimization feature of the MPC system to pursue thermal neutrality with minimum cooling energy consumption. The cooling power of the MPC case varies within a much narrower range (0 – 1.82 kW) than that of the thermostat

case (0 – 6.30 kW), which echoes the observations that the MPC generally maintained more stable indoor conditions than the thermostat did.

Figure 7.7 Statistical distributions of cooling power measured during office hours of the test period

7.3.2 Performance of adaptive ML-based building model

The prediction performance of the adaptive ML-based building dynamics model is evaluated by comparing the model predictions with the measured building operation data of the MPC case in the office testbed. Figure 7.8 (a) shows the trending of daily mean absolute error (MAE) between the model predictions and the measured room air temperature. The trending of MAE between the initial building dynamics model (non-adaptive) and the measurements are also shown as a comparison. The two models have the same MAE on the first workday as the two models are essentially the same on the first day. However, from the second workday onwards, the MAE of the adaptive model shows a general decreasing trend as time goes. This is because the adaptive model is being updated regularly by the model adaption module which greatly improved the prediction accuracy of the adaptive model. The adaptive model becomes more accurate as it undergoes further rounds of model updates. The MAE of the adaptive model has been lower than that of the initial model since the second workday, again suggesting the advantage of model adaptation. Distributions of MAE throughout the workdays of the test

period is shown in Figure 7.8 (b). The median MAE of the adaptive and the initial models are 0.06°C and 0.15°C , respectively, indicating the generally superior prediction performance of the adaptive model compared to the initial model.

Figure 7.8 Daily MAE of predictions by the initial and adaptive building dynamics models.
(a) Trend along with the workdays, (b) Statistical distribution

In the current study, only the MPC controller with the adaptive model is tested in the office. Without comparison to an MPC controller with the initial (non-adaptive) model, this study cannot quantify the impacts of model adaption on the actual control performance experimentally. However, in a previous study [7.21] using a physics-based building model for MPC, it was found that adding the model adaptation feature in the MPC controller helped in improving indoor thermal comfort without causing extra cooling energy consumption. It could be inferred that, with the advantages in model prediction shown above, the addition of model adaption to the ML-based building model could improve the MPC controller in thermal comfort performance.

7.4 Summary

This chapter presented the development, implementation, experimental testing and performance analysis of a proposed MPC system with an adaptive ML-based building model

for BAC application. The system features an adaptive building dynamic modelling scheme that was developed using a dynamic NARX ANN and a fully automated process for model adaptation. The control performance of the MPC system was experimentally evaluated in an office on the campus of NTU located in Singapore. The MPC system achieved 58.5% reduction of cooling energy in the office as compared to the original thermostat control. In parallel to the energy savings, the MPC system also significantly improved indoor thermal comfort by maintaining indoor PMV close to the thermal neutrality ($PMV=0$) for most of the occupied time during the test period, as compared to the original thermostat. The model adaptation feature greatly improves the prediction accuracy of the ML-based building dynamics model, bringing benefits to the control performance of the MPC system. The prediction accuracy continues to improve as the volume of available building operation data for model adaption increases over time.

7.5 References

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Chapter 8 Approximate Model Predictive Control Using Machine Learning

8.1 Introduction

Despite the numerous studies of MPC for BAC application, there is still no wide commercial application of MPC in buildings due to several challenges [8.1]. One challenge is that MPC requires a proper building model, which is a difficult and time-consuming task [8.2]. The building model for MPC must be simple and precise for MPC to perform accurate predictions for real-time optimisation and control [8.3]. To deal with this challenge, this thesis proposed a linear SSM of buildings and an ML-based building model in Chapter 3 and Chapter 7, respectively. The two modelling approaches have been experimentally demonstrated for real-time control in buildings in Chapter 4, 5 and 7. The second challenge is that MPC requires large computational resources such as high-speed processors and sufficient memory and software support (e.g., optimisation libraries) for solving the optimisation problem in MPC [8.3][8.4][8.5][8.6]. However, the controllers in current buildings such as programmable logic controller (PLC) or direct digital control (DDC) have very limited computational capacity, memory and functions/libraries [8.3], which makes MPC not compatible with these controllers in buildings. To deal with the second challenge, the ML technique is used to model the control laws of MPC. The control laws of MPC modelled by ML ('ML controller') is trained using the operation data of buildings controlled by MPC. The ML controller is essentially an ML model fitting the correlations between the optimal solutions to the MPC control problem and the inputs of the MPC. Thus, the ML controller can estimate the solutions ('near-optimal' solutions) to the MPC control problem rapidly without solving the optimization problem. Thus, the ML controller does not require libraries for numerical optimization and high computing power, making it more suitable to run in PLC/DDC as compared to MPC.

In this chapter, an ML controller is developed using the building operation data of the MPC case described in Chapter 7. The ML controller is then implemented in the same test room as described in Chapter 7 to control the ACMV system. The performance in terms of energy efficiency and indoor thermal comfort of the ML controller is evaluated and compared to the MPC system and the original thermostat described in Chapter 7.

8.2 Methodology

Figure 8.1 shows the overall methodology of the investigation of the proposed ML controller. The left part Figure 8.1 shows the methodology of development and implementation of the MPC system, which was already developed in Chapter 7. The MPC system acts as a ‘teacher’ in the development of the ML controller. The building operation data generated by the RTP office as it was controlled by the MPC system (MPC case described in Chapter 7) is used as input/output data for training an ML controller using machine learning. The input data include the measured disturbances and room conditions, which are the input variables for the MPC system as shown in Figure 7.4. The output data is cooling power that is the control command from the MPC system, as shown in Figure 7.4. The ML controller is based on NARX ANN and it is essentially a dynamic model that describes the relationship between the input variables and the control command for/from the MPC system. Thus, the ML controller can approximate the control command of the MPC system (‘near-optimal’ control command) based on the measured disturbances and room conditions. The developed ML controller is implemented in the RTP office to perform real-time control of the ACMV system. Finally, the control performance of the ML controller is evaluated by comparing to the MPC system and the original thermostat of the office.

Figure 8.1 Schematic view of the overall methodology

8.2.1 Test building

Experiments were carried out in the same office as described in Chapter 7. In Chapter 7, an MPC controller was developed as an additional controller for the ACMV system of the office. In this chapter, an ML controller is developed by supervised learning to approximate the control solutions of the MPC controller. The ML controller is implemented in the office as the third controller for the ACMV system. The control of the office could be switched between the three controllers. The ACMV system of the test building is on from 8 am to 6 pm, Monday to Friday and off during the remaining time.

Air temperature, humidity and PMV of the room space are measured to monitor the indoor conditions. Air temperature, humidity and flow sensors were installed in the VAV box to monitor the cooling power of supply air [defined by Equation (7.3) in Chapter 7].

8.2.2 ML controller

The schematic of the ML controller is illustrated in Figure 8.2. The ML controller can generate near-optimal control command (set point cooling power of supply air) to the ACMV system based on the measured cooling power of supply air (Q_{sa}), hour of the day (hod), operation status of ACMV (os), measured room air temperature (T_z) and measured room RH (RH_z). The set

point cooling power of supply air is fed back to the ML controller. The ML controller could be described by

$$Q_{sa,sp}(t+1) = f(Q_{sa}(t), Q_{sa,sp}(t), hod(t), os(t), T_z(t), RH_z(t)). \quad (8.1)$$

The building operation data generated by the office as it was controlled by the MPC controller (MPC case described in Chapter 7), as shown in Figure 8.3, is employed to train the ML controller. The measured input data include the room air temperature, room RH, cooling power of supply air, operation status of ACMV and hour of the day. The output data for training the ML control is the set point cooling power of supply air that is control command form the MPC controller. The building operation data are divided into three subsets randomly picked along the timeline. 70% of the data are used for training, 15% for validation, the remaining 15% are used for testing. The ML controller is trained using Levenberg-Marquardt algorithm [8.7] in MATLAB environment. 20 neurons are selected for the hidden layer for the ML controller. The R-values of training, validation and testing of ML controller are 0.993, 0.987 and 0.992.

Figure 8.2 Schematic of the ML controller

(a)

(b)

(d)

Figure 8.3 (a) Measured room air temperature and RH, (b) set point cooling power of supply air generated by the MPC system and measured cooling power of supply air, and (c) status of ACMV and hour of the day for training the ML controller

8.2.3 Experiment arrangement

The ML controller was implemented in the office to perform real-time control of the ACMV system during April - May 2019 (ML controller case). The test period is one-month-long with 20 weekdays. The test results of the original thermostat control (thermostat case) and the MPC (MPC case) for the ACMV system of the office conducted in Chapter 7 are used as reference cases for evaluating the performance of the ML controller.

8.3 Test results

The solving time of the ML controller of one time step in the control server is 0.016 s, which is more than 100 times faster than that of the MPC controller.

The statistical distributions of measured indoor PMV of the three cases during the office hours of the test period are shown in Figure 8.4. The result is plotted in daily time series. The range from 5th percentile to 95th percentile as well as the median values are shown. It is observed that the thermostat kept indoor PMV at a wide range, mostly at the cool side ($PMV < 0$), which indicates the room space was overcooled by the thermostat, especially for morning start-up period (0800 – 0930 hrs). By contrast, the MPC and ML controllers both kept indoor PMV within a narrower range around the thermal neutrality ($PMV = 0$). The distributions of indoor PMV measured during the office hours of the test period are also plotted as box-and-whisker diagrams in Figure 8.5. It shows that the interquartile ranges of indoor PMV of the thermostat, MPC and ML controller cases are (-0.2, 0), (0.01, 0.09) and (0.04, 0.15), respectively. It suggests the thermal comfort performance of the ML controller is slightly worse than the MPC but better than the thermostat.

(a)

(b)

(c)

Figure 8.4 Statistical distributions of indoor PMV measured during office hours of the test period. (a) Thermostat, (b) MPC, (c) ML controller

Figure 8.5 Box-and-whisker plot of indoor PMV measured during office hours of the test period

Figure 8.6 shows the energy performance of the three controllers. The mean cooling powers of the thermostat, MPC and ML controllers are 1.88, 0.78 and 0.91 kW, respectively. Compared to the thermostat, the MPC and ML controllers reduce 58.5% and 51.6% of cooling energy, respectively. The energy saving capacity of the ML controller is 88% of the MPC controller.

Figure 8.6 Statistical distributions of cooling power measured during office hours of the test period

8.4 Summary

This chapter developed an ML controller by performing supervised learning based on the measured inputs/output data of the MPC controller developed in Chapter 7. The ML controller generates near-optimal control commands directly based on the measured inputs without solving the optimisation problem. The ML controller was implemented in an office to regulate the VAV box to optimise indoor thermal comfort and energy consumption. The performance of the ML controller was compared to the original thermostat of the office and the MPC controller:

- The ML controller retains the best thermal comfort performance of the MPC controller. Both MPC and ML controllers have much better thermal comfort performance as compared to the thermostat.

- The MPC and ML controllers saved thermal energy of 59% and 51% as compared to the thermostat, respectively. The energy-saving capacity of the ML controller is 86% of the MPC controller.

8.5 References

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Chapter 9 Conclusions

9.1 Summary of this study

This thesis investigated the application of MPC to building automation and control targeting to improve building performance in terms of energy efficiency and occupant well-being. A series of works were conducted to chase the objective and these works include: (1) develop a MPC system suitable for real-time building control and optimisation; (2) experimental implementation of the developed MPC system in real buildings to control different building systems (e.g., ACMV, lighting and shading) for evaluating its control performance; (3) further develop MPC for BAC application by merging ML and MPC technologies and experimentally evaluate the feasibility and performance.

The major contributions and novelties of this study lie in (1) the development of MPC systems for controlling SSLC air-conditioning systems, including ACB and DOAS air-conditioning systems, and the experimental evaluation of the control performance of MPC systems; (2) the development of an MPC system for coordinated control of multiple building systems, including ACMV, lighting and shading, and the experimental evaluation of the control performance of the MPC system. Other contributions and novelties include: (1) the development of a linear state-space building model that could predict multiple room conditions including room air temperature, humidity, mean radiant temperature and indoor thermal comfort for constructing a fast MPC controller for BAC applications; (2) the development of an adaptive ML-based building modelling approach that can capture the changes of building physical characteristics over time and the experimental evaluation of the control performance of the MPC system constructed using the adaptive ML-based building model for controlling an ACMV system (3) experimental evaluation of an ML controller that approximates the control laws of MPC by supervised learning for controlling an ACMV system.

The main conclusions extracted for this study are summarized as follows:

- Buildings are dynamical systems subject to transient disturbances (e.g., weather and internal load) and multi-targets (e.g., energy efficiency and occupant's comfort). These features of buildings lead to a demand for more advanced control technology, such as MPC, to replace the conventional feedback control applied to current buildings.
- MPC using a linear building model is computationally efficient for real-time control and optimisation. One of the possible ways to create a suitable linear building model is proposed in Part II, where a building-physics based modelling approach to develop an SSM capturing building dynamics and PMV based thermal comfort. The SSM is used to develop an MPC controller, which requires less than 0.1s for solving the optimisation problem.
- MPC could perform coordinated control of multiple building systems (e.g., ACMV, lighting and shading) and multi-objective optimisation to fulfill the multiple targets (e.g., energy efficiency, thermal comfort and visual comfort) in buildings. Experimental implementation of the developed MPC for controlling ACMV systems was conducted in Part III. The MPC could perform coordinated control of multiple cooling coils in SSLC air-conditioning systems such as ACB or DOAS air-conditioning and it also optimises both energy efficiency and indoor thermal comfort. Up to 20% reduction of ACMV energy and better indoor thermal comfort was achieved by the MPC as compared to conventional feedback control. Experimental implementation of the developed MPC for coordinated multiple building systems (ACMV, lighting and shading) control was conducted in Part IV. The MPC achieved up to 20% savings of building energy (ACMV and lighting energy) and

better thermal comfort and visual comfort, as compared to the conventional feedback control.

- Merging MPC and ML technologies provide more feasibility for driving MPC for BAC application toward practice. Two approaches including (1) MPC controller using ML-based building model and (2) ML controller to approximate the control laws of MPC were studied in Part V. An adaptive ML building model was developed based on measured building data only without the need of the expertise in building physics. An MPC controller using the adaptive ML-based building model was developed and experimentally implemented in an office to control an ACMV system. The MPC controller achieved 59% energy saving for cooling and better indoor thermal comfort as compared to a thermostat. The building operation data of the office controlled by the MPC controller was used to develop an ML controller that approximates the control laws of the MPC controller. The ML controller was also implemented in the office to control the ACMV system. The ML controller was more than 100 times faster than the MPC controller and it retained the most thermal comfort performance and 86% of the energy performance of the MPC system.

The results of the study demonstrated the real-time multi-objective optimization capability of MPC for different building systems including ACMV, lighting and shading in enhancing building performance. The modelling methods, the MPC formulations, the control system architecture with MPC and the integration scheme of the MPC system to buildings proposed in this thesis could be applied to or used as a reference in developing model-based optimal control systems for different energy/thermal systems in the building industry. The benefits of MPC including improving energy efficiency and occupant well-being as compared to the conventional feedback control were quantified and analysed in three real building testbeds. The

benefits of MPC could be used as a reference to evaluate the value propositions of MPC for the BAC market.

9.2 Limitations of this study

There are some limitations of this study discussed as follows:

- This study was carried out in a Singapore that is a tropical country. Therefore, the building models and control algorithms (MPC and ML) were developed and evaluated based on tropical buildings. The application of the developed models and controllers to buildings in other regions needs further studies.
- As the electricity tariff for the test buildings in this thesis does not change over a day, the application of MPC to demand response management of buildings by making use of dynamics energy prices to reduce energy bills is not studied.
- In Part III, the MPC systems were implemented to control SSLC air-conditioning systems (ACB and DOAS) in SkyLab and LT3 testbeds. However, the two testbeds lack higher-temperature chillers to provide higher-temperature chilled water for the secondary cooling coil and the chilled beams of the DOAS and ACB air-conditioning systems. Thus, the advantage of higher thermal efficiency by high-temperature chillers for SSLC air-conditioning systems could not be taken in the experiments.
- The experimental evaluations of the developed MPC and ML control systems were all conducted in single-room testbeds. The performance of the MPC and ML control systems for large buildings with multiples rooms may need further verifications.

9.3 Future research directions

Considering the limitations of this study discussed above, several future research directions are recommended as follows:

- The building modelling approaches and control algorithms in this study can be further modified/developed for the application to non-tropical buildings. For instance, to use the linear state-space building model developed in Part II for a building with a heating system rather than an air-conditioning system, the linear ACMV model could be replaced by a heating system model and the cloth insulation variable of the linear PMV model could be changed to other values for non-summer seasons.
- The MPC algorithm [Equation (3.43)] developed in Part II can be further developed for demand response management by adding an energy-price weighting factor for the cooling energy term in Equation (3.43).
- The control performance MPC systems for the SSLC air-conditioning systems developed in Part III could be further verified by staging a test in a building equipped with a separate higher-temperature chiller for taking advantage of the full potential of the SSLC air-conditioning systems.
- The control performance of the MPC and the ML control systems for large buildings with multiple rooms could be further verified.

Appendix

Table A.1 Matrix *A* of the SSM of SkyLab Test Cell with FCU system

-4.34E-04	4.34E-04	0	0	0	0	0	0	0	0	0
9.11E-03	-1.21E-02	2.04	0	1.68E-04	0	2.20E-04	0	2.14E-04	0	5.85E-04
0	6.78E-07	-9.55E-04	0	0	0	0	0	0	0	0
0	0	0	-3.16E-05	1.08E-05	0	0	0	0	0	0
0	1.95E-05	0	1.08E-05	-3.03E-05	0	0	0	0	0	0
0	0	0	0	0	-1.08E-05	1.08E-05	0	0	0	0
0	1.95E-05	0	0	0	1.08E-05	-3.03E-05	0	0	0	0
0	0	0	0	0	0	0	-6.25E-05	2.31E-05	0	0
0	3.94E-05	0	0	0	0	0	2.31E-05	-6.25E-05	0	0
0	0	0	0	0	0	0	0	0	-9.14E-05	3.53E-05
0	4.21E-05	0	0	0	0	0	0	0	3.53E-05	-7.74E-05

Table A.2 Matrix **B** of the SSM of SkyLab Test Cell with FCU system

0	0	0	0	0	0	0	0	0
1.35E-04	0.104	-1.30E-06	3.84E-06	0	3.17E-06	0	0	0.450
-1.70E-08	7.86E-05	-1.00E-09	0	1.57E-09	0	0	0	-1.82E-04
2.08E-05	0	0	0	0	0	6.43E-07	0	0
0	0	0	0	0	1.10E-08	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	1.10E-08	0	0	0
3.94E-05	0	0	0	0	0	0	0	0
0	0	0	0	0	2.23E-08	0	0	0
5.61E-05	0	0	0	0	0	0	1.74E-06	0
0	0	0	0	0	2.39E-08	0	0	0

Table A.3 Matrix **C** of the SSM of SkyLab Test Cell with FCU system

0	1	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0
0	0.27	35.71	0	3.28E-03	0	4.30E-03	0	4.18E-03	0	1.14E-2

Table A.4 Matrix **D** of the SSM of SkyLab Test Cell with FCU system

0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
1.45E-04	0	0	0	0	6.18E-05	0	0	-88.34

Table A.5 Matrix *A* of the SSM of SkyLab Test Cell with ACB system

-4.34E-04	4.34E-04	0	0	0	0	0	0	0	0	0
9.11E-03	-1.21E-02	2.04	0	1.68E-04	0	2.20E-04	0	2.14E-04	0	5.85E-04
0	6.78E-07	-9.55E-04	0	0	0	0	0	0	0	0
0	0	0	-3.16E-05	1.08E-05	0	0	0	0	0	0
0	1.95E-05	0	1.08E-05	-3.03E-05	0	0	0	0	0	0
0	0	0	0	0	-1.08E-05	1.08E-05	0	0	0	0
0	1.95E-05	0	0	0	1.08E-05	-3.03E-05	0	0	0	0
0	0	0	0	0	0	0	-6.25E-05	2.31E-05	0	0
0	3.94E-05	0	0	0	0	0	2.31E-05	-6.25E-05	0	0
0	0	0	0	0	0	0	0	0	-9.14E-05	3.53E-05
0	4.21E-05	0	0	0	0	0	0	0	3.53E-05	-7.74E-05

Table A.6 Matrix **B** of the SSM of SkyLab Test Cell with ACB system

0	0	0	0	0	0	0	0	0	0	0	0
1.35E-04	0.104261	6.26E-05	-1.3E-06	3.84E-06	3.84E-06	3.84E-06	0	3.17E-06	0	0	0.45
-1.7E-08	7.86E-05	0	-1E-09	0	0	0	1.57E-09	0	0	0	-1.82E-04
2.08E-05	0	0	0	0	0	0	0	0	6.43E-07	0	0
0	0	0	0	0	0	0	0	1.1E-08	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1.1E-08	0	0	0
3.94E-05	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	2.23E-08	0	0	0
5.61E-05	0	0	0	0	0	0	0	0	0	1.74E-06	0
0	0	0	0	0	0	0	0	2.39E-08	0	0	0

Table A.7 Matrix **C** of the SSM of SkyLab Test Cell with ACB system

0	1	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0
0	2.72E-1	35.71	0	3.28E-3	0	4.30E-3	0	4.18E-3	0	1.14E-2

Table A.8 Matrix **D** of the SSM of SkyLab Test Cell with ACB system

0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
1.45E-04	0	0	0	0	0	6.18E-05	0	6.18E-05	0	0	-88.34

Table A.9 Matrix **A** of the SSM of the lecture theatre with conventional AHU system

$-7.94\text{E-}4*\dot{m}_{fa} - 5.02\text{E-}4*\dot{m}_{ra} - 4.33\text{E-}3$	3.10E-3	1.24E-3	$7.16\text{E-}1*\dot{m}_{ra}$
7.57E-05	-7.57E-05	0	0
1.74E-05	0	-6.40E-05	0
$3.24\text{E-}7*\dot{m}_{fa} + 2.04\text{E-}7*\dot{m}_{ra}$	0	0	$-7.94\text{E-}4*\dot{m}_{fa} - 2.92\text{E-}4*\dot{m}_{ra}$

Table A.10 Matrix **B** of the SSM of the lecture theatre with conventional AHU system

-2.90E-07	$2.92\text{E-}4*\dot{m}_{fa}$	$7.16\text{E-}1*\dot{m}_{fa}$	0	7.90E-07	0	$1.37\text{E-}1*\dot{m}_{fa} + 1.37\text{E-}1*\dot{m}_{ra}$
0	0	0	0	0	0	0
0	0	0	4.66E-05	0	0	0
-2.04E-10	$-1.19\text{E-}7*\dot{m}_{fa}$	$5.02\text{E-}4*\dot{m}_{fa}$	0	0	7.94E-4	$-5.58\text{E-}5*\dot{m}_{fa} - 5.58\text{E-}5*\dot{m}_{ra}$

Table A.11 Matrix **C** of the SSM of the lecture theatre with conventional AHU system

1	0	0	0
0	0	0	1
1.64E-1	9.65E-2	3.86E-2	35.71
3.86E-2	6.87E-1	2.75E-1	0

Table A.12 Matrix **D** of the SSM of the lecture theatre with conventional AHU system

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	-89.63
0	0	0	0	0	0	0

Table A.13 Matrix **A** of the SSM of the lecture theatre with conventional DOAS air-conditioning system

$-7.94\text{E-}4 \cdot \dot{m}_{fa} - 4.34\text{E-}3$	3.10E-3	1.24E-3	0
7.57E-05	-7.57E-05	0	0
1.74e-05	0	-6.40E-05	0
0	0	0	$-7.94\text{E-}4 \cdot \dot{m}_{fa}$

Table A.14 Matrix **B** of the SSM of the lecture theatre with conventional DOAS air-conditioning system

-7.90E-07	-2.90E-07	$2.92\text{E-}4 \cdot \dot{m}_{fa}$	$7.16\text{E-}1 \cdot \dot{m}_{fa}$	0	7.90E-07	0	$1.37\text{E-}1 \cdot \dot{m}_{fa}$
0	0	0	0	0	0	0	0
0	0	0	0	4.66E-05	0	0	0
0	-2.04E-10	$2.05\text{E-}7 \cdot \dot{m}_{fa}$	$5.02\text{E-}4 \cdot \dot{m}_{fa}$	0	0	7.94E-4	$-5.58\text{E-}5 \cdot \dot{m}_{fa}$

Table A.15 Matrix *C* of the SSM of the lecture theatre with conventional DOAS air-conditioning system

1	0	0	0
0	0	0	1
1.64E-1	9.65E-2	3.86E-2	35.71
3.86E-2	6.87E-1	2.75E-1	0

Table A.16 Matrix *D* of the SSM of the lecture theatre with conventional DOAS air-conditioning system

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	-89.63
0	0	0	0	0	0	0	0