The Hong Kong Polytechnic University

Department of Building Services Engineering

Online Supervisory and Optimal Control of Complex Building Central Chilling Systems

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A thesis submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy

April, 2008

CERTIFICATE OF ORIGINALITY

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ABSTRACT

Abstract of thesis entitled: Online Supervisory and Optimal Control of Complex Building Central Chilling Systems

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Building Heating, Ventilation, and Air-conditioning (HVAC) systems are the major energy consumers in buildings. Operation and control of HVAC systems have significant impacts on energy or cost efficiency of buildings besides proper system designs and selection and maintenance of individual components. Although a great deal of research has been carried out on the proper control of HVAC systems and various cost effective control strategies have been developed for individual components in HVAC systems, not much research has concentrated on the online supervisory and optimal control of the overall building HVAC systems, and the research on developing online supervisory and optimal control strategies for complex building HVAC systems, still seems missing.

This thesis presents the online supervisory and optimal control strategies for complex building central chilling systems to enhance their energy efficiency. The software tools and implementation guidelines for applying these strategies for energy efficient control and operation of complex building central chilling systems are

provided as well. The online supervisory and optimal control strategies developed in this thesis consist of the strategies for variable speed pumps, an optimal control strategy for complex condenser cooling water systems and an optimal control strategy for complex chilled water systems. The optimal control strategies for condenser cooling water systems and chilled water systems were formulated using a systematic approach by considering the system level and subsystem level characteristics and interactions among all components and their associated variables, as well as the requirements and constraints of practical applications, i.e., control performance, computational cost, memory demand, etc.

In order to test and analyze the control performances and economic feasibilities of different control strategies under dynamic working conditions to determine the most promising strategy that can be used in practice, prior to site implementation, a dynamic simulation platform for complex building central chilling systems was developed. Three energy performance tests associated with the optimization of major control variables (i.e., the chilled water supply temperature set-point, the condenser water supply temperature set-point and the number of chillers operating) were conducted based on this simulation platform to evaluate the energy saving potentials in complex central chilling systems. The results obtained from these tests were carefully considered during the development of the online supervisory and optimal control strategies for condenser cooling water systems and chilled water systems.

To formulate the online supervisory and optimal control strategies, simplified models of major chilling system components (i.e., chillers, cooling towers, heat exchangers, pumps, etc.) were developed or selected in this thesis. The performances of these models were validated using the field measurement data, and/or the factory performance test data, and/or the catalogue data provided by the manufacturers.

To design the optimal control strategy for chilled water systems, the speed and sequence control strategies for variable speed pumps with different configurations in complex central air-conditioning systems were developed and presented. The performances of these strategies were tested and evaluated using a *simulation-assisted test method* in which the control strategies were tested in a simulated virtual environment similar to the situation when they are actually implemented in practice.

Based on the simplified chiller model and cooling tower model developed, an optimal control strategy for complex condenser cooling water systems is developed. This strategy consists of the model-based performance predictor, cost estimator (i.e., cost function), optimization technique and supervisory strategy. The control and computation performances of this strategy were evaluated by comparing with that of a model-based control strategy using the same models but using a GA (genetic algorithm) as the optimization tool, while the energy performance of this strategy was evaluated by comparing with that of the conventional control strategies for condenser cooling water systems. The results show that this optimal control strategy has satisfactory performance and is suitable for online control applications.

An optimal control strategy for complex chilled water systems is also developed and presented. This strategy consists of the model-based performance predictor, cost estimator, optimization algorithm, supervisory strategy and a number of local control strategies. The local control strategies were used to ensure the robust operation and keep track of the control settings considering the dynamic characteristics of the local process environment. The performance of this strategy was evaluated using the *simulation-assisted test method* by comparing it with that of other control strategies. The results show that about 1.28%~2.63% energy in the system under investigation can be saved thanks to the use of this optimal control strategy as compared with that using a conventional control strategy.

Lastly, the software tools and implementation guidelines for applying these online supervisory and optimal control strategies in practice are presented.

PUBLICATIONS ARISING FROM THIS THESIS

Journal Papers Published

2008 Wang, S.W., and Z.J. Ma. 2008. Supervisory and optimal control of building HVAC systems: A review. *HVAC&R Research* 14(1):3-32.

2008 Ma, Z.J., S.W. Wang, X.H. Xu, and F. Xiao. 2008. A supervisory control strategy for building cooling water systems for practical and real time applications. *Energy Conversion and Management* 49(8):2324-36.

2008 Ma, Z.J., S.W. Wang, and W.K. Pau. 2008. Secondary loop chilled water in super high-rise. *ASHRAE Journal* 50(5):42-52.

2008 Ma Z.J., S.W. Wang, and F. Xiao. 2008. Online performance evaluation of alternative control strategies for building cooling water systems prior to In-situ implementation. *Applied Energy*. Forthcoming.

2008 Xu, X.H., S.W. Wang, and Z.J. Ma. 2008. Evaluation of plume potential and plume abatement of evaporative cooling towers in a subtropical region. *Applied Thermal Engineering* 28(11-12):1471-84.

2007 Tyagi, S.K., S.W. Wang, and Z.J. Ma. 2007. Prediction, potential and control of plume from wet cooling tower of commercial buildings in Hong Kong: A case study. *International Journal of Energy Research* 31(8):778-95.

2006 Wang, S.W., X.H. Xu, and Z.J. Ma. 2006. Energy performance evaluation and development of control strategies for the air-conditioning system of a new building at construction stage. *Journal of Harbin Institute of Technology* 13(sup.):172-78.

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Energy and Buildings.

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Conference Paper

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NOMENCLATURE

A	Area (m^2)
a_0-a_2, b_0-b_1	Coefficients
B	Ratio of the impeller channel depth at intake to that at exhaust
b_{01}-b_{04}, b_{11}-b_{14}	Coefficients
c	Specific heat {kJ/(kg·K)}
C	Capacity flow rate (kW/K)
COP	Coefficient of performance
c$_{01}$-a_{03}, c_{11}-c_{13}	Coefficients
C_1-C_6	Coefficients
C_c	Overall thermal capacity of a coil (kW/K)
c_i	Vapor velocity at the impeller exhaust (m/s)
c_{r2}	Impeller exit radial velocity (m/s)
CAP	Chiller capacity (kW)
$(C_m)_i$	Maintenance cost of the i^{th} chiller (electric or gas) per unit of runtime and capacity ($/ton/h)
D	Internal diameter of a pipe (m)
d_0-d_3	Polynomial coefficients, depending on the value of the atmospheric pressure
$D_{e,k}$	Cost per unit of electrical demand in the time interval k ($/kW)
E	Coefficient
e_{01}-e_{03}, e_{11}-e_{13}	Coefficients
$E_{e,k}$	Cost per unit of electrical energy within the time interval k ($/kWh)
E_g	Cost per unit of natural gas usage ($/therm)
f	Function
f_f	Friction factor selected from the Moody chart
fix	Function of Matlab with round toward zero

$Freq$	Frequency (Hz)
G	Coefficient
$G_{g,k}$	Total gas usage in the time interval k (therm)
g_{01}-g_{03}, g_{11}-g_{13}	Coefficients
g_{21}-g_{22}, g_{31}-g_{34}	Coefficients
h	Enthalpy (kJ/kg)
H	Head (m or kPa)
h_0-h_2	Coefficients
h_{hyd}	Hydrodynamic losses (kW/kg)
h_{pol}	Polytropical compression work (kW/kg)
$h_{g,w}$	Enthalpy of water above reference state for liquid water at T_{re} (kJ/kg)
$h_{s,w}$	Saturation air enthalpy with respect to the temperature of the water surface (kJ/kg)
h_{th}	Compressor theoretical head (kW/kg)
J	Cost function
L	Length of a pipe (m)
Le	Lewis number
m	Index
M	Flow rate (kg/s or m^3/s)
n	Index
N	Number
NTU	Number of transfer units
P	Pressure (kPa)
PD	Pressure drop/pressure differential (kPa or m)
Q	Heat transfer rate (kW)
$Q_{ch,rated,i}$	Rated cooling capacity of the i^{th} chiller (ton)
q_0-q_2	Coefficients
R	Heat transfer resistance (k/kW)
S	Flow resistance (kPa×s^2/l^2)
SG	Specific gravity of the fluid being pumped
SHR	Sensible heat ratio

T	Temperature (°C)
T'	Temperature after introducing dynamic effects (°C)
t_c	Mean temperature of the coil (°C)
T_{ref}	Reference temperature for zero enthalpy of liquid water (°C)
TYPE XX	Component type number
u_2	Impeller tip speed (m/s)
UA	Overall heat transfer coefficient (kW/K)
v	Flow velocity (m/s)
V_T	Total volume (m^3)
VP	Valve position
W	Power consumption (kW)
x	Valve opening (%)
y	True value of a measured variable
y'	Measured value of a variable

Greek symbols

α	Coefficient
β	Impeller blades angle
ρ	Fluid density at the mean temperature (kg/m^3)
ε	Heat transfer effectiveness
ω	Capacity flow rate ratio
ω_a	Air humidity ratio
$\omega_{s,w}$	Saturation air humidity ratio with respect to the temperature of the water surface
$\omega_{s,w,e}$	Effective saturation air humidity ratio with respect to the temperature of the water surface
θ	Inlet guide vane angle
ξ	Flow resistance of a component
ξ_0	Flow resistance when the control valve is fully open
ζ, χ	Constants
$\psi_1,\ \psi_2$	Constants
η	Efficiency (%)

υ_1	Specific volume at the impeller intake (m^3/kg)
υ_i	Specific volume at the impeller exhaust (m^3/kg)
$(\gamma_i)_k$	Control function that specifies whether the i^{th} chiller (electric or gas) is in operation in the time interval k
Δ	Time interval
φ_1-φ_5	Converting factors

Subscripts

a	Air
adj	Adjusted
ahx	After heat exchanger
ao	Air outlet
bench	Benchmark
bhx	Before heat exchanger
bp	Bypass
c	Cold
cd	Condenser
ch	Chiller
chws	Chilled water supply
com	Compressor
ct	Cooling tower
CTA	CTA tower
CTB	CTB tower
cv	Control valve
db	Dry-bulb
des	Design
e	Effective
ev	Evaporator
fic	Fictitious
h	Hot
hx	Heat exchanger

i	Individual
imp	Impeller
in	Inlet
inter	Internal
l	Loss
m	Motor
meas	Measurement
out	Outlet
p	Pressure
pf	Pump fitting
piping	Pipeline
pu	Pump
ref	Refrigerant
rej	Rejection
rtn	Return
s	Saturation
set	Set-point
sup	Supply
tot	Total
v	VFD
w	Water
wb	Wet-bulb
z1	Zone 1
z2	Zone 2

Superscripts

n	Near
o	Optimal

CHAPTER 1 INTRODUCTION

1.1 Motivation

Energy saving and CO_2 emission reduction are among the most important issues receiving international attention. Scientists, environmentalists, governments and international communities around the world are now taking an interest in these subjects. According to the statistics provided by the U.S. Department of Energy, the energy use in commercial and residential buildings accounted for 40% of the total energy consumption in the United States in 2005 with the remaining used in the industrial (32%) and transportation (28%) sectors (DOE 2007). The Hong Kong energy end-use data showed that the space air-conditioning is one of the major energy users in buildings, which consumed about 31% of the total electricity consumption in Hong Kong in 2003 with the remaining used in the lighting and refrigeration (22%), industrial process/equipment (7%), cooking (4%), hot water (3%) and others (33%) (EMSD 2005). Therefore, proper control and operation of building central air-conditioning systems have significant impacts on energy or/and cost efficiency of buildings besides proper system designs and selection and maintenance of individual components.

For many years, control has been a very active area of the research and development in the Heating, Ventilation, and Air-conditioning (HVAC) field aiming at operation of HVAC systems in terms of reducing the overall system operating cost, ensuring thermal comfort of occupants, and satisfying indoor air quality. Figure 1.1 presents the scattered areas of the studies associated with the control of HVAC systems, involving the local control (area 1), supervisory and optimal control (area 2) and fault tolerant control (area 4). Since sensor faults and/or component degradations in HVAC systems may cause significant energy consumption or operating cost even if the control system is designed properly, the research on the fault detection and diagnosis (area 3) is therefore illustrated in Figure 1.1 as well.

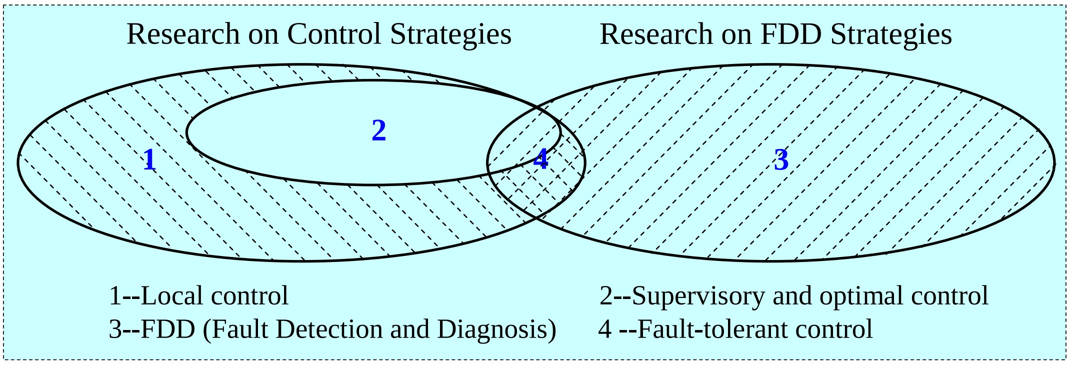

Figure 1.1 Schematic of scattered areas of the studies associated with the control of HVAC systems.

As illustrated in Figure 1.1, many efforts in the control of building HVAC systems have been typically made on the local level controls (area 1). The popularity enjoyed by the application of proportional-integral-derivative (PID) control is one of the fruitful outputs from such efforts. Local controls are the basic control and automation that allow the building services systems to operate properly and provide adequate services. The control settings of local controls might be optimal and energy efficient or cost effective when certain subsystems or certain subsystem performance criteria are concerned. However, they may not be energy efficient or cost effective when the overall system and overall system performance are of concern, and a significant amount of energy might still be wasted.

Due to the extremely high fuel oil price and the shortage of energy supply, growing concern on energy or cost efficiency has motivated society and building professionals to pay more attention on the overall system optimal control and operation and provides incentives to develop the most effective and robust control strategies for HVAC systems. Supervisory and optimal control, which addresses energy or cost efficient control of HVAC systems while providing desired indoor comfort and healthy environment under dynamic working conditions, is one of the main achievable approaches to minimizing the building energy consumption/operating cost and providing robust operational performance. Compared with the local control, supervisory and optimal control allows an overall consideration of the system level and/or subsystem level characteristics and interactions among all components and their associated variables including climate variables. The knowledge of the system level characteristics and interactions can be utilized to minimize a well-defined cost function or objective function, which would lead to an improved system response and reduced operating cost. However, the studies associated with supervisory and optimal control (area 2) are still far from adequate as compared with the research related to the local control. This is probably due to the easier implementation of local control strategies in practice and the inconvenience of collecting a large amount of online operation data required by supervisory and optimal control strategies.

Buildings nowadays are mostly equipped with comprehensive building automation systems (BASs) and building energy management and control systems (EMCSs) that allow the possibility of enhancing and optimizing the operation and control of HVAC systems. Over the last two decades or so, efforts have been made to develop supervisory and optimal control strategies for building HVAC systems thanks to the growing scale of BAS integration and the convenience of collecting a huge amount of online operation data by the application of BASs. These efforts have resulted in a number of research papers, research theses and technical articles/reports that specifically address the HVAC optimal control and operation available in literature (Bradford 1998; Flake 1998; Wang and Jin 2000; Zaheer-uddin and Zheng 2000; Sun 2004; Lu et al. 2005b; Nassif et al. 2005; Sun and Reddy 2005; Braun 2007a, 2007b; etc.). The results obtained from these studies demonstrate that a substantial amount of energy/costs in HVAC systems can be saved when supervisory and optimal control strategies are used. Even a small overall increase in the operating efficiency would result in significant energy or cost savings. Other benefits can also be achieved including improved indoor air quality, enhanced thermal comfort of occupants, reduced maintenance costs, etc. However, most of existing supervisory and optimal control strategies are either too mathematical or lack generality since the requirements and constraints of practical applications, i.e., control reliability, control stability, computational cost, memory demand, etc, were not cautiously considered during the development of these supervisory and optimal control strategies (Wang and Ma 2008).

In practice, proper and energy efficient operation of HVAC systems is a very difficult engineering issue. Due to the increasing number of high-rise buildings built and growing concern on building energy consumptions/operating costs, the configurations and design philosophies of building HVAC systems are becoming more and more sophisticated. The difficulties related to optimal control and operation of these complex building air-conditioning systems are therefore increased accordingly. How to achieve reliable and energy efficient control and operation of these complex building air-conditioning systems to minimize their energy inputs/operating costs while providing the robust control performance is one of the major challenging issues encountered by building professionals and building operators nowadays.

This research therefore aims at providing a systematic method, software tools as well as the implementation guidelines for developing and applying online supervisory and optimal control strategies for energy efficient control and operation of complex building central chilling systems.

1.2 Aim and Objectives

Online supervisory and optimal control strategies for complex building central chilling systems for real-time applications play important roles in reducing the overall energy consumption/operating cost of buildings, and in satisfying the ever-increasing requirements of indoor air quality and thermal comfort. However, the current studies on this aspect are far more insufficient. Therefore, the development of online supervisory and optimal control strategies for complex building central chilling systems for real-time applications is the main aim of this research, which addresses the following major objectives:

1. Construct a dynamic simulation platform for complex building central chilling systems to test and analyze the control performances and economic feasibilities of different control strategies to determine the most promising strategy that can be used in practice, prior to site implementation;
2. Investigate the energy saving potentials in complex building central chilling systems associated with the optimization of major control variables on the basis of the dynamic simulation platform established;
3. Develop and/or select simplified models for major chilling system components. The control reliability, control stability and computation performance are carefully considered during the development and/or selection of these models;
4. Propose an effective method for proper control and operation of variable speed pumps in complex building central air-conditioning systems to maximize their operating efficiency and extend their service life;
5. Develop the online supervisory and optimal control strategies for complex building central condenser cooling water systems and chilled water systems, respectively. These strategies should satisfy the requirements and constraints of practical applications (i.e., control accuracy, control robustness, computation performance, etc.) and can be easily implemented in practice.
6. Develop the software tools and provide the implementation guidelines for applying online supervisory and optimal control strategies in practice.

1.3 Organization of This Thesis

This chapter outlines the motivation of this research by presenting the need of online supervisory and optimal control strategies for building HVAC systems, especially for complex building HVAC systems, to enhance their energy or cost efficiency and provide robust control performance. It presents the aim and objectives of this thesis. The subsequent chapters are organized as follows.

Chapter 2 presents a comprehensive review of the state of the art of the research and development as well as application of supervisory and optimal control in HVAC systems, along with presenting a general optimal supervisory control problem for HVAC systems which can be used as a context for understanding the contributions of the studies described in this chapter. The frameworks for categorizing the main supervisory and optimal control methods and optimization techniques developed and/or utilized in the HVAC field are provided. The application characteristics of each control method and optimization technique are identified and compared as well.

In Chapter 3, a super high-rise building and its complex central chilling system are introduced. Based on this complex central chilling system, a dynamic simulation platform is constructed. The major component models and their interconnections to construct this dynamic simulation platform are presented. Three energy performance tests are conducted on the basis of the dynamic simulation platform established to test and analyze the energy saving potentials in complex building central chilling systems associated with the optimization of major control variables. The interactions among the subsystems in central chilling systems are seriously evaluated as well. The results obtained from these tests will be used to develop online supervisory and optimal control strategies for complex building central chilling systems.

Chapter 4 presents two test methods (named *simulation-assisted test method* and *computation-assisted test method*) for testing and evaluating the performances of online supervisory and optimal control strategies developed in this thesis.

Chapter 5 presents the development and/or selection of simplified models of major chilling system components (i.e., chillers, cooling towers, pumps, heat exchangers, etc.) for online control applications. The performances of these models are validated using the field measurement data, and/or the factory performance test data, and/or the catalogue data provided by the manufacturers. The computation performances, calibration efforts and convergences of most of these models are evaluated as well.

Chapter 6 presents optimal control strategies, including the speed control strategy and the sequence control strategy, for the proper control and operation of variable speed pumps with different configurations in complex building central air-conditioning systems. The performances of these strategies are tested and evaluated by comparing with that of the other conventional control strategies using the *simulation-assisted test method*.

Based on the simplified chiller model and cooling tower model developed in Chapter 5, an optimal control strategy for complex building condenser cooling water systems for online applications is developed in Chapter 7. A practical optimization technique, namely HQS (hybrid quick search) method, is also developed in this chapter and used to seek the most energy efficient control settings for the optimization problem established. The performances, including computation performance, control accuracy and energy performance, of this optimal control strategy are validated and compared with that of the other strategies on the complex building central chilling system presented in Chapter 3 using the *computation-assisted test method*.

Chapter 8 presents an optimal control strategy for complex chilled water systems for real-time applications, in which a number of local control strategies are designed to ensure the robust operation and keep track of the control settings considering the dynamic characteristics of the local process environment. The performance of this strategy is validated in this chapter by comparing with that of the other conventional control strategies using the *simulation-assisted test method*.

Chapter 9 presents the software tools and implementation guidelines for applying online supervisory and optimal control strategies in practice. An overview of the application software system to implement the online control software packages of the optimal control strategies developed in this thesis to practically control the operation of the central chilling system in the super high-rise building is demonstrated.

Chapter 10 summarizes the work reported in this thesis, and gives recommendations for future application and research in the related areas.

CHAPTER 2 SUPERVISORY AND OPTIMAL CONTROL OF BUILDING HVAC SYSTEMS: A REVIEW

Since the thesis aims mainly at online supervisory and optimal control of building HVAC systems, a comprehensive review of the research and development as well as application of supervisory and optimal control strategies in HVAC systems is essential to assist in developing the most effective control strategies and avoiding major pitfalls.

Section 2.1 presents an overview of supervisory and optimal control in HVAC systems. In Section 2.2, the general optimal control problem for HVAC systems is presented and used as a context for understanding the contributions of the studies described in this chapter. In Section 2.3, the framework for categorizing supervisory and optimal control methods in HVAC systems is provided in terms of what type of models is used in the control system. In this section, the advantages and disadvantages of the application of these methods are clearly identified. In Section 2.4, various optimization techniques utilized in supervisory and optimal control are presented, and the benefits associated with the application of these techniques in HVAC systems are critically analyzed. In Section 2.5, the research and development as well as application of supervisory and optimal control strategies in HVAC systems are reviewed comprehensively according to the classification schematic of supervisory control methods. A brief assessment for major techniques is also provided in this section. In

Section 2.6, the discussions and recommendations on supervisory and optimal control in HVAC systems are presented. A summary of this chapter is given in Section 2.7.

2.1 An Overview

The BAS is a tool that can be used for more effective and efficient management of building services systems (Carlson and Di Giandomenico 1991). One of the main achievable goals of effective use of BASs is to improve the building energy or cost efficiency and provide better operational performance. Control functions are the basic functions of BASs. Other major functions of BASs include risk management functions, information, and facilities management functions. Control functions of BASs can be divided into two categories, i.e., local control functions and supervisory control (or energy management) functions, as shown in Figure 2.1.

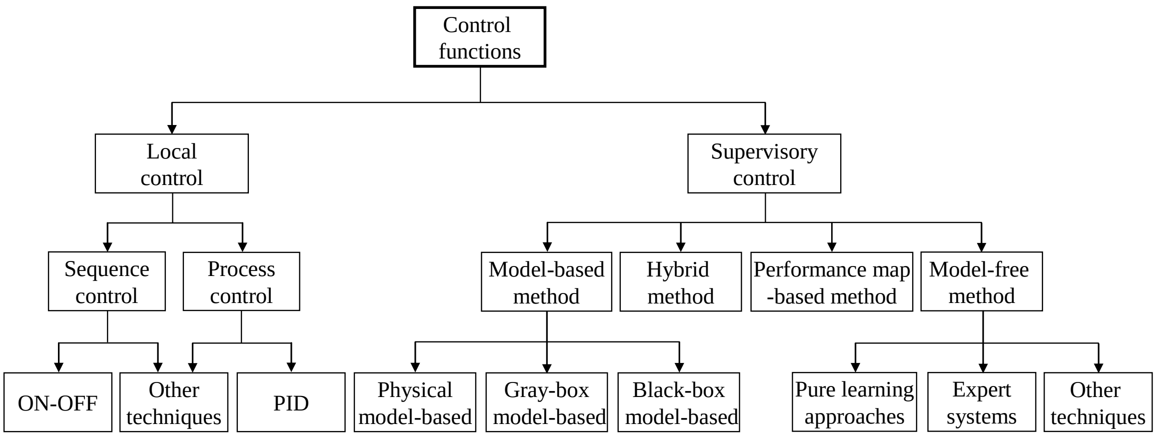

Figure 2.1 Classification schematic of control functions in HVAC systems.

Local control functions can be further sub-divided into two groups, including the sequence control and process control. The sequence control defines the order and conditions associated with bringing equipment online or moving them offline

(ASHRAE 2007). The typical sequence control in HVAC systems includes the chiller sequence control, cooling tower sequence control, pump sequence control, fan sequence control, etc. The process control is to adjust the control variables to achieve well-defined process objectives in spite of disturbances, using measurements of state and/or disturbance variables (Ramirez 1994). The typical process control used in the HVAC field is PID control. ON/OFF control (or bang-bang control), step control, and modulating control are the effective control actuation schemes of the local process control loops in HVAC practice, and they have produced a great impact and profound significance on building automation.

Supervisory control, often named *optimal control*, seeks to minimize or maximize a real function by systematically choosing the values of variables within allowed ranges. It is the total system monitoring and overall control of the local subsystems (Levenhagen and Spethmann 1993). In the control of HVAC systems, supervisory and optimal control aims at seeking the minimum energy input or operating cost to provide the satisfied indoor comfort and healthy environment, taking into account the ever-changing indoor and outdoor conditions as well as the characteristics of HVAC systems. It is worthy noticing that minimizing the system operating cost is not always equivalent to minimizing the system energy input.

Depending on the situations and objectives to be achieved, supervisory control plays different roles at different time periods (Levenhagen and Spethmann 1993). The earliest supervisory control stressed the building equipment automation, and the primary focus was on automating all equipment as much as possible to save labor.

Later, supervisory control emphasized the building energy monitoring and automatic control, and the major concern was on the energy efficiency by both automatic and manual control with the aid of system monitoring. However, the results obtained from both types of supervisory control are not likely to be energy efficient and cost effective since much attention is paid to the automatic equipment with less consideration of their operating costs. Nowadays, supervisory control highlights the importance of the overall system performance involving energy or cost efficiency, indoor environmental quality, etc. Therefore, supervisory control is to optimize the operation of HVAC systems using a systematic approach by considering the system level characteristics and interactions among the overall system. The control system in this kind of supervisory control generally provides two levels of controls: local control and supervisory control. Local control is the low level control, which is designed to ensure the robust operation and keep track of the set-point considering the dynamic characteristics of the local process environment. Supervisory control is the high level control, which is designed to utilize global optimization techniques to find energy or cost efficient control settings for all local controllers, taking into account the system level and subsystem level characteristics and interactions. These energy or cost efficient control settings are optimized in order to minimize the overall system energy input or operating cost without violating the operating constraints of each component and without harming the indoor environmental quality provided.

According to the classification scheme illustrated in Figure 2.1, supervisory and optimal control in HVAC systems could be classified into four categorizes, including model-based supervisory control, hybrid supervisory control, performance map-based supervisory control and model-free supervisory control. Such classification may not be perfect enough since there are no clear boundaries among some control methods. However, it can provide a very useful and helpful basis for comparing the advantages and disadvantages among different control methods. It is also very helpful for identifying the strengths and weaknesses of each control method, as well as for analyzing the feasibilities of their online applications. It is worthwhile to point out that whether a method is specified as a model-based method or a model-free method in this classification is dependent on whether the numerical models are used. Here, a numerical model presents the knowledge of the system/component performance by the numerical correlations between the selected performance variables and condition variables. According to this clarification, the control methods using physical models, gray-box models and black-box models can be classified into the category of model-based methods, while the methods using expert systems and pure learning approaches can be grouped into the model-free category.

2.2 The General Optimal Control Problem in HVAC Systems

Supervisory and optimal control of HVAC systems is to determine the optimal solutions (operation modes and set-points) that minimize the overall system energy input or operating cost while still maintaining the satisfied indoor thermal comfort and healthy environment. For different types of HVAC systems (i.e., electric-driven system, gas-driven system, hybrid gas/electric-driven system, the systems with and without energy storage, etc.), the optimal supervisory control problems are significantly different. For a particular optimization problem, different utility rate structures will lead to different solutions as well. Since the hybrid system with significant energy storage is the most complicated system, the other systems can be considered as simplifications of such systems. Therefore, the optimal supervisory control problem and cost function for hybrid systems with significant energy storage are presented in the following in detail.

The optimal supervisory control problem for hybrid systems with significant energy storage is extremely complex, affected by many factors including electrical and gas energy costs, electrical demand charges, maintenance costs associated with different chillers (electric or gas), chiller characteristics, storage characteristics, weather condition, load profile, etc. For a utility rate structure that includes time-of-use differentiated electricity prices and demand charges and the fixed cost of natural gas over each billing period (e.g., a month), the overall optimization problem of such systems is to minimize the utility cost over the billing period (e.g., a month), and the cost function can be mathematically described as in Equation (2.1).

$$J = \sum_{k=1}^{N} E_{e,k} W_{e,k} \Delta t + \sum_{k=1}^{N} E_g G_{g,k} + \sum_{k=1}^{N} \left(\sum_{i=1}^{N_{ch}} (\gamma_i)_k (C_m)_i Q_{ch,rated,i} \right) \Delta t + \max_{1 \le k \le N} \left(D_{e,k} W_{e,k} \right) \quad (2.1)$$

with respect to the N_c control variables and subject to certain constraints (i.e., basic energy and mass conservations, mechanical limitations, etc.) for each time interval k.

where J is the overall cost in the billing period, Δt is the time interval, typically equal to the time window over which demand charges are levied, e.g., 0.5 h, N is the number of the time intervals in a billing period, $E_{e,k}$ is the cost per unit of electrical energy within the time interval k, which can be available from the local utility tariff, $W_{e,k}$ is the total electrical power of the HVAC system in the time interval k, E_g is the cost per unit of natural gas usage, $G_{g,k}$ is the total gas usage in the time interval k, N_{ch} is the number of chillers, $(\gamma_i)_k$ is a control function that specifies whether the i^{th} chiller (electric or gas) is in operation in the time interval k (1 denotes ON and 0 denotes OFF), $(C_m)_i$ is the maintenance cost of the i^{th} chiller (electric or gas) per unit of runtime and capacity, $Q_{ch,rated,i}$ is the rated cooling capacity of the i^{th} chiller, and $D_{e,k}$ is the cost per unit of electrical demand in the time interval k.

The first and second terms on the right-hand side of Equation (2.1) are the total costs of electricity and natural gas in the billing period, respectively. The third term on the right-hand side of Equation (2.1) is the total maintenance costs associated with using different types of chillers. The last term on the right-hand side of Equation (2.1) is the demand charge for the billing period. An even more complex cost optimization would result if the utility rate includes ratchet clauses in which the demand charge is the maximum of the peak demand charge for the billing period and some fraction of the peak demand charge for the previously billing period during the cooling season, and the installation costs of different types of chillers are considered also. For a given condition, the major aim of the optimization strategy is to optimize all control variables to minimize the cost function as characterized by Equation (2.1).

As presented previously, the cost functions for other systems (i.e., all electric-driven systems with and without significant energy storage, all gas-driven systems, etc.) can be simplified on the basis of the above cost function. For instance, for a utility rate structure including both time-of-use differentiated electricity prices and demand charges, the cost function for all electric-driven systems with significant energy storage can be described as in Equation (2.2), which only includes the first and last terms on the right-hand side of Equation (2.1), while the cost function for the absorption chiller systems without significant energy storage can be simplified as in Equation (2.3), which includes the first, second and last terms on the right-hand side of Equation (2.1). It is necessary to point out that the total electrical power of the absorption chiller systems for each time interval *k* could include the water pump electrical power, fan electrical power, absorption chiller auxiliary electrical power, etc. It is also noted that the maintenance term was not included in both cost functions since the same types of chillers are used in both systems.

$$J = \sum_{k=1}^{N} E_{e,k} W_{e,k} \Delta t + \max_{1 \le k \le N} \left(D_{e,k} W_{e,k} \right) \tag{2.2}$$

with respect to the N_c control variables and subject to certain constraints for each time interval k.

$$J = \sum_{k=1}^{N} E_{e,k} W_{e,k} \Delta t + \sum_{k=1}^{N} E_g G_{g,k} + \max_{1 \le k \le N} \left\{ D_{e,k} W_{e,k} \right\} \tag{2.3}$$

with respect to the N_c control variables and subject to a series of constraints for each time interval k.

The following important factors address the nature of optimization problems that should be seriously considered in order to develop the advanced supervisory and optimal control strategies for HVAC systems:

- Both energy and demand charges are important for the optimization problems in HVAC systems. In large commercial and office buildings, the demand charges often contribute a significant amount to the monthly electric bill. The supervisory and optimal control should minimize the overall utility cost.
- The variables involved in the particular optimization problem should be identified clearly. In general, there are three kinds of variables associated with the optimization problems in HVAC systems, i.e., uncontrolled variables, continuous control variables and discrete control variables. Uncontrolled variables can be measurable but may not be controlled. However, they affect the overall utility cost. The typical uncontrolled variables in HVAC systems are the ambient air wet-bulb temperature, ambient air dry-bulb temperature and building cooling load. The continuous and discrete control variables are set-points and operation modes that minimize the overall utility cost, which are the optimal solutions for the optimization problem identified by certain optimization techniques. The typical discrete control variables in HVAC systems are the numbers of different types of components in operation, such as the number of chillers in operation, the number of cooling towers in operation, etc. The typical continuous control variables in HVAC systems could be the temperature set-points, pressure set-points, pump speeds, the rate at which energy is added or removed from storage (if significant energy storage is used), etc.

- The subsystems in HVAC systems are interacted with each other, and the fact is that the reduction of energy input or operating cost of one subsystem might result in the increase of energy input or operating cost of the other subsystem with respect to the changes of certain control variable. Therefore, the optimal solution for the related control variable is the trade-off between energy inputs or operating costs of both subsystems. For instance, for all electric-driven systems without significant energy storage, the optimal chilled water supply temperature set-point is the trade-off between the electrical power consumptions of both chillers and chilled water pumps, while the optimal condenser water supply temperature set-point is the trade-off between the electrical power consumptions of both chillers and cooling tower fans (for those with constant speed condenser water pumps). For a particular system, all types of trade-offs that occur with respect to the changes of different control variables should be identified clearly.
- The optimizations for the systems with and without energy storage are significantly different. The optimization related to the systems without storage is a quasi-steady, single-point optimization, while the optimization associated with the systems with storage is the dynamic optimization determining a trajectory of set-points. For different types of optimization problems, optimization techniques applied to seek the optimal solutions would be different. The dynamic programming or some direct search methods can be used for the dynamic optimization, while static optimization techniques can be used for the quasi-steady, single-point optimization. The optimization techniques utilized in HVAC systems will be presented in Section 2.4 in detail.

Based on the defined cost function and constraints for a particular system, considering the nature of the optimization problems related to HVAC systems, the supervisory and optimal control strategy can be formulated using certain method and optimization technique presented in Sections 2.3 and 2.4, respectively.

2.3 Supervisory Control Methods

The selection of control methods for a supervisory control application plays a critical role in the development of the effective control strategy to optimally control the operation of HVAC systems. For a given set of specifications for a targeted application, there always exist several supervisory control methods. Usually, each method has its own advantages and limitations over the others in some aspects. In the following, the detailed descriptions of each control method and the strengths and weaknesses associated with the use of each method are presented.

2.3.1 Model-free Supervisory Control Methods

Model-free supervisory control methods do not require a 'model' of the targeted system. Expert systems and reinforcement learning approaches can be utilized to design model-free supervisory control methods (Ling and Dexter 1994; Henze and Schoenmann 2003). An expert system includes two distinct control functions, i.e., advisory control and supervisory control (Hordeski 2001). When an expert system acts as a supervisory controller, it has the capability to determine energy or cost efficient control settings for HVAC systems according to the given working condition. These energy or cost efficient control settings are identified based on the combination of the rules defined in the knowledge base and information obtained from BASs. The knowledge base in an expert system is derived from the specific knowledge of one or more human experts. An expert system can imitate human reasoning to make decisions for a given working condition based on the knowledge base. It also has the ability to deduce the reasonable solutions with an incomplete data set. An expert system is easy to program and easy to manage as well. However, the application of an expert system is strongly affected by the richness of the knowledge database since the rules are static and threaten significant errors outside their domain of expertise.

Reinforcement learning control is another example of a model-free control method. This method describes a learning paradigm in which a control system attempts to improve its behavior on the results of previous actions, without the requirement of a model of the environment or the effects of actions. This method can find optimal or near optimal solutions for the control problem without any prior knowledge of the environment. However, it always takes an unacceptably long time to make the controller ‘learn’. The performance of the controller is sensitive to many factors, i.e., the selection of the state-action, learning parameters, etc. These features make it almost impossible to implement in practice (Henze and Schoenmann 2003).

There are also other possible approaches that do not utilize any model in the control system to optimize the operation of HVAC systems. For instance, one conceptually simple yet inadequate strategy for all electric-driven systems without significant energy storage is to monitor the overall system power consumption in response to the changes of the control settings continuously, and always proceed in the direction of the reduced power consumption. Since this method focuses on the overall system performance and no numerical model of the targeted system is required, it is a model-free supervisory control method. This online search procedure is fairly easy to implement in practice. However, it is inherently unstable due to the dynamic characteristics of HVAC systems and the low response to rapid changing of indoor and outdoor conditions (Braun and Diderrich 1990a).

2.3.2 Model-based Supervisory Control Methods

In the model-based supervisory control, the tools required to perform the supervisory control are the system and/or component models and optimization techniques. The main function of models is to predict the system energy or cost and environment performances, as well as the system response to the changes of control settings. All of the models are connected with the power consumption or operating cost directly. Online measurements collected from BASs are used to tune the model parameters to make them represent real systems accurately. The primary role of optimization techniques is to seek energy or cost efficient control settings to minimize the system energy input or operating cost while still maintaining the satisfied indoor environment. At a sampling instant, the optimization technique is applied to the models to evaluate the control settings that minimize the power consumption or operating cost characterized by the models. The control strategies determined in this manner can react quickly to rapid changes of indoor and outdoor conditions. According to the knowledge of the system used to formulate the models, the model-based supervisory control can be further divided into physical model-based supervisory control, gray-box model-based supervisory control, and black-box model-based supervisory control.

In the physical model-based supervisory control, physical models are utilized in the control system to predict the energy/cost and environment performances of the system of concern. A physical model begins with the description of a system or process of interest and uses a prior knowledge of the system or process to specify a model that serves as the basis for predicting the overall performance. This kind of models includes detailed physical models and simplified physical models. Based on the fundamental laws of energy, mass, heat transfer, momentum, flow balances, etc., a set of mathematical equations can be derived and solved. Generally, these detailed and simplified physical models have high performance in prediction and high control reliability within their allowed working conditions since the basic assumptions and laws utilized in the model development are effective and valid within their allowed ranges. These models require less training data as well. However, most physical models, particularly detailed physical models, are rather complicated, and the iterative process is always required in most of these models, which may result in instability and divergence as well as high computational cost and memory demand. These characteristics may seriously prevent their online applications. Concerning the advantages of physical models and problems of complex physical models for online applications, great efforts in developing simplified physical models and gray-box models have been made in recent years.

In the gray-box model-based supervisory control, gray-box models are used to formulate supervisory control methods. There are two different models that can be used to develop gray-box models. One is from black-box models. A prior knowledge of the system or process can be incorporated as constraints on model parameters or variables. The other is from a specific model structure based on physical relations. Mathematical relations, which describe the behaviors of the process or system, are simplified to formulate the model. The main advantages of gray-box models are that the complexity of the model structure and the computational cost are reduced greatly, while the parameters in the models still have certain physical significance, which can make them be used for limited extrapolation outside the range of the training data covered. It is worthy noticing that the accuracies of this type of models still strongly depend on the richness of data used to train the models.

In the black-box model-based supervisory control, black-box models are used. These models do not incorporate any kind of prior knowledge of the system or process. They are developed based on empirical behaviors of the system or process of concern, and are to mathematically relate input variables to output variables directly. The parameters in this type of models have no physical significance. Typical representatives of black-box models are polynomial curve fits and artificial neural networks (ANNs). Generally, black-box models are simple enough since they do not require the detailed physical knowledge of the system or process of concern and computational costs are generally manageable. However, most of these models cannot ensure stable performance prediction although they are simple. They are reliable only for operation points within the ranges of the training data covered, and extrapolation outside these ranges may lead to significant errors. In order to ensure the high prediction performance, extensive and adequate training data are always required.

2.3.3 Hybrid Supervisory Control Methods

In the hybrid supervisory control, different types of models (Here, the control strategies using different types of models are classified into the hybrid control method) and/or the model-based method and model-free method are combined together to formulate supervisory control strategies. For instance, some hybrid supervisory control methods utilize a mix of physical/gray-box/black-box models to design the control system, in which some component models are physical models, while others are gray-box or black-box models. Some hybrid supervisory control methods use both the model-based approach and model-free approach (e.g., reinforcement learning approach) to construct supervisory control methods, in which the features of the model-based approach and model-free approach are combined together to achieve high control performance. The supervisory control methods formulated by this manner might provide good control performance if the controllers are reasonably designed.

2.3.4 Performance Map-based Supervisory Control Methods

Compared to the three supervisory control methods presented above, the performance map-based supervisory control is somewhat different. This method often uses the results generated from the detailed simulation of the targeted system over the range of expected operation conditions to draw a performance map, and then utilizes this performance map to control the operation of HVAC systems. For instance, for an electric-driven chiller plant without significant energy storage, using component models, various combinations of the cooling load, the ambient air temperature, the number of chillers operating, the number of pumps operating, as well as the number of cooling towers operating and their individual fan speeds, can be used as inputs to the simulation platform. At each operating condition, the power consumptions or performance data for all combinations are computed, and the control settings giving the minimum energy value or the best performance are identified. A performance map can then be drawn using those combinations with minimum energy values or best performances identified from over the full operating range of the system, and can be further used as a supervisory controller to achieve energy efficient control and operation of the HVAC system. It is worthwhile to notice that the performance map is not necessarily obtained by simulations. For example, it could be obtained by testing the system over a significant range of settings and operating conditions although the simulation is an effective tool. Performance map-based supervisory control strategies might be feasible and practical for small systems. However, they might be impractical for large systems since generating such a performance map often requires considerable work, and large control errors might result when the system does not operate as the manner of the performance map generated. They lack generality as well.

2.4 Optimization Techniques Used in Supervisory Control

Optimization is an area of mathematics that is concerned with finding the “best” points, curves, surfaces, etc. (Hull 2003). Finding the optimal solution to an optimization problem is a key issue for a supervisory control application. The difficulty related to optimization is to determine whether a given minimum is the global minimum or the local minimum. Similar to supervisory control methods, for a given set of specifications, there always exist several optimization techniques, often with sharply different structures and characteristics. Each of the options is superior to all others in one or a few aspects, which is explicitly targeted during the development of the particular optimization technique. Figure 2.2 provides a relatively detailed classification schematic of optimization techniques utilized in most engineering optimization problems. It is modified and supplemented on the basis of the classification scheme provided by Nelles (2001).

In general, all optimization techniques could be summarized into two categorizes: linear optimization techniques and nonlinear optimization techniques. The linear optimization technique is the simple and straightforward technique since there is always a unique optimum in a linear optimization problem. The linear optimization technique includes, e.g., direct method, recursive method, iterative method, etc. Compared to the linear optimization technique, the nonlinear optimization technique is complex and sophisticated since many local optimums exist in a nonlinear optimization problem, and the difficulty to find the global optimum increases greatly. The nonlinear optimization technique can be further sub-divided into two categories, including nonlinear local optimization techniques and nonlinear global optimization techniques. The major difference between them is that the nonlinear local optimization technique always leads to a local not global optimum. The nonlinear local optimization technique includes, e.g., direct search techniques, gradient-based optimization techniques, etc. The nonlinear global optimization technique includes, e.g., simulated annealing, branch and bound, evolutionary algorithm, tabu search, etc. It is worth noticing that these global optimization techniques cannot always provide the global optimal solutions.

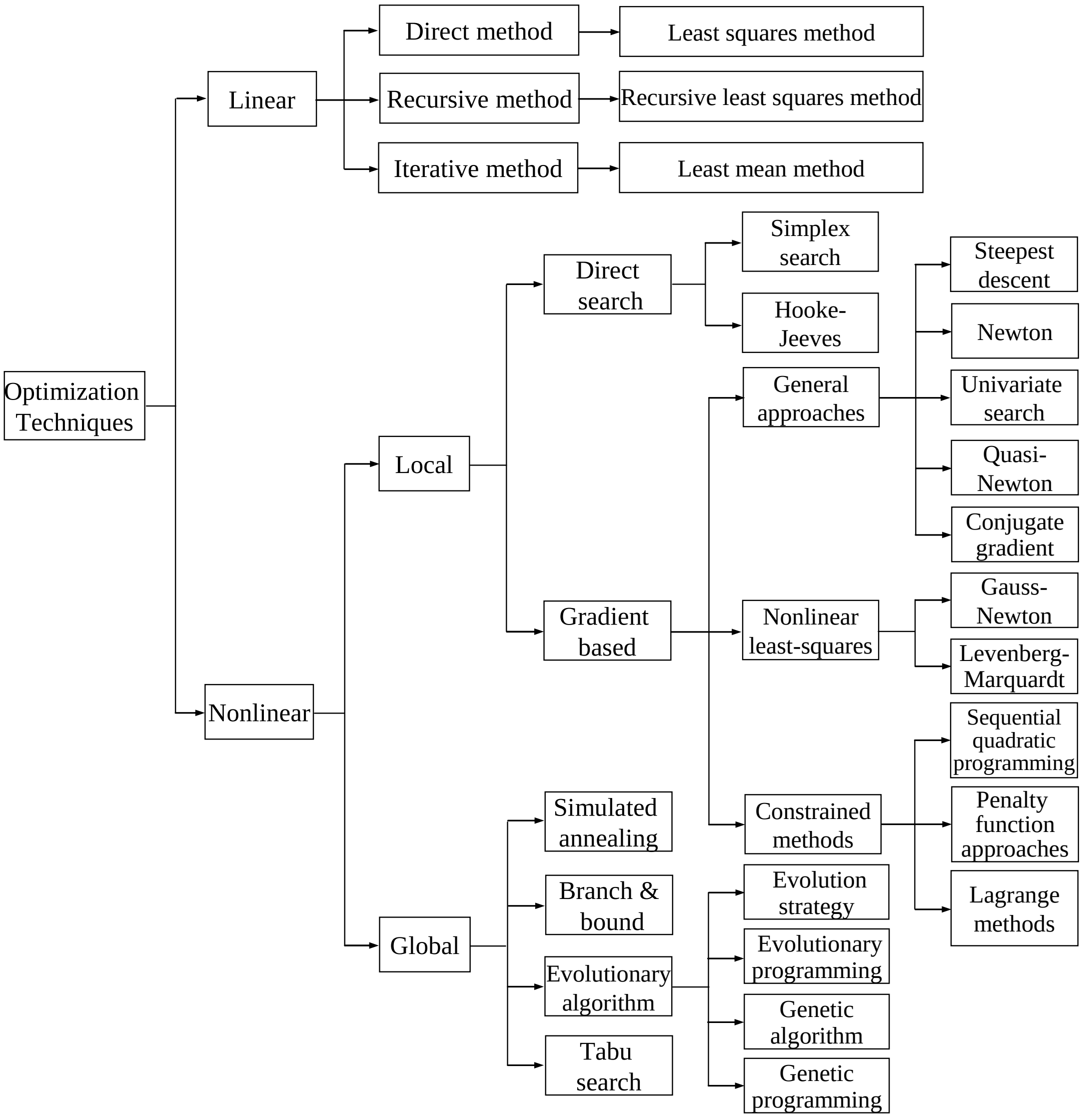

Figure 2.2 Classification schematic of optimization techniques for engineering systems.

In the HVAC field, linear optimization techniques can be used to solve many simple local optimization problems, while nonlinear optimization techniques can be utilized to handle highly nonlinear and constrained optimization problems. Since the optimization problems related to supervisory and optimal control of building HVAC systems, as presented in Section 2.2, are often characterized by discretization, nonlinearity and are highly constrained, only nonlinear optimization techniques are addressed in the following.

During the past two decades, much research has been carried out on the development and application of various nonlinear optimization techniques in HVAC systems (Olson and Liebman 1990; Koeppel et al. 1995; Kota et al. 1996; Wang and Jin 2000; Bassily and Colver 2005; etc.). These efforts have resulted in fruitful achievements, which provide building professionals an opportunity to effectively use these reliable and efficient optimization techniques for practical applications while avoiding unreliable optimization techniques. The major optimization techniques utilized in building HVAC systems are examined and summarized in Table 2.1. A more detailed description of these techniques is given as follows. They are summarized according to three categories of nonlinear local optimization techniques, nonlinear global optimization techniques and other optimization techniques. The strengths and weaknesses of each technique for online applications are also identified and presented in Table 2.1. It provides the basic information for users in selecting the appropriate optimization technique for the particular optimization problem with necessary confidence and the awareness of potential difficulties and problems that may arise in practice. The application examples of these techniques in HVAC systems are listed in Table 2.1 as well.

Table 2.1 Summary of main optimization techniques used in building HVAC systems

Techniques		Strength	Weakness	Application examples
Nonlinear Local Techniques	Direct search	Simple and easy to be understood and implemented. No derivatives are required.	Often fails to obtain an optimal solution. It is less computationally efficient.	Wright and Hanby 1987; Sreedharan and Haves 2001; Braun and Chaturvedi 2002; etc.
	Sequential quadratic programming	Can efficiently handle a large number of inequality constraints.	Has to start from initial guesses and its convergence speed is affected by its initial guesses.	Olson and Liebman 1990; House and Smith 1995; Kota et al. 1996; Sun and Reddy 2005; etc.
	Lagrange Method	Easy to implement since Lagrange formula does not depend on the order in which the nodes are arranged.	The convergence is not always guaranteed.	Hach and Katoh 2003; Chang 2004; etc.
	Conjugate gradient method	The overall computational cost is small for large number of decision variables.	Less efficient and robust as compared with some techniques, i.e., quasi-Newton method.	Nizet et al. 1984; etc.
	Univariate search	Simple and easy to be implemented.	The convergence speed is quite slow and it cannot find the optimum values at some cases.	Hanby and Angelov 2000; Bassily and Colver 2005; etc.
Nonlinear Global Techniques	Branch and bound (B&B)	Can provide a good or a sub-good solution. It is easy to incorporate any constraint into this method.	High computational cost is always required and it is possible to miss the globally optimum solution.	Sousa et al. 1997; Chang et al. 2005; etc.
	Simulated annealing	Relatively easy to implement and has strong ability to provide good solutions.	High computational cost and memory demand are required.	Koeppel et al. 1995; Flake 1998; Chang et al. 2006; etc.
	Evolutionary algorithms and genetic algorithm	With high generalities and flexibilities, and they are robust to find the global minimum in most cases.	Extensive computational cost and memory demand are always required due to high number of fitness evaluations.	Huang and Lam 1997; Wang and Jin 2000; Nassif et al. 2005; Lu et al. 2004, 2005b; Fong et al. 2006; etc.

2.4.1. Nonlinear Local Optimization Techniques

- *Direct search*: It is based on the evaluation of loss function values only. No derivatives are required. It is not reasonable to apply this method if the derivatives of the loss function are easily available with low computational efforts. Although the direct search method does not require the deviations to exist, higher performance can be expected on smooth functions (Nelles 2001).
- *Sequential quadratic programming (SQP):* Its basic idea is to linearize the constraints and set up a quadratic objective function to form a quadratic program (QP). The basic structure of an SQP includes four steps (Reklaitis et al. 1983): (1) set up and solve a QP sub-problem, yielding a search direction; (2) test for convergence--if it is satisfied, then stop; (3) take a step along the search direction to a new point and (4) update the approximated Hessian matrix H used in the QP and return to step (1).
- *Lagrange method:* It is an exact method that optimizes the objective function using Lagrange multipliers to meet Kuhn–Tucker conditions. The Lagrange multiplier of any constraint measures the change rate in the objective function, consequent upon changes in the constraint function. This information is valuable in that it indicates how sensitive the objective function is to the changes in different constraints (Luenberger 1984; Fletcher 1987).
- *Conjugate gradient method:* This method is based on conjugate search directions and the spirit of the Steepest Descent method. It is used to find the nearest local minimum of a function of n variables, which presupposes that

the gradient of the function can be computed. It uses conjugate directions instead of the local gradient for going downhill (Wolfram Mathworld 2006).

- *Univariate search:* It is primarily developed for solving unconstrained nonlinear optimization problems. A single variable is changed at a time to obtain its optimal value with respect to the current values of all other variables of the optimization problem (Rao 1984).

2.4.2 Nonlinear Global Optimization Techniques

- *Branch and bound (B&B)*: It is a tree-based search technique that is popular for the solution of combinatorial optimization problems. The basic idea of this method is to build a tree that contains all possible parameter combinations, and to search only the necessary part of this tree. This method employs tests at each node of the tree, which allows one to cut parts of the tree and, thus, saves computational cost as compared with an exhaustive search (Nelles 2001).
- *Simulated annealing:* This is a stochastic method, and the basic principle of this method is presented as follows. A warm particle is simulated in a potential field. Generally, the particle moves down toward lower potential energy, but since it has a non-zero temperature, i.e., kinetic energy, it moves around with some randomness and therefore occasionally jumps to higher potential energy. Thus, the particle is capable of escaping local minimum and possibly finding a global one. The particle is annealed in this process, and its temperature decreases gradually, so the probability of moving uphill decreases with time. It is well known that the temperature must decrease slowly to end up at the

global minimum energy (Nelles 2001). Whether this method can find the global optimal solutions is dependent on the “annealing schedule”, the choice of initial temperature, how many iterations are performed at each temperature, and how much the temperature is decremented at each step as cooling proceeds (*http://www.cs.sandia.gov/opt/survey/sa.html*).

- *Evolutionary algorithms and genetic algorithm (GA):* Evolutionary algorithms take their inspiration from natural selection and survival of the fittest in the biological world. They include a search from a ‘population’ of solutions. Each iteration process consists of a competitive selection that discards poor solutions. The solutions with high ‘fitness’ are ‘recombined’ with other solutions by swapping parts of a solution with another. Solutions are also ‘mutated’ by making a small change to a single element of the solution. Recombination and mutation are used to generate new solutions that are biased towards regions of the space for which good solutions have already been seen (Gray et al. 1997). The existing approaches to evolutionary algorithms include evolution strategy, evolutionary programming, genetic algorithm and genetic programming. They all share the same basic model, but are considerably different from the ways of their representation (binary or real-valued), the means of their selection (stochastic or deterministic) and the essentials of crossover and mutation. The genetic algorithm is the most popularly used among these algorithms.

2.4.3 Other Optimization Techniques

Other optimization techniques mean that some optimization techniques have been used in the optimization problems of building HVAC systems. However, they are used for solving the individual and/or particular rather than typical optimization problems in HVAC systems. For instance, a recursive numerical algorithm was used by Liu and He (1994) to optimize the thermal comfort level in an air-conditioned room. The Newton-Raphson solution method was used by Mullen et al. (1998) to solve the equations in an optimization problem in a room air-conditioning simulation model. Most of these conventional techniques might be effective and successful for a particular and simple optimization problem, but may not be efficient and reliable for high nonlinear and complicated typical optimization problems in HVAC systems.

2.4.4 A Brief Summary of Optimization Techniques

Most of the optimization techniques presented above have demonstrated their excellent performances for particular applications. The major difference among these techniques is that different optimization techniques possess different computation efficiencies, while some techniques may be divergent in some cases. Some optimization techniques may also result in a local optimal solution, and a globally optimal solution is not always guaranteed. Among all of these techniques, GA is attracting growing attention of building professionals and has been widely used in academic research for global optimizations (Huang and Lam 1997; Wang and Jin 2000; Chow et al. 2002; Nassif et al. 2005; Lu et al. 2005b; etc.). GA is a result-based method, and no derivatives are required during the calculation. This feature makes it possible to solve the complicated and global optimization problems. However, the extensive computational cost and memory demand may be an obstacle for online application of this technique. Further research of the robustness and feasibility of this technique for practical applications is essentially needed. It could be done from two aspects: one is to improve the algorithm itself and the other is to combine it with other methods.

In practice, optimization techniques should be selected based on the combination of the complicity and characteristics of the system of concern as well as the number of optimization variables involved in a particular optimization problem. The selected optimization technique should have less computational cost and memory demand to meet the requirements of practical applications. The convergence should be always guaranteed to improve the control stability. It should also have a simplified structure and be easy to be understood by the practicing engineers.

2.5 Research and Application of Optimal Control Strategies for HVAC Systems

Since control function is one of the major functions of a BAS, the building society and professionals have made great efforts toward the development and application of various control strategies for HVAC systems. Chapter 41 of the *2007 ASHRAE Handbook--HVAC Applications* (ASHRAE 2007) has provided a critical overview of supervisory and optimal control strategies and optimization for HVAC systems. This chapter consists of three major sections. The first section defines the systems and control variables considered. The general background on the effects and opportunities related to adjusting these control variables is also presented in this section. The second section presents a number of simple strategies, including the cooling tower fan control, chilled water reset with fixed and variable speed pumps, sequence and loading of multiple chillers, strategies for air-handling units, strategies for building zone temperature set-points, cooling thermal storage control, etc, that can be implemented in practice for near optimal control of HVAC systems. The implementation issues of most of these strategies are also presented. The third section provides basic methods for the optimization of systems both with and without significant energy storage. However, the references involved in this chapter were published before 2004, and most of them (91.2%) were published before 1999. With the rapid development of technologies, many new methods and techniques have recently been used to develop more advanced supervisory and optimal control strategies for HVAC systems. Therefore, a comprehensive review of the research and development as well as application of supervisory and optimal control strategies for HVAC systems is essential to present the state of the art. All studies were reviewed according to the classification schematic of supervisory control methods presented in Section 2.3.

2.5.1 Physical Model-based Supervisory Control Strategies

A number of studies related to the supervisory control in building HVAC systems use dynamic and/or static governing equations and detailed and/or simplified physical models to construct supervisory control methods. All these governing equations and physical models are derived based on the fundamental laws of energy, mass, heat transfer, momentum, flow balances, etc.

Kaya et al. (1982) introduced a thermal model based on the governing equations for the space along with an index of energy use to develop the optimal control method for an HVAC space. The main objective of this study was to demonstrate the improvement in control performance and the reduction in energy consumption through controlling the temperature, humidity and velocity simultaneously rather than independently. The results indicated that this control strategy, which accounted for control variable interactions among the system, can result in reduced energy use.

Cumali (1988) adopted a global optimization technique to design an optimal control strategy for HVAC systems. The optimization problem was formulated based on the laws of the first principles. The results showed that projected and/or augmented Lagrange multiplier methods did not perform well because of the equality constraints used in the problem formulation, while the generalized reduced gradient method appeared to provide consistent results if one starts with a reasonable solution.

House et al. (1991) and House and Smith (1995) described a system approach for optimal control of building HVAC systems, in which governing equations were derived from the principles of conservations of mass and energy. The interactive nature of system components, the multi-zone building system and their associated variables were of concern. A nonlinear programming (NLP) technique, in which the continuous control variables were discretized in the time domain to transform the infinite dimensional optimal control problem to a finite dimensional form, was used to solve the optimal control problem. Using discrete values of the state and control variables, the cost function was integrated numerically using the trapezoidal rule.

A predictive control policy using a finite-time horizon with end-time constraints was described by MacArthur and Foslien (1993) and MacArthur and Woessner (1993). The control system was composed of two distinct components. One was the supervisor, which was used for the sample rate selection and system identification (model development and adaptation). The other was the controller, which can generate a sequence of control signals to ensure the acceptable servo-regulatory behavior. The control law minimized the actuator movement while satisfying both process and control output constraints imposed at the end of the time horizon. The results showed that this control method offered adaptability and can easily accommodate system dynamics and interactions.

Zaheer-uddin and his collaborators have paid considerable efforts to optimal and sub-optimal control of HVAC systems in buildings (Zaheer-uddin and Patel 1993; Zheng and Zaheer-uddin 1996; Zaheer-uddin and Zheng 2000, 2001). The optimal and sub-optimal control strategies were developed based on physical models. The simulation results demonstrated that these control strategies, in which the multiple control variables were optimized simultaneously, can improve the system response and operational efficiency. They also demonstrated that the multistage optimal control technique is an effective and useful tool for computing supervisory control profiles for building systems subject to time-of-day operating schedules.

The system performance and supervisory control for a direct-fired LiBr absorption chiller system were investigated by Koeppel et al. (1995) using simulation means. The detailed and simplified component models were used to predict the system energy and environment performance. The simulated annealing as a global optimization algorithm was used to determine the optimal control settings under different control options. The results showed that the optimal operation schedule for absorption chillers can be determined from the optimal control investigation under the simulation environment.

The performance of the differential dynamic programming (DDP) technique applied to optimally control the operation of building HVAC systems was studied by Kota et al. (1996). The state equations utilized to describe the HVAC system were derived from mass and energy conservation principles. The optimization result was compared with that obtained from a nonlinear programming (NLP) technique using the SQP method. It was showed that the DDP is more efficient than the NLP for the example problems, but the NLP is more robust and can treat constraints on the state variables directly.

Henze et al. (1997, 2005) presented the predictive optimal control of building thermal storage systems using a physical model-based approach. Henze et al. (1997) developed a predictive optimal controller for thermal energy storage systems, and the performance of this controller was validated by simulations. This controller minimized the operating cost of the cooling plant over the simulation horizon. An optimal storage charging and discharging strategy was planned at every time step over a fixed look-ahead time window utilizing newly available information. The simulation results showed that this optimal controller can achieve a significant performance benefit over the conventional controls in the presence of complex rate structures, while only requiring a simple predictor. Henze et al. (2005) demonstrated the model-based predictive optimal control of the active and passive building thermal storage inventory in a test facility in real-time using time-of-use differentiated electricity prices without demand charges. The building was modeled in the transient simulation program TRNSYS, while Matlab and its optimization toolboxes were used to interface with the building simulation program. The experiment results showed that the savings associated with the passive building thermal storage inventory were small because the test facility utilized was not an ideal candidate for the investigated control technology.

Wang and Jin (2000) presented a supervisory control strategy using a system approach for VAV air-conditioning systems, in which physical models were utilized to predict the overall system performance, and a GA was used to solve the optimization problem of multiple control variables. It is the first application of the GA in solving an optimal control problem formulated using a systematic approach in the HVAC field. The simulation results showed that this strategy can improve the overall system energy performance and environment quality since it took into consideration the system level characteristics and interactions among the system variables.

The International Energy Agency (IEA) research project Annex 17 provided an example to demonstrate the advance of the system simulation in testing and evaluating EMCS supervisory control strategies for the overall building systems as well as the control strategies implemented in real EMCSs by means of emulation (Lebrun and

Wang 1993). Several simulation platforms for building HVAC systems using detailed and simplified physical component models have been established to evaluate energy performances and economic feasibilities of different supervisory control strategies for HVAC systems (Sud 1984; Wang 1998, 1999; etc.). Simulation exercises based on these simulation platforms showed that energy or cost savings can be achieved when supervisory control strategies are utilized as compared with that of using the local control strategies. These simulation platforms are extremely useful and very helpful for testing and evaluating alternative control strategies and, thus, for determining the best control strategy for building HVAC systems prior to site implementation.

Zhang and Hanby (2006) presented a model-based supervisory control strategy for renewable energy systems in buildings. The building and plant component models used were physical models. The objective of the control problem was to minimize the net external energy consumption of the system subject to a series of constraints. An evolutionary algorithm was used to search for the optimal and near optimal control settings. The simulation results indicated that significant improvements in system operation are possible as compared with the existing rule-based control scheme.

These control studies using physical model-based supervisory control strategies demonstrate that the system energy or cost efficiency and environment performance as well as the system response can be improved greatly when such techniques are used. However, many parameters in governing equations are uncertain, and many parameters in detailed physical models require detailed information of the system or process of concern. The parameter identification and performance prediction of these governing equations and detailed physical models in supervisory control strategies often require a lot of iterations, which may result in high computational cost and memory demand as well as control instability. All of these characteristics are the major obstacles that may seriously prevent their online control applications. However, the results obtained from these governing equation and/or detailed physical model-based supervisory control methods are essentially helpful and useful to develop the most effective and practical supervisory control strategies.

2.5.2 Black-Box Model-based Supervisory Control Strategies

There are also a number of studies using black-box models to construct supervisory control strategies in the HVAC field. These studies can be roughly classified into two categorizes: artificial neural networks (ANNs)-based supervisory control strategies and empirical relationship-based supervisory control strategies.

2.5.2.1 ANNs-based Supervisory Control Strategies

ANNs are simplified models of the central nervous systems. They are networks of highly interconnected neural computing elements that have the ability to respond to input stimuli and to learn to adapt to the environment (Goh et al. 2002). ANNs operate as black-box models because no detailed information about the system is required. They learn the relationships between input and output variables by studying the historical data. The main advantages of ANNs are their abilities to map nonlinear functions, to learn and generalize by experience as well as to handle multivariable problems. These desirable properties may make ANNs feasible for control applications. However, they have the inherent deficiency of black-box models in that they are only reliable at operation conditions covered by the range of training data.

The first ANNs controller was developed by Widrow and Smith (1963). They used adaline (Adaptive Linear Neuron or later Adaptive Linear Element, it was a single layer neural network) to stabilize and control the pole balancing act. interest in using anns for process control only started in the latter 1980s. Kawato et al. (1987) and Guez et al. (1988) showed the computation speed advantage and nonlinear modeling capabilities of ANNs in the feedback loop process control. The research and development on ANNs in building HVAC systems started at the early 1990s and have stressed the importance of energy management (Curtiss et al. 1994; Curtiss 1997), system control and optimization (Curtiss et al. 1993; So et al. 1995; Gibson 1997; Bradford 1998; Chow et al. 2002; Massie 2002), and energy use prediction (Kreider and Wang 1992; Massie et al. 1998; Dodier and Henze 2004).

To optimize the overall system performance, the ANNs-based supervisory control was utilized in several studies. Curtiss et al. (1993) discussed the results of a proof-of-concept experiment in which ANNs were used for both local and global control of the HVAC system in a commercial building. The data collected in a laboratory were used to train ANN models. The experiment results obtained from the laboratory testing showed that significant energy savings are possible when the supervisory control is used.

ANNs-based supervisory controllers were developed by Curtiss et al. (1994) and Massie (2002) to minimize the total energy consumption of building HVAC systems. In their studies, the supervisory controller, namely the global controller, consisted of two networks--training network and predictor network--working in parallel, as shown in Figure 2.3. The training network was used to learn the relationship between the various control and/or uncontrolled variables and the total power consumption of HVAC systems. The training network weights were then passed to the predictor network where they were used in the activation function of the predictor network. The predictor network subsequently found optimal values for the control variables that can minimize the overall system operating cost. The Curtiss et al. (1994) method was employed by Bradford (1998) for online supervisory control of a cooling plant without storage. The ANNs were generated using the historical data from a testing building. The output of the networks was the total power consumption of the HVAC system. The network was configured with two hidden layers of three and two nodes, respectively. These three studies demonstrated that the ANNs-based supervisory control is robust in finding optimal solutions since such controller does not rely on any assumption of the system or process of concern. The operating cost of building HVAC systems can also be reduced greatly.

The application of ANNs to serve as a system identifier and an intelligent controller for an air-handling system was investigated by So et al. (1995). The objectives of this study were to minimize the total energy consumption and control errors between the set-points and corresponding control variables. The ANN behaved as an identifier by continuously keeping track of all real-time parameters. Five actuating signals, which were produced based on the nonlinear error optimization of the outputs of the ANN, served as a controller. The results illustrated that the ANN identifier/controller has excellent performance over the conventional PID controller.

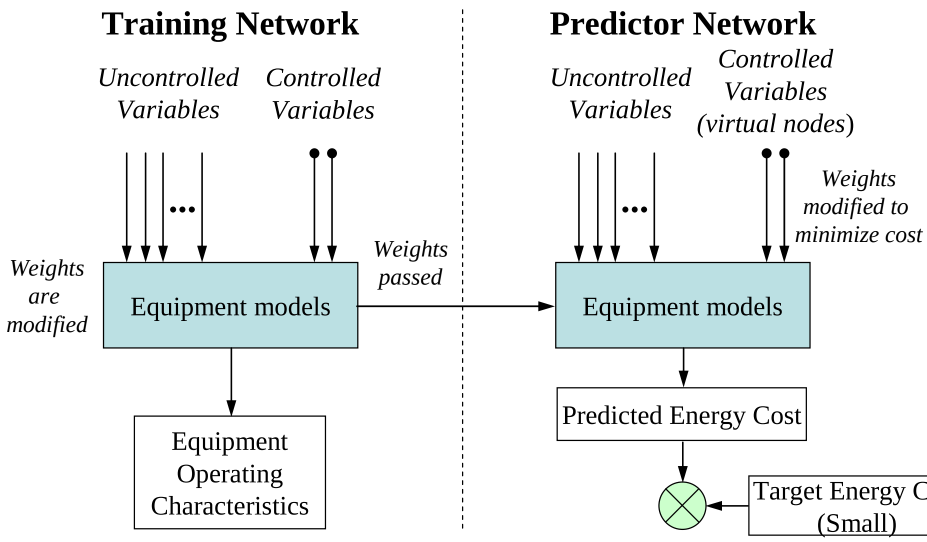

Figure 2.3 Architecture of the ANNs-based supervisory controller (Curtiss et al. 1994 and Massie 2002).

The ANNs-based supervisory control for building HVAC systems was also studied by Gibson (1997) and Chow et al. (2002), in which ANNs were used to simulate system dynamic characteristics and a GA was served as a global optimization tool. Both studies discussed how the two techniques can be integrated into a working system. Gibson (1997) installed the developed supervisory controller at the central cooling system of a building in a high school. The system operation results showed that both the GA and ANNs are effective techniques for online control applications. However, the important lessons learned by the author showed that the great care should be given since the GA and ANNs cannot always provide desirable solutions.

The results from the case studies by Chow et al. (2002) showed that considerable energy can be saved due to such supervisory controller allowing an overall consideration of the interactions among the system and their controlled variables.

For energy use prediction, Dodier and Henze (2004) used ANNs as general nonlinear regression models. A statistical test, namely Wald’s test, was applied to the ANNs to evaluate the relevance of various inputs. The results of Wald’s test applied to the energy prediction data demonstrated that day and time variables are more relevant to predicting energy use targets than the environmental variables.

Xu et al. (2005) presented an optimization-based methodology to control HVAC units in stochastic settings. Considering the difficulties related to tuning the parameters for different buildings, a neural network was used to predict the dynamics of HVAC systems instead of using system dynamic governing equations. Lagrangian relaxation, a decomposition and coordinated approach, was used to obtain near optimal solutions with quantified quality. The results obtained from the numerical testing and prototype implementation showed that this method is significantly better than the original DDC systems using a night-setback control.

These studies using ANNs-based supervisory control strategies demonstrate that ANNs can play a role in the supervisory control of building HVAC systems. Energy or cost savings are possible when such controllers are used. However, most of these studies were performed from the view point of the academic research. The practicability and effectiveness of the real-time application of such supervisory controllers are still suspended. Since ANNs operate as black-box models, significant control errors might result in when the system operates outside the range of ANNs trained, and/or the measurement faults, and/or component degradations occur. In addition, the training of ANNs always requires extensive computational cost and memory demand, which makes it almost impossible and unacceptable to apply the adaptive control in practice to improve the prediction accuracies of ANN models. The online practical application of such methods needs to be cautious.

2.5.2.2 Empirical Relationship-based Supervisory Control Strategies

The empirical relationships, involving polynomial regression models, empirical models, etc., could be the simplest way to formulate and construct the system and/or component models. They are process historical data-based models. Both inputs and outputs are known and measured from the field monitoring. In the building HVAC field, there are a few studies that use empirical relationship-based models to construct supervisory control strategies.

Braun et al. (1987, 1988, 1989a) have devoted considerable efforts on developing optimal and near optimal control strategies using quadratic relationships for the chiller and water systems. These studies included the application of two basic methodologies for determining optimal or near optimal values of the independent control variables in the system that minimize the instantaneous operating cost of the overall chiller plant. One was a component model-based nonlinear optimization algorithm, in which the power consumptions of chillers, cooling towers, condenser and chilled water pumps, and supply and return fans were expressed as quadratic relationships. This methodology was used as a simulation tool for investigating the system performance. The other was a system-based methodology for near optimal control, in which an overall empirical cost function of the total power consumption of the chiller plant was developed using a quadratic function. This method allows a rapid determination of near optimal control settings over a range of conditions. Pape et al. (1991) extended Braun's method to the overall HVAC system. The power consumption of the entire HVAC system was represented by a quadratic relationship in terms of the control variables, loads and ambient conditions. The optimal control was determined by equating the first derivative of the power with respect to each control variable to zero. This optimal control methodology can be used in fault detection. Braun's method was also further extended by Cascia (2000) through simplifying the component models and providing the equations for determining the set-points of near optimal control. The power consumptions of all components (e.g., chillers, pumps, fans, etc) were expressed as a function of the temperature difference between the chilled water supply and return temperatures. The coefficients in the model were determined from the direct measurements of the total power consumption and the temperature difference obtained from a direct digital control (DDC) system. A pilot test of this methodology was implemented at a small-scale cooling plant. A third-party energy accounting program was used to track energy savings due to the near optimal control. The results showed a monthly energy reduction ranging from 3% to 14%.

Braun et al. (1989b) identified several guidelines for near optimal control of chilled water systems without significant energy storage. They also identified that the optimal supervisory control of chilled water systems was primarily a function of the total cooling load and ambient wet-bulb temperature. These results formed the basis to develop a near optimal control algorithm for cooling towers (Braun and Doderrich 1990a). The cooling tower control algorithm was expressed as an open-loop control equation in terms of the total cooling load. This method was further extended by Braun (2007a) to develop a general control algorithm for cooling towers in cooling plants with electric and/or gas-driven chillers.

Olson and Liebman (1990) developed a nonlinear model for the chilled water plant and solved it by the SQP method together with a heuristic approach to explore discrete equipment alternatives to help decide the optimal way to operate the entire system. By establishing an empirical model that is only dependent on the cooling load, it is possible to predict the power that would be necessary to cool the building with various combinations of equipment. The results showed that the computational cost can be reduced significantly by this approach.

For the system-based optimization, Austin (1993) used bi-quadratic polynomial models of chillers and cooling towers to optimize the condenser water supply temperature set-point. Based on the detailed analysis of the chiller and cooling tower performance characteristics, the author emphasized that the system modeling can help select the best combination of chillers and condenser water supply temperature set-points to meet different loads under various outdoor working conditions with the least energy input.

Ahn and Mitchell (2001) developed an optimal supervisory control strategy for a cooling plant. A quadratic regression equation was used to predict the total power consumption of the overall cooling system in terms of the forcing function and control variables. The optimal control settings, e.g., the supply air temperature set-point, chilled water supply temperature set-point, condenser water supply temperature set-point, etc., were selected to make the total system power consumption minimized. The simulation result showed that the minimum total system power consumption was the trade-off among the power consumptions of different components. This control methodology is simple and easy to implement. However, there are 28 coefficients with no physical significance required to be identified from the monitoring data, which may result in significant prediction deviations for practical applications.

An optimal operation strategy for a large cooling system was presented by Yao et al. (2004), in which the empirical relationships among control variables, uncontrolled variables and the system performance were established using the site measurement data. A system coefficient of performance (SCOP) was introduced to analyze the effects of energy savings of the cooling system. The results obtained from the case studies showed that the energy saving was likely to reach as high as 10% by applying the optimal operation strategy to the cooling system.

Lu et al. (2004, 2005a, 2005b, 2005c) presented a series of system optimizations for HVAC systems. The interactive nature within and between components and their control variables in the system was seriously considered. The objective function of the global optimization was formulated based on the mathematical models of major components. The power consumption of chillers was predicted using an empirical model, while the power consumption of pumps/fans was modeled as a function of the ratio of the water/air flow rate to the design water/air flow rate. A modified GA was utilized to find the optimal control settings. The simulation studies based on a small pilot-scale centralized HVAC plant showed that the system level optimization can improve the overall system operating performance significantly.

Sun and Reddy (2005) presented a general and systematic methodology, termed as complete simulation–based sequential quadratic programming (CSB-SQP), to determine the optimal control strategy for HVAC systems. The linear approximation of Taylor expansion was utilized to formulate the system models. A case study on a simple cooling plant illustrated the efficiency and robustness of this methodology.

These supervisory control studies using the empirical relationships also demonstrate that a significant amount of energy or costs in HVAC systems can be saved when such methods are utilized. The empirical relationship-based supervisory control methods are easy to implement in practice since the methodologies involved in such methods are relatively simple and the computational cost is generally manageable. However, most existing strategies seem to lack generality because they were only validated by simulations or pilot tests with certain limited operation points.

The application of such methods on complex HVAC systems in large office or commercial buildings is lacking. The robustness of such methods is also a big issue in practice, especially when the system operates at the range where the training data are not covered or system degradations or measurement faults occur. Although the adaptive control can improve the prediction accuracies of these models to some extent, it is very dangerous to apply the adaptive control to complicated HVAC systems at the current stage. More research is essentially needed to further validate the feasibilities of adaptive empirical relationship-based supervisory control methods in practice and the special care should be given when such methods are used.

2.5.3 Hybrid Supervisory Control Strategies

A few studies use a mix of different types of models and/or the model-based method and model-free method to design supervisory control strategies for building HVAC systems. Braun (1990b) proposed an optimal control strategy for the building thermal storage to reduce the operating costs and peak electrical demand. In this study, the building model was a simplified physical model, while chiller plant models were quadratic relationships. The simulation results indicated that both operating costs and peak electrical use can be reduced significantly through optimal control of the intrinsic thermal storage within building structures. This control methodology was employed by Simmonds (1993) to minimize the system operating cost while maintaining the acceptable indoor comfort. The result showed that cost savings could be achieved if the control was based on maintaining the predicted mean vote (PMV) rather than the dry-bulb temperature.

Kintner-Meyer and Emery (1995) presented a comprehensive analysis of optimal control of HVAC systems considering the building thermal mass and cold storage equipment. The optimization strategy was formulated as a minimization of the operating costs over a 24-hour period. The analysis was based on the thermodynamic modeling of the HVAC system, including the thermal response of the building structure. The chiller was modeled as a function of the part-load factor, wet-bulb temperature and chilled water supply temperature set-point, while the pump power and fan power were modeled based on the pump and fan affinity laws, respectively. The results of this analysis indicated that significant cost savings can be achieved by pre-cooling the building during the hours of low electricity rate.

The optimal supervisory control using a system approach for chilled water plants was studied by Flake (1998). In his study, the chiller model was a quadratic relationship, while the steam turbine, heat exchanger and cooling tower models were physical models. The simulated annealing as a global optimization technique was used to determine the optimal control settings under different control options. The estimated cost saving using this optimal supervisory control method for a chiller plant was 4.3% over the conventional control method. The conventional control method used was based on the manual control. The chilled water supply temperature set-point was always set at 4.4°C, and another chiller was put into operation when the chilled water leaving the plant reached 6.1°C. The cooling tower fans were added or fan speeds were increased if the water temperature from the cooling tower exceeded about 21.1°C.

Nassif et al. (2005) utilized a two-objective genetic algorithm to optimize a model-based supervisory control strategy for building HVAC systems. In their study, a detail physical cooling coil model and an empirical chiller model served to calculate the energy consumption during the optimization process, and system level interactions were considered seriously. The control settings, i.e., the supply air temperature set-point, supply duct static pressure set-point, chilled water supply temperature set-point, minimum outdoor ventilation, reheat and zone air temperature set-point, were optimized with respect to the energy use and thermal comfort. This optimization process was applied to an existing VAV system. The operation results showed that the optimization of the supervisory control strategy could save energy by 16% for two summers while still satisfying the minimum zone air flow rate and zone thermal comfort. The robustness of the application of this method was not reported.

A simulation optimization approach was proposed by Fong et al. (2006) for effective energy management of building HVAC systems, in which an evolutionary programming was used to handle the discrete, nonlinear and highly constrained optimization problems, and an empirical chiller model and a simplified cooling coil physical model were used to predict the system energy and environment performances. The simulation exercises for the HVAC system in a subway station showed that 7% energy savings can be achieved by optimizing the set-points of the chilled water supply temperature and supply air temperature on a monthly basis.

A hybrid optimal control scheme combining the features of a deterministic model-based approach with the model-free learning control for an active and passive building thermal storage inventory was proposed in companion papers by Liu and Henze (2006a, 2006b). An experiment study was conducted to evaluate the performance of this controller on a full-scale laboratory facility. The results demonstrated that this hybrid control approach can provide the reliable control performance. Cost savings are possible as compared with the traditional control schemes. However, the savings were lower than that using a model-based predictive optimal control scheme.

Braun (2007b) presented a simple control strategy for hybrid cooling plants that could be readily implemented with low costs. The chiller performance was characterized in terms of *COPs* and cooling capacities, while the cooling tower was modeled using an effectiveness simplified physical model. This strategy was developed and evaluated using a simulation tool that could determine the optimal control settings for the specific simulated cooling plant. A near optimal control strategy for cool storage systems with dynamic electric rates was proposed by Braun (2007c). In this strategy, the ice storage tank was modeled using a semi-empirical model, and the ice-making chiller plant was modeled using an empirical model. This strategy was evaluated for ice storage systems using a simulation tool for different combinations of cooling plants, storage sizes, buildings, locations and real-time pricing electric rates. The results showed that 2% cost savings are possible when this strategy is used.

The hybrid supervisory control strategies might be feasible for practical applications if different types of models are selected properly and/or the features of both the model-based method and model-free method are combined effectively. However, most existing hybrid supervisory control strategies were evaluated by simulations and their practical applications seem missing. More research on the application of hybrid supervisory control strategies in practice is highly needed.

2.5.4 Performance Map-based Supervisory Control Strategies

There are also a few studies associated with using performance maps, often called control maps, to construct supervisory and optimal control strategies for building HVAC systems. The performance map-based supervisory control for chiller plants to minimize the energy use was studied by Hackner et al. (1985) and Lau et al. (1985). Both studies utilized component models to test and search for the minimum power consumption for each combination of control variables and uncontrolled variables. The optimal control strategies were expressed in the form of performance maps. The comparison studies showed that these performance maps using system optimization techniques can save more energy than the local optimization methods. The application of established performance maps for the online control was advocated by Johnson (1985). The methodology utilized in the study of Braun (1990b) also included the development of a performance map for a cooling plant.

For practical applications, the operation strategy proposed by Yao et al. (2004) included the application of performance maps inherently. Based on the field tests of the system over a significant range of settings and operating conditions, a series of empirical equations for control variables, i.e., the condenser water supply temperature, condensing temperature, evaporating temperature, etc., can be regressed and then used to optimally control the operation of HVAC systems. These empirical equations can be regarded as being regressed from control maps, while control maps were generated from the field monitoring.

For real-time applications, Sun and Reddy (2005) suggested using simple control laws for near optimal control of HVAC systems. Based on the developed CSB-SQP method, optimal control maps can be generated using detailed simulations. A regression model for each control variable can then be developed from the control map of the corresponding control variable and was then used to achieve near optimal control and operation of HVAC systems.

It might be practically beneficial to apply performance map-based supervisory control strategies for small-scale HVAC systems. However, it would be the tedious and burdensome work for large systems due to the following reasons: (1) for large systems, constructing a dynamic simulation platform is a time-consuming work; (2) there are always many control variables involved in control systems, which makes it difficult to generate effective performance maps that can characterize system performances using all major control variables. For practical applications, performance map-based supervisory control strategies might not be the best choice.

2.5.5 Supervisory Control Strategies Based on Other Techniques

The control studies addressing optimal control and operation of HVAC systems that do not fall into the above categories are grouped as supervisory control strategies based on other techniques here. They include the strategies using the model-free approach, optimization analysis, experiment investigation, etc.

Kaya and Sommer (1985) presented a four-level control structure for a chiller system. The first-level controls were the local controls for the chilled water supply temperature, vane position and condenser water supply temperature. All the first-level controls were supervised by the second-level control to provide reasonable set-points. The third-level control was used to optimally allocate the total load for each operating chiller and pump. The fourth-level control was used for supervisory coordination of the chilled water supply temperature and scheduling of the chiller system operation. There was no actual energy savings due to the application of this strategy.

An expert controller for a building HVAC system was designed by Ling and Dexter (1994) using a predictive control approach. The design of the predictive control algorithm was based on a prior knowledge of the system. A rule-based supervisory method was used to optimize the control performance. The experimental results showed that the use of this rule-based supervisory control can lead to significant cost savings without unacceptable increases in discomfort level. The result also demonstrated that this expert controller was able to compensate day-to-day variations in control performance.

Based on the system analysis, Hartman (1995) pointed out that the implementation of DDC systems can provide new approaches to the concept of the global optimization. However, the amount of data accumulated and employed in calculations can be very large for large systems. This may place huge burdens on the communication network and computing capacities of DDC systems.

A novel control strategy using a system approach for optimizing variable speed pumps in indirect water cooled chilling systems was developed by Wang and Burnett (2001). This strategy includes an adaptive and derivative method to optimize the operating speeds of pumps by resetting the pressure set-point according to the estimated derivative of the total power consumption of chillers and water pumps with respect to the pressure. The adaptive strategy identified the changes of the system parameters essential for the control strategy and updated the control accordingly. The simulation results showed that the proper reset of the seawater pressure set-point can provide up to 10% of savings in the total chilling system electricity consumption, while 5% of savings can be expected in most of cases investigated.

Henze and Schoenmann (2003) presented a model-free reinforcement learning controller for optimal operation of thermal energy storage systems. The reinforcement learning controller learns to charge and discharge a thermal storage tank based on the feedback it received from the past control actions. The controller learns to account for the time-dependent cost of electricity (both time-of-use and real-time pricing), the availability of thermal storage, part-load performance of the central chilled water plant and weather conditions. The performance of this controller was evaluated by simulations, and the result showed that it has strong capability to learn a difficult task of controlling thermal energy storages with good performance. However, cost savings were less than that using a predictive optimal controller.

To assist in improving the electrical efficiency of HVAC systems, Hartman (2005) developed a general system analysis principle, namely Equal Marginal Performance Principle (EMPP), to help in optimizing the system design and to ensure optimal operation of nearly any modern HVAC system. This EMPP simply stated that the energy performance of any system operating with multiple modulating components is optimized when the changes in the system output per unit of energy input are the same for all individual components in the system. This principle is simple and powerful. It could be useful for designers in terms of how system components can be configured and make them operate more effectively and efficiently.

These studies attempt to apply advanced techniques to achieve energy efficient control and operation of HVAC systems. Such efforts are essentially useful, which might be a way that can find more efficient and practical techniques or methods suitable for online practical control of HVAC systems.

Table 2.2 summarizes the applications, control methods, optimization tools and percentages of energy or cost savings of most studies presented in this section.

Table 2.2 Summary of the savings of major studies and the control methods as well as optimization tools used in the control systems

Author	Paper title	Control method	Optimization tool	Savings
Kaya et al. (1982)	Optimum control policies to minimize energy use in HVAC systems	Governing equation-based method	Static optimization	38.5%
Cumali (1988)	Global optimization of HVAC system operations in real time	Physical model-based	Generalized reduced gradient method	18-23%
House and Smith (1995)	A system approach to optimal control for HVAC and building system	Governing equation-based method	The nonlinear programming technique	24%
Zheng and Zaheer-uddin (1996)	Optimization of thermal processes in a variable air volume HVAC system	Physical model-based	The nonlinear programming technique	20%
Koeppel et al. (1995)	Optimal supervisory control of an absorption chiller system	Physical model-based	Simulated annealing	15~20%
Kota et al. (1996)	Optimal control of HVAC systems using DDP and NLP techniques	Physical model-based	A differential dynamic programming technique	No exact savings
Henze et al. (1997)	Development of a predictive optimal controller for thermal energy storage systems	Physical model-based	Dynamic programming	10.5-30%
Henze et al. (2005)	Experimental analysis of model-based predictive optimal control for active and passive building thermal storage inventory	Physical model-based	Dynamic programming	17%
Wang and Jin	Model-based optimal control of VAV air-conditioning	Physical model-based	GA	0.2-39.8%

(2000)	system using genetic algorithm			
Zhang and Hanby (2006)	Model-based control of renewable energy systems in buildings	Physical model-based	An evolutionary algorithm	24.8-59.0%
Curtiss et al. (1994)	Energy management in central HVAC plants using neural networks	ANNs-based	/	10%
Bradford (1998)	Optimal supervisory control of cooling plants without storage	ANNs-based	A global and a gradient search methods	4-8%
Chow et al. (2002)	Global optimization of absorption chiller system by genetic algorithm and neural network	ANNs-based	GA	19.4%
Xu et al. (2005)	An optimization-based approach for facility energy management with uncertainties	ANNs-based	Lagrangian relaxation	10-20%
Braun et al. (1987)	Performance and control characteristics of a large cooling system.	Empirical relationship-based	Lagrange multipliers	5%
Cascia (2000)	Implementation of a near-optimal global set point control method in a DDC controller	Empirical relationship-based (DDC controller)	/	3-14%
Olson and Liebman (1990)	Optimization of a chilled water plant using sequential quadratic programming	Empirical relationship-based	SQP	No exact savings
Yao et al. (2004)	Optimal operation of a large cooling system based on empirical model	Empirical relationship-based or performance map-based	/	10%
Lu et al. (2005b)	Global optimization for overall HVAC systems-Part II problem solution and simulations	Empirical relationship-based	A modified GA	around 13%

Sun and Reddy (2005)	Optimal control of building HVAC&R systems using complete simulation-based sequential quadratic programming (CSB-SQP)	Empirical relationship-based	Sequential quadratic programming (SQP)	No exact savings
Kintner-Meyer and Emery (1995)	Optimal control of an HVAC system using cold storage and building thermal capacitance	Hybrid method	The nonlinear solver NPSOL	6-18%
Flake (1998)	Parameter estimation and optimal supervisory control of chilled water plants	Hybrid method	Simulated annealing	4.3%
Nassif et al. (2005)	Optimization of HVAC control system strategy using two-objective genetic algorithm	Hybrid method	A two-objective genetic algorithm	16%
Fong et al. (2006)	HVAC system optimization for energy management by evolutionary programming	Hybrid method	An evolutionary programming	7%
Liu and Henze (2006b)	Experimental analysis of simulated reinforcement learning control for active and passive building thermal storage inventory–Part 2: results and analysis	Hybrid method	/	8.3%
Braun (2007c)	A near-optimal control strategy for cool storage systems with dynamic electric rates	Hybrid method	An iterative form of dynamic programming	2%
Ling and Dexter (1994)	Expert control of air-conditioning plant	Rule-based (model-free method)	/	30.1-33.62%
Wang and Burnett (2001)	Online adaptive control for optimizing variable-speed pumps of indirect water-cooled chilling systems	an adaptive and derivative method	/	5-10%
Henze and Schoenmann (2003)	Evaluation of reinforcement learning control for thermal energy storage systems	Model-free method	/	4.3%

2.6 Discussions and Recommendations

Based on the discussions of different supervisory control methods, the discussions of various optimization techniques and a comprehensive review of the existing supervisory and optimal control studies, some useful conclusions can be summarized and a few recommendations for future work in this direction are presented.

1. For online control applications, supervisory control methods and optimization techniques should be developed and/or selected applicable to a wide operating range of building HVAC systems, while still satisfying the requirements and constraints of practical applications. The optimization technique utilized to seek the optimal solutions should have high computation efficiency and high capability to find global minimums. It should be easy to converge as well.
2. The research and development on supervisory and optimal control in building HVAC systems demonstrate energy or cost saving potentials in buildings when optimal strategies are used. However, most existing studies related to supervisory and optimal control are too mathematical due to either using complicated detail physical models or using complex optimization tools, or lack generality. Most proposed supervisory control strategies were only validated by simulations or by pilot tests on small-scale HVAC systems with limited operation points. The practical validation of these supervisory and optimal control methods on real HVAC systems, especially on complex HVAC systems, is still missing.

3. Detailed physical model-based supervisory control strategies might not be suitable for practical applications since detailed physical models often require a lot of iterations, which may result in high computational costs and memory demands as well as the control instability. However, the results obtained from these detailed physical model-based supervisory control strategies by simulations are essentially helpful and useful to develop the most effective and practical supervisory and optimal control strategies.
4. The online practical application of black-box model-based supervisory control strategies needs to be cautious. Significant control errors may result in when the system operates outside the operating range covered by the data used to train black-box models, and/or measurement faults, and/or component degradations occur. In addition, the training of some black-box models (such as ANNs) requires extensive computational cost and memory demand, which may make it impossible to use adaptive supervisory control strategies based on these models.
5. Hybrid supervisory control methods might be feasible for practical applications if different types of models are selected properly and/or the features of both the model-based approach and model-free approach are combined effectively. However, most existing hybrid supervisory control strategies were evaluated by simulations and their validations in practice are still missing.
6. Near optimal control strategies were advocated for practical applications in Chapter 41 of the *2007 ASHRAE Handbook--HVAC Applications* (ASHRAE 2007). Near optimal control strategies are often simple and can be easily developed and implemented in practice. However, near optimal control strategies

cannot provide the true optimal settings, which might provide settings significantly different from the optimal values. The more effective (i.e., more closer to the true optimum) strategies for practical applications could be formulated by the effective combination of near optimal control strategies and simple and practical optimization techniques.

The ultimate objective of any technique development comes to a point, i.e., its application. The key issues for the development and application of supervisory and optimal control strategies for building HVAC systems may include:

- Selection of the supervisory control method
- Selection or development of models (if needed)
- Selection of the optimization technique
- Defining the cost or objective function
- Programming of control logics and strategies
- Testing and commissioning of the control program

One thing worthwhile to point out is the testing and commissioning of the control programs. Due to the increased complexity of the programs, system level parameters need to be identified, which would have high requirements on the efforts and skills of the practicing engineers to handle the testing and commissioning work.

2.7 Summary

This chapter provides a framework for categorizing the main supervisory and optimal control methods and optimization techniques developed and/or utilized in the HVAC field. The application characteristics of each control method and optimization technique are also identified and compared. A comprehensive overall review of the state of the art of the research and development as well as application of supervisory and optimal control in HVAC systems is also presented. It is clearly showed that the current research on supervisory and optimal control for HVAC systems is still inadequate in the following two aspects: (1) most strategies were developed from the view point of academic research and not from the point of online practical applications because constraints and requirements of practical applications, such as control stability, computation performance, etc., were not seriously considered during the development of these optimal control strategies; (2) the existing optimal strategies were mainly developed for simple and typical air-conditioning systems. There still seems no supervisory and optimal control strategy available for complex air-conditioning systems.

There is still a long way for building HVAC scientists and professionals to go to make supervisory and optimal control have desirable and satisfactory performance and be convenient used in practice and, hence, to fully utilize its capacity in practice to optimize the control and operation of building HVAC systems to enhance the overall energy/operating efficiency and environmental performance.

CHAPTER 3 THE BUILDING SYSTEM, DYNAMIC SIMULATION PLATFORM AND ENERGY PERFORMANCE TESTS

The dynamic simulation platform, namely virtual building system in this thesis, which is a real-time simulation of a building and/or its HVAC system, can provide an excellent platform for testing and analyzing the control, environmental and energy performances of different control strategies under dynamic working conditions to determine the most promising strategy for the optimal control and operation of HVAC systems prior to site implementation. It is also a valuable tool for evaluating the performances of various diagnosis strategies. Although there are many well-developed and successful commercial simulation software packages, e.g., EnergyPlus (Crawley et al. 2000), DOE-2 (Lawrence Berkeley Laboratory 1982), etc., readily available, it is very difficult to complete the building cooling load calculation, water system simulation and air system simulation with one single simulation package. In addition, the system configurations, i.e., the water system configuration and air system configuration, in these simulation packages are very complicated and time-consuming or even frustrated although the above software packages provide these simulation functions. For detailed dynamic simulation tests of various control strategies, these packages can only provide limited help. However, TRNSYS, HVACSIM+ and perhaps simulations based on Modelica might be appropriate. Therefore, TRNSYS was selected in this study to construct the dynamic simulation platform.

A number of dynamic simulation platforms for the water system and air system for specific usages have been established (Sud 1984, Lebrun and Wang 1993, Haves et al. 1998, Wang 1998, 1999; etc.). However, these dynamic simulation platforms are only useful for typical air-conditioning systems. They are far from adequate for complex air-conditioning systems. Therefore, a dynamic simulation platform for complex air-conditioning systems is indeed needed whether for the performance evaluation and diagnosis of existing buildings or for the performance evaluation and commissioning of the buildings in design or in construction.

A dynamic simulation platform for complex building central chilling systems constructed in this PhD study is presented in this chapter. This platform is the basis for the energy performance study and the basis for testing and evaluating the performances of online supervisory and optimal control strategies for complex building central chilling systems developed in this thesis.

Section 3.1 briefly introduces a super high-rise commercial building and its complex central chilling system concerned in this research. Based on this complex central chilling system, a dynamic simulation platform is constructed in Section 3.2. The major component models and their interconnections used to construct the complex dynamic simulation platform are presented. Section 3.3 presents the detailed tests on the energy saving potentials in complex central chilling systems associated with the optimization of major control variables respectively, on the basis of the dynamic simulation platform established. The results obtained from these tests will be used to develop online supervisory and optimal control strategies for complex central chilling systems for practical and real-time applications. A summary of this chapter is provided in Section 3.4.

3.1 Building and System Descriptions

3.1.1 Building Description

The building concerned in this research is a super high-rise building of approximately 490 m height (currently the tallest building in Hong Kong) and 321,000 m^2 of floor area. Figure 3.1 presents a rendering of this building, which involves a basement of four floors, a block building of six floors and a tower building of 98 floors. The basement is used mainly for parking with about 24,000 m^2. The block building from the ground floor to the fifth floor mainly serves as the commercial center including hotel ballrooms, shopping arcades and arrival lobbies. The gross area is about 67,000 m^2. The tower building consists of 230,000 m^2 for commercial offices and a six star hotel on the upper floors.

Figure 3.1 A rendering of the building concerned.

3.1.2 Zones and System Descriptions

The building is divided into five zones to avoid the chilled water pipelines and terminal units from suffering extremely high pressure (i.e., the highest static pressure of more than 40 bar and the designed working pressure of nearly 60 bar), and to consider the human evacuation in case of a fire. The floors below the sixth floor are Zone 1. Zone 2 involves the floors from the seventh floor to 41st floor. Zone 3 is from the 43rd to 77th floor and Zone 4 is from the 79th to 98th floor. The six star hotel located on the upper floors of the building is Zone 5. The sixth, 42nd, 78th and 99th floors are used as the mechanical floors to accommodate the mechanical equipment such as chillers, cooling towers, heat exchangers, pumps, PAUs and fans, etc. Considering the usage characteristics of the hotel, separate air-cooled chillers located on the 99th floor are designed to provide the cooling source for Zone 5. For the other zones, the cooling source is provided by the water-cooled chillers on the sixth floor. The schematics of the central chilling system of these zones are illustrated in Figure 3.2.

In this central chilling system, six identical high voltage (10,000V) centrifugal chillers with the capacity of 7,230 kW each are used to supply the chilled water at 5.5°C. The nominal power consumption of each chiller is 1,346 kW at the full load condition. Each chiller is associated with one constant condenser water pump and one constant primary chilled water pump. The heat generated by the chiller motors is mostly taken away by the refrigerant. The heat dissipated from the chiller condensers is rejected by means of eleven evaporative water cooling towers with a total design capacity of 51,709 kW. Taking into consideration plume abatement purposes, two different types of cooling towers (named CTA tower and CTB tower, respectively) are used in this building. CTB towers here are the cooling towers with a heating coil installed at the air exhaust of each tower. CTA towers are the towers without heating coils. Each of the CTA towers (total of six) has a heat rejection capacity of 5,234 kW and a nominal power consumption of 152 kW at the design condition. The rated water flow rate and air flow rate of each CTA tower are 250 L/s and 157.2m^3/s, respectively. Each of the CTB towers (total of five) has a heat rejection capacity of 4,061 kW and a nominal power consumption of 120 kW at the design condition. The rated water flow rate and air flow rate of each CTB tower are 194 L/s and 127.0m^3/s, respectively. All cooling towers are an in house type with crossover flow instead of counter flow due to the space constraints.

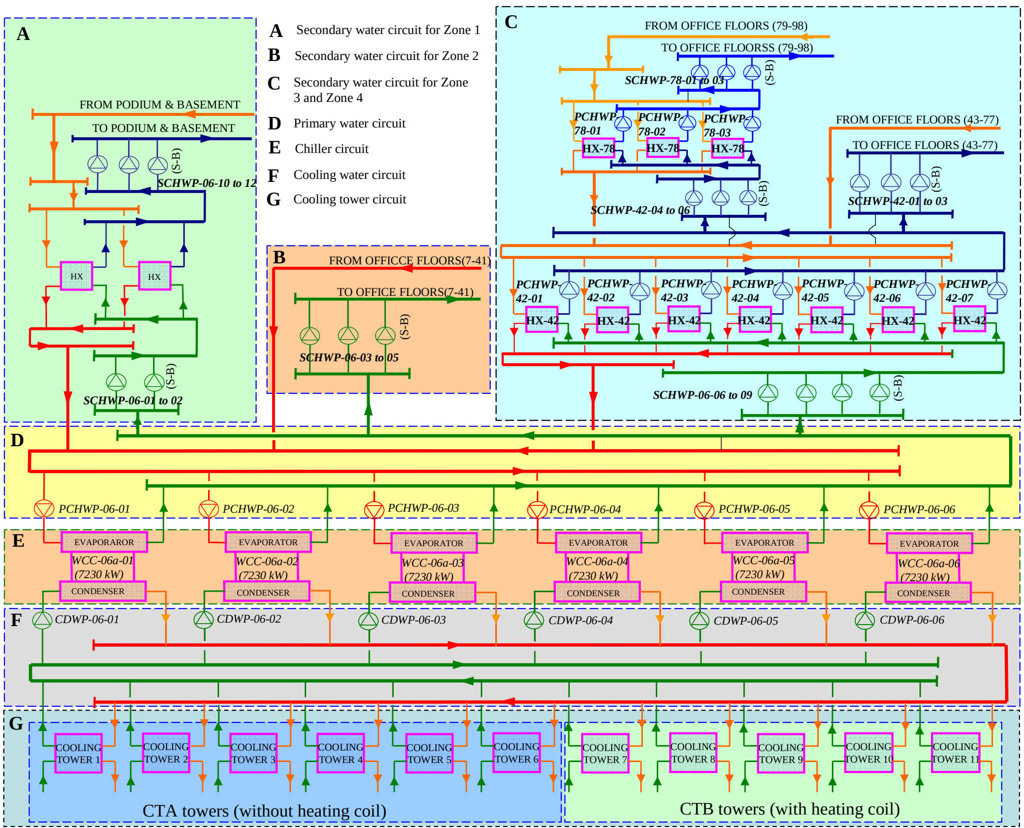

Figure 3.2 Schematics of the central chilling system.

In the secondary chilled water system, only Zone 2 (indicated as B in Figure 3.2) is supplied with the secondary chilled water directly while the heat exchangers are used in the other three zones to transfer the cooling energy from low zones to high zones to avoid the high water static pressure. The design cooling load of Zone 2 is about 30% of the design total cooling load. Zone 1 (indicated as A in Figure 3.2) is supplied with the secondary chilled water through the heat exchangers located on the sixth floor while the chilled water from chillers serves as the cooling source of the heat exchangers. The design cooling load of this zone is about 19% of the design total cooling load. The design inlet and outlet water temperatures at the secondary side of heat exchangers are 11.3°C and 6.3°C, respectively. Zone 3 and Zone 4 (indicated as C in Figure 3.2) are supplied with the secondary chilled water through the first stage heat exchangers (HX-42 in Figure 3.2) located on the 42nd floor. The design inlet and outlet water temperatures at the secondary side of the first stage heat exchangers are 11.3°C and 6.3°C, respectively. Some of the chilled water after the first stage heat exchangers is delivered to Zone 3 by the secondary chilled water pumps (SCHWP-42-01 to 03) located on the 42nd floor. Some water is delivered to the second stage heat exchangers (HX-78 in Figure 3.2) located on the 78th floor by the secondary chilled water pumps (SCHWP-42-04 to 06) located on the 42nd floor. The design inlet and outlet chilled water temperatures at the secondary side of the second stage heat exchangers are 12.1°C and 7.1°C, respectively. The water system after the second stage heat exchangers is the conventional primary-secondary chilled water system. All pumps in the chilled water system are equipped with VFDs (variable frequency drivers) to allow the energy efficiency except that the primary chilled water pumps dedicated to chillers and heat exchangers in Zone 3 and Zone 4 are constant speed pumps allowing more stable operational performances of chillers and heat exchangers. The configuration of the water piping system of this building is the reverse-return system.

Most of air-conditioning terminals are air-handling units (AHUs) except that some fan coil units are used in the block building. For each floor of the tower building, two AHUs located in the core are used to handle the mixture of the fresh air and recycled air from offices. The fresh air is delivered to each AHU through the shaft in the core by primary air units (PAUs), which are located on mechanical floors. The PAUs handle the outdoor air to 16.5°C at the machine dew point. All fans in AHUs and PAUs are equipped with VFDs allowing the energy efficiency.

The major specifications of main HVAC equipment, such as chillers, cooling towers, water pumps, AHU fans and PAU fans, are summarized in Table 3.1. The design total power load of the main equipment in this air-conditioning system is 18,619.2 kW. Chillers are the largest electricity consumer in this air-conditioning system, which occupy 43.38% of the design total power load. The second largest electricity consumer is the fans of AHUs and PAUs contributing 27.46% of the design total power load. The design power loads of the pumps and cooling tower fans are 3,918.2 kW and 1,512 kW respectively, and they contribute about 21.04% and 8.12% of the design total power load in this air-conditioning system, individually. From Table 3.1, it also can be observed that the design total power load of the central chilling system takes about 72.5% of the design total power load of the overall air-conditioning system. Therefore, the central chilling system must be controlled properly to achieve reliable and energy efficient operation.

Table 3.1 Specifications of main equipment in the air-conditioning system

Chillers	N	$M_{w,ev}$ (L/s)	$M_{w,cd}$ (L/s)	CAP (kW)	W (kW)	W_{tot} (kW)
WCC-06-01 to 06	6	345.0	410.1	7,230	1,346	8,076
Cooling Towers	N	M_w (L/s)	M_a (m^3/s)	Q_{rej} (kW)	W (kW)	W_{tot} (kW)
CTA-06-01 to 06	6	250.0	157.2	5,234	152	912
CTB-06-01 to 05	5	194.0	127.0	4,061	120	600
Pumps	N	M_w (L/s)	$Head$ (m)	η (%)	W (kW)	W_{tot} (kW)
CDWP-06-01 to 06	6	410.1	41.60	83.6	202	1,212
PCHWP-06-01 to 06	6	345.0	31.60	84.5	126	756
SCHWP-06-01 to 02	1	345.0	24.60	82.2	101	101
SCHWP-06-03 to 05	2	345.0	41.40	85.7	163	326
SCHWP-06-06 to 09	3	345.0	30.30	84.2	122	366
SCHWP-06-10 to 12	2	155.0	39.90	78.8	76.9	153.8
PCHWP-42-01 to 07	7	149.0	26.00	84.9	44.7	312.9
SCHWP-42-01 to 03	2	294.0	36.50	87.8	120	240
SCHWP-42-04 to 06	2	227.0	26.20	84.3	69.1	138.2
PCHWP-78-01 to 03	3	151.0	20.60	84.3	36.1	108.3
SCHWP-78-01 to 03	2	227.0	39.20	85.8	102	204
Air-side PAU fan	29	/	/	/	/	513
Air-side AHU fan	152	/	/	/	/	4,600

Design total power load			
Design total power load	Chillers	**8,076** kW	**43.38%**
	Cooling towers	**1,512** kW	**8.12%**
	Pumps	**3,918.2** kW	**21.04%**
	AHU and PAU fans	**5,113** kW	**27.46%**
	Total	**18,619.2** kW	---

The nomenclature in Table 3.1 is defined as follows. N is the number of components, M is the flow rate, CAP is the chiller capacity, Q is the heat transfer rate, η is the efficiency, W is the power consumption, and subscripts w, a, ev, cd, rej and tot indicate water, air, evaporator, condenser, rejection and total, respectively.

3.2 Development of the Complex Dynamic Simulation Platform

3.2.1 Outline of the Complex Dynamic Simulation Platform

TRNSYS, a Transient Simulation Program with a modular structure, is used as the platform to develop the complex dynamic simulation platform in this thesis. TRNSYS recognizes a system description language in which the user specifies the components that constitute the system and the manner in which they are connected. The TRNSYS library includes many of the components commonly found in thermal and electrical energy systems, as well as component routines to handle inputs of weather data or other time-dependent forcing functions and outputs of simulation results. The modular nature of TRNSYS gives the program tremendous flexibility, and facilitates the addition to the program of mathematical models not included in the standard TRNSYS library. TRNSYS is well suited to detailed analyses of any system whose behavior is dependent on the passage of time (Klein et al. 1990).

As presented previously, the central chilling system consumes most of energy of the overall air-conditioning system. Therefore, the dynamic simulation platform constructed in this thesis is mainly for the central chilling system. Figure 3.3 illustrates the schematics of the major interconnection between component models (information flow diagram) for the central chilling system in simulation. The component integrations for the pressure flow balance and thermal balance computation, as well as for the chiller sequence, heat exchanger sequence, pump sequence, pump speed control, cooling tower control, etc., are illustrated as well. The detailed TRNSYS simulation DECK file for this complex dynamic simulation platform is provided in Appendix. The detailed information flows among different components and their associated controllers as well as the parameters of major component models used in the simulation can be found in this DECK file.

The weather data, including the air wet-bulb temperature and air dry-bulb temperature, and cooling loads of each individual zone are provided by the data files during the simulation as the test condition. The air flow rates and AHU inlet air dry-bulb temperatures of each individual zone are simulated according to the whether data and cooling loads of each zone provided together with certain reasonable assumptions. The assumptions used are presented as follows: (1) a minimum ratio of the fresh air to supply air is assumed as 20%; (2) the room design air dry-bulb temperature is 23°C for summer and autumn cases, and 21°C for winter and spring cases with a 50% humidity ratio; (3) the air dry-bulb temperature leaving AHUs is controlled at the given set-point which can be different from season to season with a 95% humidity ratio.

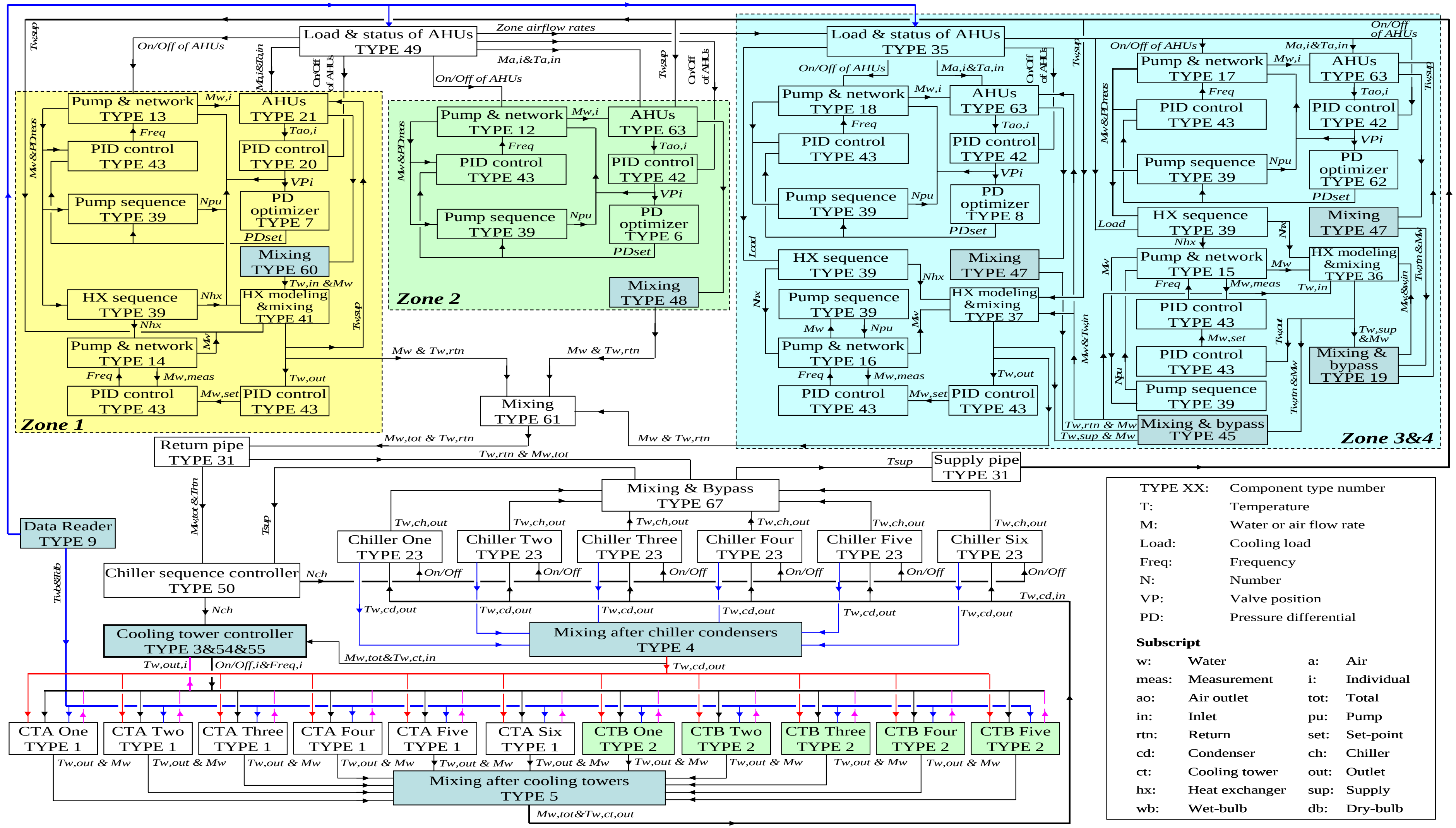

Figure 3.3 Illustration of the TRNSYS simulation DECK and control systems.

To avoid the difficulty in convergence when solving the pressure flow balances of the chilled water network and cooling water network, the pressure flow balances of the chilled water network and cooling water network are simulated by separate models. Since the chilled water system in the building under study is extremely complicated, the chilled water network is further divided into several sub-networks according to the configurations of the chilled water distribution system. The pressure flow balance of each sub-network is computed separately using a separate model as well. To analyze the performance of the design system under different cooling demands and various weather conditions, the models of major chilling system components are needed. These models are built according to TRNSYS' requirements to predict the system energy performance, environment quality as well as the system response to the changes of control settings. Since there is a limit on the total number of UNITs allowed in TRNSYS Version 13.1 (total of 75 UNITs allowed), the modeling of the same type of components, such as CTA towers, CTB towers, heat exchangers with parallel installations, etc., is organized in the same TYPE as possible to save the number of UNITs required, while six chillers are simulated using separate UNITs due to their complicated structures (referring to Appendix). All AHUs and their associated PID controllers in each zone are simulated. In this simulation, they are organized into several groups according to their operation schedules and each group uses a UNIT in order to save the number of UNITs utilized as well. The major component models used to construct this complex dynamic simulation platform are summarized in the following briefly.

3.2.2 Description of Models of the Water Network and Major Components

3.2.2.1 Chiller Modeling

The chiller model (TYPE 23 in Figure 3.3) used was developed by Wang et al. (2000) to simulate the chiller performance dynamically under various working conditions on the basis of the impeller tip speed (u_2), impeller exhaust area (A), impeller blades angle (β) and 13 other coefficients/constants. This simulation mainly involves the compressor, condenser, evaporator and motor power consumption, as well as the thermal capacitances of the components associated with heat transfer in the chiller. The compressor is modeled on the basis of mass conservation, Euler turbo-machine equation and energy balance equation. The Euler equation is modified by considering the impeller exit radial velocity (c_{r2}) distribution and derived as in Equation (3.1). Energy balance equations are applied to the compressor control volume and impeller control volume resulting in Equations (3.2) and (3.3), respectively. The hydrodynamic losses ($h_{hyd,com}$ and $h_{hyd,imp}$) in the two control volumes are considered to be composed of three elements, i.e., flow friction losses, inlet losses and incidence losses, as shown in Equations (3.4) and (3.5), respectively.

$$h_{th} = u_2 \left[u_2 - \left(\frac{\pi^2}{8} \right)^2 c_{r2} \left(ctg\beta + B \frac{\upsilon_1}{\upsilon_i} tg\theta \right) \right] \tag{3.1}$$

$$h_{th} = h_{pol.com} + h_{hyd.com} \tag{3.2}$$

$$h_{th} = h_{pol.imp} + h_{hyd.imp} + \frac{c_i^2}{2} \tag{3.3}$$

$$h_{hyd.com} = \zeta\left[1+\psi_1\left(\frac{\upsilon_1}{\upsilon_i}\frac{1}{\cos\theta}\right)^2 + \psi_2\left(\frac{\upsilon_1}{\upsilon_i}\mathrm{tg}\theta\right)^2\right]c_{r2}^2 \tag{3.4}$$

$$h_{hyd.imp} = \zeta\left[\chi+\psi_1\left(\frac{\upsilon_1}{\upsilon_i}\frac{1}{\cos\theta}\right)^2 + \psi_2\left(\frac{\upsilon_1}{\upsilon_i}\mathrm{tg}\theta\right)^2\right]{c_{r2}}^2 \tag{3.5}$$

where h_{th} is the compressor theoretical head, h_{hyd} is the hydrodynamic losses, h_{pol} is the polytropical compression work, B is the ratio of the impeller channel depth at the intake to that at exhaust, υ_1 and υ_i are the specific volumes at the impeller intake and exhaust, respectively, c_i is the vapor velocity at the impeller exhaust, θ is the inlet guide vane angle, ζ, ψ_1, ψ_2, χ are the introduced constants, and subscripts *com* and *imp* indicate compressor and impeller, respectively.

Given the evaporator pressure, condenser pressure and inlet guide vane angle, the compressor model can calculate the radial velocity and specific volume at the impeller exhaust and, thus, the refrigerant mass flow rate and internal power. For two stage chillers, single stage compressor equations are used to calculate the first stage. The second stage is assumed to have the same flow efficiency and compression ratio as the first stage. Only the first stage impeller geometric parameters are of concern.

The evaporator and condenser are simulated using the classical heat exchanger efficiency method. The chiller power consumption (W) is calculated on the basis of the internal compression power (W_{inter}), as shown in Equation (3.6), which consists of three elements, i.e., internal compression power, a variable part of the losses proportional to the internal compression power and a constant part of the losses (W_l). Two thermal storage units (one at the cooling water inlet of the condenser and the other at the chilled water inlet of the evaporator) are used to represent the dynamic responses of the chiller to the changes of working conditions (inlet temperatures) and the dynamic effects of the working condition changes on the compressor load. They are mathematically represented by two first-order differential equations as shown in Equations (3.7) and (3.8), respectively.

$$W = \alpha W_{\mathrm{int}er} + W_l \tag{3.6}$$

$$C_{ev} \frac{dT'_{ev,in}}{d\tau} = c_{p,w} M_{w,ev} (T_{ev,in} - T'_{ev,in}) \tag{3.7}$$

$$C_{cd} \frac{dT'_{cd,in}}{d\tau} = c_{p,w} M_{w,cd} (T_{cd,in} - T'_{cd,in}) \tag{3.8}$$

where α is a coefficient, T is the temperature, T' is the temperature after introducing dynamic effects, and the subscript *in* indicates inlet.

3.2.2.2 Cooling Tower Modeling

The cooling tower model (TYPE 1 for CTA towers and TYPE 2 for CTB towers in Figure 3.3) is to simulate the states of the outlet air and outlet water of the cooling tower. There are mainly two kinds of models widely used for direct contact evaporative cooling towers, i.e., the effectiveness model developed by Braun et al. (1989c) and the so-called ‘Toolkit model’ developed by Lebrun et al. (1999). The effectiveness model utilizes the effectiveness relationship developed for sensible heat exchangers by introducing an air saturation specific heat and a modified definition of the number of heat transfer units. This model was recommended by TRNSYS, and is therefore used in this study to construct the dynamic simulation platform.

Based on the steady-state energy and mass balances on an incremental volume, the differential equations as shown in Equations (3.9)-(3.11) can be derived. The effectiveness of the cooling tower (ε_a) is used to simulate heat and mass transfer processes in the cooling tower and the actual heat transfer is then calculated in terms of this effectiveness as in Equation (3.12). The outlet air state and water state are computed through the overall energy balances as in Equations (3.13)-(3.15). The number of transfer units (NTU) is simulated using Equation (3.16). Empirical formulas as shown in Equations (3.17) and (3.18) are used to predict the required air flow rate (M_a) and power consumption of the cooling tower (W_{ct}), respectively.

$$\frac{d\omega_a}{dV} = -\frac{NTU}{V_T}\left(\omega_a - \omega_{s,w}\right) \tag{3.9}$$

$$\frac{dh_a}{dV} = -Le\frac{NTU}{V_T}\left[\left(h_a - h_{s,w}\right) + \left(\omega_a - \omega_{s,w}\right)\left(1/Le - 1\right)h_{g,w}\right] \tag{3.10}$$

$$\frac{dT_w}{dV} = \frac{dh_a/dV - c_{p,w}\left(T_w - T_{ref}\right)d\omega_a/dV}{\left[M_{w,i}/M_a - (\omega_{a,o} - \omega_a)\right]c_{p,w}} \tag{3.11}$$

$$Q = \varepsilon_a M_a\left(h_{s,w,i} - h_{a,i}\right) \tag{3.12}$$

$$h_{a,o} = h_{a,i} + \varepsilon_a\left(h_{s,w,i} - h_{a,i}\right) \tag{3.13}$$

$$\omega_{a,o} = \omega_{s,w,e} + (\omega_{a,i} - \omega_{s,w,e})\exp(-NTU) \tag{3.14}$$

$$T_{w,o} = T_{ref} + \frac{M_{w,i}\left(T_{w,i} - T_{ref}\right)c_{p,w} - M_a\left(h_{a,o} - h_{a,i}\right)}{M_{w,o}c_{p,w}} \tag{3.15}$$

$$NTU = c\left[\frac{M_w}{M_a}\right]^{1+n} \tag{3.16}$$

$$M_a = M_{a,des}\left[c_{01} + c_{02}\left(\frac{Freq}{Freq_{des}}\right) + c_{03}\left(\frac{Freq}{Freq_{des}}\right)^2\right] \tag{3.17}$$

$$W_{ct} = W_{ct,des}\left[c_{11} + c_{12}\left(\frac{Freq}{Freq_{des}}\right) + c_{13}\left(\frac{Freq}{Freq_{des}}\right)^2\right] \tag{3.18}$$

where ω_a is the air humidity ratio, $\omega_{s,w}$ and $\omega_{s,w,e}$ are the saturation air humidity ratio and effective saturation air humidity ratio with respect to the temperature of the water surface, respectively, V_T is the total volume, Le is the Lewis number, T_w is the temperature of water, T_{ref} is the reference temperature for zero enthalpy of liquid water, h_a is the enthalpy of the moist air per mass of dry air, $h_{s,w}$ is the saturation air enthalpy with respect to the temperature of the water surface, $h_{g,w}$ is the enthalpy of water above the reference state for liquid water at T_{ref}, M_w and M_a are the mass flow rates of water and dry air, respectively, $W_{ct,des}$ and $M_{a,des}$ are the power consumption and air flow rate of the cooling tower at the design condition, $Freq$ is the fan operating frequency, and c_{01}-a_{03} and c_{11}-c_{13} are coefficients.

3.2.2.3 Pump and Water Network Modeling

The variable speed pump set (TYPE 12-TYPE 18 for different subsystems in different zones) is simulated by a steady-state pump, a steady-state frequency inverter and a dynamic actuator of the inverter (Wang 1998). The frequency at the outlet of the inverter is linear to the input signal from the actuator. The efficiency of the inverter is included within the model of the pump energy performance. The energy performance and pump characteristics at various speeds are simulated using fourth-order polynomial functions as shown in Equations (3.19) and (3.20), respectively. The coefficients in the equations can be determined by regression using the performance data from the manufacturer's catalogues.

$$W_{pu}(Freq, M_{pu}) = \sum_{i=0}^{m}\sum_{j=0}^{n} G_{ij} Freq^{i} M_{pu}^{j} \tag{3.19}$$

$$P_{pu}(Freq, M_{pu}) = \sum_{i=0}^{m}\sum_{j=0}^{n} E_{ij} Freq^{i} M_{pu}^{j} \tag{3.20}$$

where W_{pu} *and* P_{pu} are the pump power consumption and pressure head, respectively, *Freq* is the frequency input to the pump, M_{pu} is the water flow rate through a pump, *G* and *E* are coefficients.

The pressure flow balance of the water network of each zone (integrated with the TYPEs for pumps) is simulated individually. For the zones with heat exchangers, the pressure flow balances of the water networks at the primary side and secondary side of heat exchangers are simulated individually as well. For the water networks with pumps distributing water to terminal units, the openings of the water control valves, the pump operating frequency, the number of pumps in operation and/or the number of heat exchangers in operation, are the inputs of the network models. During the simulation, the control signals collected from the outputs of PID controllers for the AHU supply air temperature are used to represent the openings of water control valves. The water flow rates through each AHU coil are computed by these network models and returned to the AHU coil thermal model for the AHU temperature loop simulation. These models calculate the flow resistances of AHU coils according to the positions of associated valves. The number of heat exchangers in operation is controlled by a heat exchanger sequence controller, in which the water flow rate of the system of concern is used to stage and de-stage the operation of a heat exchanger. The number of pumps operating is controlled by a pump sequence controller, in which the system water flow rate is utilized to determine the operating number of pumps. The pump operating frequency is controlled by resetting the pressure differential set-point at the critical loop. For the water networks with pumps distributing water to heat exchangers, the pressure flow balance models are relatively simple. The inputs of these network models are the pump operating frequency, the number of pumps in operation and the number of heat exchangers in operation. The flow resistances of main supply and return pipelines in these network models are considered constant.

The pressure flow balance of the condenser cooling water system network is relatively simple since constant speed condenser water pumps are used. In this system, a simple cooling tower sequence controller (TYPE 3) is used to control the operating number of cooling towers based on the number of chillers in operation. The operating frequency of each cooling tower fan is controlled using a fan frequency controller (TYPE 54 for CTA towers and TYPE 55 for CTB towers). The condenser water supply temperature set-point is set using the conventional control methods, i.e., the fixed set-point control method, the fixed approach method, etc. The overall flow balance in the condenser cooling water system is expressed as in Equation (3.21).

$$M_{tot} = \sum_{i=1}^{N_0} M_{w,cd,i} = \sum_{m=1}^{N_1} M_{w,CTA,m} + \sum_{n=1}^{N_2} M_{w,CTB,n} + M_{bp} \tag{3.21}$$

where $M_{w,cd,i}$ is the water flow rate of the i^{th} chiller condenser, $M_{w,CTA,m}$ is the water flow rate of the m^{th} CTA tower, $M_{w,CTB,n}$ is the water flow rate of the n^{th} CTB tower, M_{bp} is the bypass water flow rate, N_0, N_1 *and* N_2 are the numbers of chillers, CTA towers and CTB towers in operation, respectively.

The pressure losses (P_l) across pipes, components, e.g., heat exchangers, AHU coils, gate valves, control valves, etc., caused by the fluid friction are computed using Darcy-Weisbach equation as in Equation (3.22) (ASHRAE 2005). For a given pipe size and given fluid, Equation (3.22) can be further simplified as in Equation (3.23). The flow resistance of the control valve is related to its opening. The pressure loss across a control valve ($P_{l,cv}$) at a given opening (x) is computed using Equation (3.24).

$$P_l = f_f \left(\frac{L}{D}\right)\left(\frac{\rho v^2}{2}\right) \tag{3.22}$$

$$P_l = \xi \frac{v^2}{2} \tag{3.23}$$

$$P_{l,cv} = \frac{\xi_0}{x^{\alpha}} \frac{v^2}{2} \tag{3.24}$$

where f_f is the friction factor selected from the Moody chart, L is the length of a pipe, D is the internal diameter of a pipe, ρ is the fluid density at the mean temperature, v is the average fluid flow velocity in a pipe, ξ is the flow resistance of a pipe or a component, ξ_0 is the flow resistance when the control valve is fully open, α is a coefficient dependent on the control valve flow characteristics.

3.2.2.4 AHU Coil Modeling

The AHU coil model (TYPE 21 and TYPE 63 in Figure 3.3) is to simulate the outlet water and outlet air states. In this simulation, the physical model developed by Wang (1998) is used. In this simulation, the AHU coil is modeled using a dynamic approach. A first-order differential equation, as shown in Equation (3.25), is used to represent the dynamics of a coil with lumped thermal mass. The dynamic equation based on the energy balance ensures that the energy is conserved. The outlet air and water temperatures ($t_{a,out}$, $t_{w,out}$) are computed using Equations (3.26) and (3.27) respectively, by the heat balances of both sides. The heat transfer calculation applies the classical number of transfer units (NTU) and heat transfer effectiveness methods. The classical method to calculate the effect of the fins in the air side on the thermal resistance is used.

$$C_c \frac{dt_c}{d\tau} = \frac{t_{a,in} - t_c}{R_1} - \frac{t_c - t_{w,in}}{R_2} \tag{3.25}$$

$$t_{a,out} = t_{a,in} - \frac{SHR(t_{a,in} - t_c)}{R_1 C_a} \tag{3.26}$$

$$t_{w,out} = t_{w,in} - \frac{t_c - t_{w,in}}{R_2 C_w} \tag{3.27}$$

where t_c is the mean temperature of the coil, $t_{a,in}$ and $t_{w,in}$ are the inlet air and water temperatures, C_c is the overall thermal capacity of the coil, C_a and C_w are the capacity flow rates of air and water, R_1 and R_2 are the overall heat transfer resistances at air and water sides, *SHR* is the sensible heat ratio.

3.2.2.5 Heat Exchanger Modeling

The dynamic performance of a heat exchanger is represented by a classical steady-state heat transfer model and a simple dynamic model (Wang 1998). The heat transfer model (TYPE 36, TYPE 37 and TYPE 41) computes the number of transfer units and heat transfer efficiency (ε) using Equation (3.28) for a counter flow heat exchanger and Equation (3.29) for a crossover flow heat exchanger. The dynamic models, similar to that represented in Equations (3.7) and (3.8), are used to represent the thermal storage characteristics of the heat exchanger and then to simulate its dynamic response.

$$\varepsilon = \frac{1-\exp[-NTU(1-\omega)]}{1-\omega\exp[-NTU(1-\omega)]} \tag{3.28}$$

$$\varepsilon = \frac{1-\exp[-\omega(1-\exp(NTU))]}{\omega} \tag{3.29}$$

where ω is the capacity flow rate ratio.

3.2.2.6 Sensor and Pipe Modeling

The dynamics of the temperature and pressure sensors are simulated by using the time constant method (Wang 1998). A first-order differential equation as shown in Equation (3.30) is used to represent the dynamic characteristics of a sensor.

$$\frac{dy'}{d\tau} = \frac{y - y'}{T_c} \tag{3.30}$$

where y is the true value of the measured variable, y' is the measured value of the variable, and T_c is the time constant.

The thermal dynamic characteristics of the water pipes are simulated by using the pipe model TYPE 31 using variable size segments of the fluid available in the TRNSYS library. The entering fluid shifts the position of existing segments. The mass of the new segment equals to the flow rate of the simulation time step. The temperature of the new segment is that of the incoming fluid. The outlet of the pipe is a collection of the elements pushed out by the inlet flow (Klein et al. 1990).

3.3 Energy Performance Tests of the Central Chilling System

The central chilling system consists of three subsystems: the chiller system, condenser cooling water system (i.e., heat rejection system) and chilled water distribution system. These three subsystems are highly interactive. Testing the effects of the interactions within these subsystems on the energy performance is essential for developing online supervisory and optimal control strategies for complex central chilling systems.

In the following, typical points, which represent the typical operation conditions of the air-conditioning system, are selected to test and evaluate energy performances of these subsystems using alternative control and operation strategies. The selected typical points are also used to evaluate the interactions within these subsystems using alternative control and operation strategies. The strategies include different chilled water supply temperature set-point control, different condenser water supply temperature set-point control and the control of the number of chillers operating. All of the tests were conducted on the dynamic simulation platform constructed.

3.3.1 Building Cooling Load Simulation

To test the performance of the central chilling system under different control strategies, the building cooling load as one of the test condition is needed. The hourly-based annual cooling load profile of each zone of the building under study was calculated using EnergyPlus (2005) based on the design data. The necessary inputs for EnergyPlus simulation representing the real building are the detailed descriptions of building envelopes, floors and ceiling, the design peak occupancy, lighting power, equipment power, set-points of the indoor temperature and relative humidity, the fresh air flow rate, etc. The indoor mass including the furniture and carpets are simplified as the specific wood plate and specific carpet plate with certain areas, respectively. The weather data used is the typical year data of Hong Kong (1989). The building is simulated for one year (8760 h).

The simulated building cooling loads for typical days in different seasons are illustrated in Figure 3.4. It can be observed that cooling load profiles of typical days in different seasons are significantly different. The cooling load in the typical sunny-summer day is the highest and the maximum value is about 38,000 kW, while the cooling load in the typical winter day is the lowest, which is less than half of that in the typical sunny-summer day. It also can be seen that the cooling loads within a day are also significantly different. Such large variations of cooling loads in different seasons over a year and in different times within a day will provide great energy saving potentials in buildings.

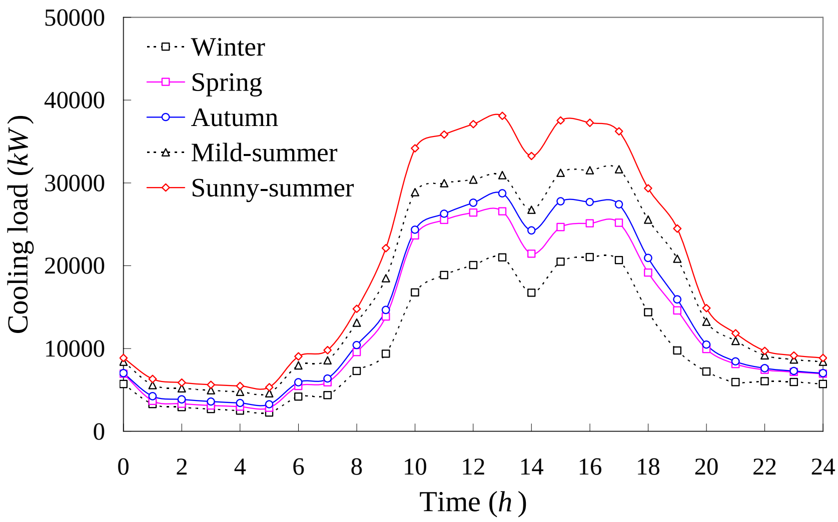

Figure 3.4 Profiles of the cooling loads for typical days in different seasons.

3.3.2 Optimization of the Chilled Water Supply Temperature Set-point

The systematic optimization of chillers and the chilled water distribution system aims at minimizing the overall power consumption of chillers and chilled water pumps while fulfilling the cooling demands of all air-conditioning terminal units. When the evaporating temperature rises as a result of increased chilled water supply temperature set-point, the power consumption of chiller compressors will be reduced as the suction pressure rises. However, as the chilled water supply temperature set-point increases, the heat transfer efficiency of terminal units will de decreased. Therefore, more chilled water will be required to compensate the efficiency deterioration, which will increase the power consumption of pumps. In contrast, a lower chilled water supply temperature set-point can save the power consumption of pumps, but it deteriorates the efficiency of chillers, which results in more power consumption of chillers.

To investigate the synthetic effect of the chilled water supply temperature set-point on the total power consumption of chillers and chilled water pumps quantitatively, simulation exercises using different chilled water supply temperature set-point control for the typical points in various seasons were conducted. The selected typical operation points (test conditions) of the air-conditioning system are presented in Table 3.2. In these simulation exercises, a conventional chiller sequence strategy was used to control the number of chillers operating according to the total cooling load and the maximum cooling capacity of the chiller. An additional chiller is activated when the operating chillers have insufficient capacity to meet the current load. One of the operating chillers is deactivated when the current load can be met with one fewer chillers operating (Sane et al. 2006). A dead band was employed in this controller for staging and de-staging a chiller to avoid frequent ON and OFF of a chiller.

Table 3.2 Selected typical test conditions in different seasons

Test No.	Season	Load Ratio (%)	T_{db} (°C)	T_{wb} (°C)	Q_{load} (kW)
Test 1	Winter	50	16.93	11.28	21647.18
Test 2	Spring	60	20.95	14.56	26102.57
Test 3	Autumn	70	24.93	17.82	30237.25
Test 4	Summer-mild	80	28.82	21.0	34624.85
Test 5	Summer-sunny	90	31.45	23.15	39361.16

The nomenclature in Table 3.2 is presented as follows. *Load ratio* is the ratio of the actual cooling load to the design cooling load, Q_{load} is the building cooling load, T_{db} and T_{wb} are the ambient air dry-bulb and wet-bulb temperatures, respectively.

Figure 3.5 shows the power consumptions of chillers and pumps (including primary chilled water pumps and condenser water pumps) respectively, as well as the total power consumption of chillers and pumps using different chilled water supply temperature set-point control in the typical operation point in winter (Test 1). The results show that the power consumption of chillers was decreased, but the power consumption of pumps was increased with the increase of the chilled water supply temperature set-point. The results also show that the total power consumption of chillers and pumps decreased when the chilled water supply temperature set-point was changed from 4.5°C to 7.0°C, but the total power consumption increased with the increase of the chilled water supply temperature set-point over 7.0°C. The minimum total power consumption (5131 kW) was achieved when the chilled water supply temperature set-point was about 7.0°C. The power saving was 23 kW (0.44%) as compared with the power consumption at the design temperature set-point of 5.5°C.

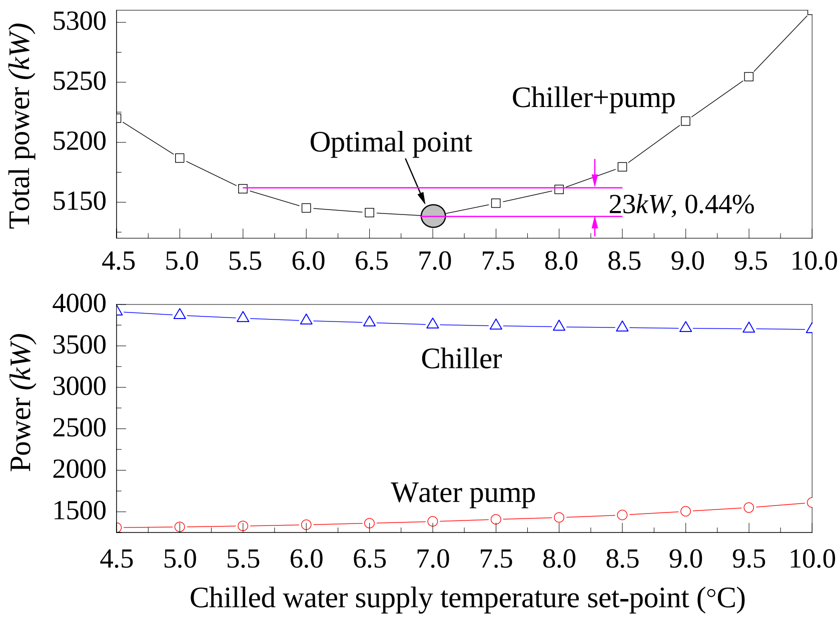

Figure 3.5 The power consumptions of chillers and pumps with different chilled water supply temperature set-point control in the winter case.

Figures 3.6 and 3.7 show the test results using different chilled water supply temperature set-point control in the typical spring and autumn operation points, respectively. For the typical spring case with about 60% of the design cooling load, the optimal chilled water supply temperature set-point was about 6.6°C, resulting in the minimum total power consumption of 6246 kW. The energy saving using this optimal temperature set-point was 19.2 kW (0.31%) over the use of the design temperature set-point of 5.5°C. Since the weather condition and building cooling load in the typical autumn season were very similar to that in the typical spring season, the optimal chilled water temperature set-point in the typical autumn case (6.4°C) was therefore very close to that in the typical spring case. The energy saving was 15.8 kW (0.21%) when the system operated at this optimal temperature set-point as compared with that operated at the design temperature set-point of 5.5°C.

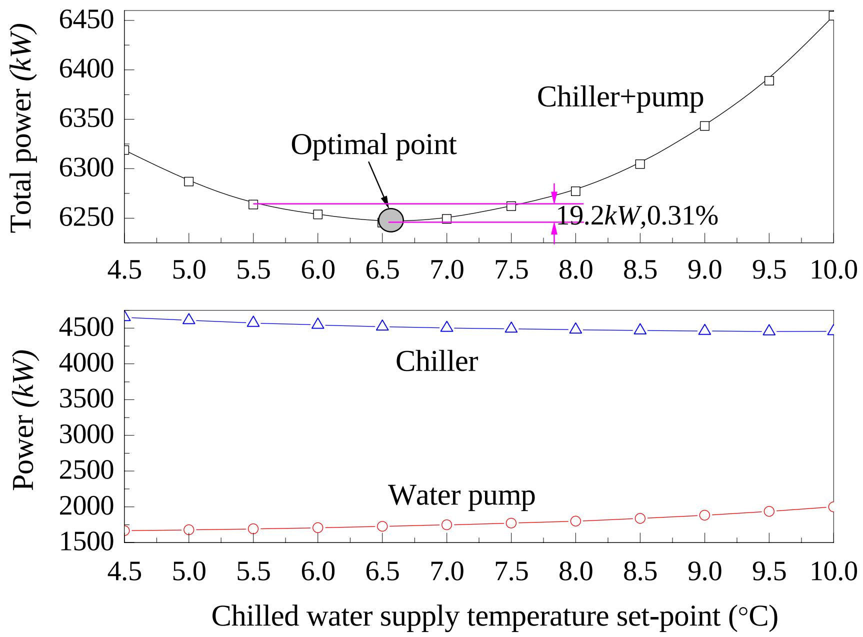

Figure 3.6 The power consumptions of chillers and pumps with different chilled water supply temperature set-point control in the spring case.

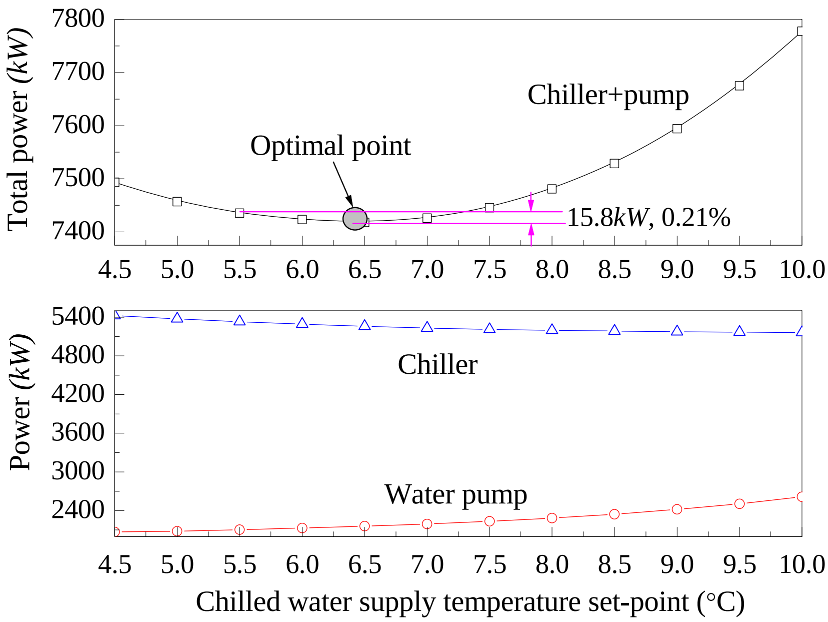

Figure 3.7 The power consumptions of chillers and pumps with different chilled water supply temperature set-point control in the autumn case.

For the case of the typical mild-summer point, the outdoor dry-bulb and wet-bulb temperatures are higher than that in the other seasons and the building cooling load is also much higher. The typical cooling load in this weather condition is about 80% of the design cooling load. Figure 3.8 shows that the optimal chilled water supply temperature set-point for this case was about 5.65°C, which was very close to the design temperature set-point. The energy saving was very limited and only about 6 kW (0.07%) energy can be saved by comparing with that at the original design temperature set-point of 5.5°C.

For the typical sunny-summer case, the building cooling load is very high, about 90% of the design cooling load. Figure 3.9 illustrates that the optimal chilled water temperature set-point for this case was about 5.0°C, which was lower than the design temperature set-point of 5.5°C. The energy saving associated with the use of this optimal temperature set-point was 11.5 kW (0.12%) over the use of the original design temperature set-point.

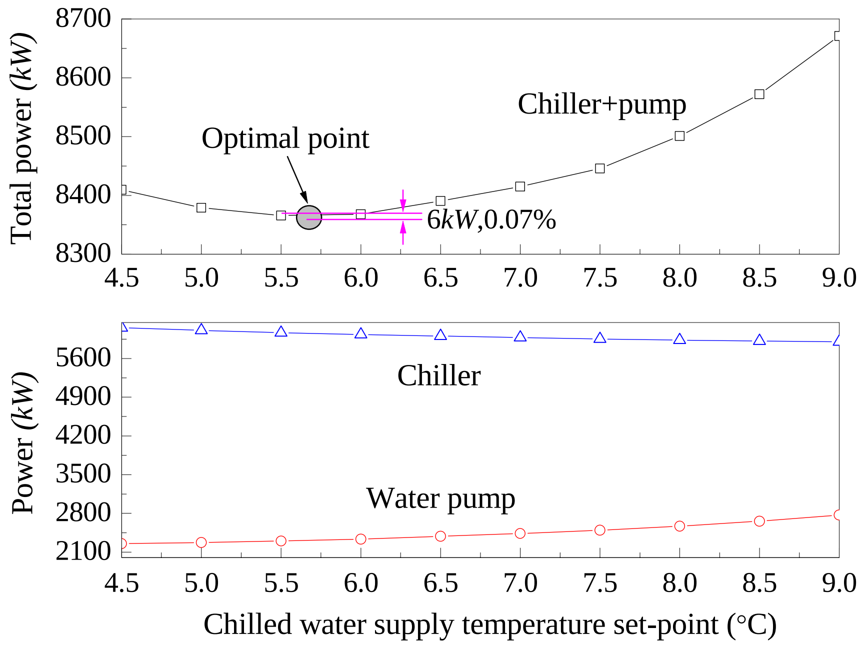

Figure 3.8 The power consumptions of chillers and pumps with different chilled water supply temperature set-point control in the mild-summer case.

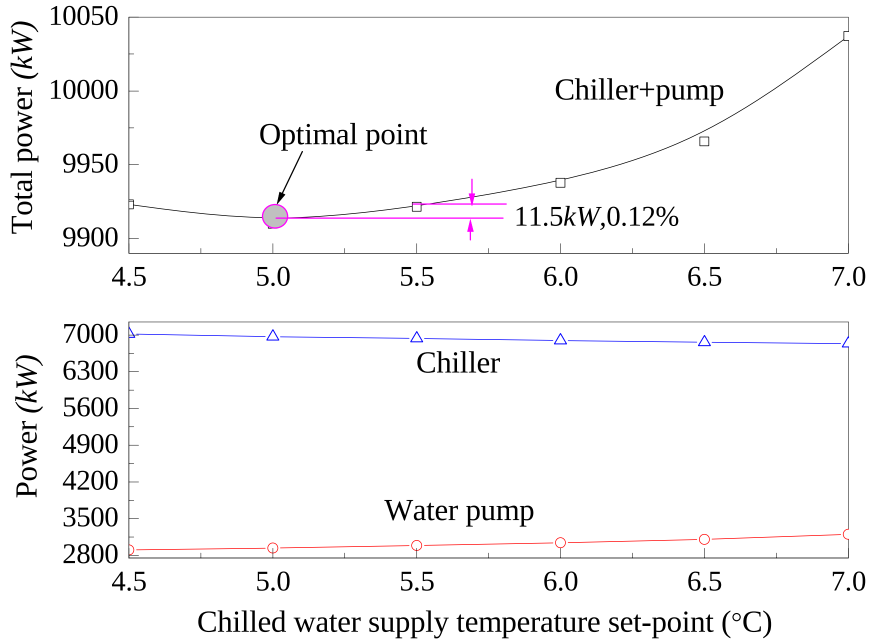

Figure 3.9 The power consumptions of chillers and pumps with different chilled water supply temperature set-point control in the sunny-summer case.

The above test results demonstrate that the power consumptions of chillers and water pumps are affected by the chilled water supply temperature set-point. The optimal chilled water temperature set-point is the trade-off between the power consumptions of both chillers and pumps. The optimization of the chilled water supply temperature set-point is to seek the optimal temperature set-point that can result in the minimum total power consumption, while still meeting the cooling load requirements of all air-conditioning terminal units. It is worthwhile to point out that the condenser water supply temperature set-point was not optimized during the above calculations.

3.3.3 Optimization of the Condenser Water Supply Temperature Set-point

The chiller performance and cooling tower performance are highly interactive, and they are affected in different directions by the condenser water supply temperature set-point. A lower condenser water supply temperature set-point can improve the COP of chillers, resulting in less power consumption of chillers, but the lower temperature set-point requires more air flow rate to achieve the higher heat rejection efficiency of cooling towers and, hence, more power is consumed by cooling tower fans. In contrast, a higher condenser water supply temperature set-point can save the power consumption of cooling tower fans, but it deteriorates the efficiency of chillers, which will result in more power consumption of chillers. To evaluate the effect of the condenser water supply temperature set-point on the total power consumption of chillers and cooling tower fans quantitatively, the similar tests as the 'optimization of the chilled water supply temperature set-point' are conducted subsequently. The same test conditions as listed in Table 3.2 and the same chiller sequence strategy as presented in Section 3.3.2 are used as well.

Figure 3.10 illustrates the power consumption profiles of chillers and cooling tower fans as well as the total power consumption of chillers and cooling tower fans using different condenser water supply temperature set-point control in the typical winter test point. The results show that the power consumption of chillers increased, but the power consumption of cooling tower fans decreased with the increase of the condenser water supply temperature set-point. The optimal temperature set-point was the trade-off between the power consumptions of chillers and cooling tower fans. If taking 25°C as the benchmark of the operation condition for the winter case (selected only for comparison), a substantial amount of energy (131 kW) can be saved when the system operated at the optimal temperature set-point of 19.6°C.

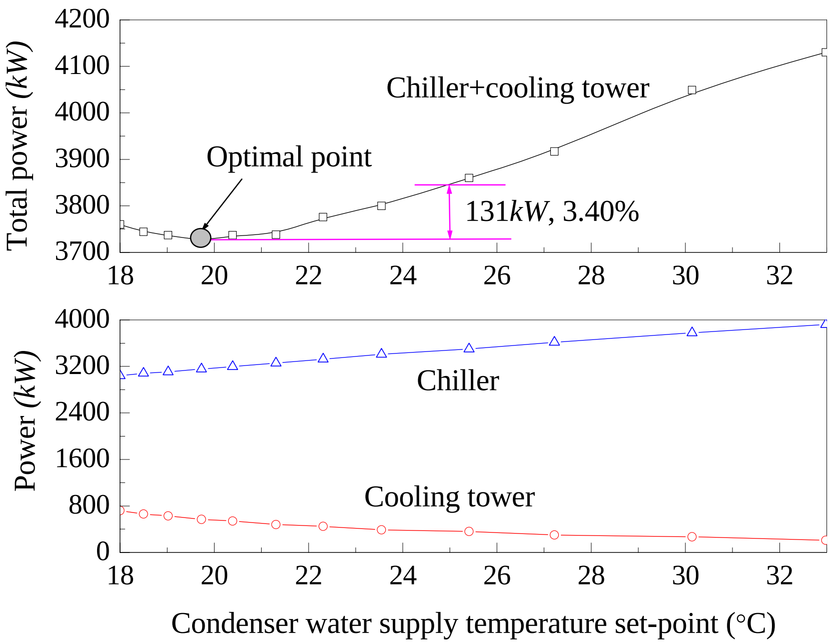

Figure 3.10 The power consumptions of chillers and cooling tower fans with different condenser water supply temperature set-point control in the winter case.

The test results for the typical sunny-summer test point are presented in Figure 3.11. The minimum total power consumption was achieved when the condenser water supply temperature set-point was about 30°C, which was much higher than that in the typical winter case. The energy saving was about 118 kW (1.60%) when compared with the power consumption at the design temperature set-point of 32°C.

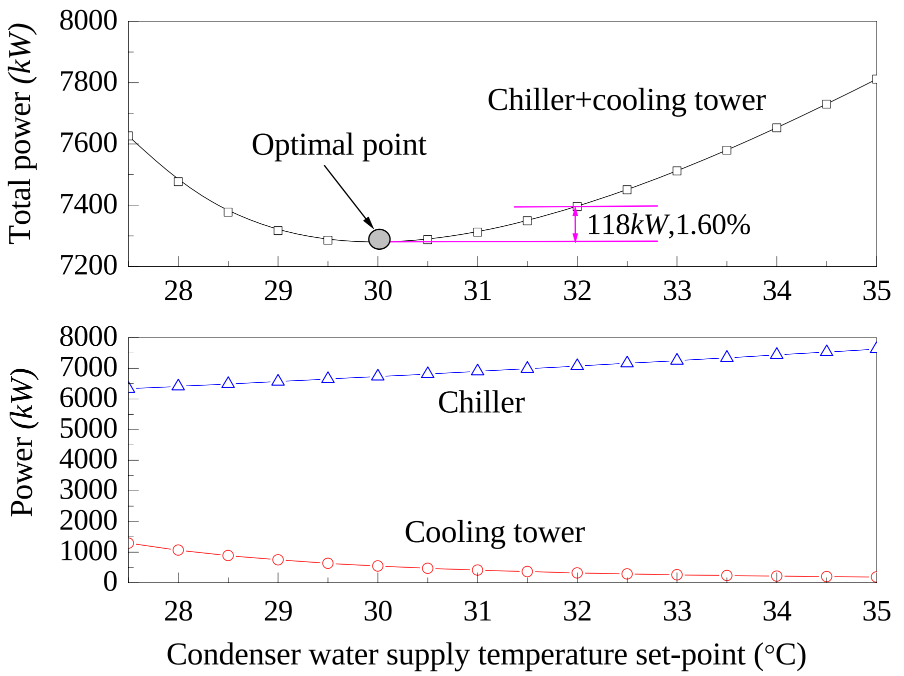

Figure 3.11 The power consumptions of chillers and cooling tower fans with different condenser water supply temperature set-point control in the sunny-summer case.

The trends of the power consumption profiles associated with the changes of the condenser water supply temperature set-point in the other three cases (i.e., spring case, autumn case and mild-summer case) were similar to that in the winter case and sunny-summer case and, therefore, are not provided in this thesis.

From the above tests, it can be found that a significant amount of energy in the condenser cooling water system can be saved when the optimal condenser water supply temperature set-point is used. The optimal condenser water supply temperature set-point is the trade-off between the power consumptions of chillers and cooling tower fans. The optimal temperature set-point varies with the changes of working conditions. Therefore, the condenser water supply temperature set-point should be optimized in online supervisory and optimal control strategies for building condenser cooling water systems. It is noted that the chilled water supply temperature set-point was not optimized and was maintained as a constant (5.5°C) during the above calculations.

3.3.4 Optimization of the Number of Chillers in Operation

In central chilling systems, chillers always operate at different energy efficiencies (different COP values) under various working conditions, e.g., the condenser water supply temperature set-point, chilled water supply temperature set-point, etc. Normally, the chiller operates with a relatively high COP value at about 60%~100% of its maximum cooling capacity (Jayamaha 2007). For a given condition, one more chiller in operation may lead to less power consumption if one more chiller addition can make all chillers operate at 60%~100% of their design cooling capacities, resulting in high COP values. However, one more chiller in operation means that more energy will be consumed by pumps because of one more condenser water pump and one more primary chilled water pump dedicated to the corresponding chiller in operation (for primary-secondary chilled water pumping systems). The more power consumption of pumps may partially or fully offset by the power savings of chillers.

Therefore, the number of chillers in operation should be optimized to minimize the total power consumption of chillers and pumps.

To test the system performance associated with the changes of the number of chillers operating, five test points as listed in Table 3.3 were used for the purpose. At each selected test point, the chillers operated at almost their design cooling capacities, as shown in Table 3.4 (Case *I*), using the conventional chiller sequence strategy presented in Section 3.3.2. For Case *II*, one more chiller joined in operation based on that of Case *I*.

Table 3.3 Test conditions for the optimization of the number of chillers operating

Typical point	T_{db} (°C)	T_{wb} (°C)	Q_{load} (kW)
Point 1	18.42	12.47	7,229.85
Point 2	20.08	13.84	14,455.80
Point 3	24.76	17.67	21,685.88
Point 4	27.27	19.72	28,915.85
Point 5	29.79	21.80	36,145.57

The test results at different test points for both cases with different numbers of chillers in operation are presented in Table 3.4. The profiles of the power consumptions of chillers and pumps (all constant and variable speed pumps) as well as the total power consumption of chillers and pumps are presented in Figure 3.12 schematically. At the test point 1, the two chillers operated at about 50% of their maximum cooling capacities when one more chiller was added in operation. Although the total power consumption of the two chillers (*Case II*) decreased as compared with that of only one chiller in operation (*Case I*), the power consumption of pumps increased greatly due to one more condenser water pump and one more primary chilled water pump in operation. The total power consumption using the two chillers in operation increased 304 kW (16.50%) by comparing with that only using one chiller in operation at the test point 1.

Table 3.4 Test results using different numbers of chillers in operation

	Test point	***1***	***2***	***3***	***4***	***5***
Case I	Chiller operating number	1	2	3	4	5
	Load ratio of each chiller (%)	100	99.97	99.98	99.99	99.99
	Power of chillers (kW)	1,343	2,685	4,026	5,368	6,712
	Power of pumps (kW)	499	1,059	1,696	2,250	2,930
	Total power (kW)	1,842	3,744	5,722	7,618	9,642
Case II	Chiller operating number	2	3	4	5	6
	Load ratio of each chiller (%)	50	66.65	74.99	79.99	83.32
	Power of chillers (kW)	1,319	2,355	3,487	4,730	5,895
	Power of pumps (kW)	827	1,387	2,024	2,578	3,258
	Total power (kW)	2,146	3,742	5,511	7,308	9,153
Power saving of chillers (kW)		*24*	*330*	*539*	*638*	*817*
Total power saving (kW)		***-304***	***2***	***211***	***310***	***489***
Total power saving (%)		***-16.50***	***0.05***	***3.69***	***4.07***	***5.07***

At the test point 2, the total cooling load was 14,455.80 kW for the two chillers operated at their design cooling capacities (*Case I*). When one more chiller joined in operation (*Case II*), the cooling capacity of each chiller was 66.65% of its design cooling capacity. At this situation, the efficiency of chillers increased significantly, resulting in about 330 kW power savings of chillers by comparing with that using the two chillers in operation. However, this part of savings was almost fully offset by the increased power consumption of pumps.

For test points 3-5, a certain amount of power can be saved associated with the addition of one more chiller in operation based on that of *Case I*. When one more chiller was put into operation for these three test points, the chillers operated at around

75%-85% of their design cooling capacities, where the COPs were almost the highest meaning the highest operating efficiency of chillers. The savings of the power consumption of chillers can greatly surpass the additional increased power consumption of one more condenser water pump and one more primary chilled water pump. The total power savings using one more chiller in operation for these three test points were 211 kW (3.69%), 310 kW (4.07 %) and 489 kW (5.07%), respectively.

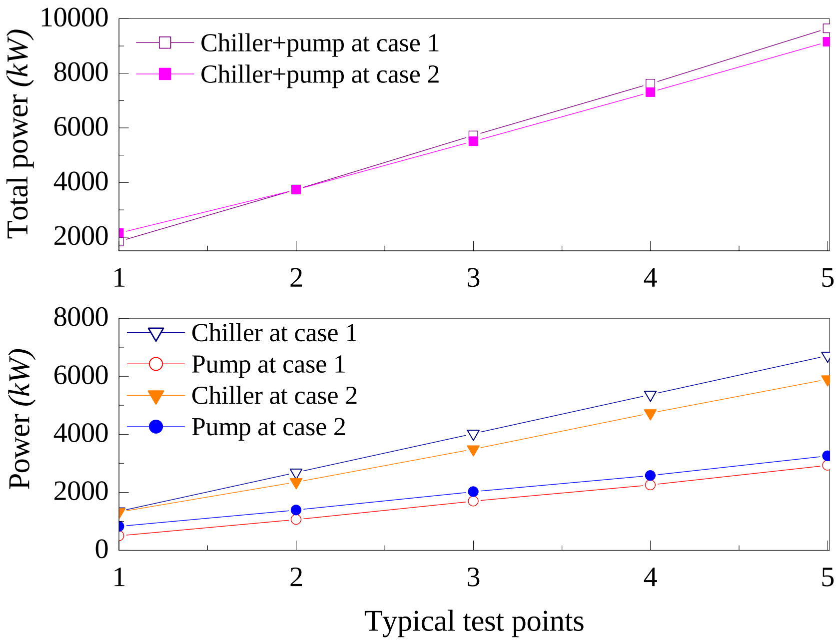

Figure 3.12 Profiles of the power consumptions of chillers and pumps with different numbers of chillers in operation under different test points.

From the above tests, it can be concluded that the power consumption of the central chilling system is significantly affected by the number of chillers operating. To achieve energy efficient control and operation of central chilling systems, the number of chillers operating needs to be optimized.

3.4 Summary

This chapter introduces a super high-rise building and its complex central chilling system concerned in this research. Based on this complex central chilling system, a dynamic simulation platform was constructed. Three energy performance tests, i.e., the optimization of the chilled water supply temperature set-point, optimization of the condenser water supply temperature set-point and optimization of the number of chillers in operation, were then conducted on the basis of this dynamic simulation platform to investigate the energy saving potentials in complex central chilling systems. The results show that the condenser cooling water system, chiller system and chilled water distribution system are highly interactive. The optimal control settings (set-points and operation modes) indeed exist for a given condition. These optimal control settings vary with the changes of working conditions. To develop online supervisory and optimal control strategies for the central chilling system, the interactions among these subsystems need to be carefully considered, and the major control variables should be optimized to minimize the overall system energy consumption/operating cost.

CHAPTER 4 TEST OF ONLINE CONTROL STRATEGIES PRIOR TO SITE IMPLEMENTATION

In order to determine the most promising strategy that can be used to achieve energy efficient control and operation of building services systems, the control performances and economic feasibilities of different control strategies are better tested and evaluated by means of appropriate methods prior to site implementation. In this chapter, two different methods for testing the performances of control strategies are presented. Both methods will be used to test and evaluate the performances of online supervisory and optimal control strategies developed in this PhD thesis.

Section 4.1 presents a brief overview of the major test methods for HVAC control strategies. In Section 4.2, a test method, namely *simulation-assisted test method*, for testing online control strategies is put forward. In this test method, the control strategy is tested and evaluated in a simulated virtual environment similar to the situation when it is actually implemented in practice. In Section 4.3, another test method, named *computation-assisted test method*, is presented. In this test method, the online control strategies are mainly evaluated by means of comparisons. A summary of this chapter is given in Section 4.4.

4.1 A Brief Overview of Test Methods for HVAC Control Strategies

During the last two decades, considerable efforts have been made on the development of proper and feasible test methods for HVAC control strategies (Annex17 1992, 1993; Kärki and Lappalainen 1994; Clarke et al. 2001; Lahrech et al. 2002; Xu et al. 2004; etc.). In general, there are two methods, i.e., by means of emulation and simulation, that are widely used to test and evaluate the performances of control strategies based on the virtual building systems. The application of the emulators to assess the performance of the real EMCS was well studied under the framework of the International Energy Agency (IEA) in a completed collaborative research project Annex 17. An emulator commonly consists of a virtual building system (i.e., dynamic simulation platform) and a hardware interface that allows the virtual building system to be connected to a real control system (Peitsman and Wang et al. 1994). The outputs of Annex 17 proved that the emulation is technically feasible for testing the real EMCSs (Annex17 1992, 1993). The control strategies can also be tested and evaluated by means of simulation. In this approach, various control strategies can be programmed and integrated into the virtual building systems directly to evaluate their operational performance (Wang 1998, 1999). Both approaches are flexible and convenient for testing the HVAC control strategies with a low cost.

Two different test methods are presented in the following to test the performances of online supervisory and optimal control strategies developed in this thesis. Both methods are somewhat different from the existing test methods of emulation and simulation.

4.2 Simulation-assisted Test Method

To test the performances of online control strategies prior to site implementation, a test method, named *simulation-assisted test method*, is developed. The overall structure of this test method is illustrated in Figure 4.1.

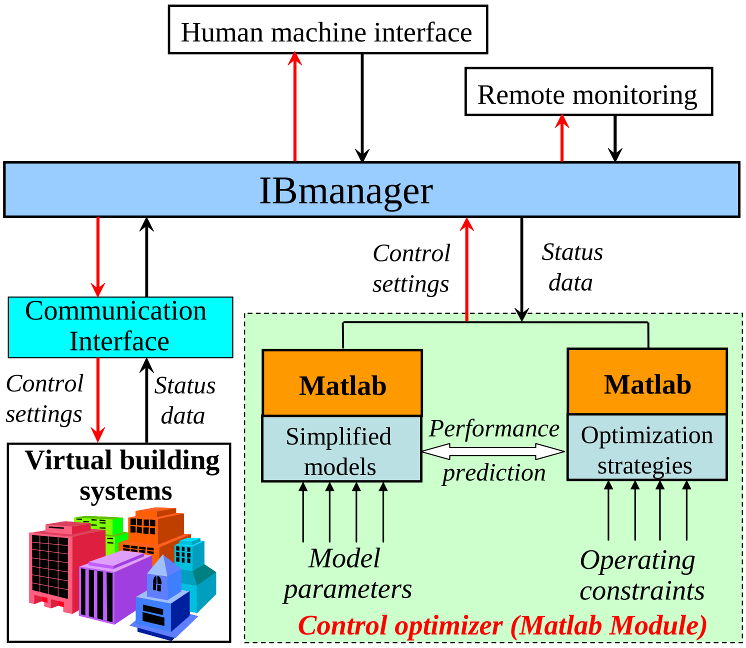

Figure 4.1 Overall structure of the *simulation-assisted test method*.

In this test method, the virtual building system (i.e., dynamic simulation platform) representing the real building and its central air-conditioning system is used to produce the online operation data (i.e., status data), while the package of the control strategy is computed in another separate platform, as the control optimizer. For a given working condition, the control optimizer identifies the necessary control settings according to the online operation data collected from the virtual building system. These control settings are then used to achieve energy efficient control and operation of the virtual building system. The data exchanger (i.e., status data and control settings) between the virtual building system and the control optimizer are managed by a management and communication platform based on IBmanager (intelligent building integration and management system) via an interface. The control strategy is computed by the application program of Matlab (2005) and compiled as a DLL (dynamic link library) module invoked by IBmanager. For in-situ implementation, the virtual building system will be replaced by the real building, and the package of the control strategy will communicate with the BAS by means of this management and communication platform through a proper interface, i.e., BACnet driver, OPC or XML driver, etc.

The major characteristic of this test method is that the control strategy is tested in a simulated virtual environment similar to the situation when it is actually implemented in practice. After the most promising strategy identified by using this method, the package of the control strategy and the management and communication platform can be implemented in practice directly without requiring any additional modification. During the tests, the pre-generated yearly cooling loads of each individual zone and weather data, including air wet-bulb temperature and air dry-bulb temperature, which represent the working conditions of the air-conditioning system, can be provided via a data file for the virtual building system.

The detailed information of the management and communication platform and the programming of the control strategy will be described in Chapter 9 “In-Situ Implementation of Online Control Software”.

This test method will be used to test the performances of optimal control strategies for variable speed pumps developed in Chapter 6 and the performance of the optimal control strategy for the central chilled water system developed in Chapter 8 since the openings of all water control valves need to be continuously monitored to validate these strategies.

4.3 Computation-assisted Test Method

In the *computation-assisted test method*, the control strategy is computed by the application program of Matlab. The application program can be easily complied as a DLL module to be invoked by IBmanager and, therefore, can be easily implemented in practice using the same way for implementing the strategies tested by using the *simulation-assisted test method*, as presented in Section 4.2.

The methodology involved in this test method is very simple and straightforward. In this method, different control strategies are tested under the same computation environment and their performances are compared with each other. The best strategy can then be identified among the selected strategies in terms of certain criteria, i.e., energy performance, control accuracy, computation performance, etc.

This test method will be used to test the performance of the online optimal control strategy for the central condenser cooling water system developed in Chapter 7.

4.4 Summary

This chapter presents two methods (i.e., *simulation-assisted test method* and *computation-assisted test method*) that will be used to test and evaluate the performances of the online control strategies developed in this thesis, prior to site implementation. In both test methods, the control strategies are computed by the application program of Matlab. The application programs can be implemented in practice by means of a management and communication platform based on IBmanager via an interface. In the *simulation-assisted test method*, the control strategies are tested in a simulated virtual environment similar to the situation that they are actually implemented in practice. The data exchanger between the simulated virtual environment and the package of the control strategy are supported by the management and communication platform via a proper interface. In the *computation-assisted test method*, different control strategies are tested under the same computation environment and their energy and computation performances are compared with each other in order to identify the best strategy that can satisfy the requirements and constraints of the particular application.

The *simulation-assisted test method* is mainly used to test the performances of control strategies for pumps and for chilled water systems since both strategies require online opening signals of control valves to predict the optimal settings. The *computation-assisted test method* is mainly used to test the performance of the control strategy for condenser cooling water systems since this strategy only requires weather data and building cooling loads as the forcing variables to predict the optimal settings.

CHAPTER 5 SIMPLIFIED MODELS OF MAJOR CHILLING SYSTEM COMPONENTS FOR ONLINE APPLICATIONS

As discussed in Chapter 2, the model-based supervisory and optimal control strategies are widely used to optimize the operation of HVAC systems. In a model-based control strategy, the system/component models are essential for the control system to predict the system performances under different control settings and ever-changing wording conditions.

In this chapter, simplified models of major chilling system components, i.e., chillers, cooling towers, pumps, heat exchangers, etc., are developed or selected. These models will be used to formulate the online supervisory and optimal control strategies presented in Chapters 6-8. The performances of these models were validated using the field measurement data, and/or the factory performance test data, and/or the catalogue data provided by the manufacturers. To formulate the optimal control strategy for complex chilled water systems, a water network pressure drop model and a pressure differential set-point incremental model are also developed in this chapter.

Section 5.1 presents the need of simplified models for online control applications. Sections 5.2 and 5.3 present simplified models of chillers and cooling towers, respectively. The performance of the simplified chiller model was validated by both the field measurement data and the factory performance test data for the centrifugal chillers with different capacities, while the performance of the cooling tower model was validated using the factory performance test data. The computation performance and calibration effort as well as convergence associated with the application of both models for the online control were also evaluated in both sections. Sections 5.4 and 5.5 present simplified models of heat exchangers and variable speed pumps, respectively. Both models were validated using the catalogue data provide by the manufacturers. The issues, i.e., computational cost, convergence, etc., related to their online applications, were evaluated as well. A water network pressure drop model and a pressure differential set-point incremental model for chilled water systems are developed in Sections 5.6 and 5.7, respectively. A summary of this chapter is given in Section 5.8.

5.1 Why Are Simplified Models Needed?

As discussed in Chapter 2, for online control applications, detailed physical models and purely data-driven models are not the proper choice. In general, purely data-driven models cannot always ensure the stable performance prediction although they are simple. Detailed physical models always require high computational costs and memory demands as well as a lot of iterations, which may seriously prevent their online applications, although they are effective. For online applications, the models utilized in the control system should preferably have simplified structures with certain physical significance to ensure the stable performance prediction and acceptable accuracy over a wide range of operation conditions. The models should also require less training or calibration efforts with readily or easily available operation data, less computational costs and memory demands. According to these criteria, simplified models might be the proper choice for online control applications. Therefore, the development and/or selection of the effective simplified models for major chilling system components are needed in order to formulate the online model-based supervisory and optimal control strategies for central chilling systems.

5.2 Chiller Model

5.2.1 Model Development

As shown in Figure 5.1, a typical chiller refrigeration system includes four necessary processes, i.e., the heat absorption in the evaporator, the refrigerant compression in the compressor, the heat rejection in the condenser and the refrigerant throttling in the expansion device. The chilled water is circulated between the chiller evaporator and air-conditioning terminal units forced by the chilled water pumps to provide the adequate cooling energy for buildings. The condenser transfers the indoor cooling load and the heat generated by the chiller compressor into the cooling water. The heat absorbed by the cooling water is rejected to the ambient air by means of cooling towers or to the natural resources (i.e., sea water, river, canal, etc.) by means of heat exchangers.

To develop the simplified chiller model, a fictitious refrigeration cycle (1'-2'-3'-4'), as shown in Figure 5.2, is assumed to simplify these complicated thermodynamic processes occurring in the refrigeration system. The major assumptions employed to derive the basic modeling equations are summarized as follows:

- The heat rejected in the condenser equals the sum of the evaporator cooling energy and the chiller power input;
- The refrigerant is throttled through the expansion device isenthalpically;
- The refrigerant leaves the evaporator as saturated vapor at the evaporating temperature;
- The refrigerant leaves the condenser as saturated liquid at the condensing temperature;
- A fictitious point (2') is assumed as saturated vapor at the condensing temperature.

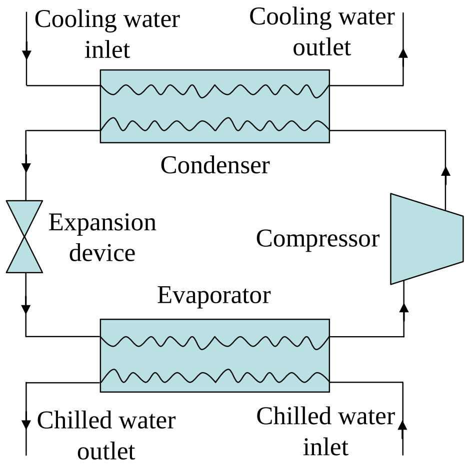

Figure 5.1 Schematic of the typical chiller refrigeration system.

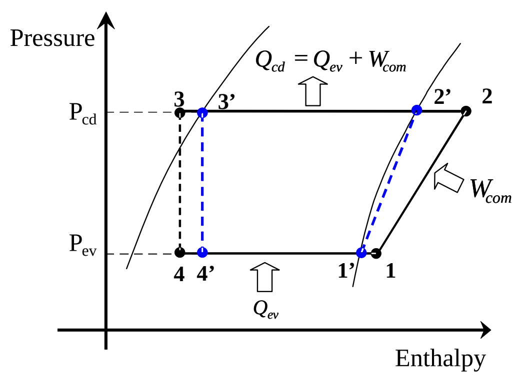

Figure 5.2 Schematic of the pressure-enthalpy diagram
(actual cycle: 1-2-3-4; fictitious cycle: 1'-2'-3'-4').

The evaporator and condenser are simulated using the classical heat exchanger efficiency method. The overall heat transfer coefficients of the evaporator and condenser (UA_{ev}, UA_{cd}) are represented as in Equations (5.1) and (5.2), respectively (Wang et al. 2000). The fictitious refrigerant mass flow rate ($M_{ref,fic}$) is calculated as in Equation (5.3), which is based on the evaporator cooling energy (Q_{ev}) and the enthalpy difference between the point 1' and point 3' in the fictitious refrigeration cycle. The fictitious power (W_{fic}), as in Equation (5.4), is the product of the fictitious refrigerant mass flow rate and the enthalpy difference between the point 2' and point 1' in the fictitious refrigeration cycle. The enthalpy of each point is calculated on the basis of the condensing temperature and evaporating temperature. The condensing temperature and evaporating temperature are determined by the inlet water temperatures and water mass flow rates in the condenser and evaporator together with the evaporator cooling energy by an iterative manner. A second-order polynomial, as shown in Equation (5.5), is used to characterize the relationship between the actual chiller power consumption (W_{com}) and the fictitious power consumption (W_{fic}).

$$C_1 M_{w,ev}{}^{-0.8} + C_2 Q_{ev}{}^{-0.745} + C_3 = \frac{1}{UA_{ev}} \tag{5.1}$$

$$C_4 M_{w,cd}{}^{-0.8} + C_5 (Q_{ev} + W_{com})^{1/3} + C_6 = \frac{1}{UA_{cd}} \tag{5.2}$$

$$M_{ref,fic} = \frac{Q_{ev}}{h_1' - h_3'} \tag{5.3}$$

$$W_{fic} = M_{ref,fic} \cdot \left(h_2' - h_1'\right) \tag{5.4}$$

$$W_{com} = a_0 + a_1 W_{fic} + a_2 W_{fic}^2 \tag{5.5}$$

where M is the mass flow rate, Q is the heat transfer rate, h is the enthalpy, C_1-C_6 and a_0-a_2 are coefficients, and subscripts *w*, *ev*, *cd*, *com*, *ref*, and *fic* represent water, evaporator, condenser, compressor, refrigerant and fictitious, respectively.

Using chiller normal operation data, the model parameters can be identified easily. The overall heat transfer coefficients of the evaporator and condenser are calculated using the calculated evaporator cooling energy and measured chiller power consumption together with the calculated evaporator and condenser logarithmic mean temperature differences. The coefficients of C_1-C_6 can then be identified using the measured water flow rates, calculated evaporator cooling energy and measured chiller power consumption together with the calculated overall heat transfer coefficients. The coefficients of a_0-a_2 can be regressed using the calculated fictitious power consumption (W_{fic}) and measured actual chiller power consumption (W_{com}). After the model parameters are identified, the power consumption of the chiller at any given working condition can be predicted easily using the above equations.

5.2.2 Model Validation

The performance of this simplified chiller model was validated by using both the field measurement data and the factory performance test data. The chiller field measurement data were collected during 78 days from 1 July 2005 to 16 September 2005 in an office building in Hong Kong. The sampling interval is one hour. All of the collected data were divided into two groups: one as the training data for the model training (i.e., parameter identification) and the other as the validation data for the model validation. The identified parameters using the training data are given as follows: C_1=-0.0243, C_2=0.6711, C_3=0.0005, C_4=0.2230, C_5=0.0, C_6=-0.0025, a_0=192.2716, a_1=0.3687, a_2=0.0006. Figure 5.3 presents the comparison between the model predicted power consumptions and measured power consumptions using the validation data. It can be observed that the model predicted power consumptions excellently agreed with the measurements for most of operation points. The power consumption deviations from the model prediction for most of operation points were within ±10.0% which is acceptable for online control applications.

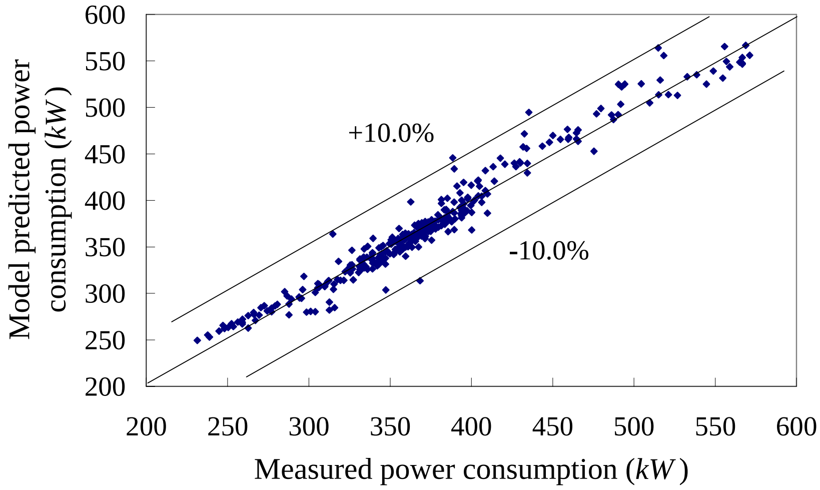

Figure 5.3 Comparison between the model predicted and measured power consumptions using the field measurement data.

The performance of this simplified chiller model was compared with the universal NG model (Gordon and Ng 2001), as shown in Equation (5.6), using the same training and validation data sets of the field measurement data. Figure 5.4 is the comparison of the model predicted and measured power consumptions of the NG model using the validation data. By comparing between Figure 5.3 and Figure5.4， it can be found that the simplified chiller model developed has the same performance in prediction as the NG model.

$$\left(\frac{1}{COP}+1\right)\frac{T_{ch,i}}{T_{cd,i}}-1=a_1\frac{T_{ch,i}}{Q_{ev}}+a_2\frac{(T_{cd,i}-T_{ch,i})}{T_{cd,i}Q_{ev}}+a_3\frac{\left(\frac{1}{COP}+1\right)Q_{ev}}{T_{cd,i}} \tag{5.6}$$

where COP is the coefficient of performance.

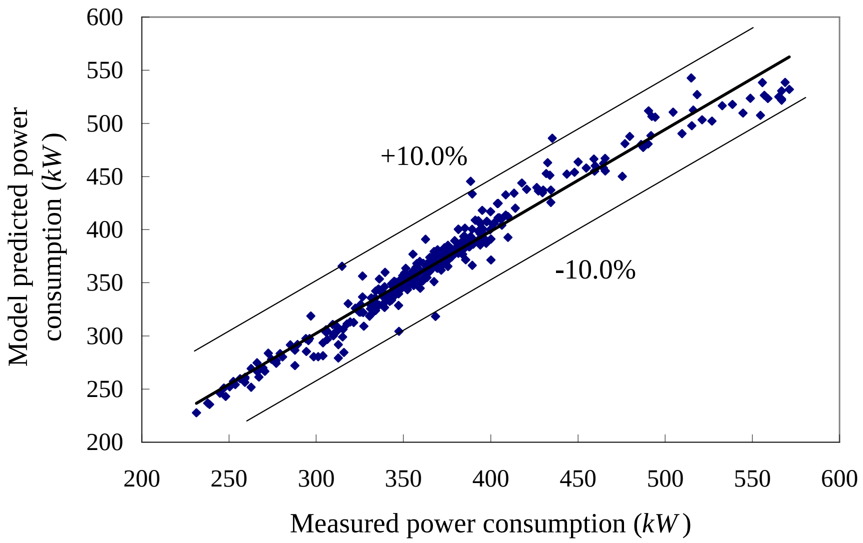

Figure 5.4 Comparison between the model predicted and measured power consumptions of the NG model.

The performance of this simplified chiller model was further validated using the factory performance test data provided by the chiller manufacturer for the super-huge chillers utilized in the building presented in Chapter 3. A part of the factory performance test data was used to train the model, resulting in the identified parameters as follows: C_1=0.0, C_2=0.0325, C_3=0.0003, C_4=0.0, C_5=0.0, C_6=0.0001, a_0=557.2680, a_1=0.4071, a_2=0.0001. The comparison of the model predicted power consumptions with the measured power consumptions using the rest of the factory performance test data is shown in Figure 5.5. The good agreement also can be found in the comparisons, which demonstrates that this simplified chiller model has satisfactory performance in prediction.

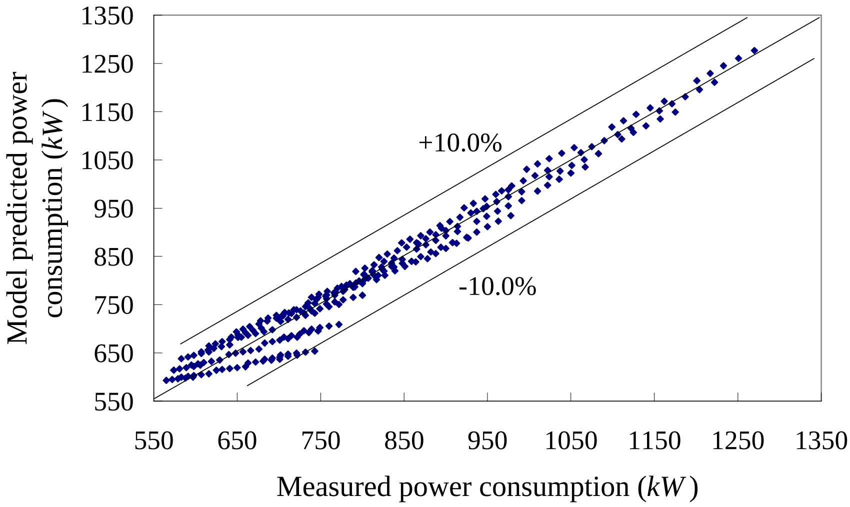

Figure 5.5 Comparisons between the model predicted and measured power consumptions using the factory performance test data.

5.2.3 Computation Performance, Calibration Effort and Convergence

The computational cost and memory demand are among the critical issues for models utilized for online control applications. It is therefore essential and necessary to evaluate the computation performance of the simplified chiller model developed before it is used to design the online supervisory and optimal control strategies.

The computational cost of this simplified chiller model was tested in the Matlab environment. The test result was evaluated by comparing with that of a detailed physical model developed by Wang et al. (2000), which has been presented in Section 3.2.2.1. The computer configurations used in the test are described as follows. The operation system is the Microsoft windows XP professional, the processor is the Intel(R) Pentium(R) 4 CPU 3.20GHz (2 CPUs) and the memory is 2040MB RAM.

The average computational costs of this simplified model and the detailed physical model for the performance prediction were 3.766 ms and 16.668 ms, respectively. It is noted that this simplified chiller model can save significantly more computational cost (77.41%) than the detailed physical model. Although the computational cost required by a single model is relatively low, there are always many models involved in the control system, and the optimization algorithm is also integrated together, which may significantly increase the computational cost.

The calibration or training effort is another critical issue that needs to be addressed when using the models for online control applications. The parameter identification of the detailed physical model developed by Wang et al. (2000) requires a considerable amount of the chiller performance data at the full load condition, and it is always very difficult to obtain these performance data in the site. However, the parameter identification of this simplified model only requires the chiller performance data at normal operating conditions, and the calibration effort is therefore reduced greatly.

The convergence is also very important for models applied for online control applications. When the iterative process is required by models for the performance prediction, the convergence problem may occur at some cases, which may result in the control instability and divergence. This is the main weakness of the models requiring iterations, particularly a lot of iterations, for real-time applications. Compared with the detailed model developed by Wang et al. (2000) which often requires 10-15 iterations, this simplified model only requires 2-3 iterations. If the condensing temperature and evaporating temperature can be available from the BAS directly, this simplified chiller model can be further simplified and the iterative process can be eliminated.

According to the above results, it can be concluded that this simplified chiller model has satisfactory performance in prediction and its computational cost is manageable. This model is easy to be trained and converged as well. All these characteristics make it suitable for online control applications.

5.3 Cooling Tower Model

5.3.1. Model Development

The energy dissipation within a direct-contact evaporative cooling tower is realized by a combination of the heat and mass transfer. For the simplified modeling of the cooling tower, the classical assumptions as presented by Lebrun and Silva (2002) are used as follows: (1) the air and water vapor are assumed to behave as the fictitious perfect gases; (2) the interfacial air film is assumed to be saturated; (3) the effect of the water loss due to the evaporation is neglected; (4) Lewis number is equal to one; (5) the temperature of the thin film between the water and air equals the water temperature; (6) the moist air enthalpy is assumed to be fully dominated by its wet-bulb temperature. In addition, the minimum capacity flow rate is assumed on the air side.

The conceptual schematic of the cooling tower modeling is illustrated in Figure 5.6, in which the cooling tower was modeled as an equivalent heat exchanger.

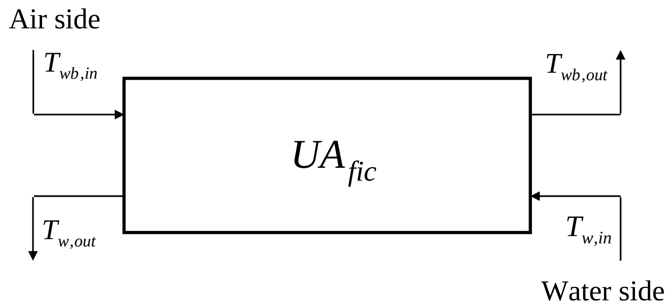

Figure 5.6 Conceptual schematic of the cooling tower.

In terms of the fundamental laws of heat and mass transfer phenomena occurring in the cooling tower, the energy balance equations applied to the air side and water side result in Equations (5.7) and (5.8), respectively. The heat transfer rate between the water and air can be simulated as in Equation (5.9) using a fictitious heat transfer effectiveness. The effectiveness of the equivalent heat exchanger is computed using Equations (3.28) and (3.29) presented in Chapter 3 for the counter flow and crossover flow heat exchangers, respectively. The fictitious number of transfer units (NTU_{fic}) and the fictitious heat transfer coefficients (UA_{fic}) of the equivalent heat exchanger are defined as in Equations (5.10) and (5.11), respectively. The capacity flow rate ratio (ω) is computed using Equation (5.12) according to the additional assumption.

$$Q = M_a \cdot (h_{a,out} - h_{a,in}) \tag{5.7}$$

$$Q = M_w \cdot c_{p,w} \cdot (T_{w,in} - T_{w,out}) \tag{5.8}$$

$$Q = \varepsilon_{fic} \cdot C_{\min} \cdot (T_{w,in} - T_{wb,in}) \tag{5.9}$$

$$NTU_{fic} = \frac{UA_{fic}}{C_{\min}} \tag{5.10}$$

$$UA_{fic} = \frac{c_{p,a,fic}}{c_{p,a}} \cdot UA_{des} \cdot \left(\frac{M_w}{M_{w,des}} \right)^m \cdot \left(\frac{M_a}{M_{a,des}} \right)^n \tag{5.11}$$

$$\omega = \frac{C_{\min}}{C_{\max}} = \frac{M_a \cdot c_{p,a,fic}}{M_w \cdot c_{p,w}} \tag{5.12}$$

where h and T are the enthalpy and temperature, respectively, C is the capacity flow rate, c is the specific heat, m and n are indexes, and subscripts w, a, p, in, out, wb, des and fic indicate water, air, pressure, inlet, outlet, wet-bulb, design and fictitious, respectively.

The moist air enthalpy (h_a) can be expressed by a third-order polynomial as in Equation (5.13) in terms of the web-bulb temperature according to the assumption (6). Since the outlet status in the cooling tower is strongly dependent on the four inlet parameters (M_a, M_w, $T_{w,in}$, $T_{wb,in}$), the air average fictitious specific heat ($c_{p,a,fic}$) is simplified as a function of the air mass flow rate (M_a), water mass flow rate (M_w) and the difference between the inlet water temperature and inlet air wet-bulb temperature ($T_{w,in}$-$T_{wb,in}$), as shown in Equation (5.14).

$$h_a = d_0 + d_1 T_{wb} + d_2 T_{wb}^{\ 2} + d_3 T_{wb}^{\ 3} \tag{5.13}$$

$$c_{p,a,fic} = \frac{h_{a,out} - h_{a,in}}{T_{wb,out} - T_{wb,in}} = f_0\left(M_a, M_w, (T_{w,in} - T_{wb,in})\right) \tag{5.14}$$

where f is the function, d_0-d_3 are polynomial coefficients, dependent on the value of the atmospheric pressure.

The fictitious number of transfer units (NTU_{fic}) in Equation (5.10) can be derived as a function of M_a and M_w as in Equation (5.15) since the values of UA_{des}, $M_{w,des}$ and $M_{a,des}$ are constant at the design condition and the moist air specific heat ($c_{p,a}$) can be considered as a constant. Since $c_{p,a,fic}$ is a function of M_a, M_w and ($T_{w,in}$-$T_{wb,in}$), and the water specific heat ($c_{p,w}$) can be considered constant, the capacity flow rate ratio (ω) as in Equation (5.12) is also a function of M_a, M_w and ($T_{w,in}$-$T_{wb,in}$) as in Equation (5.16).

$$NTU_{fic} = \frac{UA_{fic}}{C_{\min}} = \frac{UA_{des}}{M_a \cdot c_{p,a}} \cdot \left(\frac{M_w}{M_{w,des}} \right)^m \cdot \left(\frac{M_a}{M_{a,des}} \right)^n = f_1\left(M_a, M_w\right) \tag{5.15}$$

$$\omega = f_2\left(M_a, M_w, (T_{w,in} - T_{wb,in})\right) \tag{5.16}$$

The heat transfer effectiveness of the equivalent heat exchanger in Equations (3.28) and (3.29) can be considered as a function of the fictitious number of transfer units (NTU_{fic}) and the capacity flow rate ratio (ω). Since ω is a function of M_a, M_w and ($T_{w,in}$-$T_{wb,in}$) and NTU_{fic} is a function of M_a and M_w, the fictitious heat transfer effectiveness (ε_{fic}) is still a function of M_a, M_w and ($T_{w,in}$-$T_{wb,in}$), as shown in Equation (5.17). The heat transfer rate between the water and air as expressed in Equation (5.9) can then be further simplified as in Equation (5.18) since both ε_{fic} and $c_{p,a,fic}$ are functions of M_a, M_w and ($T_{w,in}$-$T_{wb,in}$).

$$\varepsilon_{fic} = f_3(NTU_{fic}, \omega) = f_4\left(M_a, M_w, (T_{w,in} - T_{wb,in})\right) \tag{5.17}$$

$$Q = \varepsilon_{fic} \cdot M_a \cdot c_{p,a,fic} \cdot (T_{w,in} - T_{wb,in}) = f_5\left(M_a, M_w, (T_{w,in} - T_{wb,in})\right) \tag{5.18}$$

For practical applications, the heat rejection as in Equation (5.18) can be re-written in the form of Equation (5.19) approximately. This is the final form of the cooling tower model. For the application of this model, the critical issue is to identify these four parameters (b_{01}-b_{04}). They can be regressed easily using the calculated heat rejections, measured air and water mass flow rates together with the measured inlet water and ambient air wet-bulb temperatures.

For the online predictive control, this model can be easily reformed as in Equation (5.20) to predict the required air flow rate that can control the system to operate at an identified optimal condenser water supply temperature set-point. The fan operating frequency (*Freq*) and power consumption (W_{ct}) can then be predicted using the empirical formulas as in Equations (5.21) and (5.22), respectively. The coefficients in these equations can also be easily regressed using the field measurement data together with the design data.

$$Q = b_{01} \cdot (M_a)^{b_{02}} \cdot (M_b)^{b_{03}} \cdot (T_{w,in} - T_{wb,in})^{b_{04}} \tag{5.19}$$

$$M_a = b_{11} \cdot Q^{b_{12}} \cdot (M_w)^{b_{13}} \cdot (T_{w,in} - T_{wb,in})^{b_{14}} \tag{5.20}$$

$$Freq = Freq_{des}\left[e_{01} + e_{02}\left(\frac{M_a}{M_{a,des}}\right) + e_{03}\left(\frac{M_a}{M_{a,des}}\right)^2\right] \tag{5.21}$$

$$W_{ct} = W_{ct,des}\left[e_{11} + e_{12}\left(\frac{M_a}{M_{a,des}}\right) + e_{13}\left(\frac{M_a}{M_{a,des}}\right)^2\right] \tag{5.22}$$

where b_{01}-b_{04}, b_{11}-b_{14}, e_{01}-e_{03} and e_{11}-e_{13} are coefficients.

5.3.2 Description of the Factory Performance Test

The performance test of a 1/4 cell of the CTA tower described in Chapter 3 was conducted in the thermal test laboratory of the manufacturer factory in separate 8 days from the later August to the middle September 2006 in Shenzhen, China, whose climate is similar to that of Hong Kong. The schematic diagram of the cooling tower test bench is illustrated in Figure 5.7. This test bench consists of two circuits: the hot water generating circuit and the cooling water circuit. Three boilers are used to provide the heating source for the heat exchanger. Each boiler is correlated with a variable speed pump. In the cooling water circuit, the water circulation is forced by two variable speed pumps. The heat absorbed by the cooling water from the heat exchanger is rejected to the ambient air by means of the heat and mass transfer in the cooling tower. Three boilers are controlled to provide a constant heat rejection in the cooling tower under a given test condition.

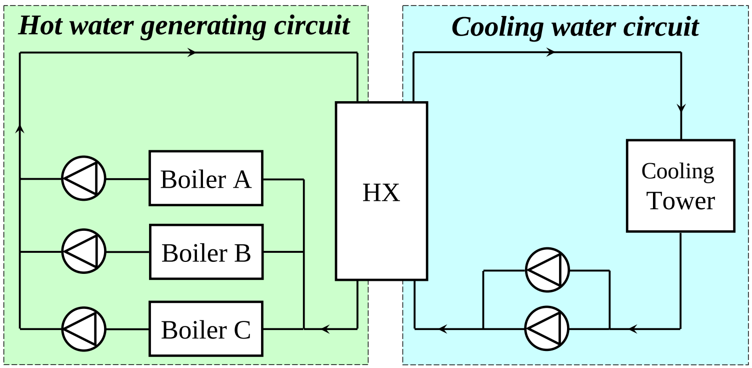

Figure 5.7 Schematic diagram of the cooling tower test bench.

A rendering of the 1/4 cell of the experimental CTA tower is illustrated in Figure 5.8. This cooling tower consists of six important parts, including the water distribution basin, fill packing, cold water collecting basin, axial fan, air plenum and silencer. The warmed water to be cooled falls freely down to the fill packing from the water distribution basin located on the top of the cooling tower. The water exchanges the heat and mass in the fill packing with the ambient air inhaled by the huge axial fan. In this process, the warmed water is cooled down and collected in the cold water collecting basin, while the inhaled air is heated to almost saturated state and exhausted finally after flowing through the air plenum and silencer. The air plenum is used to distribute the warmed air uniformly before entering into the silencer, while the silencer is installed to abate the noise of the outlet air to meet the noise requirement of the surrounding atmosphere.

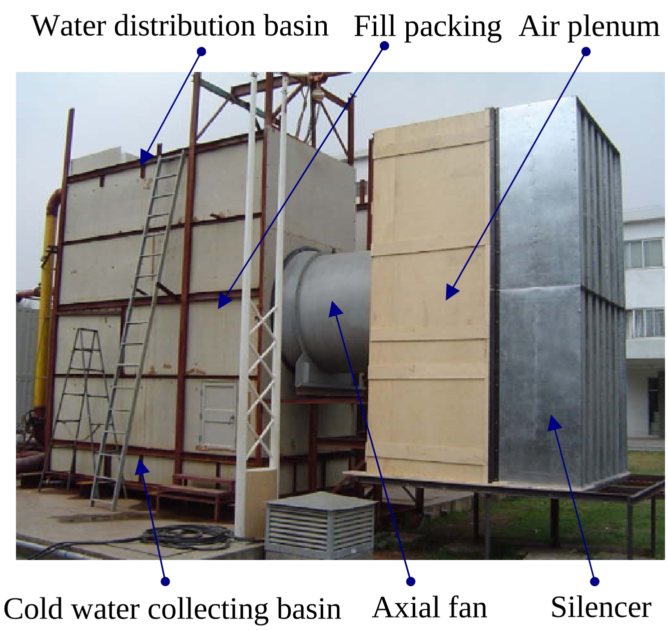

Figure 5.8 A rendering of the experimental CTA tower.

The instrumentations used in the test are presented schematically in Figure 5.9. The main measurements include: the inlet water temperature, outlet water temperature, outdoor air wet-bulb temperature, outdoor air dry-bulb temperature, water flow rate, air flow rate, fan power consumption and the pressures at the inlet and outlet sides of the axial fan.

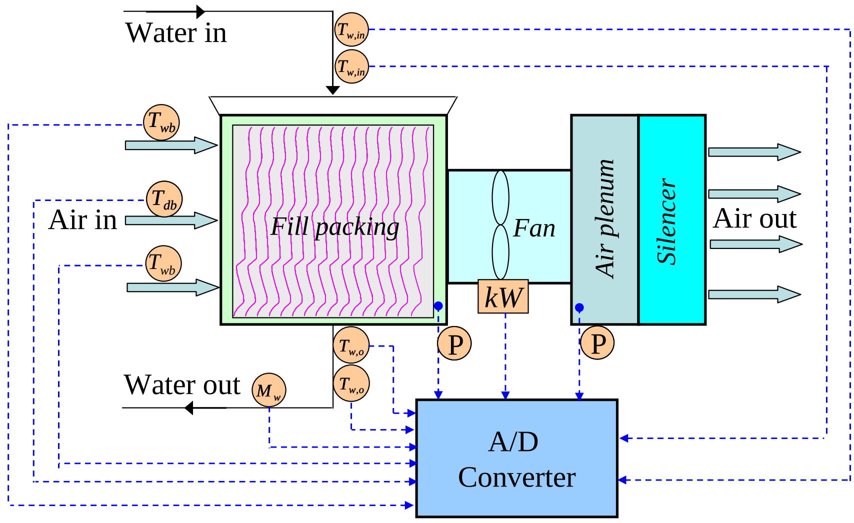

Figure 5.9 Main measurements used in the factory performance test.

The temperatures were measured using the platinum resistance thermometers. Since the inlet and outlet water temperatures as well as the outdoor air wet-bulb temperature have significant impacts on the outlet status of the cooling tower, double thermometers were installed for these measurements respectively, to reduce the random noise on the measurements by using their average values. The pressures were measured by the pressure transducers to evaluate the performance and characteristics of the axial fan. The water flow rate through the cooling tower was measured by a magnetic flow transducer installed at the outlet water pipeline of the cooling tower. The water loss due to the evaporation was ignored when evaluating the thermal performance of the cooling tower. The power consumption of the axial fan was measured using a power transducer. All of these sensors and transducers were connected to an A/D converter. The air inlet surface of the cooling tower was divided into 180 grids with the same area and the air velocity flowing through each grid was measured using a portable hot wire anemometer. The total air flow rate was calculated by the product of the average measured air velocity and the inlet air surface area.

5.3.3 Model Validation

The performance of this simplified cooling tower model was validated using the data collected from the factory performance test. All of the testing data were divided into two groups. One group as the training data was used to train the model and the other group as the validation data was used to validate the model effectiveness.

The standard least-square regression method was used to identify the model parameters directly after the logarithmic transformation was applied to Equation (5.19). The identified parameters are as follows: b_{01}=3.326, b_{02}=0.2278, b_{03}=0.6716, b_{04}=1.0663. Figure 5.10 presents the comparison between the model predicted heat rejections and 'measured' heat rejections using the validation data. The 'measured' heat rejection was calculated using the measured water mass flow rate and the temperature difference between the measured inlet and outlet water temperatures. The validation results show that the model predicted heat rejections agreed well with the 'measured' heat rejections for all operation points. The deviations due to the model prediction were within ±6.9% which is tolerable for online control applications.

After the heat rejection was predicted using the trained cooling tower model, the outlet water temperature of the cooling tower can be computed using the energy balance equation as expressed in Equation (5.8). The comparison of the model predicted outlet water temperatures with the measurements is presented in Figure 5.11.

The good agreement can also be observed. The deviations from the predictions of this model were within ±1.0%.

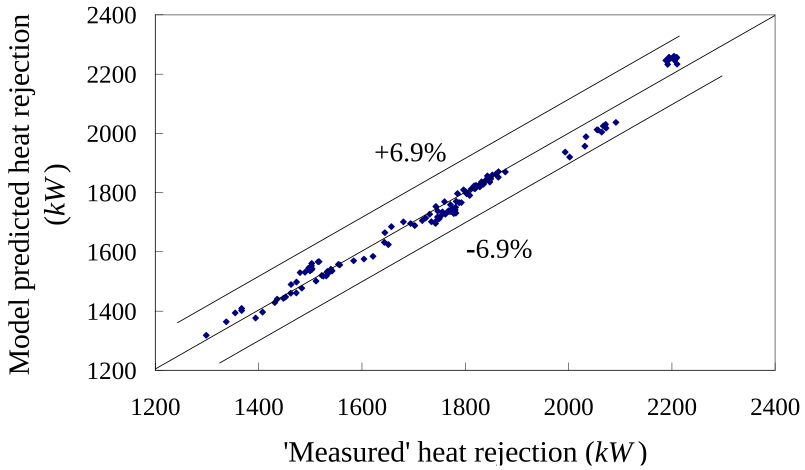

Figure 5.10 Comparison between the model predicted and 'measured' heat rejections using the validation data.

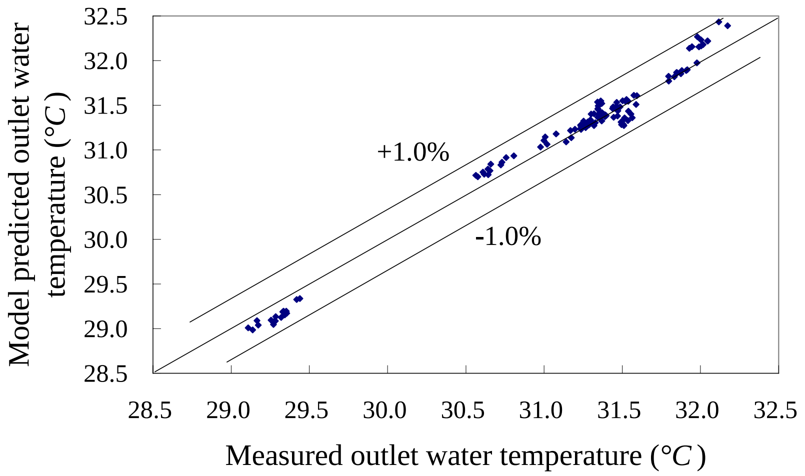

Figure 5.11 Comparison of the model predicted and measured outlet water temperatures of the cooling tower.

It is noted that the changing range of the outlet water temperatures presented in Figure 5.11 was relatively narrow due to the narrow changing range of the outdoor weather conditions during the test period. In fact, it is practically unfeasible that the test can cover all conditions for one whole year operation of the cooling tower due to the high cost of the factory performance test.

5.3.4 Computation Performance, Calibration Effort and Convergence

The computation performance of this simplified cooling tower model was tested on the same computer as described in Section 5.2.3 under the Matlab environment. The test result was compared with that of the so-called “Toolkit model” (Lebrun et al. 1999). In the “Toolkit model”, the energy balances on the air side and water side are computed using Equations (5.7) and (5.8), respectively. The heat transfer between the water and air is simulated using Equation (5.9). Since both the air flow rate and water flow rate flowing through cooling towers can be varied, the number of transfer unit (NTU) is modified and computed using Equation (5.23). The water temperature leaving cooling towers can be calculated through the energy balance on the water side.

$$NUT = b_0 (M_w / M_a)^{b_1} \tag{5.23}$$

The average computational cost of this simplified cooling tower model for the performance prediction was 0.141 ms, while the average computational cost of the so-called “Toolkit model” was 0.199 ms. Compared to the so-called “Toolkit model”, about 29.15% computational cost can be saved when this simplified model is used.

The calibration process and performance prediction of this simplified cooling tower model are straightforward and very simple, and no iterative process is required. These features are extremely important for real-time control and optimization. However, the parameter identification and performance prediction of the so-called “Toolkit model” require a lot of iterations, and the convergence is not always guaranteed. In the so-called “Toolkit model”, the outlet variables were obtained in an iterative manner by initially assuming a temperature difference of 5 K between the inlet and outlet air wet-bulb temperatures.

According to the above results, it can be concluded that this simplified cooling tower model is suitable for online control applications in terms of the prediction performance, computation performance, calibration effort, etc.

It is worthy noticing that the AHU coil can also be modeled as an equivalent heat exchanger. Therefore, this cooling tower model can be adapted to predict the outlet status of the air and water leaving AHU coils.

5.4 Heat Exchanger Model

In some central chilling systems, the water-to-water heat exchanger is used to transfer the cooling energy from low zones to high zones to avoid the high water static pressure, or used to transfer the heat absorbed by the cooling water from the chiller condenser to nature resources, etc. The model of the water-to-water heat exchanger is used to predict the outlet water temperatures in both sides of the heat exchanger under various conditions. In this study, the classical ε-*NTU* method was used to model the performance of the heat exchanger (Wang 1998). The basic modeling equations used were similar to that presented in Section 5.3.1 for the modeling of the cooling tower (i.e., the equivalent heat exchanger), and most of the modeling equations are therefore not provided here. The actual heat transfer rate in the heat exchanger can be computed using Equation (5.24). The overall heat transfer coefficient is modified and simulated as in Equation (5.25). The capacity flow rate ratio (ω) is computed using Equation

(5.26). The outlet water temperatures of both sides of heat exchangers can be calculated through the use of the energy balance equation.

$$Q = \varepsilon \cdot C_{\min} \cdot (T_{h,w,in} - T_{c,w,in}) \tag{5.24}$$

$$UA = UA_{des} \cdot (\frac{M_{c,w}}{M_{c,w,des}})^{m} \cdot (\frac{M_{h,w}}{M_{h,w,des}})^{n} \tag{5.25}$$

$$\omega = \frac{C_{\min}}{C_{\max}} = \frac{\min(C_{c,w,}, C_{h,w})}{\max(C_{c,w}, C_{h,w})} \tag{5.26}$$

where $C_{c,w}$ and $C_{h,w}$ are the cold and hot water capacity flow rates, respectively, m and n are indexes, and subscripts c, h and in represent cold, hot and inlet, respectively.

In this model, there are three parameters (UA_{des}, m and n) required to be identified. The parameter of UA_{des} can be easily identified using the heat exchanger performance data at the design condition. The indexes of m and n can be regressed using the measured hot and cold water mass flow rates and calculated UA values at given conditions together with the identified parameter of UA_{des}. The UA value at any given condition can be calculated using the calculated logarithmic mean temperature difference and calculated heat transfer rate.

The performance of this heat exchanger model was validated using the catalogue data provided by the manufacturer for the counter flow plate heat exchangers used in the building presented in Chapter 3. The identified parameters for the heat exchangers in Zone 1 of that building are: UA_{des}=4072.5 kW/K, m=0.2675, n=0.2675. The comparison of the model predicted heat transfer rates with the measured heat transfer rates is illustrated in Figure 5.12. It can be seen clearly that the model predicted heat transfer rates agreed well with the measurements. This model is relatively simple and the computation time is manageable.

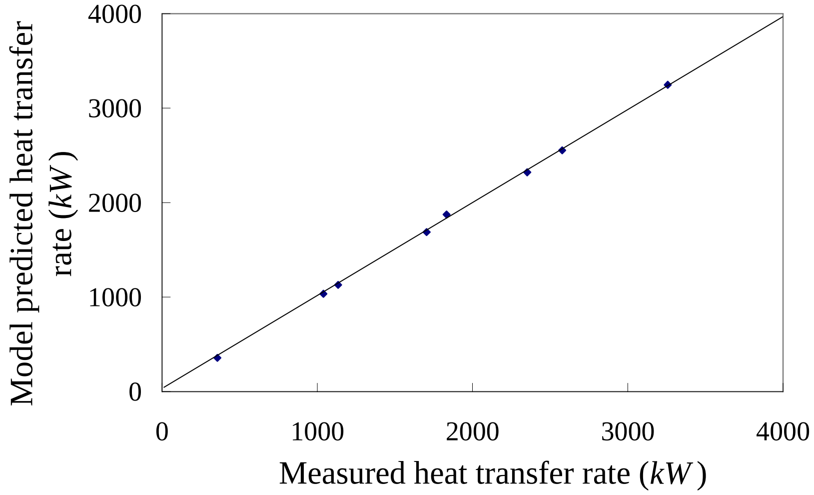

Figure 5.12 Comparison of the model predicted and measured heat transfer rates.

5.5 Variable Speed Pump Model

For variable speed pumps, the equipment efficiency, namely wire to water efficiency, is often used to characterize how much energy applied to a pump-motor-VFD set results in useful energy to deliver the water. As shown in Figure 5.13, a typical pump-motor-VFD set consists of three sub-efficiencies, including the pump efficiency (η_{pu}), motor efficiency (η_m) and VFD efficiency (η_v). These three sub-efficiencies should be included in the model of the variable speed pump.

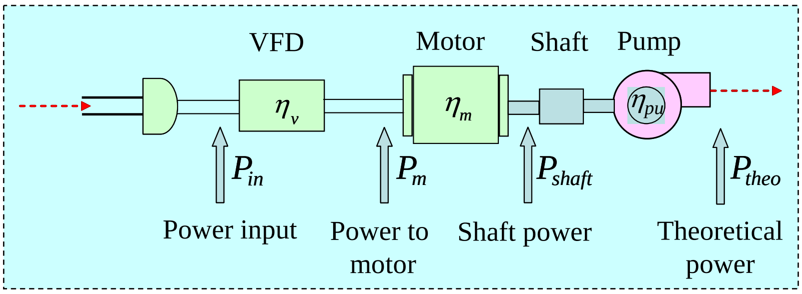

Figure 5.13 Schematics of the typical pump-motor-VFD set.

In this thesis, the performance of the variable speed pump is modeled using a series of polynomial approximations. They are comprised of polynomials representing head versus flow and speed, and efficiency versus flow and speed, as expressed in Equations (5.27) and (5.28), respectively. The head and efficiency characteristics are based on the manufacturers' data at the full speed operation and extended to the variable speed operation using the pump affinity laws (Bahnfleth and Peyer 2001, Bahnfleth et al. 2006). The motor efficiency (η_m) is modeled using Equation (5.29), which is a function of the fraction of the nameplate brake horsepower (Bernier and Bourret 1999). The VFD efficiency is modeled using Equation (5.30), which is a function of the fraction of the nominal speed (Bernier and Bourret 1999). The power input ($W_{pu,in}$) to a pump-motor-VFD set can be finally computed using Equation (5.31). The coefficients in these polynomials can be easily regressed using the pump performance data, the motor efficiency curve and VFD efficiency curve provided by the manufacturers.

$$H_{pu} = g_{01}M_w^2 + g_{02}\left(\frac{n}{n_0}\right)M_w + g_{03}\left(\frac{n}{n_0}\right)^2 \tag{5.27}$$

$$\eta_{pu} = g_{11}\left(\frac{n_0}{n}\right)^2 M_w^2 + g_{12}\left(\frac{n_0}{n}\right)M_w + g_{13} \tag{5.28}$$

$$\eta_m = g_{21}\left(1 - e^{g_{22}x}\right) \tag{5.29}$$

$$\eta_v = g_{31} + g_{32}x + g_{33}x^2 + g_{34}x^3 \tag{5.30}$$

$$W_{pu,in} = \frac{M_w \times H_{pu} \times SG}{102 \times \eta_v \times \eta_m \times \eta_{pu}} \tag{5.31}$$

where H is the pump head, n is the pump speed, SG is the specific gravity of the fluid being pumped (SG=1), x is the fraction of the nameplate brake horsepower or the nominal speed, g_{01}-g_{03}, g_{11}-g_{13}, g_{21}-g_{22} and g_{31}-g_{34} are coefficients, and subscripts *pu*, *m*, *v* and *in* represent pump, motor, VFD and input, respectively.

Figure 5.14 shows the motor efficiency and VFD efficiency curves along with the fraction of the nameplate brake horsepower/nominal speed. Figure 5.15 shows the sample of the pump catalogue data at the design speed.

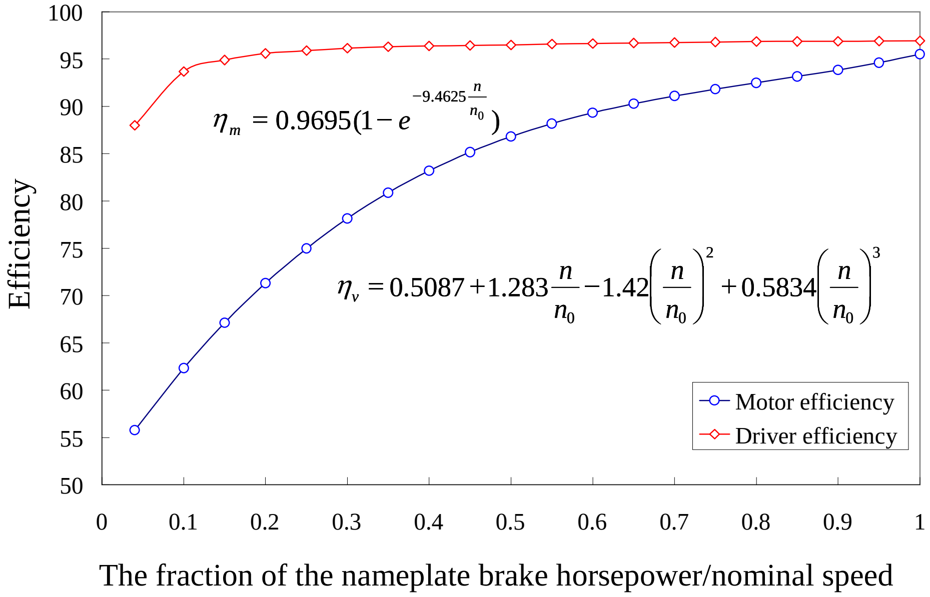

Figure 5.14 The samples of the motor and VFD efficiencies.

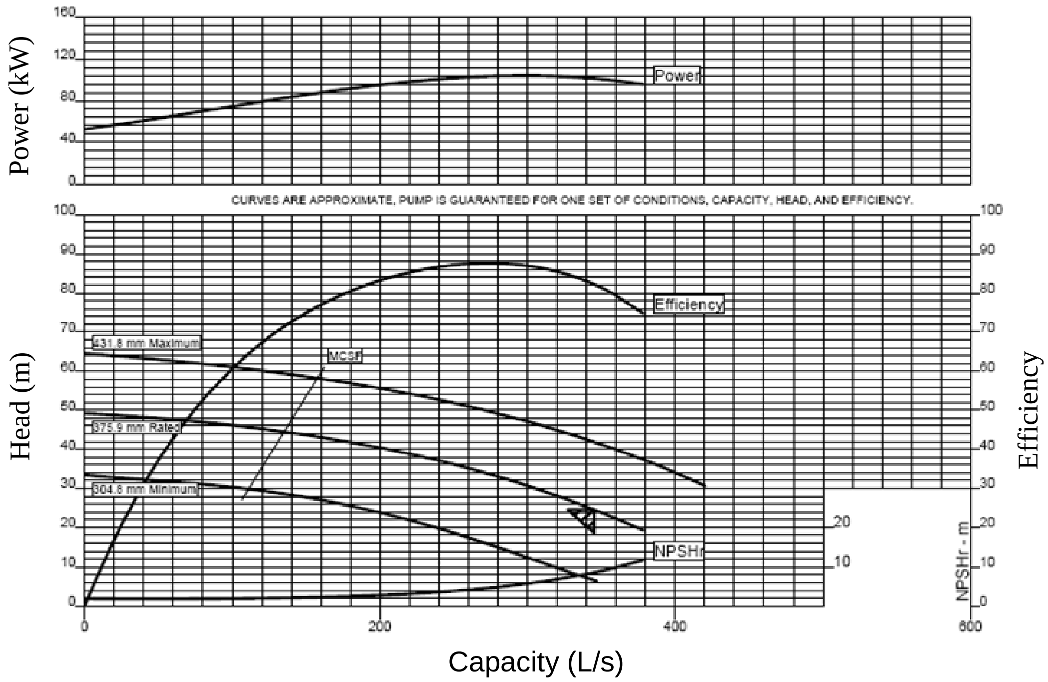

Figure 5.15 The sample of the pump catalogue data at the design speed.

The performance of this pump model was validated using the catalogue data provided by the manufacturer for the variable speed pumps utilized in the building presented in Chapter 3. The identified parameters for the pumps (SCHWP-06-01 to 02) in Zone 1 of that building are given as follows: g_{01}=-0.00020, g_{02}=-0.00173, g_{03}=48.48079, g_{11}=-0.00001, g_{12}=0.00615, g_{13}=0.08511, g_{21}=0.96950, g_{22}=-9.46250, g_{31}=0.50870, g_{32}=1.28300, g_{33}=-1.42000, g_{34}=0.58340.

Since the power consumption and efficiency of the pump under various operating speeds were not provided in the catalogue data, the model was therefore only validated in terms of the pump head. Figure 5.16 gives the validation results. The good agreement can be found in the comparisons, which demonstrates that this simplified pump model has acceptable performance to predict the pump head under various operating speeds. Since there is no iterative process involved in this model, the computational cost and memory demand are manageable.

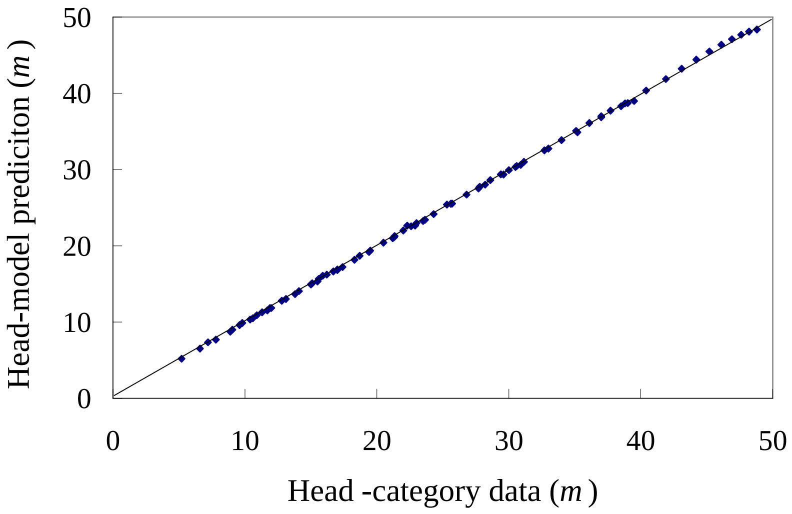

Figure 5.16 Comparison of the model predicted pump head with the head obtained from the catalogue data.

5.6 Water Network Pressure Drop Model

To develop the optimal control strategies for variable speed pumps in the secondary chilled water systems and the optimal control strategy for the entire chilled water systems, a water network pressure drop model that characters the pressure drop on each individual component in the system of concern is needed. For the water subsystems with different configurations, the water network pressure drop models will be significantly different. In the complex central chilling system presented in Chapter 3, the water subsystem of the secondary side of heat exchangers with pumps distributing water to terminal units would be the most complicated system, and the other water systems can be considered as the simplifications of such systems. Therefore, a water network pressure drop model for such systems is presented in the following in detail. Figure 5.17 illustrates the simplified structures of the water network pressure drop model for such systems with the reverse-return piping configuration, in which only 6 terminal units are illustrated for example.

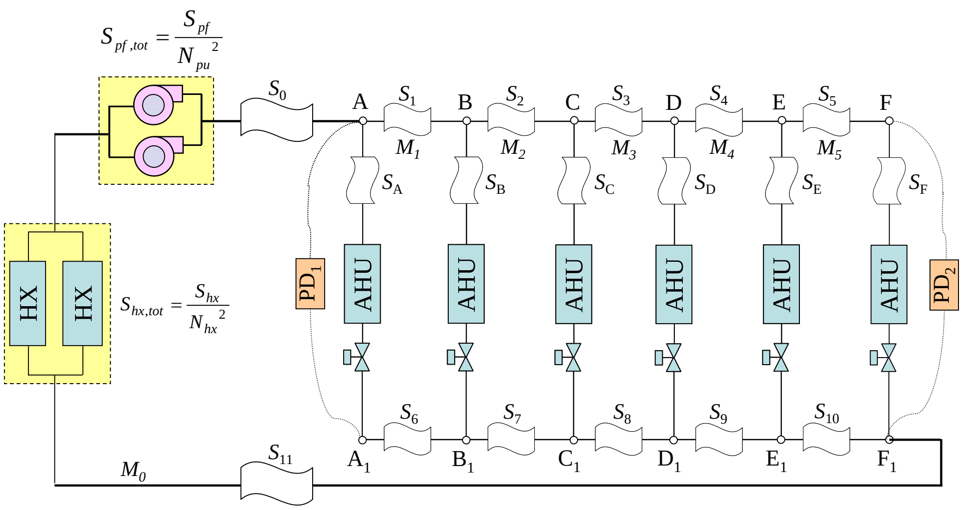

Figure 5.17 Structures of the water network pressure drop model.

The overall pressure drop of this system, i.e., along the sub-branch F-F$_1$, can be mathematically described as in Equation (5.32), which includes the pressure drop on the heat exchangers (including the pressure drops on the heat exchangers and on the headers that direct the flow into and from each heat exchanger), the pressure drop on the fittings around pumps (including the pressure drop on the headers that direct the flow into and from each pump and the pressure drop on the valves in pump headers), the pressure drop on main supply and return pipelines, the pressure drop across the sub-branch (i.e., F-F$_1$), and the pressure drops on the pipeline sections of A-B, B-C, C-D, D-E and E-F.

Equation (5.32) can be further re-written as in Equation (5.33) by representing the water flow rate in each pipeline section (i.e., A-B, B-C, C-D, D-E and E-F) as a function of the total system water flow rate by multiplying a converting factor (i.e., φ_1, φ_2, φ_3, φ_4, φ_5). For simplifying the calculations, the factors (φ_1-φ_5) in the same zone can be considered constant under various load conditions since the usage characteristic and load profile of each floor in the same zone are similar in the building under study. The overall system pressure drop can therefore be finally expressed as in Equation (5.34).

$$PD = \frac{S_{hx}}{N_{hx}^2} M_0^2 + \frac{S_{pf}}{N_{pu}^2} M_0^2 + (S_0 + S_{11}) M_0^2 + S_1 M_1^2 + S_2 M_2^2 + S_3 M_3^2 + S_4 M_4^2 + S_5 M_5^2 + PD_{FF_1} \quad (5.32)$$

$$PD = \frac{S_{hx}}{N_{hx}^2} M_0^2 + \frac{S_{pf}}{N_{pu}^2} M_0^2 + (S_0 + S_{11}) M_0^2 + (S_1 \phi_1^2 + S_2 \phi_2^2 + S_3 \phi_3^2 + S_4 \phi_4^2 + S_5 \phi_5^2) M_0^2 + PD_{FF_1} \quad (5.33)$$

$$PD = \frac{S_{hx}}{N_{hx}^2} M_0^2 + \frac{S_{pf}}{N_{pu}^2} M_0^2 + \{(S_0 + S_{11}) M_0^2 + S_{fic} M_0^2\} + PD_{FF_1} \quad (5.34)$$

where PD is the pressure drop, S is the flow resistance, and subscripts hx, pu and pf indicate heat exchanger, pump and pump fitting, respectively.

The last term on the right-hand side of Equation (5.34) is the optimal pressure differential set-point (named PD_{set}) at a given chilled water supply temperature set-point. The other three terms on the right-hand side of Equation (5.34) are the pressure drop across the heat exchangers, the pressure drop across the fittings around pumps and the pressure drop across the distribution pipelines. These three pressure drops are named *piping pressure drop* (PD_{piping}) uniformly. The overall system pressure drop can therefore be divided into two parts: PD_{set} and PD_{piping}, as shown in Figure 5.18. It can be observed that the pump operation point is the intersection of both the pump curve and control curve. It is worthy noticing that both PD_{set} and

PD_{piping} in Figure 5.18 vary with the changes of working conditions. The piping head loss curve is not constant, which varies with the changes of the number of pumps in operation and/or the number of heat exchangers in operation.

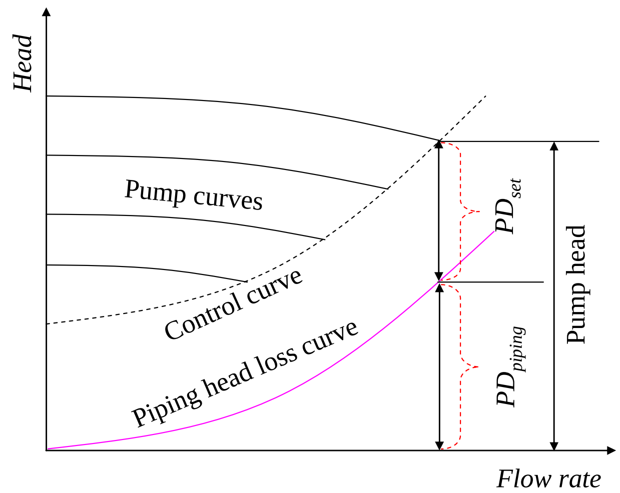

Figure 5.18 Schematics of the system control curve and piping head loss curve as well as pump curves.

For online applications, there are five parameters (S_{hx}, S_{pf}, S_0, S_{11} and S_{fic}) required to be identified. In fact, the parameters of S_0, S_{11} and S_{fic} can be integrated as a single parameter ($\bar{S}_{fic}$) to represent the flow resistance on the distribution pipelines, including the main supply and return pipelines and the pipeline sections of A-B, B-C, C-D, D-E and E-F. The parameters (S_{hx} and S_{pf}) can be determined using the measured pressure drops across the heat exchanger sub-circuit and the pump fitting sub-circuit, as shown in Figure 5.17, together with the measured system water flow rate. The parameter ($\bar{S}_{fic}$) can be determined using the system water flow rate, pump head and the pressure differential set-point at the design condition as well as the identified parameters of S_{hx} and S_{pf}. The water network pressure drop model for any other subsystem can be simplified based on Equation (5.32).

It is noted that the above water network pressure drop model is only suitable for reverse-return piping configurations. The water network pressure drop model for direct-return piping configurations is somewhat different and could be more complex.

5.7 Pressure Differential Set-point Incremental Model

To develop the optimal control strategy for complex chilled water systems, a pressure differential set-point incremental model is developed to predict the optimal pressure differential set-points under different chilled water supply temperature set-points for a given condition. In fact, at a given chilled water supply temperature set-point, the water flow rate required by the terminal units in the zone of concern is unique if the cooling load, and inlet and outlet air status of terminal units in the zone of concern keep unchanged. Therefore, the pressure differential set-point under any given chilled water supply temperature set-point can be characterized by using the system water flow rate, and the basic form of this incremental model can be expressed using a second polynomial as shown in Equation (5.35) in terms of the water flow rate instead of using the temperature set-point.

$$PD_{set} - PD_{set,bench} = q_0 (M_w - M_{w,bench})^2 + q_1 (M_w - M_{w,bench}) + q_2 \qquad (5.35)$$

where *PD* is the pressure differential, *M* is the water flow rate, q_0-q_2 are coefficients, and subscripts *w*, *set* and *bench* indicate water, set-point and benchmark, respectively.

Figure 5.19 illustrates the basic working principle of this pressure differential set-point incremental model. For a given condition, the online opening signals of all water control valves concerned are used to determine an optimal pressure differential set-point at the given chilled water supply temperature set-point, (i.e., the water flow rate in the zone of concern). How to optimize the pressure differential set-point based on the valve positions will be described in Section 6.2.1 in Chapter 6. The optimal pressure differential set-point and the water flow rate at the given chilled water supply temperature set-point are then used as the benchmark values ($PD_{set,bench}$, $M_{w,bench}$) to predict the optimal pressure differential set-point under any other chilled water supply temperature set-point. The water flow rate in the zone of concern under any other chilled water supply temperature set-point is predicted using a global AHU model (i.e., the adaptation of the simplified cooling tower model presented previously). To deliver the adequate chilled water to satisfy the cooling demands of all terminal units and to allow the system to operate properly, a low limit and an upper limit are constrained on the pressure differential set-point, as shown in Figure 5.19.

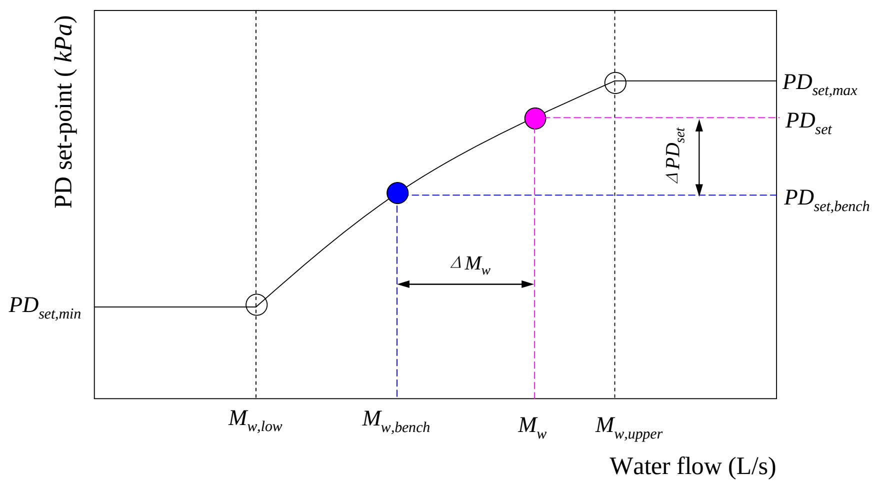

Figure 5.19 Working principle of the pressure differential set-point incremental model.

This model is currently validated using the online monitoring data collected from the complex dynamic simulation platform constructed in Chapter 3. Figure 5.20 gives the validation results. It can be observed that this model has acceptable performance in prediction. It is worthy noticing that the accuracy of this model is strongly affected by the richness of the data used to train the model since it is a purely data-driven model.

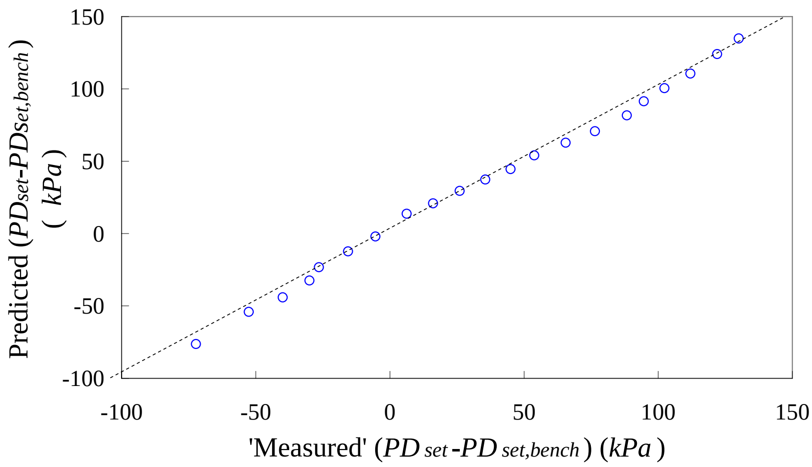

Figure 5.20 Validation results of the pressure differential set-point incremental model.

5.8 Summary

This chapter presents simplified models of major chilling system components for online control applications. The simplified chiller and cooling tower models were developed based on the fundamental principles of the thermodynamic and/or heat/mass transfer processes occurring in the chiller and cooling tower. The performances of both models were validated by using the field measurement data and/or the factory performance test data. The validation results demonstrate that both models have acceptable performance in prediction. The calibration efforts and computational costs of both models were reduced greatly as compared to that of the other models.

The simplified models of the water-to-water heat exchangers and variable speed pumps were also briefly introduced in this chapter. The performances of both models were validated using the catalogue data provided by the manufacturers. The good agreement between the prediction values and the catalogue data was observed in the comparison studies. To develop the optimal control strategy for chilled water systems, a water network pressure drop model and a pressure differential set-point incremental model were also developed in this chapter.

The models developed or selected in this chapter will be used to formulate the online supervisory and optimal control strategies presented in Chapters 6-8 for real-time applications.

CHAPTER 6 BASIC AND OPTIMAL CONTROL OF VARIABLE SPEED PUMPS IN THE CHILLING SYSTEM

During the last two or three decades, the costs of variable speed devices have come down significantly due to the advances in technology, which allowed the widespread applications of variable speed pumps in water distribution systems. An increased issue associated with the use of variable speed pumps is to properly control their operation. In this chapter, the optimal control strategies, including the speed control strategy and the sequence control strategy, for variable speed pumps in building HVAC systems, especially in complex building HVAC systems, are developed and presented. These strategies will be used to formulate the optimal control strategy for the overall chilled water system for real-time applications in Chapter 8.

Section 6.1 presents a brief overview of the major control methods prompted for variable speed pumps. In Section 6.2, the optimal speed control strategies for variable speed pumps with different configurations in complex air-conditioning systems are developed and/or addressed. Based on the water network pressure drop model established in Chapter 5 and the results obtained from the investigation of variables influencing the pump sequence control, a model-based near optimal sequence control strategy for multiple variable speed pumps with parallel installations is put forward in Section 6.3. Using the *simulation-assisted test method* presented in Chapter 4, the performances of these optimal control strategies are evaluated in Section 6.4. A summary of this chapter is given in Section 6.5.

6.1 A Brief Overview of Control Methods for Variable Speed Pumps

The energy costs of variable speed pumps form an important part of the total energy consumption worldwide. Therefore, proper control of variable speed pumps is of great importance to reduce their energy consumption and extend their service life. Many practitioners in the control engineering have made great contributions on the energy efficient control and operation of variable speed pumps during the last two decades (Jack et al. 1991; Chase and Ormsbee 1993; Yu et al. 1994; Engelbrecht and Harrhoff 1996; Rishel 2002; McCormick and Powell 2003; etc.). A number of researchers and experts in the HVAC field have also devoted considerable efforts on developing proper and optimal control methodologies for variable speed pumps to enhance their energy efficiency (Ahmed 1991; Hansen 1995; Rishel 2003; ASHRAE 2007; etc.). Based on the detailed analysis of both direct-return and reverse-return variable volume piping systems, Ahmed (1991) addressed the need and scope of the direct digital control (DDC) in variable water volume (VWV) systems. A DDC system with a closed-loop scheme for controlling the terminal unit's output was proposed. The simulated flow head curves showed that substantial operating costs can be saved with the use of the DDC for hydronic systems.

Hegberg (1991) demonstrated the energy saving potentials due to the converting of constant speed hydronic pumping systems to variable speed pumping systems. The issues associated with the control and payback periods were also discussed. The parallel operation of variable speed pumps in chilled water systems was studied by Hansen (1995). The results showed that the benefits gained from the unequal speed operation of parallel pumps were minimal, and all pumps in a given installation were not necessary to be equipped with the speed control devices. Burke (1995) pointed out that when pumps operate within ±20% of their best efficiency points, there would seldom have any operation problems, which will prolong their service life and reduce the maintenance requirements. Bernier and Bourret (1999) examined the cumulative effects of the deteriorating values of the motor efficiency and VFD efficiency as the speed of a pump is reduced. The results showed that the power required at the inlet of a pump-motor-VFD set was significantly higher, especially for oversized motors, than the power predicted by using the classic pump affinity laws.

Rishel et al. (Rishel 1991, 2001, 2002, 2003) and Tillack and Rishel (1998) paid great efforts on control and optimization of the operation of variable speed pumps in HVAC water systems. The pumps can be sequenced properly based on the wire-to-water efficiency or kW input to the pumping system. The central idea in this method was to operate pumps as closely as possible to their best efficiency curves (Rishel 2003). The speed of pumps can be controlled through the use of pressure differential transmitters located at the critical loops and continuous interrogation of them (Rishel 1991).

Several studies presented that the valve position can be a valuable tool to optimize the pressure differential set-point to control the pump speed. To keep one control valve almost fully open at all times can minimize the pump energy (Rishel 1998; Moore and Fisher 2003; Jin et al. 2007; ASHRAE 2007). In the optimization strategy for air-conditioning systems developed by Lu et al. (2005c), an adaptive neuro-fuzzy inference system was utilized to obtain the optimal pressure differential set-point and to model the duct and pipe networks based on the limited sensor information. To evaluate the energy use and economic feasibilities of alternative designs of chilled water pumping systems, simple polynomial models for pumps, the motor efficiency and VFD efficiency were developed by Bahnfleth and Peyer (2001).

In Chapter 41 of the *2007 ASHRAE Handbook--HVAC Applications* (ASHRAE 2007), it was stated that the speed of the variable speed pump is practically controlled to maintain a constant pressure differential between the main chilled water supply and return pipelines, although this approach is far from optimal. To maintain a constant pressure differential with changing flow, the control valves for the terminal units must close as the load (i.e., flow) is reduced, resulting in an increase in the flow resistance. Therefore, an additional energy is wasted at part-load conditions. Pumps can be sequenced based on the continuous monitoring of the outputs of the pump controllers. If the pump controller is saturated at 100%, then bring the next pump online; If the pump control output is significantly less (i.e., 5%) than the value associated with the first time interval after the last pump was brought online, then bring that pump offline.

It is noted that the pump speed control has been addressed in most of the above studies and the best strategy is to reset the pressure differential set-point based on the positions of water control valves, while the studies on the pump sequence control seem relatively few, and this is probably due to one pump installation designed or simple sequence control strategies used in practice. In addition, the research associated with the proper control of variable speed pumps in complex building air-conditioning systems still seems missing. The investigation of the synthetic effects of using both the optimal pump sequence control and the optimal pump speed control on the energy performance of complex air-conditioning systems seems lacking as well. The major objectives of the following sections are therefore to fill these gaps.

6.2 Optimal Pump Speed Control

In the complex building central air-conditioning system presented in Chapter 3, the heat exchangers are used in the chilled water distribution system to transfer the cooling energy from low zones to high zones to avoid the high water static pressure, which makes the configurations of variable speed pumps somewhat different from that in the typical air-conditioning systems. In general, all variable speed pumps in this complex chilled water distribution system could be classified into two groups: the pumps distributing water to terminal units and the pumps distributing water to heat exchangers. Although the major functions of both groups of pumps are the same, i.e., to deliver the adequate chilled water to satisfy the indoor cooling demands, their speed control methods are significantly different. In the following, the methods used to control the operating speeds of both groups of pumps are presented in detail along with a description of a pressure differential set-point optimizer.

6.2.1 Pressure Differential Set-point Optimizer

In HVAC water systems, variable speed pumps distributing water to terminal units are often controlled by monitoring the pressure differential between the main supply and return pipelines or the pressure differential at the critical loops (i.e., the most remote loop for the direct-return system). The monitored pressure differential is then compared with the pressure differential set-point to carry out the pump speed control. The pressure differential set-point can be fixed or varied. Many years' experience with the pump speed control on HVAC water systems has proved that the pressure differential transmitter located at the critical loops and the pressure differential set-point optimized using the positions of water control valves are the most cost effective means to vary the speed of the pump (Rishel 2003; Moore and Fisher 2003; Jin et al. 2007; ASHRAE 2007).

In this thesis, the pressure differential set-point is reset using the positions of water control valves also. The set-point is reset enough and just enough to maintain all desired supply air temperature set-points with one control valve in a fully open condition. In order to maintain the robust and stable control, the pressure differential set-point should be reset at a smaller time interval (e.g., 5 min) than that for the chilled water supply temperature set-point reset and for the operating number of pumps reset (ASHRAE 2007). The detailed reset procedures utilized in this study are very similar to that of presented in Chapter 41 of the *2007 ASHRAE Handbook—HVAC Applications* (ASHRAE 2007) and are described as follows.

1. Collect the opening signals of all water control valves (or outputs of PID controllers for the supply air temperature).
2. Check the opening signals of all water control valves (i.e., PID outputs) to find the maximum opening signals among them, and then count the number of control valves with the maximum opening signals.
3. If the searched maximum position is less than 100% open, which means none of control valves have been saturated, then decrease the pressure differential set-point by a fixed value (e.g., 5% of the design value) and go to Step 5. Otherwise, go to Step 4.
4. If more than one control valve has been saturated at 100% open, then increase the pressure differential set-point by a fixed value (e.g., 5% of the design value).
5. Limit the pressure differential set-point between the upper and low constraints.
6. Check the time interval since the last time the set-point is changed. If this time interval is less than a predetermined time interval, then keep the set-point unchanged. Otherwise, reset the set-point using the above optimized value.

6.2.2 Speed Control of the Pump Distributing Water to Terminal units

Based on the pressure differential set-point optimizer presented above, the speed control strategy for variable speed pumps distributing water to terminal units can be designed. The structures of the speed control strategies for variable speed pumps distributing water to terminal units for direct-return and reverse-return systems are illustrated in Figure 6.1 and 6.2, respectively. As illustrated in Figure 6.1, only one pressure differential transmitter needs to be located at the most remote loop in the direct-return systems. However, for the reverse return systems, a pressure differential transmitter is required to be installed at each end of the loop, as shown in Figure 6.2. A representative measured pressure differential (PD) is selected based on the larger deviation of the measurements of both pressure differential transmitters from the set-point optimized, and then used to perform the pump speed control (Rishel 2003).

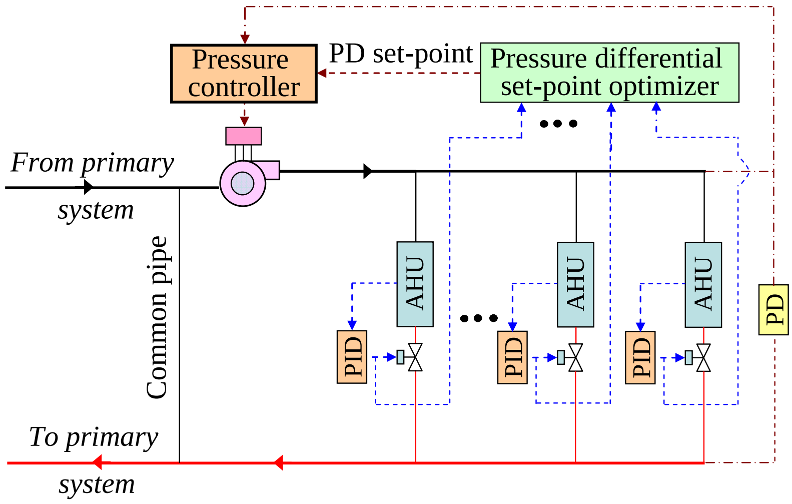

Figure 6.1 The speed control strategy for variable speed pumps distributing water to terminal units in direct-return systems.

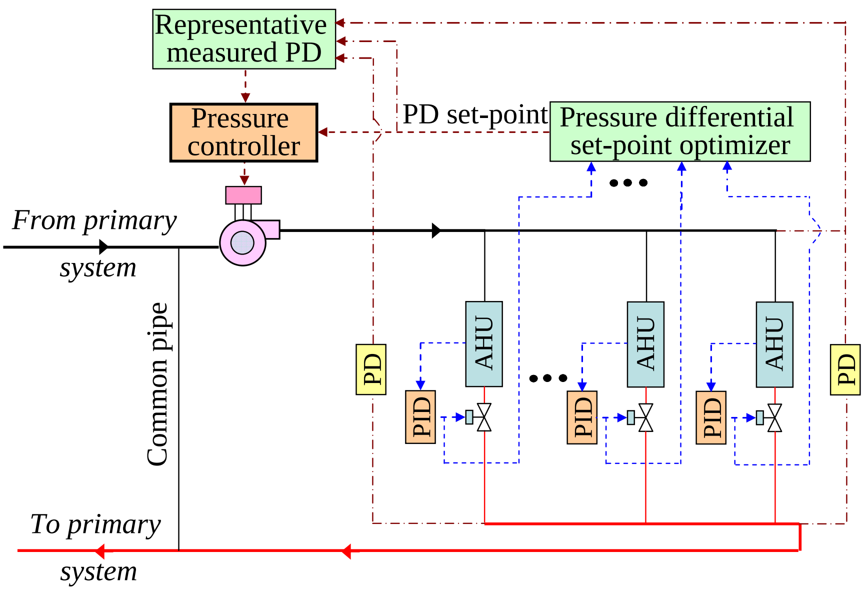

Figure 6.2 The speed control strategy for variable speed pumps distributing water to terminal units in reverse-return systems.

6.2.3 Speed Control of the Pump Distributing Water to Heat Exchangers

For variable speed pumps distributing water to heat exchangers (i.e., the pumps at the primary side of heat exchangers), their speeds can be controlled by using two different strategies as presented subsequently.

Water Flow Controller

The operating speed of the variable speed pump distributing water to heat exchangers can be controlled using a water flow controller, as illustrated in Figure 6.3. In this controller, a water flow meter is installed on the primary side and secondary side of heat exchangers, respectively. Since the difference between the water flow rates in both sides of heat exchangers in most applications is not very large, therefore, the pump can be controlled to maintain the water flow rate in the primary side of heat exchangers that is equal to the actual water flow rate in the secondary side of heat exchangers. This controller is straightforward and easy to tune in practice.

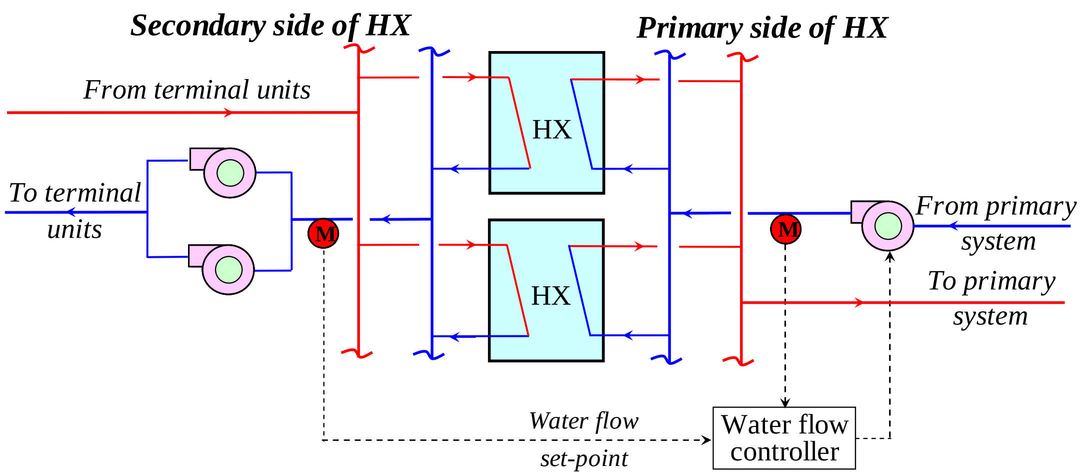

Figure 6.3 The speed control strategy for variable speed pumps distributing water to heat exchangers using the water flow controller.

Cascade controller

In some cases, the outlet water temperature at the secondary side of heat exchangers needs to be controlled. Since the water flow controller presented above cannot provide this function, a cascade controller, as illustrated in Figure 6.4, can be used to control the operating speed of the pump distributing water to heat exchangers for these cases.

In this cascade controller, a water flow meter is installed on the primary side of heat exchangers and a temperature sensor is installed on the outlet pipeline of the secondary side of heat exchangers. The temperature monitored by the temperature sensor is used to determine the required water flow rate with respect to the temperature set-point and the required water flow rate is then compared with the measured water flow rate in the primary side of heat exchangers to carry out the pump speed control. In this controller, a predetermined function needs to be embedded to set the set-points of the outlet water temperature at the secondary side of heat exchangers and the inlet water temperature at the primary side of heat exchangers with proper differences, allowing the water flow rates at both sides to remain roughly the same as needed for the proper control of the system.

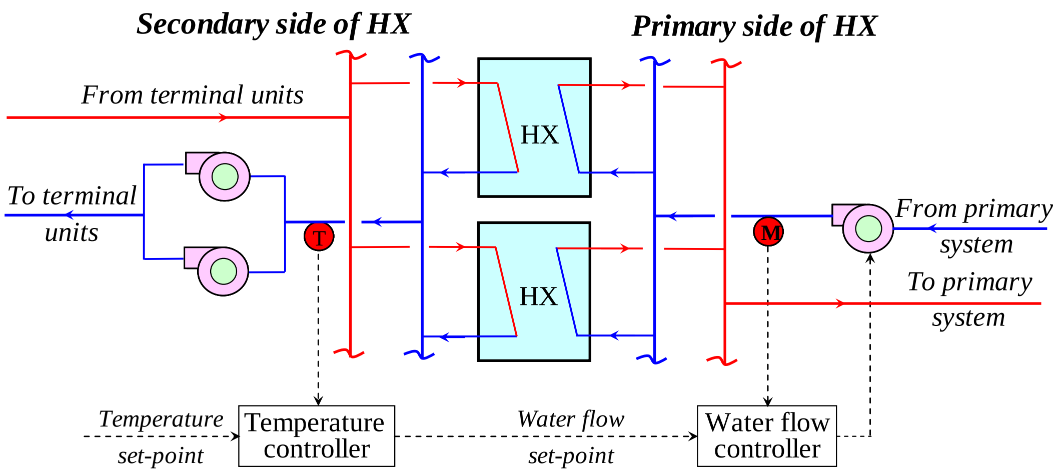

Figure 6.4 The speed control strategy for variable speed pumps distributing water to heat exchangers using the cascade controller.

6.3 Near Optimal Pump Sequence Control

The pump sequence control is to determine both the order and point that pumps should be brought online and offline (ASHRAE 2007). For small systems where only one pump operates at all time, there is no problem with the pump sequence control. However, for large systems, multiple variable speed pumps with parallel installations are often designed. The proper sequence control of these variable speed pumps has an important effect on their energy consumption and useful life. For the complex building central air-conditioning system presented in Chapter 3, the heat exchangers are used in the chilled water distribution system. The complexities and difficulties associated with the sequence control of variable speed pumps in such complex systems are increased accordingly.

Since the general sequence control strategy for variable speed pumps at the secondary side of heat exchangers (e.g., the pumps of SCHWP-06-10 to 12 in Figure 3.2 in Chapter 3) could provide some coverage for most of the possible sequence control problems for variable speed pumps encountered in HVAC water systems, the sequence control strategy for variable speed pumps at the secondary side of heat exchangers is therefore presented in the following in detail, and the sequence control strategies for variable speed pumps with other types of installations can be simplified based on it.

6.3.1 Investigation of Variables Influencing the Pump Sequence Control

To develop the near optimal/optimal sequence control strategy for variable speed pumps, the variables influencing the pump sequence control should be analyzed carefully. In the available literature, the best strategy to sequence the operation of variable speed pumps is to use the wire-to-water efficiency or kW input (Rishel 1991, 2003). In this approach, variable speed pumps were finally sequenced as a form of the performance map in terms of the water flow rate only. The performance map can be generated through complete simulations. In fact, the pump sequence control is not only dependent on the system water flow rate, but also is strongly affected by the value of the pressure differential set-point.

To investigate the influences of the pressure differential set-point and the system water flow rate on the pump sequence control, the total power consumptions of the pumps under various operating combinations (i.e., the system water flow rate and pressure differential set-point) for different numbers of pumps in operation for a given condition were simulated using the pump model and water network pressure drop model presented in Chapter 5. Figure 6.5 shows the simulation results. It can be observed that both the system water flow rate and the value of the pressure differential set-point have significant impacts on the power consumption of pumps. The power consumptions of pumps using different operation modes (one pump in operation and two pumps in operation) under the same pressure differential set-point and system water flow rate were significantly different. The optimal operating number of pumps for a given condition is the one with the minimum total power consumption while still satisfying the system head and flow rate requirements. Therefore, the most effective pump sequence control strategy can be developed based on the serious consideration of the influences of the system water flow rate and the value of the pressure differential set-point simultaneously.

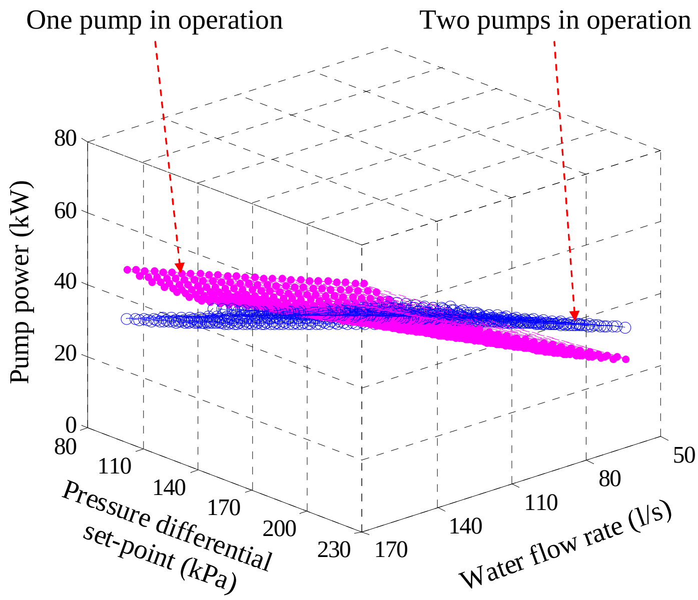

Figure 6.5 The power consumptions of the pumps under various operating combinations.

6.3.2 Heat Exchanger Sequence Controller

The operating number of heat exchangers has significant impacts on the sequence control strategies for pumps at the primary and secondary sides of heat exchangers. Therefore, a sequence control strategy for heat exchangers should be developed firstly.

In the central chilling system presented in Chapter 3, the heat exchangers used can be classified into two groups. One is the heat exchangers in Zone 1 and the other is the heat exchangers in Zones 3 and 4. Since each heat exchanger in Zones 3 and 4 is associated with one constant primary chilled water pump, these heat exchangers can be sequenced using a simple strategy as follows. Another heat exchanger is switched on when the operating heat exchangers are fully loaded (i.e., reach their design water flow rates) and one of the operating heat exchangers is switched off when the remaining heat exchangers can handle the system water flow.

For the heat exchangers in Zone 1, the sequence strategy is somewhat different since the water systems in the primary and secondary sides of heat exchangers are both equipped with variable speed pumps. In general, operating more heat exchangers can increase their heat transfer areas and reduce the power consumptions of both pumps in the primary and secondary sides of heat exchangers to some extent due to the reduction of the total pressure drop on the heat exchangers. However, operating more heat exchangers will increase their maintenance costs and shorten their service life in the long run. In addition, the minimal water flow rates in the primary and secondary sides of heat exchangers are inherently constrained by the low bound of the pump operating frequency (e.g., 20 Hz).

Taking into account all these factors, a simple sequence strategy based on the water flow rate in the secondary side of heat exchangers can be designed and used to control the operation of the heat exchangers in Zone 1. Using this strategy, another heat exchanger is brought online when the water flow rate of each operating heat exchanger exceeds 80% of its design water flow rate. One of the operating heat exchangers is brought offline if the water flow rate in the secondary side of heat exchangers can be handled by the remaining heat exchangers at 80% or below 80% of their design water flow rates. A dead band is used in this controller for bringing online and offline a heat exchanger to avoid frequent ON and OFF of a heat exchanger.

6.3.3 Outline of the Near Optimal Pump Sequence Control Strategy

Based on the heat exchanger sequence control strategy developed above, and the water network pressure drop model and pump model presented in Chapter 5, as well as the pressure differential set-point optimizer presented in Section 6.2.1, a model-based pump sequence control strategy for variable speed pumps in the secondary side of heat exchangers can be formulated. An outline of this sequence control strategy for two pump installations is illustrated in Figure 6.6, which consists of the model-based performance predictor, energy estimator, decision maker, supervisory strategy and local control strategies, etc. The central idea covered in this strategy is to operate pumps as economically as possible considering their power consumptions and maintenance costs.

In this strategy, the pressure differential set-point optimizer is used to determine the optimal pressure differential set-point at a given chilled water supply temperature set-point. The heat exchanger sequence controller is applied to determine the number of heat exchangers operating according to the measured water flow rate. The performance predictor utilizes the water network pressure drop model and pump model to predict the total power consumptions of pumps under different operation modes (one pump in operation and two pumps in operation) at the given water flow rate and pressure differential set-point optimized. The detailed optimization procedures of this strategy are presented subsequently along with the descriptions of major functions of the energy estimator, decision maker and supervisory strategy.

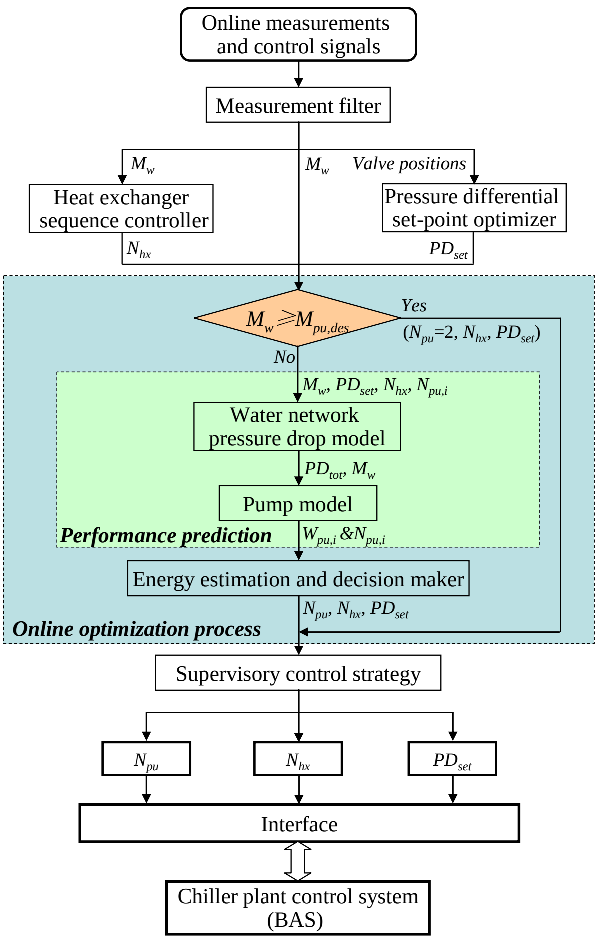

Figure 6.6 Outline of the model-based pump sequence control strategy.

6.3.4 Description of the Detailed Optimization Procedures

For a given working condition, this model-based sequence control strategy seeks the optimal number of pumps operating with the following procedures.

1) Collect the online measurements and control signals, including the water flow rate and opening signals (i.e., PID outputs) of all water control valves from the BAS, and then send them to a measurement filter. Only the validated measurements are used for the control supervision.
2) Determine the number of heat exchangers operating and the optimal pressure differential set-point at the given chilled water supply temperature set-point using the heat exchanger sequence controller and the pressure differential set-point optimizer, respectively.
3) If the monitored water flow rate in the system of concern is larger than the design water flow rate of one pump, two pumps are set to operate, and then go to Step 6. Otherwise, go to Step 4.
4) Using the water network pressure drop model and pump model to predict the power consumptions of pumps under different operation modes (one pump in operation and two pumps in operation) at the given water flow rate and the pressure differential set-point optimized.
5) The energy estimation and decision maker then determine the optimal number of pumps operating based on the prediction results of two possible operating modes considering their power consumptions and associated maintenance costs. If the difference of the power consumptions between the two operation modes is

significantly less than a value (e.g., 5% of the design value), one pump is set to operate in order to reduce the maintenance costs of pumps in the long run. Otherwise, two pumps are set to operate to reduce the energy input.

6) The supervisory strategy then provides the final decision, including the number of pumps operating, the number of heat exchangers operating and the optimal pressure differential set-point for the BAS taking into account the operating constraints for practical applications, i.e., the time interval between the changes of two sets of control settings should avoid an alternating fashion of ON/OFF of the pumps, etc.

6.4 Performance Tests and Evaluation of Optimal Control Strategies

6.4.1 Set up the Tests

The performances of optimal control strategies for variable speed pumps were tested and evaluated on the complex building central chilling system presented in Chapter 3 using the *simulation-assisted test method* presented in Chapter 4. During the tests, the simulated hourly-based annual building cooling loads and the hourly-based weather data for the typical year in Hong Kong were used, and they are provided by a data file for the dynamic simulation platform. The online measurements and control signals, including the water flow rate in each subsystem, the chilled water supply temperature set-point and the opening signals of all water control valves in each individual zone were continuously monitored and collected from the dynamic simulation platform and then transferred to the control optimizer (i.e., the package of the control strategies) by the management and communication platform for the control supervision. The control optimizer seeks the most energy efficient control settings (i.e., the operating numbers of pumps and heat exchangers in each parallel installation and the optimal pressure differential set-point for each individual zone) for the given condition based on the received status data and then transferred them to the dynamic simulation platform through the management and communication platform to achieve energy efficient control and operation.

Three typical days, which represent the typical operation conditions of the air-conditioning system in the typical spring, mild-summer and sunny-summer days respectively, were selected to test and evaluate the energy performances of the proposed optimal control strategies for variable speed pumps. The building cooling loads varied from 2500 kW to 23000 kW, from 4600 kW to 31600 kW and from 5300 kW to 37600 kW in the selected typical spring day, mild-summer day and sunny-summer day, respectively. To calculate the air flow rate requirement and AHU inlet air dry-bulb temperature of each individual zone, the same assumptions as presented in Section 3.2.1 were used in the flowing study.

During the tests, the input frequency to variable speed pumps was bounded between 20 Hz and 50 Hz. The pressure differential set-points for Zone 1 and Zone 2 were bounded between 80 kPa and 215 kPa and between 90 kPa and 230 kPa, respectively, while the pressure differential set-points for Zone 3 and Zone 4 were bounded between 80 kPa and 200 kPa, considering the design cooling load of each individual zone and the pump heads at the design condition. The chillers were sequenced using the simple sequence control strategy presented in Chapter 3. The operation of the constant primary chilled water pumps associated with chillers and heat exchangers in Zone 3 and Zone 4 was dedicated to the operation of their correlated chillers or heat exchangers that they serve.

Since the outlet water temperature at the secondary side of heat exchangers is a control variable that is required to be controlled, the cascade controller presented in Section 6.2.3 was therefore used in the following studies. A fixed temperature difference (e.g., 0.8 K) between the outlet water temperature at the secondary side and the inlet water temperature at the primary side of heat exchangers at the design condition was used to reset this temperature set-point.

6.4.2 Test and Evaluation Results

To demonstrate the energy saving potentials associated with the use of optimal control strategies for variable speed pumps, four different strategies were tested and compared in the following studies. They include the strategy using the fixed pressure differential set-point at the critical loops and the simple pump sequence control strategy (named Strategy #1), the strategy using the fixed pressure differential set-point at the critical loops and the near optimal pump sequence control strategy (named Strategy #2), the strategy using the optimal pressure differential set-point at the critical loops and the simple pump sequence control strategy (named Strategy #3), and the strategy using the optimal pressure differential set-point at the critical loops and the near optimal pump sequence control strategy (named Strategy #4).

Here, the near optimal pump sequence control strategy is the control strategy developed in Section 6.3. The simple pump sequence control strategy used is a conventional strategy presented as follows: bring another pump online when the frequencies of the operating pumps exceed 40 Hz. One of the operating pumps is switched off if the remaining pumps can handle the system water flow rate and head requirements at the frequency of 40 Hz or below 40 Hz. A dead band is employed in this controller for staging and de-staging a pump to avoid frequent ON and OFF of a pump. The fixed pressure differential set-point used for each individual zone is the upper limit of the pressure differential set-point bounded for each zone in Section 6.4.1.

Table 6.1 summarizes the daily power consumptions of all variable speed pumps in the secondary chilled water system in that building in the three typical days under different control strategies. Compared with Strategy #1, Strategy #4 saved about 3226.6 kWh (32.43%), 2835.3 kWh (22.49%) and 2023.5 kWh (12.69%) energy in the typical spring day, mild-summer day and sunny-summer day, respectively. It also can be found that Strategy #2 saved about 504.4 kWh (5.07%), 231.5 kWh (1.84%) and 111.3 kWh (0.70%) energy, while Strategy #3 saved about 2405.0 kWh (24.17%), 2169.9 kWh (17.21%) and 1786.4 kWh (11.20%) energy in the typical spring day, mild-summer day and sunny-summer day respectively, as compared with Strategy #1.

From Table 6.1, it also can be observed that the strategies using the optimal pressure differential set-points (Strategies #3 and #4) can save significantly more energy than the strategies using the fixed pressure differential set-points (Strategies #1 and #2). However, the energy saving potential related to the use of the near optimal pump sequence control strategy (Strategy #2) was insignificant and very limited as compared with that using the simple pump sequence control strategy (Strategy #1). Figure 6.7 provides more details of the hourly-based power consumptions using different control strategies in the selected typical mild-summer case.

Table 6.1 Comparison of the daily power consumptions of variable speed pumps in the secondary chilled water system under different control strategies

Typical day	Control strategy	W_{pu} (kWh)	*Saving* (kWh)	*Saving* (%)
Spring	Strategy #1	9948.7	---	---
	Strategy #2	9444.3	504.4	***5.07***
	Strategy #3	7543.7	2405.0	***24.17***
	Strategy #4	6722.1	3226.6	***32.43***
Mild-summer	Strategy #1	12609.2	---	---
	Strategy #2	12377.7	231.5	***1.84***
	Strategy #3	10439.3	2169.9	***17.21***
	Strategy #4	9773.9	2835.3	***22.49***
Sunny-summer	Strategy #1	15948.2	---	---
	Strategy #2	15836.9	111.3	***0.70***
	Strategy #3	14161.8	1786.4	***11.20***
	Strategy #4	13924.7	2023.5	***12.69***

Based on the above studies, it can be found that Strategy #4 using the optimal pressure differential set-points and the near optimal sequence control strategy can save a significant amount of energy as compared with the other three control strategies. It is worthwhile to notice that the speeds of the variable speed pumps at the primary side of heat exchangers in these four control strategies were all controlled using the same cascade controller presented in Section 6.2.3. Therefore, these pumps in Strategy #1 used as the benchmark in this study have already been optimized. The actual energy savings associated with the use of Strategy #4 could be significantly more than the energy savings presented above since the control strategies utilized in practice might be simpler and more inadequate. It is also noted that the chilled water supply temperature set-point was not optimized and was maintained as a constant (5.5°C) during the above calculations.

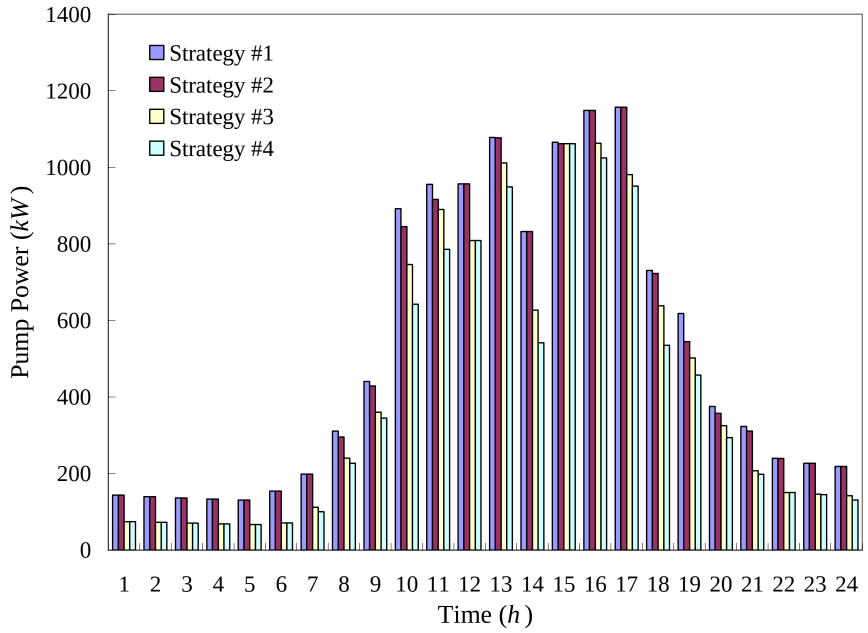

Figure 6.7 Comparison of the hourly-based power consumptions among different control strategies in the selected typical mild-summer case.

6.5 Summary

This chapter presents the optimal control strategies for variable speed pumps in complex building central air-conditioning systems. All variable speed pumps in the complex air-conditioning system are classified into two groups: the pumps distributing water to terminal units and the pumps distributing water to heat exchangers. The speeds of pumps distributing water to terminal units can be controlled by resetting the pressure differential set-point enough and just enough for the most heavily loaded loops using the positions of water control valves. The speeds of pumps distributing water to heat exchangers can be controlled using a cascade controller or a water flow controller. To properly sequence control the operation of multiple variable speed pumps with parallel installations, a near optimal pump sequence control strategy was developed on the basis of the water network pressure drop model and pump model presented in Chapter 5. This sequence control strategy seeks the optimal number of pumps operating considering their energy consumptions and maintenance costs.

The performances of these optimal control strategies (the speed and sequence control strategies) were tested and evaluated on the complex central chilling system presented in Chapter 3 using the *simulation-assisted test method*. The results show that a substantial amount of energy can be saved when applying the strategy using the optimal pressure differential set-points and the near optimal sequence control strategy (Strategy #4) as compared with the other three control strategies (Strategies #1, #2 and #3). It is noted that this part of energy savings was achieved by applying the optimal control algorithms only and without adding any additional cost.

It is worthy noticing that the optimal control strategies presented in this chapter can be easily adapted to, but not limited to, control of variable speed pumps in most of HVAC water systems. These optima control strategies are still simple and easy to implement in practice.

CHAPTER 7 ONLINE OPTIMAL CONTROL OF CENTRAL CONDENSER COOLING WATER SYSTEMS

In complex central chilling systems, there are many control variables to be optimized. If the optimal control strategy is developed for the overall system, the optimization tool used in the control system should optimize all control variables simultaneously. Currently, global optimization tools, such as GAs, simulated annealing etc., seem to be the proper choice to solve such optimization problem with many control variables. However, these global optimization tools cannot always provide global optimal solutions. They also require high computational cost and memory demand. More importantly, there still seems no report related to the use of these global optimization tools in HVAC systems for practical applications successfully. Since the control strategies developed in this thesis will be actually implemented and applied in the super high-rise building. The control stability, control reliability and computation performances are therefore the most important issues. To provide stable and robust control in practice, the optimal control strategies are therefore developed for the condenser cooling water system and chilled water system separately to simplify the control systems. Although this separation is not optimal, it is really for practical reasons.

The central condenser cooling water systems are among the major functions in building HVAC systems, and their operation often consumes a significant amount of the total energy consumption of the overall HVAC systems (Lu et al. 2004). To enhance the energy efficiency and provide better operational performance, an optimal control strategy using a hybrid quick search (HQS) method is developed in this chapter for the online control of the central condenser cooling water systems. The HQS method combines a performance map-based near optimal control strategy and the exhaustive search method to find the optimal solutions for the optimization problem. This method has advantages especially for the use in the control of complex condenser cooling water systems. The performance of this HQS-based optimal control strategy was validated on the complex condenser cooling water system presented in Chapter 3 by using the *computation-assisted test method* presented in Chapter 4.

Section 7.1 presents a brief overview of the main control methods used for the control and optimization of central condenser cooling water systems. The formulation of the optimal control strategy for complex building condenser cooling water systems is presented in Section 7.2. The optimization problem was formulated to minimize the overall energy consumption of the entire condenser cooling water system, taking into account the characteristics and interactions of the condenser cooling water system as well as the requirements and constraints of practical applications. A practical optimization technique, namely HQS method, was also developed in this section and used to seek the most energy efficient control settings for the optimization problem established. The performance test and evaluation of this HQS-based optimal control strategy is presented in Section 7.3. A summary of this chapter is provided in Section 7.4.

7.1 A Brief Overview of Control Methods for Condenser Cooling Water Systems

To maximize the building energy efficiency and provide satisfactory control performance, many control strategies for building central condenser cooling water systems have been proposed during the past two decades (Klein et al. 1988; Braun and Diderrich 1990a; Shelton and Joyce 1991; Austin 1993; Schwedler 1998; Wang and Burnett 2001; Crowther and Furlong 2004; Lu et al. 2004; Yao et al. 2004; Sun and Reddy 2005; etc.). Among the existing control strategies, two simple strategies are the fixed set-point control method and the fixed approach control method. The fixed set-point control method varies the cooling tower air flow rate to maintain a constant condenser water supply temperature set-point, while the fixed approach control method varies the cooling tower air flow rate to maintain a constant temperature difference between the cooling tower outlet water temperature and the ambient air wet-bulb temperature. Both are simple and easy to implement and have been widely used strategies in practice. However, a significant amount of energy is consumed as compared with the use of optimal control strategies (Braun and Diderrich 1990a).

For the real-time control and optimization of condenser cooling water systems, near optimal control strategies were proposed by several researchers (Braun and Diderrich 1990a; Yao et al. 2004; Sun and Reddy 2005). Braun and Diderrich (1990a) presented a near optimal control algorithm for cooling towers in which a relationship between the cooling tower air flow rate and chiller cooling load was built and used to control the operation of cooling towers directly. Yao et al. (2004) proposed an empirical equation to determine a near optimal condenser water supply temperature set-point, in which the near optimal condenser water supply temperature set-point was expressed in the form of a second-order polynomial in terms of the ambient air wet-bulb temperature. Sun and Reddy (2005) regressed a linear model for resetting the condenser water supply temperature set-point. The near optimal condenser water supply temperature set-point was expressed as a linear relationship of the ambient air wet-bulb temperature and the ratio of the building cooling load to the design total cooling capacity of chillers. These near optimal strategies are simple and easy to implement in practice. However, they cannot provide the true optimal settings, which might provide the settings significantly different from the true optimal values, and a substantial amount of energy might still be wasted, which will be demonstrated later.

There are also a few optimal control strategies using a systematic approach to optimize the operation of condenser cooling water systems, and these strategies have been summarized in Chapter 2 (Austin 1993; Lu et al. 2004). As discussed in Chapter 2, these strategies cannot satisfy the requirements of practical applications when the system operating efficiency, control robustness, computation performance, etc., are of concern simultaneously.

A more effective control strategy for condenser cooling water systems, particularly for complex condenser cooling water systems, is therefore essential and indeed needed for online control applications.

7.2 Formulation of the HQS-based Optimal Control Strategy

As discussed in Chapter 2, the model-based optimal control strategies can react quickly to the rapid changes of indoor and outdoor conditions and the performance map-based near optimal control strategies can simplify the control system greatly to save the computational cost while still providing relatively reliable estimates. Therefore, an optimal control strategy that combines the features of both the model-based optimal control and the performance map-based near optimal control is developed for complex condenser cooling water systems using cooling towers for the heat rejection purposes, for online applications.

According to the energy investigation results obtained in Chapter 3, the building condenser cooling water system is highly interactive, and the optimal condenser water supply temperature set-point is the trade-off among the electricity consumptions of all energy consumers in the overall condenser cooling water system. Therefore, the condenser water supply temperature set-point should be optimized, and the optimal control strategy should provide two major control functions. One is to seek the optimal condenser water supply temperature set-point and the other is to identify the best combination of the number of cooling towers operating and their individual fan speeds and the number of condenser water pumps operating and their individual pump speeds (if variable speed pumps are used) that can control the system to operate at the desired temperature set-point.

In a number of condenser cooling water systems using cooling towers for the heat rejection purposes, the condenser water pumps are often designed as the constant speed. The individual condenser water pump is commonly physically dedicated to the individual chiller to provide the more stable operation. In this configuration, the operation of each condenser water pump is dedicated to the operation of the correlated chiller that it serves. Therefore, the optimal control strategy for such systems is to identify the optimal condenser water supply temperature set-point and the most energy efficient combination of the number of cooling towers operating and their individual fan speeds that can control the system to operate at the optimal temperature set-point identified. Based on the characteristics of the condenser cooling water systems and major control functions needed, an optimal control strategy can be formulated using a systematic approach as follows.

7.2.1 Outline of the HQS-based Optimal Control Strategy

An outline of the overall online optimization procedures of the HQS-based optimal control strategy is illustrated in Figure 7.1, which is developed on the basis of the complex condenser cooling water system presented in Chapter 3. It can be observed that this HQS-based optimal control strategy is mainly comprised of the performance predictor (i.e., simplified models), cost estimator (i.e., cost function), optimization technique, supervisory strategy, etc.

The simplified chiller and cooling tower models developed in Chapter 5 were used as the performance predictor to predict the system energy performance and environment quality as well as the system response to the changes of the control settings under various conditions. The cost function, operating constraints, optimization technique, etc., used to formulate this HQS-based optimal control strategy are presented in the subsequent sections in detail along with a comprehensive description of the optimization process.

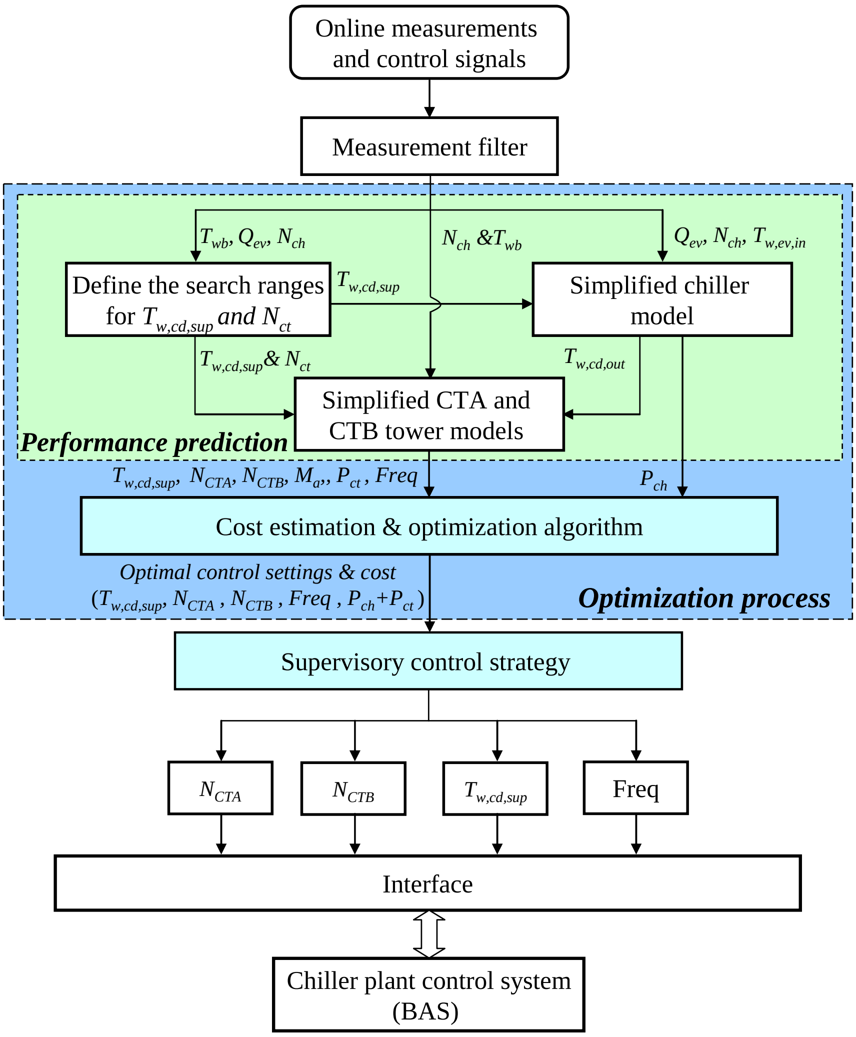

Figure 7.1 Illustration of the online optimization procedures of the HQS-based optimal control strategy.

7.2.2 Definition of the Cost Function

As presented in Chapter 2, the cost function for any other system can be simplified based on the cost function established for the hybrid system with significant energy storage. For a utility rate structure without considering time-of-use differentiated electricity prices and demand charges and for all electric-driven systems without significant energy storage, the cost function for the overall condenser cooling water system can be simplified based on Equation (2.1) presented in Chapter 2, and is finally expressed as in Equation (7.1).

$$J = \min(W_{tot}) = \min\left(W_{ch,tot} + W_{ct,tot} + W_{cd,pu,tot}\right) \tag{7.1}$$

where J is the cost function, W_{tot} is the total electricity consumption of the entire condenser cooling water system, $W_{ch,tot}$, $W_{ct,tot}$ and $W_{cd,pu,tot}$ are the total electricity consumption of the chillers, cooling towers and all condenser water pumps, respectively.

For the complex condenser cooling water system presented in Chapter 3, different types of cooling towers with different heat rejection capacities are used for the particular purpose. The optimization of this system would be therefore more complicated than that only using one type of cooling towers with the same capacity. The cost function for this complex system with constant speed condenser water pumps can be mathematically expressed as in Equation (7.2), where two types of cooling towers (named CTA tower and CTB tower) are introduced. Since the power consumption of constant speed condenser water pumps keeps constant for a given condition, it is therefore not included in the above cost function. This cost function is to minimize the instantaneous total power consumption of the chillers and both types of cooling towers.

$$J = \min_{T_{w,cd,\sup}} W_{tot} = \min_{T_{w,cd,\sup}} \left(\sum_{k=1}^{N_{ch}} W_{ch,k} + \sum_{i=1}^{N_{CTA}} W_{CTA,i} + \sum_{j=1}^{N_{CTB}} W_{CTB,i} \right) \tag{7.2}$$

where N is the number of the equipment operating, W is the power consumption, and subscripts w, ch, cd, CTA, CTB and sup represent water, chiller, condenser, CTA tower, CTB tower and supply, respectively.

7.2.3 Definition of the Operating Constraints

The operation of condenser cooling water systems has to obey a number of constraints, i.e., the basic energy and mass balances, mechanical limitations, etc. The heat rejected in the cooling towers equals the heat absorbed by the cooling water from the chiller condensers, as expressed by Equation (7.3). The heat generated in the chiller condensers is assumed equal to the sum of the evaporator cooling energy and the power consumed by the chiller compressors as expressed by Equation (7.4). The cooling water is assumed to be distributed to each operating cooling tower evenly to allow all cooling towers to operate at good efficiency. For the CTA towers and CTB towers, the distributed water mass flow rates can be determined according to Equations (7.5) and (7.6), respectively. The search range of the number of cooling towers operating is bounded as in Equation (7.7), in which the minimum number approximately guarantees that the cooling water distributed to each cooling tower does not overflow from the water distribution basin on the top of the cooling towers. To avoid the low condenser water supply temperature set-point causing low pressure problems in chillers, the low limit of the condenser water supply temperature set-point is bound to 18°*C*. The input frequency to the cooling tower fans is bounded between

20 Hz and 50 Hz.

$$\sum_{i=1}^{N_{CTA}} Q_{CTA,i} + \sum_{j=1}^{N_{CTB}} Q_{CTB,j} = \sum_{k=1}^{N_{ch}} Q_{cd,k} \tag{7.3}$$

$$\sum_{k=1}^{N_{ch}} Q_{cd,k} = \sum_{k=1}^{N_{ch}} Q_{ev,k} + \sum_{k=1}^{N_{ch}} W_{com,k} \tag{7.4}$$

$$M_{w,CTA,i} = \frac{M_{w,CTA,des} \cdot \sum_{k=1}^{N_{ch}} M_{w,cd,k}}{M_{w,CTA,des} \cdot N_{CTA} + M_{w,CTB,des} \cdot N_{CTB}} \tag{7.5}$$

$$M_{w,CTB,j} = \frac{M_{w,CTB,des} \cdot \sum_{k=1}^{N_{ch}} M_{w,cd,k}}{M_{w,CTA,des} \cdot N_{CTA} + M_{w,CTB,des} \cdot N_{CTB}} \tag{7.6}$$

$$fix\left(\frac{\sum_{k=1}^{N_{ch}} M_{w,cd,k}}{M_{w,CTA,des}} \right) + 1 \le N_{ct} \le N_{CTA,tot} + N_{CTB,tot} \tag{7.7}$$

where Q is the heat transfer rate, M is the mass flow rate, *fix* is a function of Matlab with round toward zero, and subscripts *ct*, *ev*, *com* and *des* indicate cooling tower, evaporator, compressor and design, respectively.

7.2.4 Development of the Optimization Technique

The optimization technique plays an important role in a model-based supervisory and optimal control strategy to seek the most energy efficient control settings. As presented in Chapter 2, the optimization technique used in practice should be effective and reliable, but is still simple enough and easy to implement and easy to convergence. To design the optimal control strategy, a practical optimization technique, namely

HQS (hybrid quick search) method, was developed on the basis of the effective combination of a performance map-based near optimal control strategy and the exhaustive search method taking into account the requirements and constraints of practical applications, i.e., computation efficiency, convergence, etc.

Usually, the performance map-based near optimal control strategies (Hackner et al. 1985; Lau 1985; Sun and Reddy 2005) are practically simple enough, easy to implement and can provide "near optimal" control settings for the control variables to be optimized. However, the settings provided by the performance map-based near optimal control strategies might be significantly different from the true optimal settings, as will later be shown. In the HQS optimization technique, the "near optimal" control setting ($x_i^{n,o}$) determined by the performance map-based control strategy was alternatively used as the search center to define a relatively narrow search range, as illustrated in Figure 7.2, for a control variable to be optimized. This search range can be mathematically defined as in Equation (7.8).

$$x_i^{n,o} - \Delta x \leq x_i \leq x_i^{n,o} + \Delta x \tag{7.8}$$

where, x_i is the i^{th} control variable to be optimized, Δx is the increment, and superscripts *n* and *o* represent near and optimal, respectively.

Based on this narrow search range defined, the proper and simple optimization technique, e.g., the exhaustive search method, can then be adopted to seek the global optimal solution for the given working condition within this range and with a proper increment. The optimization technique determined by this manner can find the global optimal solutions with a reliable manner, while still satisfying the requirements and constraints of practical applications. It is worthwhile to point out that the efficiency and computation performance of this HQS optimization technique is strongly affected by the effectiveness and efficiency of the performance map-based control strategy used.

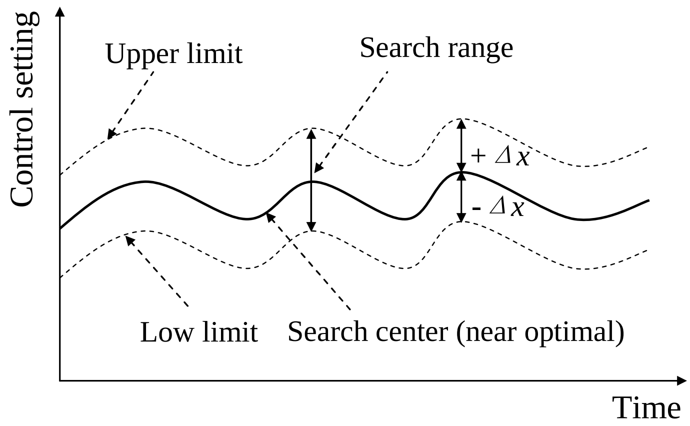

Figure 7.2 Schematic of the defined search ranges based on the near optimal settings.

In the optimal control strategy for the complex condenser cooling water system, this HQS optimization technique was used to search for the optimal condenser water supply temperature set-point. Since a performance map-based control strategy was needed in the HQS optimization technique to generate the near optimal control settings as the search centers for the control variable to be optimized, a linear model, as shown in Equation (7.9), which is a performance map-based control strategy advocated by Sun and Reddy (2005), was used to determine the near optimal control settings for the condenser water supply temperature set-point. The search range as in Equation (7.8) can then be expressed as in Equation (7.10), in which the near optimal control setting is alternatively used as the search center. Since the low limit of the condenser water supply temperature set-point is bound to 18°*C*, the search range as in Equation (7.10) can therefore be finally bounded as in Equation (7.11).

$$T_{w,cd,\sup}^{n,o} = h_0 + h_1 T_{wb} + h_2 \left(\frac{Q_{ev}}{Q_{ev,des}} \right) \tag{7.9}$$

$$T_{w,cd,\sup}^{n,o} - \Delta T \le T_{w,cd,\sup} \le T_{w,cd,\sup}^{n.o} + \Delta T \tag{7.10}$$

$$\max\left(18^\circ C, T_{w,cd,\sup}^{n,o} - \Delta t\right) \le T_{w,cd,\sup} \le \max\left(18^\circ C, T_{w,cd,\sup}^{n,o} + \Delta t\right) \tag{7.11}$$

where h_0-h_2 are coefficients.

7.2.5 Description of the Detailed Optimization Process

Based on the cost function defined, operating limitations constrained and the HQS optimization technique developed together with the simplified chiller and cooling tower models presented in Chapter 5, an optimal control strategy can be formulated using a systematic approach by considering the system level and subsystem level characteristics and interactions within the overall condenser cooling water system. This optimal control strategy will act as the control optimizer to optimize the operation of the complex condenser cooling water system.

During an optimization process, the online measurements and control signals collected from the BAS are firstly sent to a measurement filter. Only the validated measurements are used for the control supervision. The control optimizer will then define the search ranges for the number of cooling towers operating and the condenser water supply temperature set-point according to Equations (7.7) and (7.11), respectively. The condenser outlet water temperatures and the power consumptions of chillers at various condenser water supply temperature set-points can then be predicted by using the simplified chiller model. At each temperature set-point, the power consumptions of the cooling tower fans and the required air flow rate of the cooling towers that can control the system to operate at the desired temperature set-point under different combinations of the numbers of CTA towers and CTB towers in operation and their fan speeds (frequencies) can be predicted by using the simplified CTA tower model and CTB tower model.

The cost estimation (i.e., the cost function illustrated in Equation (7.2)) and the HQS optimization technique developed in Section 7.2.4 are used to determine the optimal control settings (i.e., the optimal condenser water supply temperature set-point, the number of CTA towers operating, the number of CTB towers operating and their individual fan speeds) for the given working condition. The supervisory strategy will provide the final decision (i.e., control settings) for the BAS taking into account the operating constraints of practical applications, i.e., the time interval between the changes of two sets of control settings should avoid an alternating fashion of ON/OFF of the corresponding equipment, etc.

7.3 Performance Tests and Evaluation of the HQS-based Optimal Control Strategy

Using the calculated hourly-based annual building cooling loads presented in Chapter 3 and the hourly-based weather data for the typical year (1989) in Hong Kong, the performance of this HQS-based optimal control strategy was validated using the *computation-assisted test method* presented in Chapter 4 by evaluating its control accuracy and computation performance as well as the energy performance on the central condenser cooling water system presented in Chapter 3. In that building, two types of cooling towers (named CTA towers and CTB towers) were used. The layout of both types of cooling towers is illustrated in Figure 7.3. The six CTA towers are installed as a group. The outdoor air is drawn into a common plenum through an intake air louver before entering the six CTA towers. The five CTB towers are installed as another separate group, and the outdoor air is drawn into another common plenum before entering these CTB towers. There is a large distance between the two groups of cooling towers due to the space restriction of the building. The operation sequence of the cooling towers in two groups is recommended as follows by taking into account the flow resistances in both separate common passages (plenums and air louvers) for the CTA towers and CTB towers. When an even number of cooling towers is needed, the operating numbers of CTA towers and CTB towers are the same. When an odd number of cooling towers is needed, the number of CTA towers used might be one more or one less than the number of CTB towers used, depending on which combination results in less energy consumption.

In the following performance test, the search range in Equation (7.11) is bounded within 2.0 K and the exhaustive search method seeks the global optimal solutions within the limited search range with 0.1 K increments. The chillers are sequenced using the conventional sequence strategy presented in Section 3.3.2.

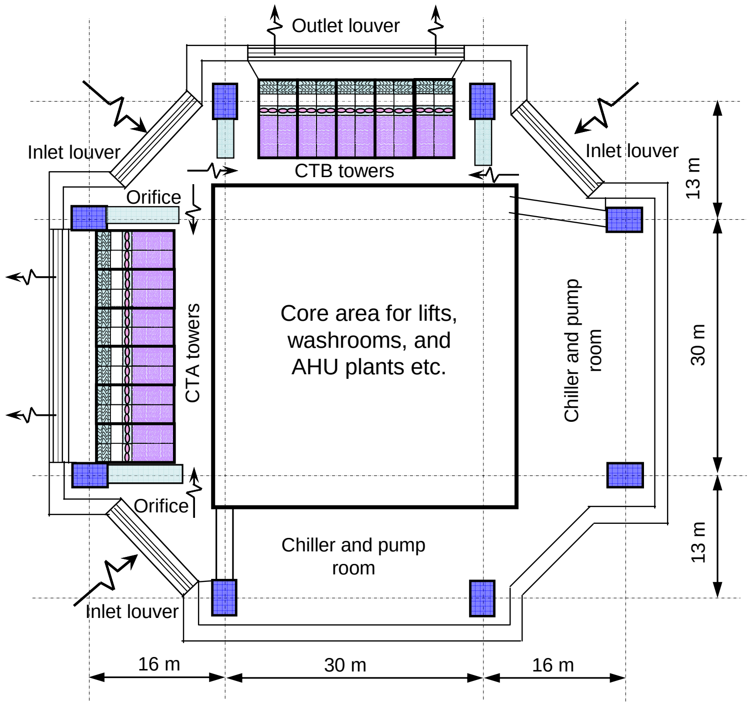

Figure 7.3 Layout of the cooling towers at the mechanical floor.

7.3.1 Training of the Performance Map-based Control Strategy

To validate the effectiveness of the HQS-based optimal control strategy, the performance map-based near optimal control strategy as illustrated in Equation (7.9) needs to be trained firstly. Using the simplified chiller and cooling tower models developed in Chapter 5 as the performance predictor and the exhaustive search method as the optimization tool, a model-based optimal control strategy can be easily formulated using the same cost function and operating constraints as that of the HQS-based optimal control strategy used. Based on the calculated hourly-based whole year building cooling loads and the hourly-based weather conditions of the typical year (1989) in Hong Kong, the hourly-based optimal condenser water supply temperature set-points for all working conditions in a whole year operation of that building can then be simulated using this model-based optimal control strategy within a wide search range of the condenser water supply temperature set-point (low limit is 18°C and the upper limit is 34°C) and with an increment of 0.1 K. A performance map can be generated using these identified optimal condenser water supply temperature set-points and the coefficients in Equation (7.9) can then be identified. The regression using the least-square regression method gives the coefficients as follows: h_0=7.33666, h_1=0.79998, h_2=3.78266. Figure 7.4 shows the comparison between the near optimal condenser water supply temperature set-points predicted by the trained linear model (i.e., the performance map-based control strategy) and the optimal condenser water supply temperature set-points simulated by the model-based optimal strategy using the exhaust search method as the optimization tool based on the whole year data.

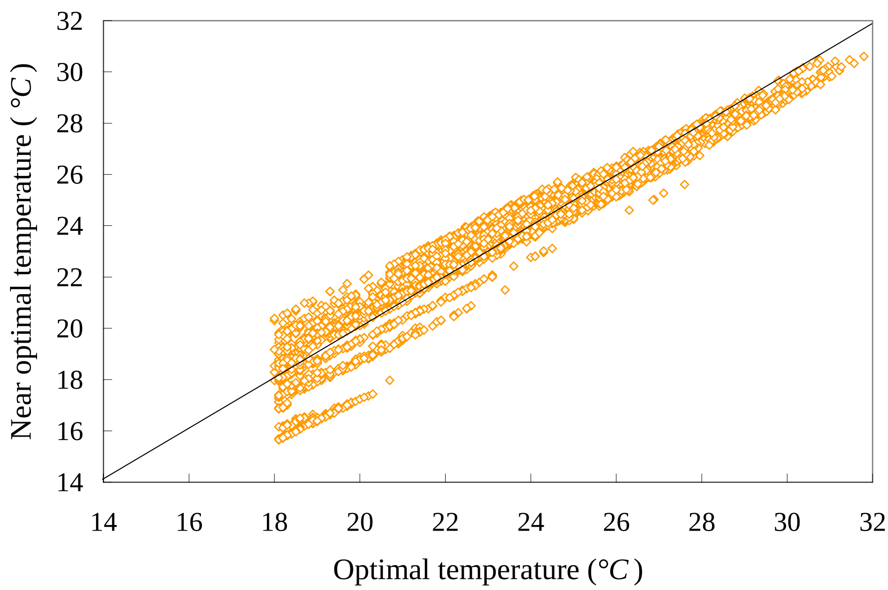

Figure 7.4 Comparison between the temperature set-points using different methods.

The results show that the near optimal temperature set-points given by the performance map-based strategy agreed well with the optimal values (where the coefficient of determination R^2 is 0.9370), which demonstrates that this performance map-based strategy is effective and can provide the near optimal control settings. It is noted that there is a relatively large deviation occurred at some low temperature set-points. This is because the low limit (18°C) was introduced when determining the optimal temperature set-points.

7.3.2 Evaluation of Control Accuracy and Computation Performance

In this case, the control accuracy and computation performance of the HQS-based optimal control strategy were evaluated by comparing with those of the model-based optimal control strategy using a GA as the optimization technique. Genetic algorithms have been shown to solve linear and nonlinear problems by exploring all regions of the state space and exponentially exploiting promising areas through mutation, crossover and selection operations applied to individuals in the population (Michalewicz 1994). In this study, the GA used is a free software package developed for Matlab by Huck et al. (1996). Since different models may result in different predicted deviations, the models used in the optimal control strategy using the GA as the optimization tool are the same as that of the HQS-based optimal control strategy used. The search range of the condenser water supply temperature set-point for the optimal control strategy using the GA as the optimization tool is constrained between 18°C and 34°C. The parameter settings used in this study are as follows: Maximum number of generations is 100; Population size is 20; Probability mutation is 0.01; Probability crossover is 0.7; Type of crossover method is one point crossover. Three typical cases, which represent the typical operation conditions of the air-conditioning system in the spring, mild-summer and sunny-summer respectively, were selected to test and evaluate the performance of the HQS-based optimal control strategy.

Table 7.1 presents the selected three typical working conditions and the test results of the HQS-based optimal control strategy and the model-based optimal control strategy using the GA as the optimization tool.

Table 7.1 Typical test conditions and optimization results using different strategies

Items	Seasons					
	Spring		Mild-summer		Sunny-summer	
Typical working conditions						
Q_{load} (kW)	25520.11		31213.61		37547.74	
N_{ch}	4		5		6	
$T_{w,ev,in}$ (°C)	9.92		9.82		9.83	
$T_{w,ev,out}$ (°C)	5.50		5.50		5.50	
T_{db} (°C)	22.55		27.76		33.66	
T_{wb} (°C)	15.86		20.11		24.99	
$M_{w,cd}$ (L/s)	410.10		410.10		410.10	
Items	Tools					
	HQS	GA	HQS	GA	HQS	GA
Optimization results						
W_{ch} (kW)	3628.07	3644.90	5004.21	4994.37	6794.24	6799.59
W_{ct} (kW)	285.74	268.91	386.11	396.08	538.74	533.42
W_{ch}+W_{ct} (kW)	3913.81	3913.81	5390.32	5390.45	7332.98	7333.01
Optimal $T_{w,cd,sup}$ (°C)	21.85	21.88	26.65	26.64	31.80	31.80
N_{CTA}	6	6	6	6	6	6
N_{CTB}	5	5	5	5	5	5
Freq (Hz)	25.99	25.35	29.33	29.62	33.39	33.26
Computational cost(s)	0.152	3.610	0.144	3.512	0.134	3.589

All of the tests were conducted on the same computer as described in Section 5.2.3 in Chapter 5 and under the Matlab environment. It can be found clearly that the HQS-based optimal control strategy can find the global optimal solutions as can the model-based optimal control strategy using the GA as the optimization tool for the three typical cases, but the computational costs of the HQS-based optimal control strategy were reduced greatly, from 3.512-3.610 s for the GA optimization strategy to

0.134-0.152 s for the proposed strategy in these test cases. The reduction of the average computational cost of the HQS-based optimal control strategy was about 96.0% compared with the strategy using the same models but using the GA as the optimization tool. It is also worthy noticing that the computational cost of the spring case was somewhat higher than that of the mild-summer case and the sunny-summer case. The reason is that the search range of the cooling tower operating number in the spring case was larger than that in the mild-summer case and in the sunny-summer case, which can be verified from Equation (7.7). It is also worthwhile to point out that this time saving is important. In practice, there are many control strategies with different control functions implemented together, and they will be normally computed by every 2 or 3 minutes, and no more than 5 minutes. This is because some settings, such as the pressure differential set-points for each individual zone, need to be reset by every 2 or 3 minutes although some settings might be reset by every 5 minutes or even 20 minutes. The computational cost required by a single model or an individual control strategy might be low. However, the total computational cost and memory demand required by all control strategies in the control system will become large. In addition, the commutation between the control system and the BMS station also requires the time. Therefore, the computation performances of the models and strategies are very important for practical applications.

By comparing the optimal control strategy using the HQS optimization technique and the model-based optimal control strategy using the GA as the optimization technique, the only difference between them is the optimization tools while others (i.e., cost function, performance models, operating constraints, etc.) are the same and, therefore, the above results also demonstrated the effectiveness and efficiency of the HQS optimization technique.

Figure 7.5 shows the search process of the optimal condenser water supply temperature set-point within the defined search ranges for the selected typical spring case using the HQS-based optimal control strategy. It can be observed clearly that the same conclusion as obtained from the energy performance tests in Chapter 3 can be drawn. The optimal condenser water supply temperature set-point is the trade-off between the chiller power and cooling tower fan power. The minimum total power consumption of the chillers and cooling tower fans occurs at the point where the rate of the power increase of the chillers equals the rate of the power reduction of the cooling tower fans. It also can be found that this HQS-based strategy searched for the global optimal minimum within a 4°C defined search range.

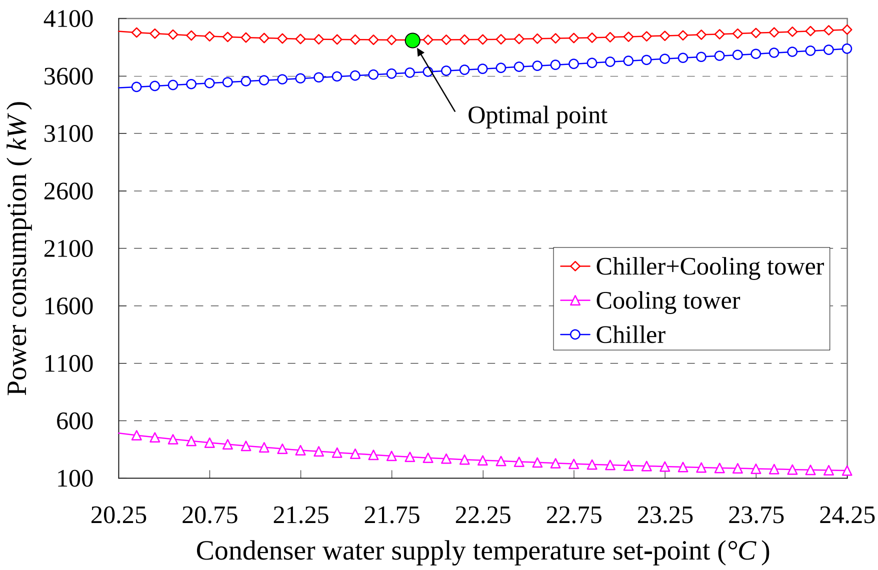

Figure 7.5 Search process of the optimal temperature set-point using the HQS-based optimal control strategy in the typical spring case.

Under a given condenser water supply temperature set-point, there always exist several different operating combinations of cooling towers (i.e., the operating number of CTA towers, the operating number of CTB towers and their fan speeds) that can control the system to operate at this temperature set-point, while different operating combinations will result in different cooling tower fan power consumptions although the power consumption of the chillers remains unchanged. Table 7.2 presents the search process of the best operating combination of the cooling towers for a given condenser water supply temperature set-point, i.e., 21.85°C. The HQS-based optimal control strategy seeks the best combination that can result in the minimum total power consumption of the chillers and cooling towers, based on the defined search range for the operating number of cooling towers as expressed in Equation (7.7).

Table 7.2 Search process of the best operating combination of towers and their fan frequencies under a given temperature set-point (21.85°C) in the spring case

N_{CTA}	N_{CTB}	*Freq* (Hz)	W_{ct} (kW)	W_{ch} (kW)	$W_{ch}+W_{ct}$ (kW)
3	4	38.21	472.66	3628.07	4100.73
4	3	38.21	488.83	3628.07	4116.90
4	4	34.46	420.87	3628.07	4048.94
4	5	30.73	347.40	3628.07	3975.47
5	4	30.73	356.61	3628.07	3984.68
5	5	28.42	320.62	3628.07	3948.69
6	5	25.99	285.74	3628.07	3913.81

The trace of the best fitness and the average fitness along the evolution using the GA as the optimization tool in the typical spring case is illustrated in Figure 7.6. It can be found that the GA can find the global optimal solutions within 100 generations. It is worthwhile to point out that the GA utilized in this study intended to search for the maximum values, while the optimization problem was to seek the minimum power consumption. Thus, all fitness was converted into negative values during the search process, and the values in the vertical axis in Figure 7.6 are therefore negative values.

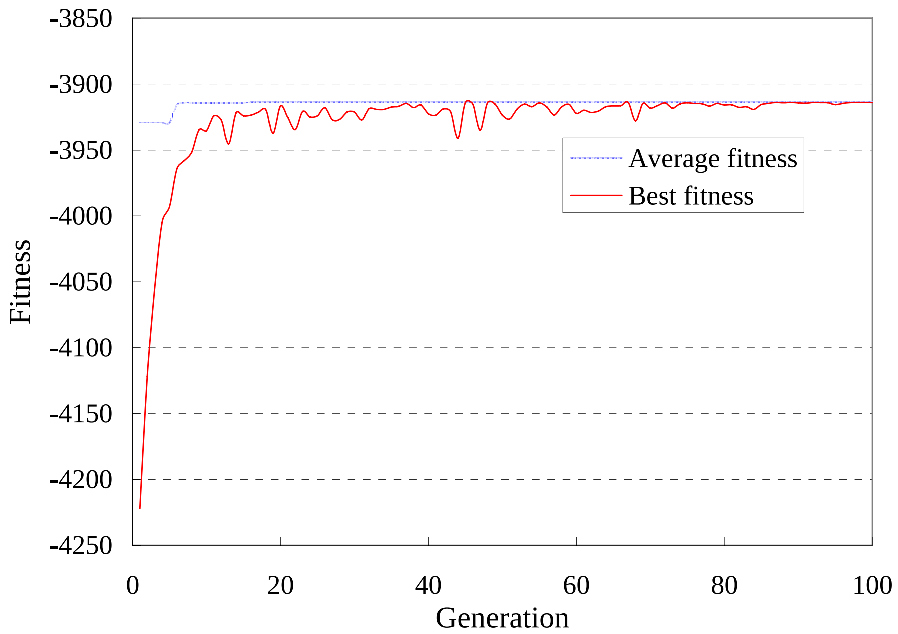

Figure 7.6 Trace of the best fitness and average fitness along the evolution using the GA as the optimization technique in the typical spring case.

From the above comparisons, it can be concluded that the HQS-based optimal control strategy has the same control accuracy as the model-based optimal control strategy using the GA as the optimization tool, but the computational cost was reduced greatly. The reduction of the average computational cost related to the use of the HQS-based optimal control strategy was about 96.0% for the three test cases when compared with that of the model-based optimal control strategy using the GA as the optimization tool. This characteristic makes it suitable for online practical applications. The results also demonstrated the effectiveness of the HQS optimization technique.

7.3.3 Evaluation of the Energy Performance

The energy performance of the HQS-based optimal control strategy was evaluated by comparing it with that of the performance map-based near optimal control strategy (as illustrated in Equation (7.9)) in terms of the condenser water supply temperature set-point and the entire power consumption of the chillers and cooling towers. In this study, the performance of the fixed approach control method (the approach temperature is 5°C) was used as the benchmark.

It is worthy noticing that the performance map-based near optimal control strategy and the fixed approach control method can only provide the condenser water supply temperature set-point. However, for a given temperature set-point, there always exist several possible operating combinations of the number of cooling towers in operation and their individual fan speeds that can control the system to operate at the desired temperature set-point. Therefore, the performance map-based near optimal control strategy and the fixed approach control method need to be further designed to make them have capabilities to identify the best combination among all possible operating combinations of the number of cooling towers operating and their fan speeds at a given temperature set-point.

Since different performance predictors, energy estimators and supervisory strategies may result in different prediction results although the working condition is the same, the performance predictor, energy estimator and supervisory strategy used to further design the performance map-based near optimal control strategy and the fixed approach control method are the same as that used to design the HQS-based optimal control strategy while the exhaustive search method as the optimization tool is used in both strategies to search for the most energy efficient combination of the number of cooling towers in operation and their fan speeds.

Three typical days, which represent the typical operation conditions of the air-conditioning system in the spring, mild-summer and sunny-summer respectively, were selected to test and evaluate the energy performance of the HQS-based optimal control strategy. The building cooling loads in these three typical days were the same as those presented in Figure 3.4 in Chapter 3.

Figures 7.7, 7.8 and 7.9 present the profiles of the condenser water supply temperature set-points obtained by using the HQS-based optimal control strategy and the performance map-based near optimal control strategy for the typical spring day, mild-summer day and sunny-summer day, respectively. The weather conditions and the search ranges are also shown in these figures. It is obvious that the optimal condenser water supply temperature set-points (indicated as 'Optimal Temp. set-point' in figures) searched by using the HQS-based optimal control strategy deviated from the values (indicated as 'Near optimal Temp. set-point' in figures) found using the performance map-based near optimal control strategy. These near optimal temperature set-points are, in fact, the search centers. It also can be found that the optimal condenser water supply temperature set-points were all within the defined search ranges for the three typical days, which can further verify the effectiveness of the HQS optimization technique. It is worthy pointing out that the search ranges for the typical spring day (Figure 7.7) were further narrowed since the low limit of the search range of the condenser water supply temperature set-points was constrained to 18$°C$, and the optimal condenser water supply temperature set-points at some working conditions may occur at this low limit.

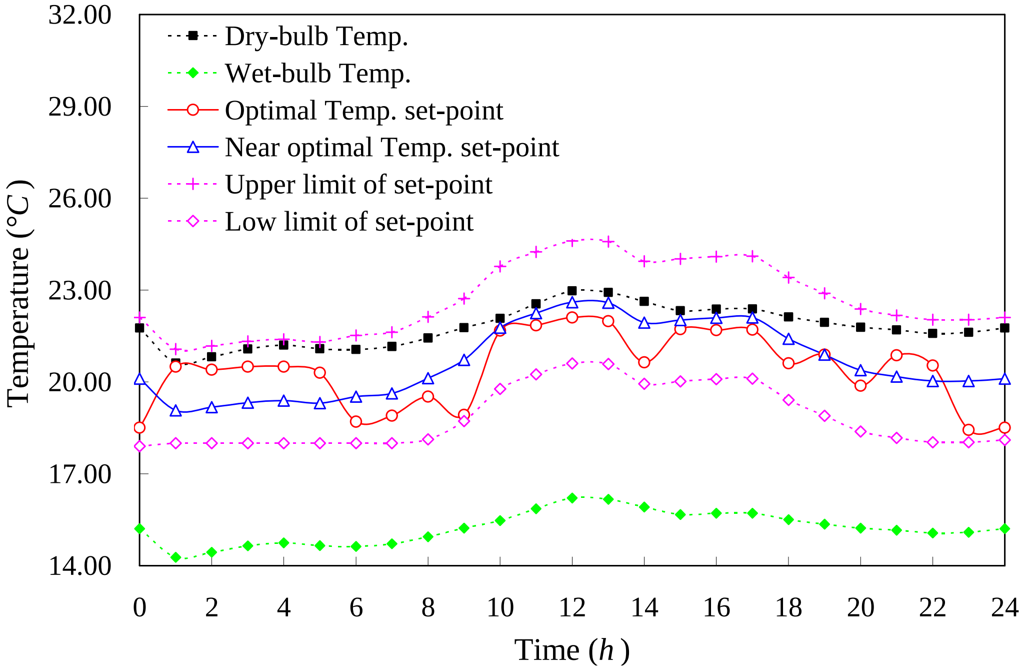

Figure 7.7 Optimal and near optimal temperature set-points as well as the weather conditions in the typical spring day.

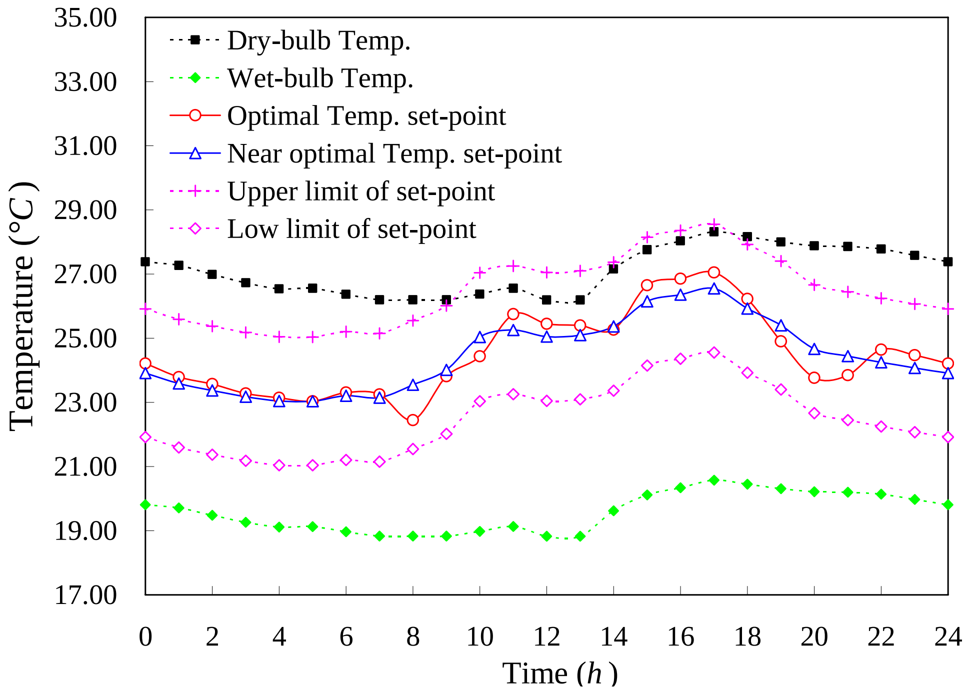

Figure 7.8 Optimal and near optimal temperature set-points as well as the weather conditions in the typical mild-summer day.

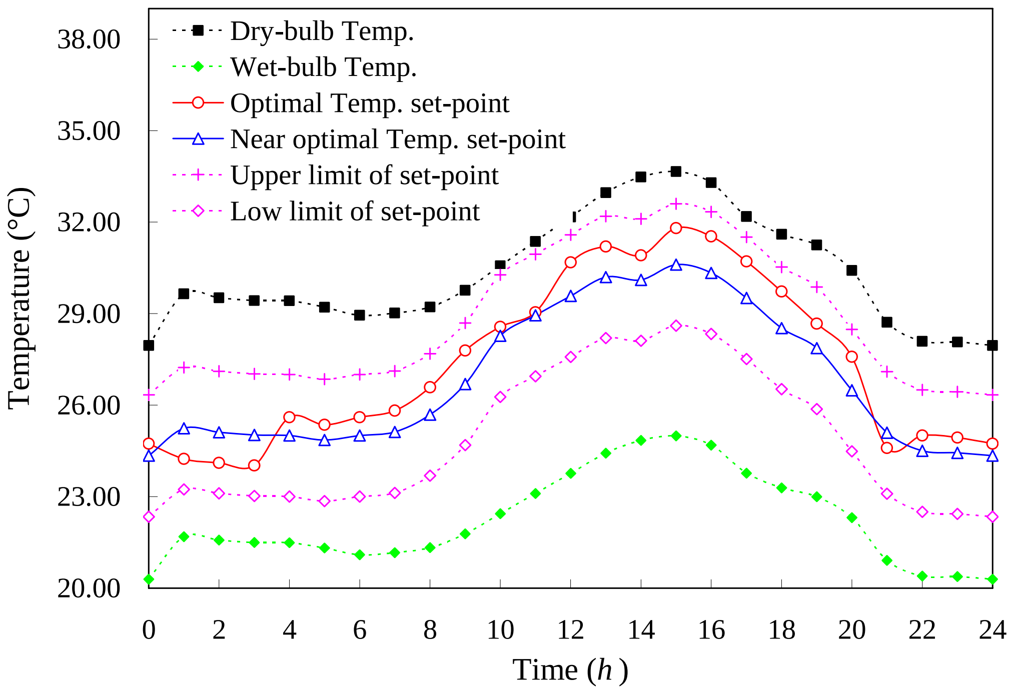

Figure 7.9 Optimal and near optimal temperature set-points as well as the weather conditions in the typical sunny-summer day.

The performance of this HQS-based optimal control strategy was further validated concerning the system power consumption. Figures 7.10, 7.11 and 7.12 present the differences between the hourly-based power consumption using the fixed approach control method and the HQS-based optimal control strategy (indicated as 'Optimal strategy' in figures), and the differences between the hourly-based power consumption using the fixed approach control method and the performance map-based near optimal control strategy (indicated as 'Near optimal strategy' in figures) in the typical spring day, mild-summer day and sunny-summer day, respectively. It can be seen that a significant amount of energy can be saved when the HQS-based optimal control strategy is used. The maximum differences between the hourly-based power consumption using the fixed approach control method and the HQS-based optimal control strategy were about 33 kW, 98 kW and 191 kW in the typical spring day, mild-summer day and sunny-summer day, respectively. The maximum differences between the hourly-based power consumption using the fixed approach control method and the performance map-based near optimal control strategy were about 33 kW, 92 kW and 126 kW in the typical spring day, mild-summer day and sunny-summer day, respectively. It also can be found that the performance map-based near optimal control strategy was not always better than the fixed approach control method. For instance, at some working conditions, the power consumptions using the performance map-based near optimal control strategy were more than that using the fixed approach control method, which further reveals that the HQS-based optimal control strategy can provide much better energy efficient control than the performance map-based near optimal control strategy.

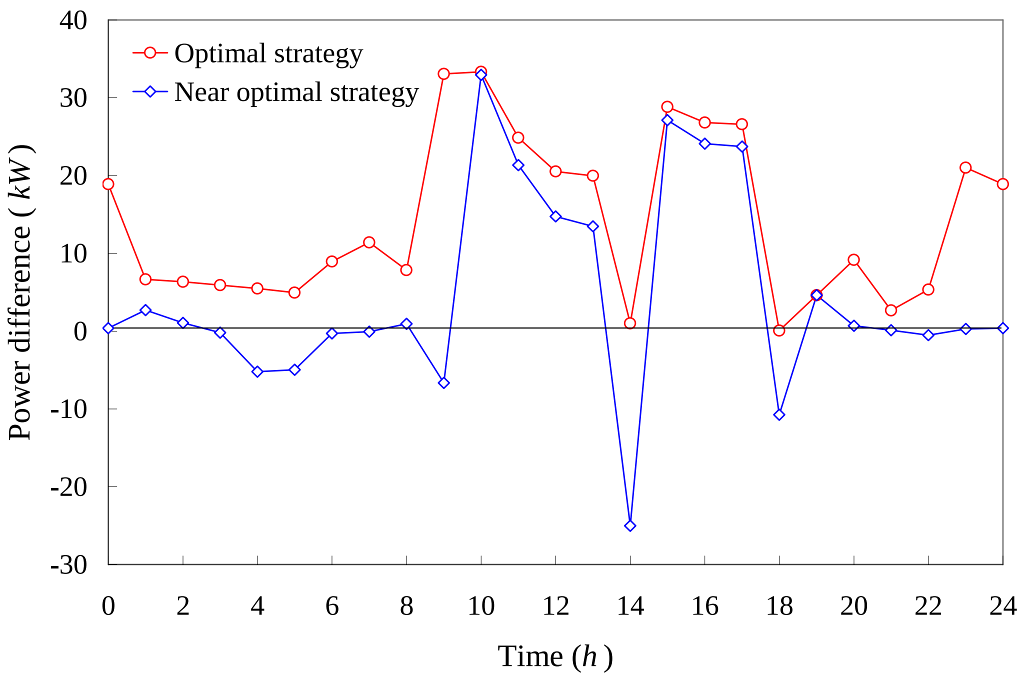

Figure 7.10 Savings in power consumptions of the optimal/near optimal strategies compared to the fixed approach control method in the typical spring day.

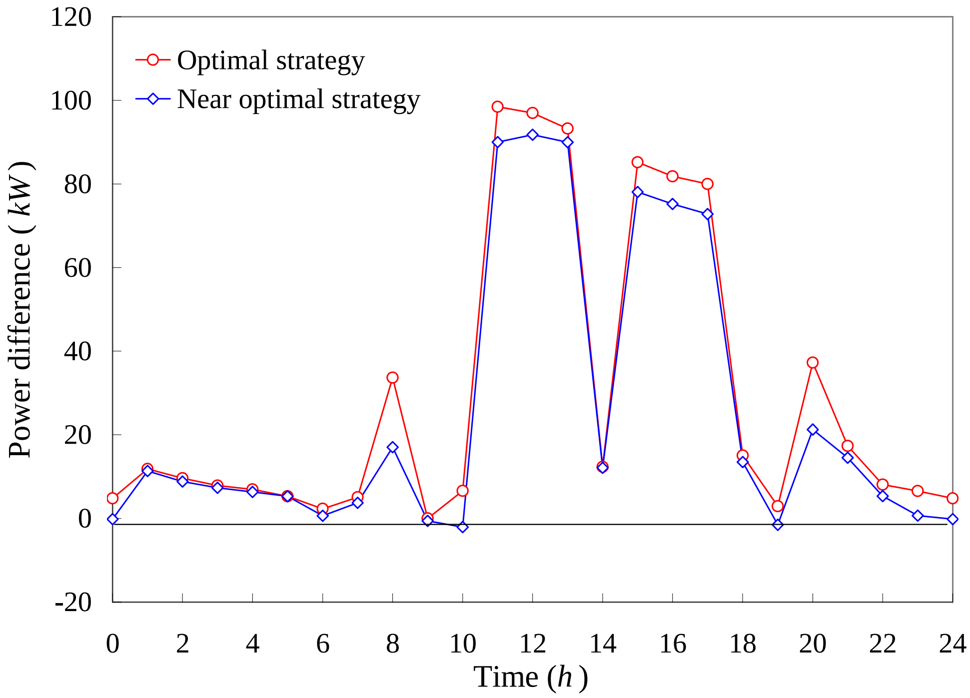

Figure 7.11 Savings in power consumptions of the optimal/near optimal strategies compared to the fixed approach control method in the typical mild-summer day.

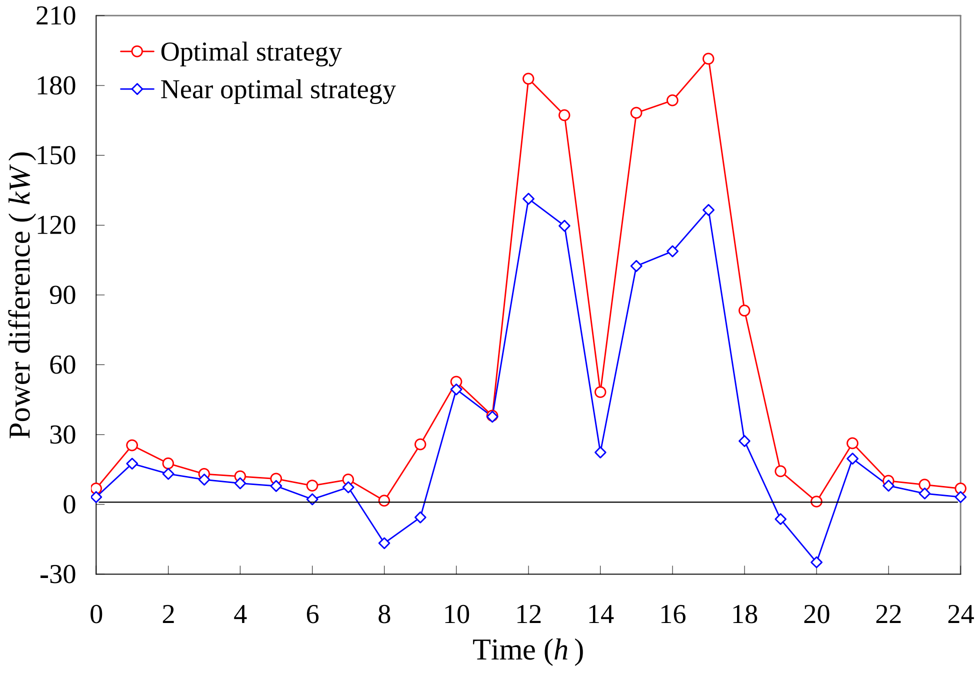

Figure 7.12 Savings in power consumptions of the optimal/near optimal strategies compared to the fixed approach control method in the typical sunny-summer day.

It is worth noticing that the power difference between the HQS-based strategy and the performance map-based strategy is largest in the sunny-summer day, as shown in

Figure 7.12. This is because the performance map-based strategy has larger prediction deviations at sunny-summer days than that of other days.

Table 7.3 presents the power consumptions of the condenser cooling water system (chillers + cooling towers) in the three typical days when using different control methods. Compared with the fixed approach control method, the HQS-based optimal control strategy saved about 334.30 kWh (0.646%), 729.36 kWh (1.023%) and 1297.50 kWh (1.416%) energy in the typical spring day, mild- summer day and sunny-summer day, respectively. It also can be found that the performance map-based near optimal control strategy saved about 114.53 kWh (0.221%), 621.49 kWh (0.872%), 775.44 kWh (0.846%) energy in the typical spring day, mild-summer day and sunny-summer day respectively, over the fixed approach control method, although the hourly-based power consumptions of the performance map-based near optimal control strategy were not always less than that of the fixed approach control method.

Table 7.3 Comparison of daily power consumptions (chiller + cooling tower) using different control strategies in the three typical days

Operation Strategies	Fixed approach	Near optimal strategy			HQS-based strategy		
	$W_{ct}+W_{ch}$ (kWh)	$W_{ct}+W_{ch}$ (kWh)	Saving (kWh)	Saving (%)	$W_{ct}+W_{ch}$ (kWh)	Saving (kWh)	Saving (%)
Spring	51,738	51,623	114.53	0.221	51,404	334.30	0.646
Mild-summer	71,289	70,668	621.49	0.872	70,560	729.36	1.023
Sunny-summer	91,653	90,878	775.44	0.846	90,356	1,297.50	1.416

The annual electricity consumption of the central condenser cooling water system of this building was also evaluated using different control strategies and the results are shown in Table 7.4. Compared with the fixed approach control method, a significant amount of energy can be saved by applying the HQS-based optimal control strategy and the performance map-based near optimal control strategy. The annual energy savings using the HQS-based optimal control strategy and the performance map-based near optimal control strategy were 183,496 kWh (0.747%) and 130,236 kWh (0.530%), respectively. It also can be observed that the HQS-based optimal control strategy can save a significant amount of energy when compared with the performance map-based near optimal control strategy. It is worthy noticing that the chiller operating number was not optimized and the same chiller sequence control strategy was used during the above calculations and, therefore, the power consumptions of the condenser water pumps were the same for the three different control strategies.

All of these results illustrate that the HQS-based optimal control strategy is more energy efficient and cost effective than the other control methods. It is also demonstrated that the condenser water supply temperature set-points determined by the performance map-based near optimal control strategy could still be far from optimal, although this strategy is simple and easy to implement in practice.

Table 7.4 Comparison of the annual electricity consumptions of the central condenser cooling water system using different control strategies

Operation strategies	W_{ch} (kWh)	W_{ct} (kWh)	$W_{cd,pu}$ (kWh)	W_{tot} (kWh)	Saving (kWh)	Saving (%)
Fixed approach	18,464,812	1,882,583	4,210,690	24,558,085	---	---
Near optimal	18,715,458	1,501,701	4,210,690	24,427,849	130,236	0.530
HQS-based	18,715,134	1,448,765	4,210,690	24,374,589	183,496	0.747

Figure 7.13 shows the identified operating numbers of CTA towers and CTB towers as well as the identified cooling tower fan operating frequencies using the HQS-based optimal control strategy for the typical spring day. The operating number

of chillers is also showed in the same figure. It can be found that all CTA towers and CTB towers were in operation in most working conditions (from 9 a.m. to 19 p.m.), while the fan operating frequencies were relatively low (lower than 27 Hz for all working conditions), which demonstrates that operating more cooling towers with relatively low fan frequencies is an energy efficient and cost effective means to save the power consumption of the condenser cooling water system.

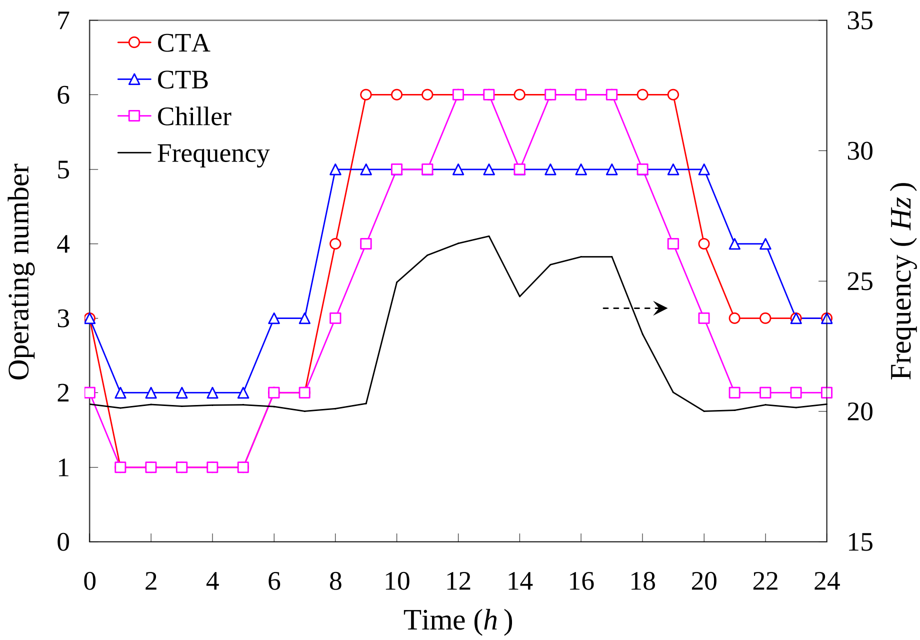

Figure 7.13 Operating numbers of chillers, CTA/CTB towers and the fan frequencies in the typical spring day.

Figure 7.14 presents the power consumptions of the chillers and cooling towers as well as the total power consumption of the chillers and cooling towers in the typical spring day using the HQS-based optimal control strategy. Compared with the cooling towers, the chillers consumed a tremendous amount of energy. Although the power consumption of the cooling tower fans was relatively small, the absolute value was also high (the hourly-based maximum value was about 310 kW for the selected typical spring day).

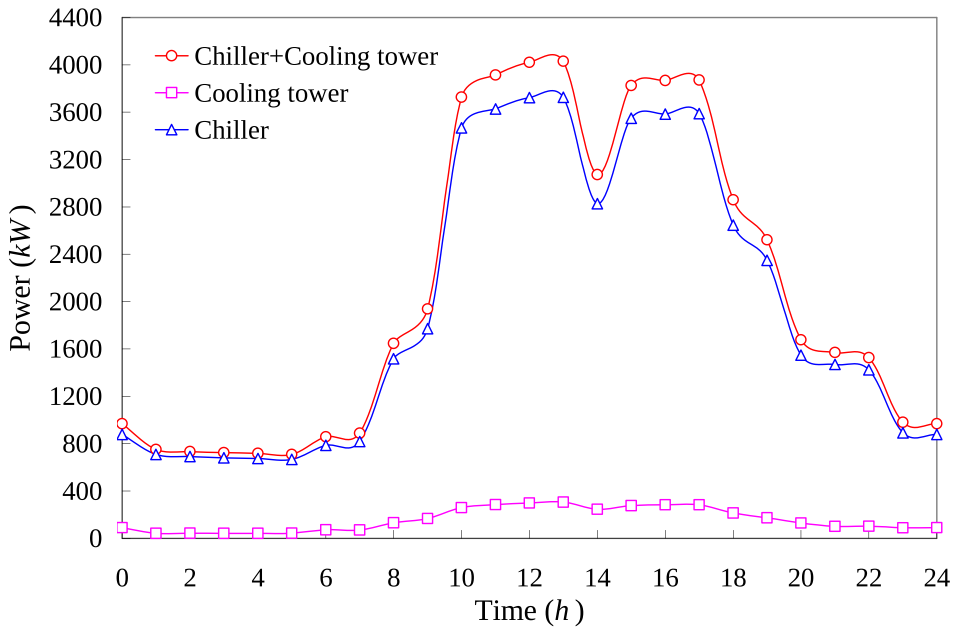

Figure 7.14 The power consumptions of chillers and cooling towers in the typical spring day.

Based on the above tests and evaluation, it can be found that the HQS-based optimal control strategy can save significantly more energy than the performance map-based near optimal control strategy and the conventional fixed approach control method. It is worthwhile to notice that the chilled water supply temperature set-point was not optimized and was maintained as a constant (5.5°C) during the above calculations. The impact of this fixed temperature set-point on the optimization of the condenser cooling water system is small since the results obtained from the energy performance tests in Chapter 3 showed that energy savings related to the optimization of the chilled water supply temperature set-point in this building were small.

7.4 Summary

To sum up, this chapter presents a HQS (hybrid quick search)-based optimal control strategy for the online control of complex central condenser cooling water systems in buildings. The HQS-based optimal control strategy is developed by the combined use of the model-based optimal control and the performance map-based optimal control. The simplified chiller and cooling tower models were used in the strategy to predict the system energy performance and environment quality as well as the system response to the changes of the control settings. The HQS optimization technique was developed and used to seek the most optimal control settings efficiently..

The performance of this HQS-based optimal control strategy was validated on the complex central condenser cooling water system presented in Chapter 3 in terms of the control accuracy, computation performance and energy performance. The results demonstrated that this HQS-based optimal control strategy has good performance and is suitable for online control applications.

It is worth noticing that the performance map-based strategy needs to be further designed to make it have capability to identify the best combination among all possible operating combinations of the numbers of cooling towers operating and their fan speeds at a given condenser water supply temperature set-point since it can provide the temperature set-point only. After it is further designed, the difference between the performance map-based strategy and the HQS-based strategy is that the performance map-based strategy determines a near optimal temperature set-point directly while the HQS method uses the HQS optimization tool to find the global optimal temperature set-point within a small defined search range. Therefore, the HQS-based strategy is still simple and easy to implement in practice.

CHAPTER 8 ONLINE OPTIMAL CONTROL OF CENTRAL CHILLED WATER SYSTEMS

Central chilled water systems have many components that consume a substantial amount of energy over the course of a year (Kelly and Chan 1999; Lu et al. 2005c). Due to the increasing energy costs and the pursuit of the energy efficiency in buildings over the past decade, design practitioners in the HVAC field have made the configurations of chilled water systems unbelievably complex, which, however, might result in a significant negative impact on energy economics of buildings if the system cannot be controlled properly. Therefore, the development of proper and optimal control strategies for complex building central chilled water systems is essential and necessary to enhance their operating efficiency. In this chapter, an optimal control strategy for complex building central chilled water systems is presented. The performance of this optimal control strategy is tested and evaluated on the complex central chilled water system presented in Chapter 3 by comparing with those of other control strategies.

Section 8.1 presents a brief summary of major control methods for chilled water systems. The formulation of the optimal control strategy for complex central chilled water systems is outlined in Section 8.2. The optimal control strategy was formulated using a model-based approach considering the system level and subsystem level characteristics and interactions among the overall system, and the requirements and constraints of practical applications. Based on the dynamic simulation platform constructed in Chapter 3, the performance of this optimal control strategy is validated in Section 8.3. A summary of this chapter is given in Section 8.4.

8.1 A Brief Summary of Control Methods for Chilled Water Systems

To reduce the energy consumption and provide better operational performance in buildings, many studies that specifically address the energy efficient control and operation of building central chilled water systems have been reported during the last few decades (Braun et al. 1989a, 1989b; Ahmed 1991; Baird 1999; Cascia 2000; Lu et al. 2005c; Sun and Reddy 2005; Jin et al. 2007; ASHRAE 2007; etc.). These studies have demonstrated the importance of the optimization of the chilled water supply temperature set-point (Kaya 1991; ASHRAE 2007), the pump speed control (Moore and Fisher 2003; Rishel 2003), the pump sequence control (Rishel 1991, 2003; ASHRAE 2007), the chiller sequence control (Meckler 2002; Chang 2005), and the global optimization of the overall chilled water systems (Braun et al. 1989b; Cascia 2000; Lu et al. 2005c; Sun and Reddy 2005). Most of these existing studies have been comprehensively reviewed and summarized in Chapter 2 and, therefore, are not repeated here. As discussed in Chapter 2, the settings of the local control strategies might not be energy efficient and cost effective when the overall system and overall system performance are of concern. The existing optimization strategies for the overall chilled water systems were mainly developed for simple and typical chilled water systems either using the global optimization techniques that often require high computational costs and memory demands or using the empirical models that cannot always ensure stable performance prediction. More importantly, the studies related to the control of complex chilled water systems are still missing. Therefore, the development of the optimal control strategy for complex central chilled water systems for practical and real-time applications is the major objective of this chapter.

8.2. Formulation of the Optimal Control Strategy

In general, the control of complex chilled water systems is strongly affected by the system design. Different design configurations (i.e., the primary-secondary pumping system or variable primary pumping system, the water distribution systems with or without heat exchangers to transfer the cooling energy from low zones to high zones, the primary-secondary pumping systems with dedicated pumps or manifold pumps, etc.) may require different control strategies. It is very difficult and almost impossible to develop a general optimal control strategy that can be used for the proper control of all possible configurations of chilled water systems. In complex central chilled water systems, there are many variables to be controlled, and a small change of the system design may result in significant variations of the control system (i.e., the sequence controls of chillers with the same capacities and with different capacities, the controls of dedicated pumps with chillers and manifold pumps with chillers, etc.). The difficulties related to developing the general optimal control strategy for complex chilled water systems are therefore increased dramatically.

The optimal control strategy for complex chilled water systems presented in this chapter is developed based on the actual complex chilled water system presented in

Chapter 3. Since Zone 1 and Zone 2 in the secondary chilled water system of that building cover all possible control issues (i.e., the speed control of the pump distributing water to terminal units, the speed control of the pump distributing water to heat exchangers, the pump sequence control, the heat exchanger sequence control, the optimization of the pressure differential set-point, etc.) of the overall secondary chilled water system of the building, the optimal control strategy presented in the following is therefore mainly focused on Zone 1 and Zone 2 only in order to reduce the complexity of the control system. This optimal control strategy can be easily adapted to Zone 3 and Zone 4 in the secondary chilled water system of that building. It also can be easily adapted to most of other complex chilled water systems with primary-secondary pumping paradigms since most issues associated with the control of complex chilled water systems are included in this strategy.

8.2.1 Outline of the Optimal Control Strategy

The optimal control strategy developed is to optimize the operation of the central chilled water system using a systematic approach by considering the system level and subsystem level characteristics and interactions among the overall system. Figure 8.1 illustrates the outline of this optimal control strategy, which includes the model-based performance predictor, cost estimator (i.e., cost function), optimization algorithm, supervisory strategy and a number of local controllers.

The model-based performance predictor utilizes component/system models presented in Chapter 5 to predict the system energy performance and environment quality as well as the system response to the changes of the control settings under various conditions. The models utilized in this strategy include: the simplified chiller model, the global AHU model (i.e., the adaptation of the simplified cooling tower model), the water network pressure drop model, the pump model, the heat exchanger model and the pressure differential set-point incremental model.

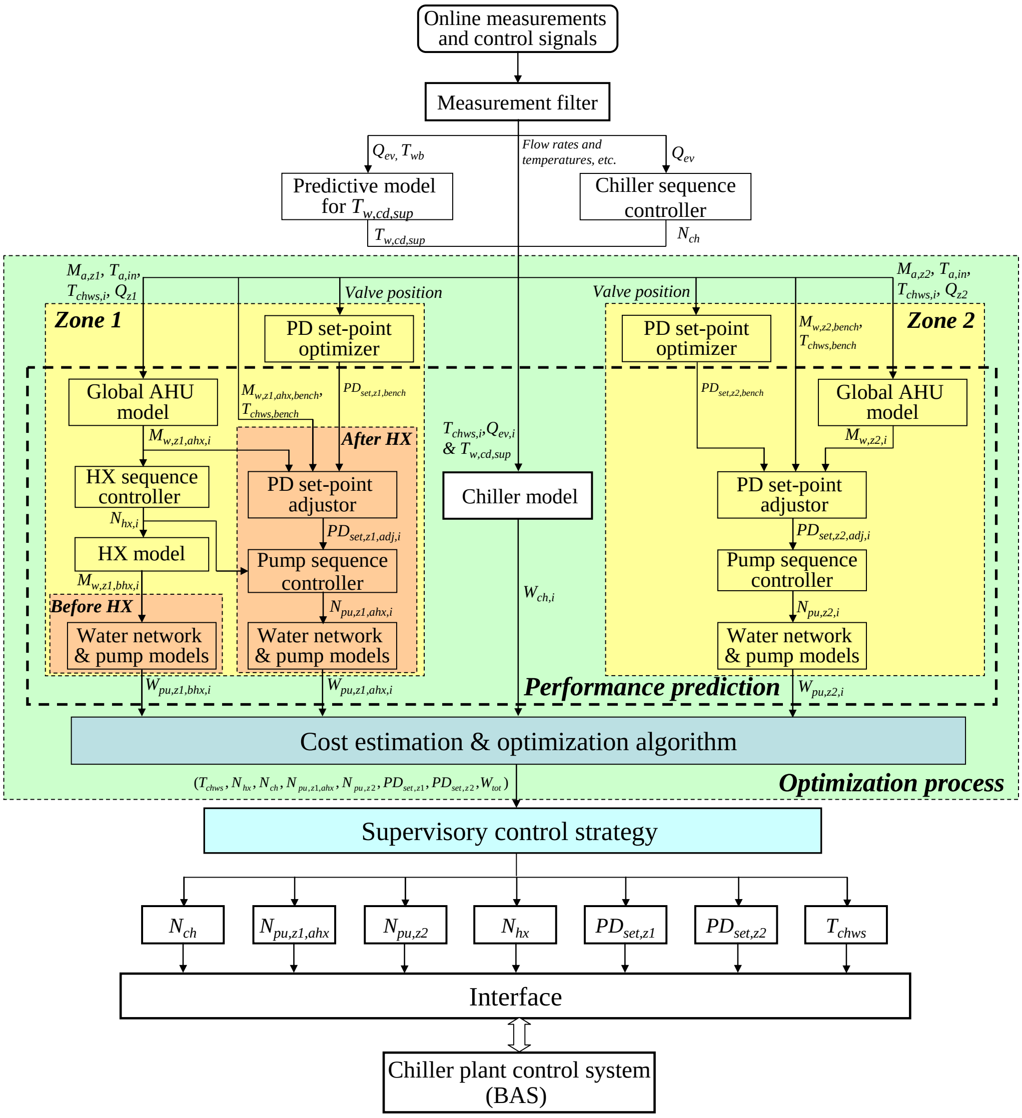

Figure 8.1 Illustration of the structures of the optimal control strategy.

The nomenclature in the figure is defined as follows. M is the water/air flow rate, Q is the heat transfer rate, T is the temperature, PD is the pressure differential, N is the number, W is the power consumption, and subscripts w, a, ch, cd, ev, pu, $z1$, $z2$, wb, set, sup, adj, ahx, bhx, $bench$, $chws$ and tot represent water, air, chiller, condenser, evaporator, pump, Zone 1, Zone 2, wet-bulb, set-point, supply, adjusted, after heat exchangers (i.e., secondary side of heat exchangers), before heat exchangers (i.e., primary side of heat exchangers), benchmark, chilled water supply and total, respectively.

The local controllers are utilized to ensure the robust operation and keep track of the control settings considering the dynamic characteristics of the local process environments. The local controllers utilized consist of a chiller sequence controller, a heat exchanger sequence controller, a pump sequence controller, a pressure differential set-point optimizer, etc. It is worthwhile to point out here that the simple pump sequence controller as that of Strategy #1 in Chapter 6 utilized was used to formulate this optimal control strategy instead of using the near optimal pump sequence controller developed in Chapter 6 due to the following reasons: (1) the energy evaluation results obtained from Chapter 6 show that the energy saving potentials associated with the use of the near optimal pump sequence controller in this complex central chilled water system is very limited as compared with that using the simple pump sequence controller; (2) since the optimal control strategy for complex chilled water systems developed in this chapter is for online applications, the simple pump sequence controller might simplify the control system and can provide more stable operation to some extent without wasting much energy as compared with using the near optimal pump sequence controller.

The definitions of the cost function and operating constraints as well as the description of the detailed optimization process of this optimal control strategy are presented in the following in detail.

8.2.2 Definition of the Cost Function

The systematic optimization of the chilled water system aims at minimizing the total power consumption of chillers and chilled water pumps while fulfilling the cooling demands of all terminal units. Similar to the definition of the cost function for the HQS-based optimal control strategy for complex condenser cooling water systems presented in Chapter 7, the cost function for the chilled water system, including Zone 1 and Zone 2 of the building under study, can also be simplified based on Equation (2.1) presented in Chapter 2, and is finally expressed as in Equation (8.1).

$$J = \min_{T_{chws}} W_{tot} = \sum_{k=1}^{N_{ch}} W_{ch,k} + \sum_{m=1}^{N_1} W_{pu,z1,bhx,m} + \sum_{i=1}^{N_2} W_{pu,z1,ahx,i} + \sum_{j=1}^{N_3} W_{pu,z2,j} \tag{8.1}$$

8.2.3 Definition of the Operating Constraints

To properly control the operation of chilled water systems, certain constraints are necessary to be bounded. The heat generated in chiller condensers is assumed equal to the sum of the evaporator cooling energy and the power consumed by chiller compressors as shown in Equation (8.2). The chilled water is assumed to be distributed to each operating chiller evenly to allow all chillers to operate at good efficiency. It is also assumed that the chilled water is distributed to each operating variable speed pump or each operating heat exchanger with parallel installations evenly to achieve good efficiency of the pumps or heat exchangers. To avoid the low chilled water supply temperature set-point causing the problems of ice in evaporators and the low efficiency of chillers, and the high chilled water supply temperature set-point resulting in the problems of the humidity control for the air-conditioned spaces and inadequate cooling load provided, the chilled water supply temperature set-point is constrained between 5°C and 10°C. To avoid the low condenser water supply temperature set-point causing low pressure problems in chillers, the low limit of the condenser water supply temperature set-point is bounded to 18°C. The input frequency to variable speed pumps is bounded between 20 Hz and 50 Hz. The constraints of the pressure differential set-points for Zone 1 and Zone 2 are the same as that used in Chapter 6 (from 80 kPa to 215 kPa for Zone 1, and from 90 kPa to 230 kPa for Zone 2).

$$\sum_{k=1}^{N_{ch}} Q_{cd,k} = \sum_{k=1}^{N_{ch}} Q_{ev,k} + \sum_{k=1}^{N_{ch}} W_{ch,k} \tag{8.2}$$

8.2.4 Description of the Detailed Optimization Process

During an optimization process, the online measurements and control signals collected from the BAS are firstly sent to a measurement filter. Only the validated measurements are used for the control supervision. For a given condition, the strategy determines the condenser water supply temperature set-point ($T_{w,cd,sup}$) and the number of chillers operating (N_{ch}) first according to the calculated building cooling load using the difference of the chiller water supply and return temperatures and water flow rate measurements, and the air wet-bulb temperature measurements. In this strategy, a predictive model, as shown in Equation (7.9) in Chapter 7, was used to determine a near optimal condenser water supply temperature set-point to reduce the impact of the condenser water supply temperature set-point on the optimization of the chilled water system. The simple chiller sequence controller presented in Section 3.3.2 in Chapter 3 was utilized to control the number of chillers operating.

The online opening signals (i.e., PID outputs) of all water control valves in Zone 1 and Zone 2 are used to determine the optimal pressure differential set-points for Zone 1 and Zone 2, respectively, at the given chilled water supply temperature set-point, using the pressure differential set-point optimizer presented in Section 6.2.1 in Chapter 6. These pressure differential set-points at the given chilled water supply temperature set-point are then used as the benchmarks to predict the optimal pressure differential set-points for Zone 1 and Zone 2 under any other chilled water supply temperature set-point. At any other given chilled water supply temperature set-point, the water flow rate required by each zone is predicted by using the global AHU model. The predicted water flow rate is then used to estimate the optimal pressure differential set-point for each zone at the desired chilled water supply temperature set-point using the pressure differential set-point incremental model presented in Chapter 5. This process is named PD (pressure differential) set-point adjustor in Figure 8.1. For Zone 1, this water flow rate is also used to determine the number of heat exchangers in operation using the heat exchanger sequence controller presented in Section 6.3.2 in Chapter 6. Based on the optimal pressure differential set-point and the number of heat exchangers operating at the desired chilled water supply temperature set-point, the operating number of pumps in the secondary side of heat exchangers in Zone 1, the operating number of pumps in Zone 2, and their power consumptions can be predicted using the simple pump sequence control strategy, and the pump model and the water network pressure drop model presented in Chapter 5.

The outlet water temperature at the secondary side of heat exchangers in Zone 1 is determined using the method presented in Chapter 6.4.1 (i.e., a fixed temperature difference, e.g., 0.8 K, between the outlet water temperature at the secondary side and the inlet water temperature at the primary side of heat exchangers at the design condition is used to set this temperature set-point). Based on this temperature set-point, the water flow rate and the power consumption of the pump in the primary side of heat exchangers in Zone 1 can be predicted, respectively, using the heat exchanger model, pump model and water network pressure drop model presented in Chapter 5. The power consumptions of chillers under different chilled water supply temperature set-points are predicted using the simplified chiller model developed in Chapter 5.

The cost estimation and optimization algorithm are then employed to determine the energy efficient control settings that minimize the overall system energy consumption. The settings optimized include: the chilled water supply temperature set-point (T_{chws}), the operating number of pumps distributing water to terminal units in Zone 1 ($N_{pu,z1,ahx}$), the operating number of pumps in Zone 2 ($N_{pu,z2}$), the operating number of heat exchangers in Zone 1 (N_{hx}), the optimal pressure differential set-point for Zone 1 ($PD_{set,z1}$), and the optimal pressure differential set-point for Zone 2 ($PD_{set,z2}$) as well as the number of chillers operating (N_{ch}). Since the search range of the chilled water supply temperature set-point is relatively narrow (from 5°C to 10°C), the exhaustive search method is used to seek the global optimal solutions within this limited search range defined with 0.1 K increments. The primary function of the supervisory strategy is the same as that for the HQS-based optimal control strategy presented in Chapter 7, i.e., to provide the final control settings for the BAS to avoid an alternating fashion of ON/OFF of corresponding components, etc.

8.3. Performance Tests and Evaluation of the Optimal Control Strategy

8.3.1 Set up the Tests

The performance of this optimal control strategy was tested and evaluated on the complex central chilled water system presented in Chapter 3 using the *simulation-assisted test method* presented in Chapter 4. The test process is similar to that presented in Section 6.4.1 in Chapter 6 for variable speed pumps. To calculate the air flow rate and AHU inlet air dry-bulb temperature of each individual zone, the same assumptions as presented in Section 3.2.1 were used.

Three typical days were selected to test and evaluate the energy performance of the proposed optimal control strategy. These days represent the typical operation conditions of the air-conditioning system in the typical spring, mild-summer and sunny-summer days, respectively. The cooling loads in Zone 1 varied from 870 kW to 6000 kW, from 1000 kW to 6500 kW and from 1120 kW to 7300 kW, while the cooling loads in Zone 2 varied from 970 kW to 8900 kW, from 1320 kW to 9800 kW and from 1540 kW to 11500 kW in the selected typical spring day, mild-summer day and sunny-summer day, respectively. Figure 8.2 presents the cooling load profiles in both zones in the typical mild-summer day. It can be observed that the cooling load profiles in both zones are significantly different due to the different usage characteristics of both zones.

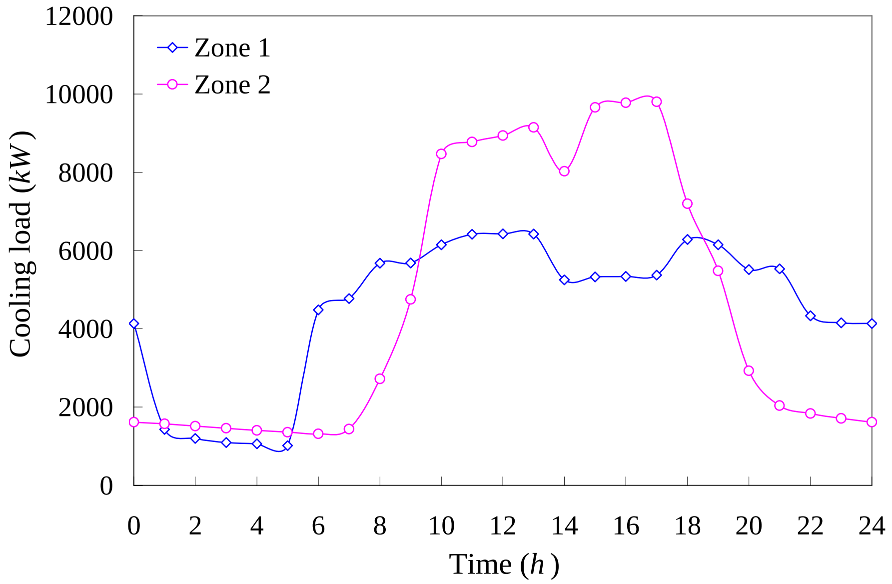

Figure 8.2 Cooling load profiles in Zones 1 and 2 in the typical mild-summer day.

8.3.2 Results of Tests and Evaluation

The energy performance of this optimal control strategy (named Strategy #4 in the following) was evaluated by comparing with those of the conventional control strategy using the fixed chilled water supply temperature set-point and the fixed pressure differential set-point at the critical loops (named Strategy #1), and the control strategy using the optimal chilled water supply temperature set-point and the fixed pressure differential set-point at the critical loops (named Strategy #2), as well as the control strategy using the fixed chilled water supply temperature set-point and the optimal pressure differential set-point at the critical loops (named Strategy #3). It is worthy noticing that the same performance predictor, cost function, optimization technique, supervisory strategy and local control strategies except the speed control strategy for pumps distributing water to terminal units, as the developed strategy (Strategy #4) utilized were used in the other three strategies. The fixed chilled water supply temperature set-point used was the design temperature set-point of 5.5°C. The fixed pressure differential set-points used for Zone 1 and Zone 2 were the upper limits of the pressure differential set-points bounded in Section 8.2.3 (215 kPa for Zone 1, and 230 kPa for Zone 2). In the following, the performance of Strategy #1 was used as the benchmark for comparisons.

Table 8.1 summarizes the daily power consumptions of the pumps (except the primary chilled water pumps) and chillers as well as the total power consumption of the chillers and pumps in the chilled water system of concern (only including Zone 1 and Zone 2) in the three typical days under different control strategies. Compared with Strategy #1, the optimal control strategy (Strategy #4) saved about 986.9 kWh (2.63%), 1012.7 kWh (2.27%) and 682.5 kWh (1.28%) energy in the typical spring day, mild-summer day and sunny-summer day, respectively. It also can be found that Strategy #2 saved about 103.6 kWh (0.28%), 149.9 kWh (0.34%) and 143.3 kWh (0.27%) energy, while Strategy #3 saved about 836.7 kWh (2.23%), 848.1 kWh (1.90%) and 513.2 kWh (0.96%) energy in these three test days respectively, as compared with Strategy #1.

Table 8.1 Comparison of the daily power consumptions under different control strategies

Spring Case

Control strategies	W_{pu} kWh	W_{ch} kWh	$W_{pu}+W_{ch}$ kWh	W_{pu} saving kWh	W_{pu} saving %	W_{ch} saving kWh	W_{ch} saving %	Total Saving kWh	Total Saving %
Strategy #1	4138.3	33421.8	37560.1	---	---	---	---	---	---
Strategy #2	4213.5	33243.0	37456.5	-75.2	***-1.82***	178.8	***0.53***	103.6	***0.28***
Strategy #3	3301.6	33421.8	36723.4	836.7	***20.22***	0.0	***0.00***	836.7	***2.23***
Strategy #4	3109.6	33463.6	36573.2	1028.7	***24.86***	-41.8	***-0.13***	986.9	***2.63***

Mild-summer Case

Control strategies	W_{pu} kWh	W_{ch} kWh	$W_{pu}+W_{ch}$ kWh	W_{pu} saving kWh	W_{pu} saving %	W_{ch} saving kWh	W_{ch} saving %	Total Saving kWh	Total Saving %
Strategy #1	5169.5	39436.6	44606.1	---	---	---	---	---	---
Strategy #2	5311.7	39144.5	44456.2	-142.2	***-2.75***	292.1	***0.74***	149.9	***0.34***
Strategy #3	4321.4	39436.6	43758.0	848.1	***16.41***	0.0	***0.00***	848.1	***1.90***
Strategy #4	4180.2	39413.1	43593.3	989.3	***19.14***	23.5	***0.06***	1012.8	***2.27***

Sunny-summer Case

Control strategies	W_{pu} kWh	W_{ch} kWh	$W_{pu}+W_{ch}$ kWh	W_{pu} saving kWh	W_{pu} saving %	W_{ch} saving kWh	W_{ch} saving %	Total Saving kWh	Total Saving %
Strategy #1	6687.2	46654.4	53341.6	---	---	---	---	---	---
Strategy #2	6796.4	46401.9	53198.3	-109.2	***-1.63***	252.5	***0.54***	143.3	***0.27***
Strategy #3	6174.0	46654.4	52828.4	513.2	***7.67***	0.0	***0.00***	513.2	***0.96***
Strategy #4	5885.5	46773.6	52659.1	801.7	***11.99***	-119.2	***-0.26***	682.5	***1.28***

Remarks: *Strategy #1: Fixed T_{set} + Fixed PD_{set},* *Strategy #2: Optimal T_{set} + Fixed PD_{set},*

Strategy #3: Fixed T_{set} + Optimal PD_{set}, *Strategy #4: Optimal T_{set} + Optimal PD_{set}.*

From Table 8.1, it also can be observed that the strategies using the optimal pressure differential set-points (Strategy#3 and Strategy #4) can save a significant amount of energy as compared with the strategies using the fixed pressure differential set-points (Strategy#1 and Strategy #2). This conclusion is coincident with the results obtained in Chapter 6. Compared with Strategy #1 (the fixed pressure differential set-point), about 836.7 kWh (20.22%), 848.1 kWh (16.41%) and 513.2 kWh (7.67%) pump energy can be saved by using Strategy #3 (the optimal pressure differential set-point) in the typical spring day, mild-summer day and sunny-summer day, respectively. Figure 8.3 presents the hourly-based power consumptions of the pumps using Strategies #1 and #3 in the typical mild-summer day to demonstrate more details of the energy saving potentials using the optimal pressure differential set-points.

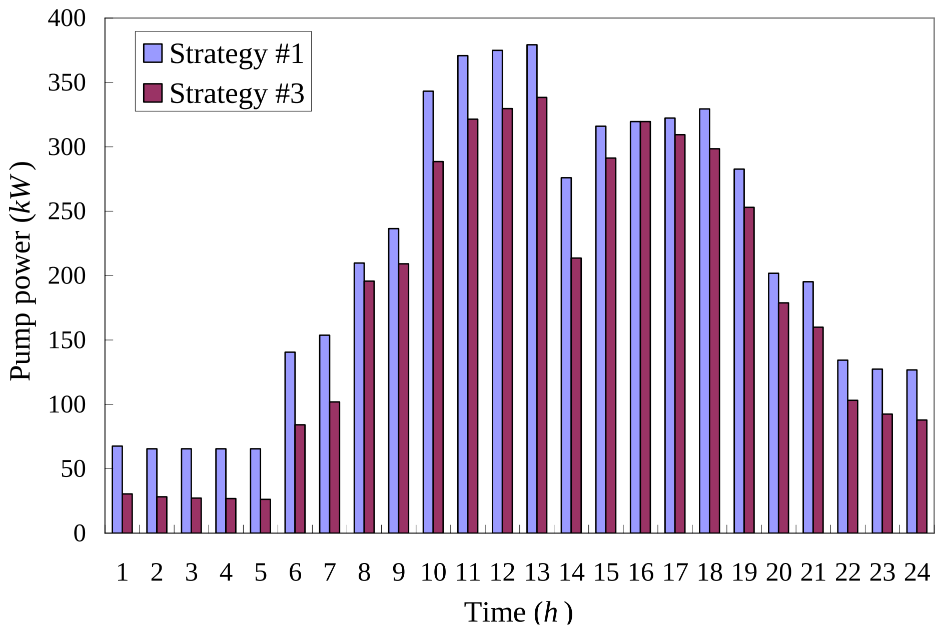

Figure 8.3 Comparison of the pump powers between the strategies using the fixed and optimal pressure differential set-points in the typical mild-summer day.

Compared with the strategies using the fixed chilled water supply temperature set-point, the energy saving potential related to the use of the optimal chilled water supply temperature set-points was very limited in this particular building. Only about 0.27%~0.34% energy can be saved. The reasons are that the usage characteristics and load profiles of Zone 1 and Zone 2 are different (see Figure 8.2), and the inlet water temperatures of the terminal units in Zone 1 and Zone 2 are significantly different due to the application of the heat exchangers in Zone 1. Therefore, the actual optimal chilled water supply temperature set-points for Zone 1 and Zone 2 would be significantly different. The optimal chilled water supply temperature set-points identified were the trade-offs of the power consumptions among chillers, pumps in Zone 1 and pumps in Zone 2.

Figure 8.4 presents the hourly-based total power consumptions of the chilled water system concerned by using Strategy #1 (the fixed temperature set-point) and Strategy #2 (the optimal temperature set-point) in the typical mild-summer day. The power savings of using Strategy #2 over Strategy #1 are also illustrated in this figure. It can be seen that the power consumption profiles of both strategies were very similar since the optimal chilled water temperature set-points found by Strategy #2 were very close to the fixed temperature set-point (5.5°C) for most cases.

Based on the above comparisons, it is obvious that the proposed optimal control strategy can save a significant amount of energy as compared with the other three control strategies. It is also demonstrated that most of energy savings in the proposed strategy were contributed by using the optimal pressure differential set-points. The energy saving potential associated with the use of the optimal chilled water temperature set-points for the building under study was very limited.

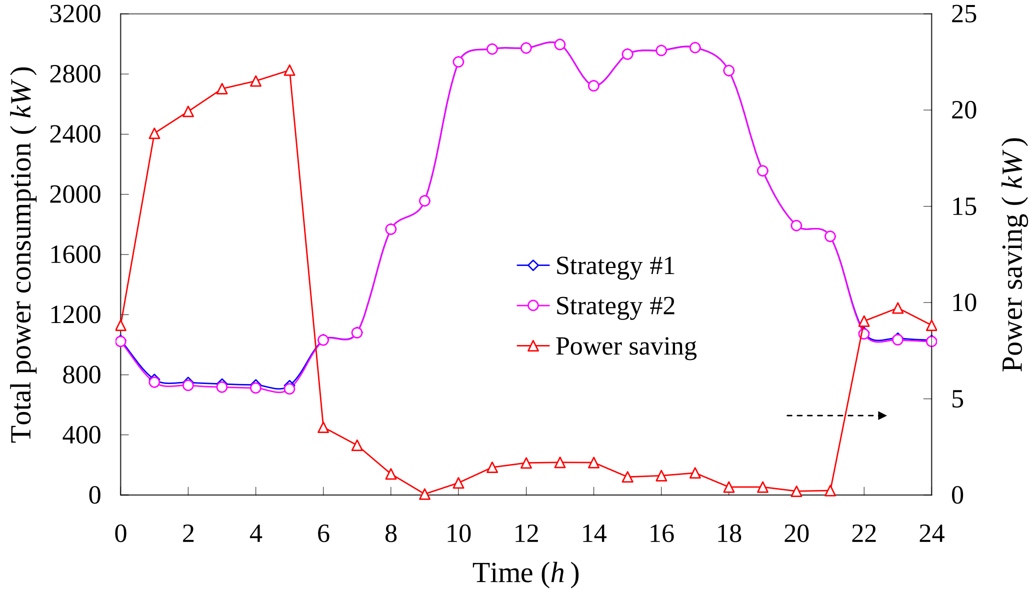

Figure 8.4 Comparison of the total power consumptions between the strategies using the fixed and optimal temperature set-points in the typical mild-summer day.

8.4 Summary

An optimal control strategy for complex building central chilled water systems is presented in this chapter for real-time applications. Although this strategy is developed based on the specific chilled water system, it can be easily adapted to most chilled water systems since most of control issues associated with the control and optimization of central chilled water systems are included in this strategy.

The performance of this optimal control strategy was validated on the complex central chilled water system presented in Chapter 3 by simulation tests. The results show that a substantial amount of energy can be saved associated with the use of this optimal control strategy as compared with the other three control strategies. It is expected that about 1.28%~2.63% energy in the system under investigation can be saved associated with the use of this optimal control strategy as compared with the use of Strategy #1 (the strategy using the fixed chilled water supply temperature set-point and the fixed pressure differential set-point at the critical loops). This optimal control strategy is still simple and easy to implement in practice as well.

CHAPTER 9 IN-SITU IMPLEMENTATION OF THE ONLINE CONTROL STRATEGIES

This chapter presents the in-situ implementation of the online control strategies developed in previous chapters for the optimal control of complex building central chilling systems. A management and communication platform based on IBmanager (intelligent building integration and management system) and the online control software packages of the optimal control strategies for implementing these technologies/tools are presented. The online control software packages can be integrated with BASs with the support of the management and communication platform to achieve energy efficient control and operation of complex building central chilling systems.

Section 9.1 briefly introduces the management and communication platform based on IBmanager. Section 9.2 presents the online control software packages of optimal control strategies and their implementation architectures. An overview of the application software system to implement the online control software packages to the super high-rise building presented in Chapter 3 is provided in Chapter 9.3. A summary of this chapter is given in Section 9.4.

9.1 Briefing on the Management and Communication Platform

The management and communication platform used was developed based on

IBmanager. IBmanager was developed in the term in The Hong Kong Polytechnic University.

IBmanager is an open IBMS integration and management platform based on middleware and web services technologies to support the integration and management of building automation systems from different vendors as well as remote monitoring and management services. It provides a convenient platform for integrating full scale building automation and industrial automation (IA) systems. IBmanager integrates various subsystems, involving data acquisition, network communication, automation and information management, and provides relevant software platforms for the supervision, management and customized development. IBmanager supports the customized development of various IB subsystems.

Figure 9.1 presents the interface connection and function blocks of IBmanager, which is actually a middleware platform. This platform can be divided into several parts, i.e., OPC (OLE for Process Control) servers, historical database, BMS function components, BMS HMI (human machine interface) based on the LAN (Local Area Network) version, web services server and building management web server. The OPC servers are distributed on various PCs in the LAN. The BMS function components execute the tasks of real-time data access, alarms & events process, historical data access, scheduling, parameter optimization of control strategies, performance/fault diagnosis of HVAC systems, etc. The BMS HMI based on the LAN version realizes the full BAS functions in the LAN applications. The web services server converts the COM/DCOM interfaces to web services interfaces. The Active

Service Pages (ASP) and dynamic link library (DLL) files are deployed in the building management web server to communicate with the web services server and provide the user access interface (web pages) to users. There are several important functions that should be implemented in BASs, such as real-time data sharing, alarm/event, historical data and trending, scheduling and network management. The real-time data access is accomplished by OPC DA (Data Access). The historical data access is accomplished by OPC HDA (historical data access) and the alarms & events are accomplished by OPC AE (Alarm & Event). These functions are wrapped as public web services interfaces for the communication and integration on Internet.

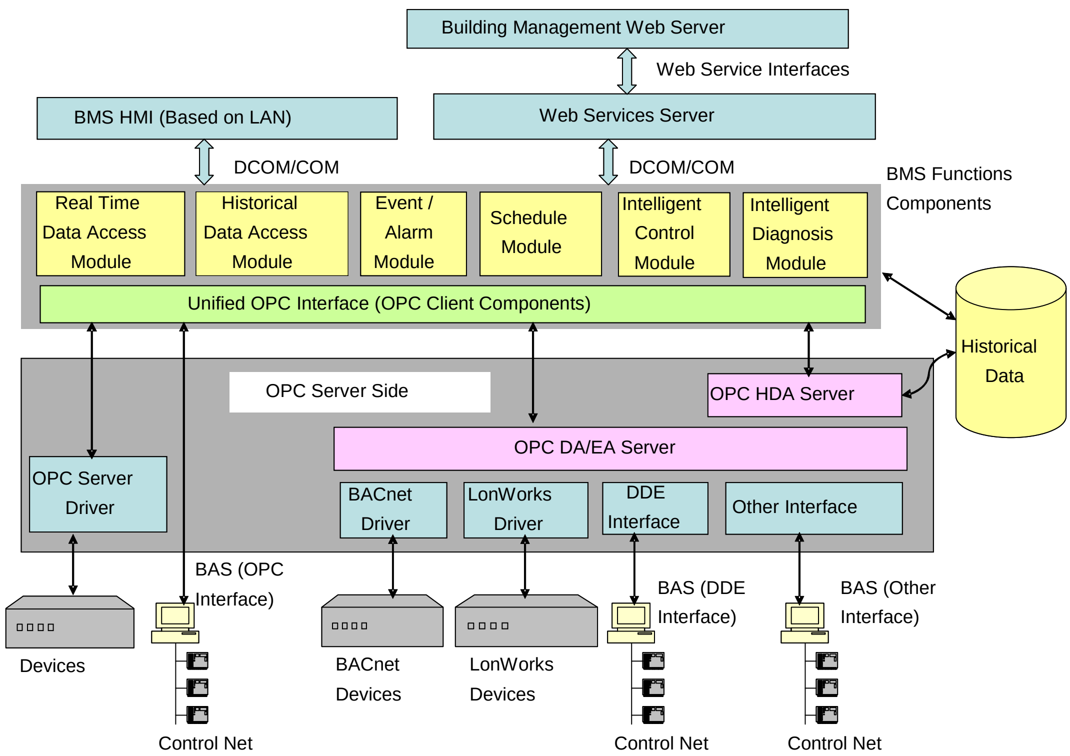

Figure 9.1 Interface connection and function blocks of IBmanager.

Typical applications of IBmanager are listed as follows:

- *Internet-based centralized management platform integrating multiple (vendor)* *systems:* support centralized services and management on Intranet/Internet;

- *Supervision, integration and development platform for BA and IA systems:* integrate field control stations of different vendors (protocols);
- *Supporting and management platform for independent online applications:* add third-party or complicated application programs of added-value services to BA systems.

9.2 Online Control Software Packages of Optimal Control Strategies and Their Implementation Architectures

The online control software packages of optimal control strategies were developed in the application program of Matlab. The optimal control strategies for the central condenser cooling water system and chilled water system were complied using separate packages. All strategies (i.e., control functions) in the same package were programmed as a form of subroutines, and were compiled as a DLL module for the convenient implementation in IBmanager. To improve the control robustness of the online control software packages, an upper limit on the number of iterations was constrained for the models (i.e., chiller model, etc.) that need the iteration process.

Figure 9.2 shows the in-situ implementation architectures of the online control software packages. The online control software packages developed in this thesis run on a separate PC (Personal Computer) station interfaced with the main station of the chiller control system (BMS). These standalone control software packages will run in parallel with the chiller sequence program provided by the MVAC&BMS contractors.

The contractors provide the protocol or an interface for the communication between the control software packages and the main station of the chiller control system. When the plant (chiller, cooling tower, pump, etc.) sequence is of concern, the online control software packages will only provide the number of them to be operated and the chiller control system will determine which one is used. A decision supervisor in the chiller control system is designed for the operators to set whether the settings given by the online control software packages developed are used or ignored (not used). This implementation approach provides adequate spaces and freedoms for further improving the performances of optimal control strategies developed in this thesis to make them have satisfactory performances and be convenient used in practice.

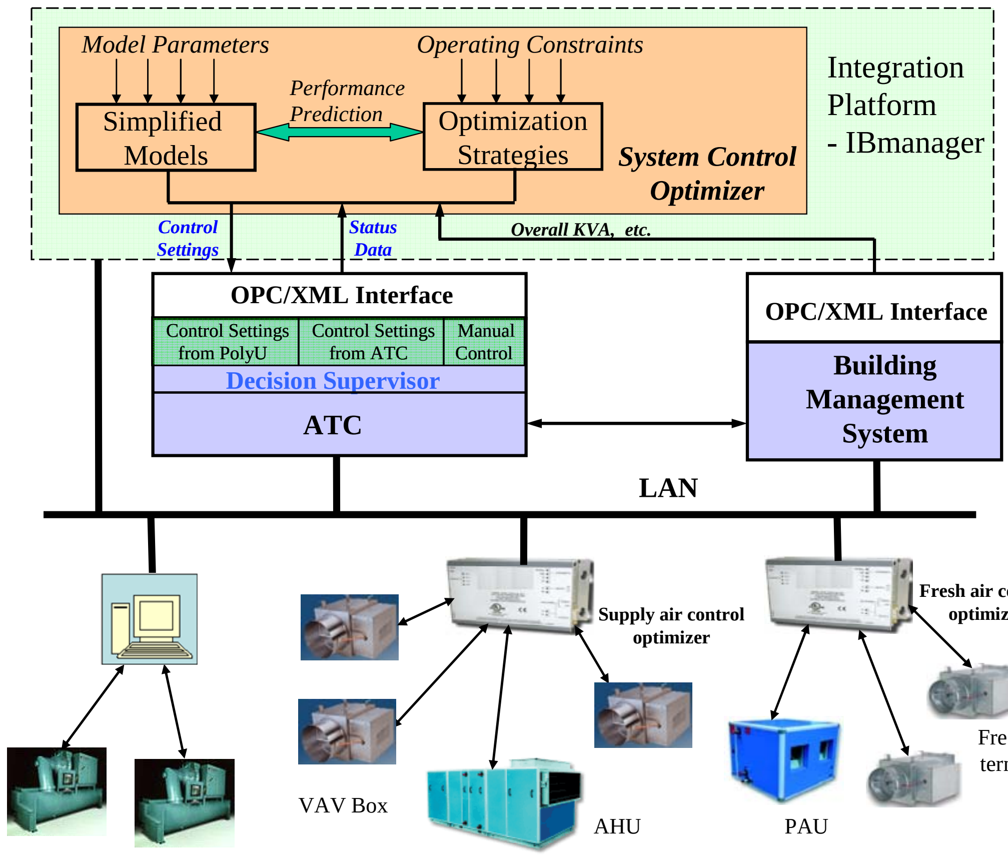

Figure 9.2 In-situ implementation architectures of online control software packages.

The interface used for the interoperation of the management and communication platform based on IBmanger and ATC (Automatic Temperature Control) system is shown in Figure 9.3. This interface was developed based on a trial version of the BACnet SDK (Software Development Kit) since the network of the BMS system was based on the BACnet protocol. IBmanager can receive the system operation data through a NAE connecting with local controllers, and BA outstations connecting with sensors, actuators, etc. At the meantime, IBmanager can send the optimal control settings to the ATC systems through the NAE for the practical control of the building services systems to improve their operating efficiency.

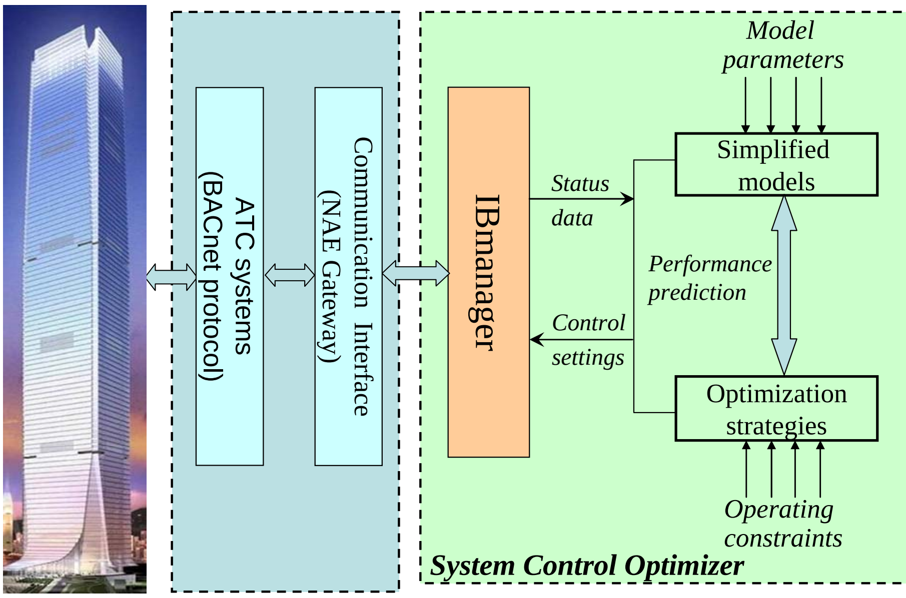

Figure 9.3 Interface between the management and communication platform and the ATC system.

9.3 An Overview of the Application Software System

The IBMS (intelligent building management system) for the application of the online control software packages to achieve reliable and energy efficient control and operation of the central chilling system in the super high-rise building presented in Chapter 3, is shown in Figure 9.4. This platform includes six main functions, i.e., *Access Management*, *History Data*, *System Setting*, *System Configuration*, *System Maintenance* and *Real-Time Monitoring*.

Figure 9.4 Front page of the IBMS.

Access Management is to control the authorities of different users including supervisory user, advanced users (including programming) and usual operators. The supervisory user has the highest authority and can manage the access of all other users. *History Data* is to record the system operation data into the database. The recorded operation data can be used for many purposes, i.e., modeling training, fault detection and diagnosis, etc. *System Setting* is to configure this system in terms of the protocols used in building automation systems and/or the building management systems. *System Configuration* is to configure the data points of IBmanager based on the field installation information provided by the MVAC&BMS contractors. It can also set the parameters for different control strategies. *System Maintenance* is to provide the log services. *Real-Time Monitoring* is to monitor the system operation, component operation, etc. It has friendly human machine interface (HMI). Some operation data can be monitored with visualization while some can be monitored in the form of tables.

Figures 9.5 and 9.6 show the monitoring interfaces of the real-time operation data with visualization for the chiller group and cooling tower group, respectively. The main operation data (i.e., chilled water supply and return temperatures, cooling water supply and return temperatures, etc.) can be displayed on these monitoring interfaces to allow the operators to know whether or not the system/corresponding component is operated properly. Since the operation status of each individual chiller has significant impacts on the overall system energy efficiency, the major measurements of each chiller are monitored and displayed on a separate interface, as shown in Figure 9.7.

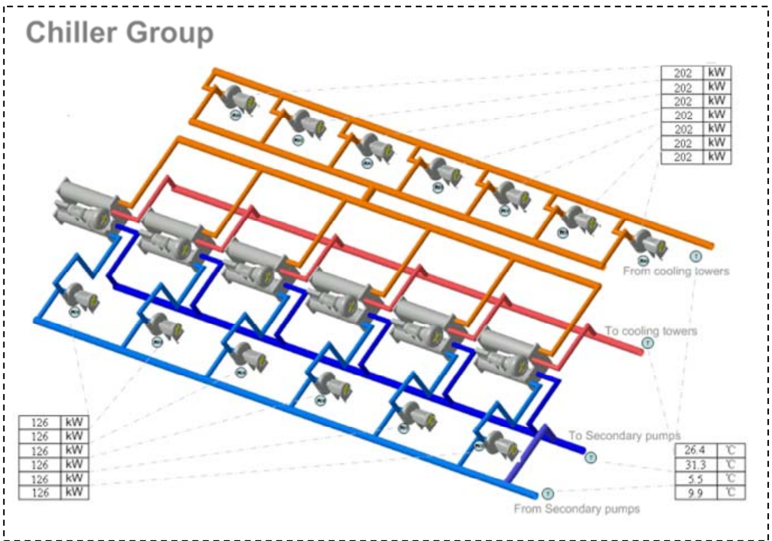

Figure 9.5 Monitoring interface of the chiller operation status.

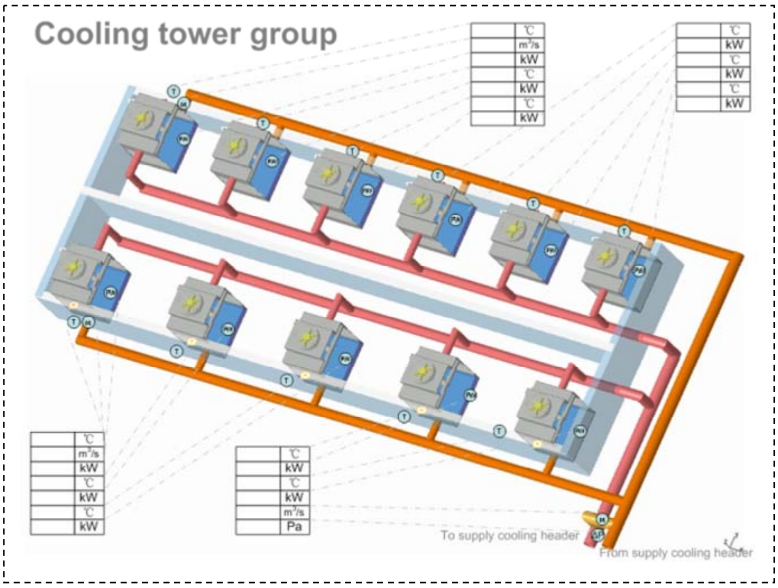

Figure 9.6 Monitoring interface of the cooling tower operation status.

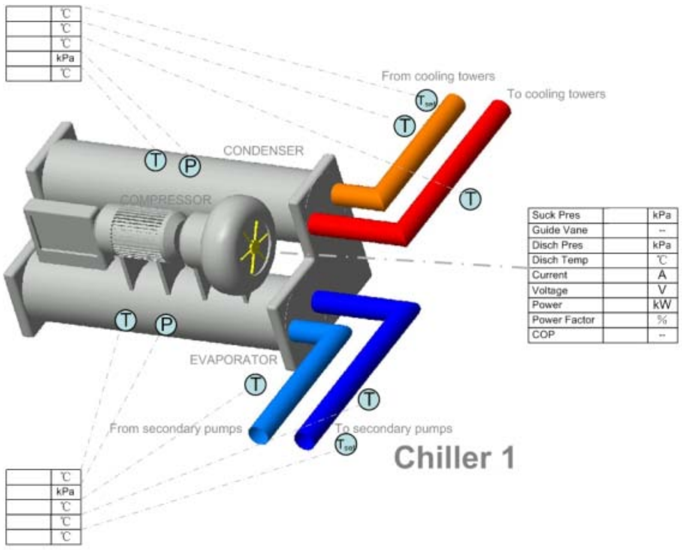

Figure 9.7 Monitoring interface of the individual chiller operation status.

9.4 Summary

The in-situ implementation and validation of online optimal control strategies are of great importance to further improve their operational performance in practice. To implement the online control software packages of optimal control strategies in real building systems, many issues, i.e., data communication, interface, etc., need to be seriously considered. In this chapter, the management and communication platform based on IBmanager used to implement the online control software packages of optimal control strategies and the programming of optimal control strategies are presented briefly. The interface used for interoperation of the management and communication platform and ATC system and the implementation architectures of the online control software packages are introduced as well. Finally, an overview of the application software system to implement the online control software packages to practically control the operation of the central chilling system in the super high-rise building is demonstrated. The system presented in this chapter is being tested and evaluated in the super high-rise building.

CHAPTER 10 SUMMARIES AND RECOMMENDATIONS

Proper control and operation of building central air-conditioning systems have significant impacts on energy or cost efficiency of buildings besides proper system designs and selection and maintenance of individual components. It is therefore highly desirable to develop cost effective control strategies for building air-conditioning systems, especially for complex building air-conditioning systems, to enhance their energy efficiency. The present thesis has addressed this need through making the following contributions.

Conclusions on Main Contributions

i. The main contributions of this thesis are the development of the online supervisory and optimal control strategies for complex building central chilling systems. The software tools and implementation guidelines for applying these online supervisory and optimal control strategies for energy efficient control and operation of complex building central chilling systems have also been provided.

ii. Another contribution of this thesis is the development of a dynamic simulation platform for the complex building central chilling system, which was used for testing and analyzing the control, environmental and energy performances of different control strategies under dynamic working conditions to determine the most promising strategies that can be used in practice, prior to site implementation.

iii. The simplified models for major chilling system components have been developed or selected in this thesis to formulate the online supervisory and optimal control strategies. These models have simplified structures with certain physical significance of their parameters that make them suitable for online control applications. This is another contribution of this thesis.

iv. The optimal control strategies, including the speed control strategy and the sequence control strategy, for variable speed pumps with different configurations in complex building central air-conditioning systems have been developed and presented, which is also a contribution of this thesis.

v. Another important contribution of this thesis is that the recommendations for future work in the direction of supervisory and optimal control of HVAC systems have been provided based on the comprehensive review of the state of the art of the research and development as well as application of supervisory and optimal control in the HVAC field. This provides the building professionals with the basic information to select these reliable and efficient control methods and optimization techniques for practical applications with necessary confidence so as to avoid unreliable control methods and optimization techniques.

Summary of Results of Energy Performance Tests

To investigate the energy saving potentials in complex building central chilling systems associated with the optimization of major control variables, three energy performance tests, i.e., the optimization of the chilled water supply temperature set-point, the optimization of the condenser water supply temperature set-point and the optimization of the number of chillers operating, have been conducted on the basis of the dynamic simulation platform constructed.

The simulation results show that the condenser cooling water system, chiller system and chilled water distribution systems are highly interactive. The optimal control settings (set-points and/or operation modes) indeed exist for a given condition. These optimal control settings vary with the changes of working conditions. To minimize the system or subsystem energy consumption, major control variables should be optimized in supervisory and optimal control strategies. These results were carefully considered during the development of the online supervisory and optimal control strategies for central condenser cooling water systems and chilled water systems, respectively.

Summary of Performances of Simplified Models of Chilling System Components

Since detailed physical models always require high computational costs and memory demands as well as a lot of iterations, and purely data-driven models cannot always ensure stable performance prediction, simplified models of major chilling system components (i.e., the chiller model, cooling tower model, heat exchanger model, pump model, etc.) have been developed or selected in this thesis and used to design the online supervisory and optimal control strategies for central condenser cooling water systems and chilled water systems.

The performances of most of these models have been validated using the field measurement data, and/or the factory performance test data, and/or the catalogue data provided by the manufacturers. The results show that these models have satisfactory performance in prediction, and the deviations due to the model prediction can be acceptable for online control applications.

Summary of Performances of Optimal Control Strategies for Variable Speed Pumps

To minimize the energy input and extend the service life of variable speed pumps, the optimal control strategies, including the speed control strategy and the sequence control strategy, for variable speed pumps with different configurations in the complex building central chilling system have been proposed and presented. All variable speed pumps in the complex building central chilling system are classified into two groups: the pumps distributing water to terminal units and the pumps distributing water to heat exchangers. The speed of the pump distributing water to terminal units can be controlled by resetting the pressure differential set-point enough and just enough for the most heavily loaded loops using the positions of water control valves, while the speed of the pump distributing water to heat exchangers can be controlled using a cascade controller or a water flow controller. A near optimal pump sequence control strategy has been developed based on a water network pressure drop model and a pump model to control the number of pumps in operation.

The performances of these optimal control strategies have been evaluated on the complex building central chilling system using the *simulation-assisted test method* in which the control strategies were tested in a simulated virtual environment similar to the situation when they are actually implemented in practice. The results show that about 12.69%-32.43% pump energy can be saved when applying the method with the combined use of the optimal pump speed control strategy and the near optimal pump sequence control strategy as compared with the method using the conventional pump speed control strategy (i.e., the fixed pressure differential set-point at the critical loops) and the simple pump sequence control strategy.

Summary of Performance of the Optimal Control Strategy for Condenser Cooling Water Systems

A HQS (hybrid quick search)-based optimal control strategy that combines the features of both the model-based optimal control and performance map-based near optimal control has been developed for the online control of complex building central condenser cooling water systems. This strategy was formulated using a systematic approach by considering the system and subsystem level characteristics and interactions among all components and their associated variables in central condenser cooling water systems, and the requirements and constraints of practical applications. It consists of the model-based performance predictor, cost estimator (i.e., cost function), optimization technique, supervisory strategy, etc.

The performance of this HQS-based optimal control strategy has been validated on the complex building central condenser cooling water system using the *computation-assisted test method*, in terms of the control accuracy, computation performance and energy performance. The results show that this HQS-based optimal control strategy has the same control accuracy as the model-based optimal control strategy using a GA as the optimization tool, while the computational cost was reduced greatly. The reduction of the average computational cost related to the use of the HQS-based optimal control strategy was about 96.0% when compared with that of the model-based optimal control strategy using the GA as the optimization tool. The results also show that about 0.646%-1.416% of the total condenser cooling water system energy can be saved by using this HQS-based optimal control strategy over the use of the fixed approach control method.

Summary of Performance of the Optimal Control Strategy for Chilled Water Systems

An optimal control strategy using a systematic approach has been developed for the online control of the complex building central chilled water system. This optimal control strategy consists of the model-based performance predictor, cost estimator (i.e., cost function), optimization algorithm, supervisory strategy and a number of local controllers (i.e., the chiller sequence controller, the heat exchanger sequence controller, the pump sequence controller, the pressure differential set-point optimizer, etc.).

The performance of this optimal control strategy has been evaluated on the complex central chilled water system using the *simulation-assisted test method*. The results show that about 1.28%~2.63% energy in the air-conditioning system under investigation can be saved associated with the use of this optimal control strategy over the control method using the fixed chilled water supply temperature set-point and the fixed pressure differential set-point at the critical loops. The results also show that the energy saving potential related to the use of the optimal chilled water supply temperature set-points in the system under study was very limited. Only about 0.27%~0.34% energy can be saved as compared with that using the fixed temperature set-point. The reasons are that the load characteristics and load profiles in different zones in the system under study are different, and the heat exchangers used in some zones causing the inlet water temperatures of terminal units in different zones are different. Therefore, the actual optimal chilled water supply temperature set-points for different zones could be significantly different. The optimal chilled water supply temperature set-point identified for the overall system was the trade-off of the power consumptions among the chillers and pumps in different zones.

It is worthwhile to point out that the energy savings presented in this thesis were achieved by applying the optimal control algorithms only and without adding any additional cost. It is also worthy noticing that the control methods used as the benchmarks in this thesis have already somehow optimized. Therefore, the actual energy savings using the optimal control strategies developed could be significantly more than the energy savings presented in this thesis since the control strategies utilized in practice might be simpler and more inadequate. However, the optimal control strategies developed in this thesis are still simple and easy to implement in practice.

Recommendations for Future Work

Major efforts of this thesis are made on the development of the online supervisory and optimal control strategies for complex building central chilling systems. It would be very desirable and valuable to make further efforts on the following three aspects related to the research presented in this thesis.

- In-situ implementation and validation of the online supervisory and optimal control strategies developed in this thesis on complex building central chilling systems are needed to make these strategies attain desirable and satisfactory performances and prove to be convenient in practice. The optimal control strategies developed in this thesis are being implemented in a super high-rise commercial building in Hong Kong. However, it is a rather difficult task and there is still a long way to go. Efforts are therefore essentially needed.
- Since the configuration of the complex building central chilling system under study is rather complicated, the optimal control strategies developed in this thesis are therefore separated into the strategy for the condenser cooling water system and the strategy for chilled water system, respectively. It would be more beneficial to develop the online supervisory and optimal control strategies viewing the central chilling system, even the overall air-conditioning system, as a whole.

- The simple chiller sequence control strategy was used throughout in this study. To maximize the operating efficiency of the overall air-conditioning system, an effective and practical chiller sequence control strategy is needed, which could be developed based on the reliable cooling load prediction and maximum chiller cooling capacity prediction as well as the constraints of practical applications.

APPENDIX ----TRNSYS SIMULATION DECK FILE

```
********************************************************************************
*          TRNSYS SIMULATION DECK FOR THE COMPLEX CENTRAL                      *
*                  CHILLING SYSTEM OF ICC BUILDING                             *
*                                                                              *
*                 Developer: Ma Zhenjun, June, 2006                            *
*              Department of Building Services Engineering                     *
*                  The Hong Kong Polytechnic University                        *
********************************************************************************
SIMULATION 0.0, 86400, 5.0
TOLERANCES 0.00001 0.00001
LIMITS 100 100
WIDTH 132
NOLIST
MAP
ASSIGN OUT.INF 6
ASSIGN SUMMER-M.DAT 9
ASSIGN OUT1.DAT 21
ASSIGN OUT2.DAT 22
ASSIGN OUT3.DAT 23
ASSIGN OUT4.DAT 24
********************************************************************************
UNIT 1 TYPE 9 Date Reader
PARAMETERS 4
9,    120,    9,    -1
********************************************************************************
UNIT 72 TYPE 65 Drawing Graphics on Screen
PARAMETERS 9
10,    9,    3,    40,    0,    2500,    1,    1,    1
INPUTS 20
16,1    14,2    14,4    20,1    44,1     54,1     35,8    48,16    58,8    7,1
27,4    18,4    42,4    52,4    42,13    52,13    49,6    64,1     65,1    36,6
0.0     0.0     0.0     0.0     0.0      0.0      0.0     0.0      0.0     0.0
0.0     0.0     0.0     0.0     0.0      0.0      0.0     0.0      0.0     0.0
********************************************************************************
UNIT 3 TYPE 1 CTA Towers (total of six)
PARAMETERS 10
-0.0106,    0.7915,    0.2192,    0.1845,    -0.8656,    1.6811,    20000,    2,    1.0,    25
INPUT 16
5,12    5,13    5,14    5,15    5,16    5,17    2,1    2,2    2,3    2,4    2,5    2,6    6,2    1,3    1,2    0,0
0.0     0.0     0.0     0.0     0.0     0.0     0.0    0.0    0.0    0.0    0.0    0.0    30     26     29     25
DERIVATIVES 6
```

25.0,   25.0,   25.0,   25.0,   25.0,   25.0
****
UNIT 4 TYPE 2 CTB Towers (total of five)
PARAMETERS 10
-0.0106,   0.7915,   0.2192,   0.1845,   -0.8656,   1.6811,   20000,   2,   1.0,   25
INPUT 14
5,18   5,19   5,20   5,21   5,22   73,1   73,2   73,3   73,4   73,5   6,2   1,3   1,2   0,0
0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   30   26   29   25
DERIVATIVES 5
25.0,   25.0,   25.0,   25.0,   25.0
****
UNIT 5 TYPE 3 Cooling Tower Sequence Controller
PARAMETERS 3
250,   194,   410.1
INPUT 1
15,8
0.0
****
UNIT 2 TYPE 54 PID Controllers for Fans of CTA Towers
PARAMETERS 8
-4,   50.0,   0.0,   5.0,   20,   50,   1.0,   1.0
INPUT 13
3,1   3,2   3,3   3,4   3,5   3,6   5,1   5,2   5,3   5,4   5,5   5,6   0,0
0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   28
****
UNIT 73 TYPE 55 PID Controllers for Fans of CTB Towers
PARAMETERS 8
-4,   50.0,   0.0,   5.0,   20,   50,   1.0,   1.0
INPUT 11
4,1   4,2   4,3   4,4   4,5   5,7   5,8   5,9   5,10   5,11   0,0
0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   28
****
UNIT 6 TYPE 4 Ideal Flow Mixing after Chiller Condensers
PARAMETERS 1
410.1
INPUT 12
15,1   15,2   15,3   15,4   15,5   15,6   8,2   9,2   10,2   11,2   12,2   13,2
0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
****
UNIT 7 TYPE 5 Ideal Flow Mixing after Cooling Towers
INPUT 24
3,1   3,2   3,3   3,4   3,5   3,6   4,1   4,2   4,3   4,4   4,5   5,12
5,13   5,14   5,15   5,16   5,17   5,18   5,19   5,20   5,21   5,22   5,23   6,2
25   25   25   25   25   25   25   25   25   25   25   0.0
0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0

```
********************************************************************************
UNIT 8 TYPE 23 Chiller ONE
PARAMETERS 19
229.4,   3.234E-02,   0.5236,   351.7,   0.6943,   0.8031,   0.02052,   1.18,   0.0,
0.0,   0.3383E-03,   0.0,   0.0,   0.4602E-03,   2.0,   40000,   40000,   2.0,   2.0
INPUT 7
14,4   7,1    0,0     0,0     15,7   15,1   0,0
10.0   30.0   345.0   410.1   5.5    1.0    25.0
DERIVATIVES 2
25.0,   25.0
********************************************************************************
UNIT 9 TYPE 23 Chiller TWO
PARAMETERS 19
229.4,   3.234E-02,   0.5236,   351.7,   0.6943,   0.8031,   0.02052,   1.18,   0.0,
0.0,   0.3383E-03,   0.0,   0.0,   0.4602E-03,   2.0,   40000,   40000,   2.0,   2.0
INPUT 7
14,4   7,1    0,0     0,0     15,7   15,2    0,0
10.0   30.0   345.0   410.1   5.5    1.0     25.0
DERIVATIVES 2
25.0,   25.0
********************************************************************************
UNIT 10 TYPE 23 Chiller THREE
PARAMETERS 19
229.4,   3.234E-02,   0.5236,   351.7,   0.6943,   0.8031,   0.02052,   1.18,   0.0,
0.0,   0.3383E-03,   0.0,   0.0,   0.4602E-03,   2.0,   40000,   40000,   2.0,   2.0
INPUT 7
14,4    7,1    0,0     0,0     15,7   15,3   0,0
10.0    30.0   345.0   410.1   5.5    0.0    25.0
DERIVATIVES 2
25.0,   25.0
********************************************************************************
UNIT 11 TYPE 23 Chiller FOUR
PARAMETERS 19
229.4,   3.234E-02,   0.5236,   351.7,   0.6943,   0.8031,   0.02052,   1.18,   0.0,
0.0,   0.3383E-03,   0.0,   0.0,   0.4602E-03,   2.0,   40000,   40000,   2.0,   2.0
INPUT 7
14,4   7,1    0,0     0,0     15,7    15,4    0,0
10.0   30.0   345.0   410.1   5.5     0.0     25.0
DERIVATIVES 2
25.0,   25.0
********************************************************************************
UNIT 12 TYPE 23 Chiller FIVE
PARAMETERS 19
229.4,   3.234E-02,   0.5236,   351.7,   0.6943,   0.8031,   0.02052,   1.18,   0.0,
0.0,   0.3383E-03,   0.0,   0.0,   0.4602E-03,   2.0,   40000,   40000,   2.0,   2.0
```

INPUT 7
14,4   7,1   0,0   0,0   15,7   15,5   0,0
10.0   30.0   345.0   410.1   5.5   0.0   25.0
DERIVATIVES 2
25.0,   25.0
****
UNIT 13 TYPE 23 Chiller SIX
PARAMETERS 19
229.4,   3.234E-02,   0.5236,   351.7,   0.6943,   0.8031,   0.02052,   1.18,   0.0,
0.0,   0.3383E-03,   0.0,   0.0,   0.4602E-03,   2.0,   40000,   40000,   2.0,   2.0
INPUT 7
14,4   7,1   0,0   0,0   15,7   15,6   0,0
10.0   30.0   345.0   410.1   5.5   0.0   25.0
DERIVATIVES 2
25.0,   25.0
****
UNIT 14 TYPE 67 Ideal Chilled Water Mixing and Bypass
PARAMETERS 1
345.6
INPUT 14
15,1   15,2   15,3   15,4   15,5   15,6   8,1   9,1   10,1   11,1   12,1   13,1   63,1   62,2
0.0   0.0   0.0   0.0   0.0   0.0   8.0   8.0   8.0   8.0   8.0   8.0   14.0   400.0
****
UNIT 15 TYPE 50 Chiller Sequence Controller
INPUT 2
1,9   0,0
0.0   5.5
****
UNIT 16 TYPE 31 Chilled Water Supply Pipe
PARAMETERS 6
0.25,   80.0,   1E-10,   1000.0,   4.187,   25.0
INPUT 3
14,3   62,2   0,0
5.5   1200.0   25.0
****
UNIT 17 TYPE 49 Zone Air Flow Rates and ON/OFF Status of AHUs in Zones 1&2
PARAMETERS 27
0.2, 0.8, 13, 95, 50, 0.63884, 1, 1, 1, 1, 1, 3, 3, 3, 3, 3, 6, 6, 6, 6, 6, 6, 6, 6, 2, 2, 2
INPUT 9
1,9   1,4   1,5   1,6   1,7   1,2   1,3   0,0   27,1
0.0   0.0   0.0   0.0   0.0   0.0   0.0   23   0.0
****
UNIT 18 TYPE 12 Water Flow Network of Zone 2
PARAMETERS 21
0.00029,   0.0015,   1.06,   0.000023,   0.00025,   1.0,   1.0,   1.0,   1.0,   1.0,

3.0,   3.0,   3.0,   3.0,   3.0,   6.0,   6.0,   6.0,   6.0,   6.0,   450
INPUT 32
19,1 74,2 17,8 17,9 17,10 17,11 17,12 17,13 17,14 17,15 17,16
17,17 17,18 17,19 17,20 17,21 17,22 23,2 23,4 23,6 23,8 23,10
24,2 24,4 24,6 24,8 24,10 25,2 25,4 25,6 25,8 25,10
50.0 1.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
****
UNIT 19 TYPE 43 PID Controller for Pumps (SCHWP-06-03 to 05) in Zone 2
PARAMETERS 8
0.1,   30.0,   0.0,   5.0,   20,   50,   1.0,   1.0
INPUT 3
18,4   34,1   0,0
0.0   230   1.0
****
UNIT 34 TYPE 6 Pressure Difference Set-Point Optimizer for SCHWP-06-03 to 05
PARAMETERS 3
230,   90.0,   0.15
INPUT 15
23,2 23,4 23,6 23,8 23,10 24,2 24,4 24,6
24,8 24,10 25,2 25,4 25,6 25,8 25,10
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
0.0 0.0 0.0 0.0 0.0 0.0 0.0
****
UNIT 20 TYPE 63 AHUs in Zone 2 (Group 1-5, each has one AHU)
INPUT 13
17,6 0,0 17,23 17,24 17,25 17,26 17,27 16,1 18,7 18,8 18,9 18,10 18,11
25.0 0.0115 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
PARAMETERS 15
0.0,   4.0,   22.0,   22.0,   0.42,   1.35,   2.55,   0.03294,   0.0015,   3.0,
0.48405E-2,   0.609E-3,   1.0,   0.1036,   -0.29804
DERIVATIVES 5
20.0,   20.0,   20.0,   20.0,   20.0
****
UNIT 21 TYPE 63 AHUs in Zone 2 (Group 6-10, each has three AHUs)
INPUT 13
17,6 0,0 17,28 17,29 17,30 17,31 17,32 16,1 18,12 18,13 18,14 18,15 18,16
25.0 0.0115 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
PARAMETERS 15
0.0,   4.0,   22.0,   22.0,   0.42,   1.35,   2.55,   0.03294,   0.0015,   3.0,
0.48405E-2,   0.609E-3,   1.0,   0.1036,   -0.29804
DERIVATIVES 5
20.0,   20.0,   20.0,   20.0,   20.0
****

UNIT 22 TYPE 63 AHUs in Zone 2 (Group 11-15, each has six AHUs)
INPUT 13
17,6 0,0 17,33 17,34 17,35 17,36 17,37 16,1 18,17 18,18 18,19 18,20 18,21
25.0 0.0115 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
PARAMETERS 15
0.0, 4.0, 22.0, 22.0, 0.42, 1.35, 2.55, 0.03294, 0.0015, 3.0,
0.48405E-2, 0.609E-3, 1.0, 0.1036, -0.29804
DERIVATIVES 5
20.0, 20.0, 20.0, 20.0, 20.0
****
UNIT 23 TYPE 42 PID Controllers for AHUs in Zone 2 (Group 1-5)
PARAMETERS 9
0.0, 9999.0, 0.0, 0.3, 20.0, 0.0, 5.0, 2.0, 0.5
INPUTS 11
20,1 20,2 20,3 20,4 20,5 17,8 17,9 17,10 17,11 17,12 0,0
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 13.0
****
UNIT 24 TYPE 42 PID Controllers for AHUs in Zone 2 (Group 6-10)
PARAMETERS 9
0.0, 9999.0, 0.0, 0.3, 20.0, 0.0, 5.0, 2.0, 0.5
INPUTS 11
21,1 21,2 21,3 21,4 21,5 17,13 17,14 17,15 17,16 17,17 0,0
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 13.0
****
UNIT 25 TYPE 42 PID Controllers for AHUs in Zone 2 (Group 11-15)
PARAMETERS 9
0.0, 9999.0, 0.0, 0.3, 20.0, 0.0, 5.0, 2.0, 0.5
INPUTS 11
22,1 22,2 22,3 22,4 22,5 17,18 17,19 17,20 17,21 17,22 0,0
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 13.0
****
UNIT 27 TYPE 13 Water Flow Network of the Secondary Side of Heat Exchangers in Zone 1
PARAMETERS 13
0.00089, 0.0015, 1.26, 0.00006, 0.0012, 0.0025, 6, 6, 6, 2, 2, 2, 420
INPUT 15
28,1 74,1 17,39 17,40 17,41 17,42 17,43 17,44
32,2 32,4 32,6 33,2 33,4 33,6 74,11
50.0 1.0 0.0 0.0 0.0 0.0 0.0 0.0
0.3 0.3 0.3 0.3 0.3 0.3 0.0
****
UNIT 28 TYPE 43 PID Controller for Pumps (SCHWP-06-10 to 12) in Zone 1
PARAMETERS 8
0.15, 35.0, 0.0, 5.0, 20, 50, 5.0, 1.0
INPUT 3
27,4 29,1 0,0

0.0 0.0 1.0
****
UNIT 29 TYPE 7 Pressure Differential Set-Point Optimizer for SCHWP-06-10 to 12
PARAMETERS 3
215, 80.0, 0.15
INPUT 6
32,2 32,4 32,6 33,2 33,4 33,6
0.0 0.0 0.0 0.0 0.0 0.0
****
UNIT 30 TYPE 21 AHUs in Zone 1 (Group 1-3, each has six AHUs)
INPUT 9
17,6 0,0 17,45 17,46 17,47 35,8 27,8 27,9 27,10
25.0 0.0115 0.0 0.0 0.0 0.0 0.0 0.0 0.0
PARAMETERS 15
0.0, 5.0, 24.0, 24.0, 0.42, 1.35, 2.55, 0.03294, 0.0015, 3.0,
0.48405E-2, 0.609E-3, 1.0, 0.1036, -0.29804
DERIVATIVES 3
20.0, 20.0, 20.0
****
UNIT 31 TYPE 21 AHUs in Zone 1 (Group 4-6, each has two AHUs)
INPUT 9
17,6 0,0 17,48 17,49 17,50 35,8 27,11 27,12 27,13
25.0 0.0115 0.0 0.0 0.0 0.0 0.0 0.0 0.0
PARAMETERS 15
0.0, 5.0, 24.0, 24.0, 0.42, 1.35, 2.55, 0.03294, 0.0015, 3.0,
0.48405E-2, 0.609E-3, 1.0, 0.1036, -0.29804
DERIVATIVES 3
20.0, 20.0, 20.0
****
UNIT 32 TYPE 20 PID Controllers for AHUs in Zone 1 (Group 1-3)
PARAMETERS 9
0.0, 9999.0, 0.0, 0.3, 60.0, 0.0, 5.0, 6.0, 0.5
INPUTS 7
30,1 30,2 30,3 17,39 17,40 17,41 0,0
13.1 13.5 14.0 1.0 1.0 1.0 13.0
****
UNIT 33 TYPE 20 PID Controllers for AHUs in Zone 1 (Group 4-6)
PARAMETERS 9
0.0, 9999.0, 0.0, 0.3, 60.0, 0.0, 5.0, 6.0, 0.5
INPUTS 7
31,1 31,2 31,3 17,42 17,43 17,44 0,0
13.1 13.5 14.0 1.0 1.0 1.0 13.0
****
UNIT 35 TYPE 41 Heat Exchangers (HX-06-01 to 02) in Zone 1
PARAMETERS 5

20000,   2,   4072.5,   155,   155
INPUT 6
27,1   36,1   38,1   16,1   74,11   0,0
310   345   11.3   5.5   2.0   25.0
DERIVATIVES 4
25.0,   25.0,   25.0,   25.0
****
UNIT 36 TYPE 14 Water Flow Network of the Primary Side of Heat Exchangers in Zone 1
PARAMETERS 2
0.00153,   0.002
INPUT 3
71,1   0,0   74,11
50.0   1.0   1.0
****
UNIT 37 TYPE 43 Temperature Controller for SCHWP-06-01 to 02 in Zone 1
PARAMETERS 8
-3,   20.0,   0.0,   5.0,   50,   345,   9.0,   1.0
INPUT 3
35,8   0,0   0,0
0.0   6.3   1.0
****
UNIT 71 TYPE 43 Water Flow Controller for SCHWP-06-01 to 02 in Zone 1
PARAMETERS 8
0.3,   30.0,   0.0,   5.0,   20,   50,   9.0,   1.0
INPUT 3
36,1   37,1   0,0
0.0   0.0   1.0
****
UNIT 38 TYPE 60 Mixing of Zone 1 Return Flow
PARAMETERS 6
6,   6,   6,   2,   2,   2
INPUT 13
30,7   30,8   30,9   31,7   31,8   31,9   27,8   27,9   27,10   27,11   27,12   27,13   16,1
0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
****
UNIT 39 TYPE 48 Mixing of Zone 2 Return Flow
PARAMETERS 15
1,   1,   1,   1,   1,   3,   3,   3,   3,   3,   6,   6,   6,   6,   6
INPUT 32
20,11   20,12   20,13   20,14   20,15   21,11   21,12   21,13   21,14   21,15   22,11
22,12   22,13   22,14   22,15   18,7   18,8   18,9   18,10   18,11   18,12   18,13
18,14   18,15   18,16   18,17   18,18   18,19   18,20   18,21   16,1   18,24
0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0

****

UNIT 41 TYPE 35 ON/OFF Status of AHUs in Zones 3& 4

PARAMETERS 10

18, 10, 10, 6, 6, 8, 8, 8, 5, 5

INPUT 4

17,4 17,5 1,6 1,7

0.0 0.0 0.0 0.0

****

UNIT 42 TYPE 18 Water Flow Network of Zone 3

PARAMETERS 11

0.00032, 0.002, 1.28, 0.000026, 0.00038, 18, 10, 10, 6, 6, 380

INPUT 12

43,1 74,4 41,1 41,2 41,3 41,4 41,5 45,2 45,4 45,6 45,8 45,10

50.0 1.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0

****

UNIT 43 TYPE 43 PID Controller for SCHWP-42-01 to 03 in Zone 3

PARAMETERS 8

0.1, 10.0, 0.0, 5.0, 20, 50, 1.0, 1.0

INPUT 3

42,4 26,1 0,0

0.0 190 1.0

****

UNIT 26 TYPE 8 Pressure Differential Set-Point Optimizer for SCHWP-42-01 to 03

PARAMETERS 3

190, 80.0, 0.15

INPUT 5

45,2 45,4 45,6 45,8 45,10

0.0 0.0 0.0 0.0 0.0

****

UNIT 44 TYPE 63 AHUs in Zone 3 (5 Groups)

INPUT 13

17,6 0,0 41,6 41,7 41,8 41,9 41,10 47,1 42,7 42,8 42,9 42,10 42,11

25.0 0.0115 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0

PARAMETERS 15

0.0, 4.0, 26.0, 26.0, 0.42, 1.35, 2.55, 0.03294, 0.0015, 3.0,

0.48405E-2, 0.609E-3, 1.0, 0.1036, -0.29804

DERIVATIVES 5

20.0, 20.0, 20.0, 20.0, 20.0

****

UNIT 45 TYPE 42 PID Controllers for AHUs in Zone 3

PARAMETERS 9

0.0, 9999.0, 0.0, 0.3, 20.0, 0.0, 5.0, 2.0, 0.5

INPUTS 11

44,1 44,2 44,3 44,4 44,5 41,1 41,2 41,3 41,4 41,5 0,0

0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 13.0

****
UNIT 46 TYPE 47 Mixing of Building Return Flow of Zone 3
PARAMETERS 5
18, 10, 10, 6, 6
INPUT 12
44,11 44,12 44,13 44,14 44,15 42,7 42,8 42,9 42,10 42,11 47,1 42,14
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
****
UNIT 47 TYPE 45 Chilled Water Mixing and Bypass after the First Stage HXs in Zones 3&4
INPUT 6
48,16 46,1 58,7 74,10 46,2 59,1
0.0 0.0 0.0 0.0 0.0 0.0
****
UNIT 48 TYPE 37 The First Stage Heat Exchangers (HX-42 01 to 07) in Zones 3&4
PARAMETERS 5
20000, 2, 3770.5, 149, 149
INPUT 6
74,10 49,1 47,2 16,1 74,8 0,0
310 345 11.3 5.5 2.0 25.0
DERIVATIVES 14
25.0, 25.0, 25.0, 25.0, 25.0, 25.0, 25.0, 25.0, 25.0, 25.0, 25.0, 25.0, 25.0, 25.0
****
UNIT 49 TYPE 16 Water Flow Network of the Primary Side of the First Stage HXs in Zones 3&4
PARAMETERS 3
0.00015, 0.0027, 0.0006
INPUT 3
75,1 74,3 74,8
50.0 1.0 1.0
****
UNIT 50 TYPE 43 Temperature Controller for SCHWP-06-06 to 09
PARAMETERS 8
-0.5, 10.0, 0.0, 5.0, 50, 345, 9.0, 1.0
INPUT 3
48,16 0,0 0,0
0.0 6.3 1.0
****
UNIT 75 TYPE 43 Water Flow Controller for SCHWP-06-06 to 09
PARAMETERS 8
0.5, 25.0, 0.0, 5.0, 20, 50, 9.0, 1.0
INPUT 3
49,10 50,1 0,0
0.0 0.0 1.0
****
UNIT 52 TYPE 17 Water Flow Network of Zone 4
PARAMETERS 11

0.0006,   0.002,   1.30,   0.00006,   0.0008,   8,   8,   8,   5,   5,   420
INPUT 12
53,1   74,6   41,11   41,12   41,13   41,14   41,15   55,2   55,4   55,6   55,8   55,10
50.0   1.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
****
UNIT 53 TYPE 43 PID Controller for SCHWP-78-01 to 03 in Zone 4
PARAMETERS 8
0.1,   10.0,   0.0,   5.0,   20,   50,   1.0,   1.0
INPUT 3
52,4   51,1   0,0
0.0   180   1.0
****
UNIT 51 TYPE 62 Pressure Differential Set-Point Optimizer for SCHWP-78-01 to 03
PARAMETERS 3
200,   80.0,   0.15
INPUT 5
55,2   55,4   55,6   55,8   55,10
0.0   0.0   0.0   0.0   0.0
****
UNIT 54 TYPE 63 AHUs in Zone 4 (5 Groups)
INPUT 13
17,6   0,0   41,16   41,17   41,18   41,19   41,20   57,1   52,7   52,8   52,9   52,10   52,11
25.0   0.0115   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
PARAMETERS 15
0.0,   4.0,   27.0,   27.0,   0.42,   1.35,   2.55,   0.03294,   0.0015,   3.0,
0.48405E-2,   0.609E-3,   1.0,   0.1036,   -0.29804
DERIVATIVES 5
20.0,   20.0,   20.0,   20.0,   20.0
****
UNIT 55 TYPE 42 PID Controllers for AHUs in Zone 4
PARAMETERS 9
0.0,   9999.0,   0.0,   1.0,   60.0,   0.0,   5.0,   2.0,   0.5
INPUTS 11
54,1   54,2   54,3   54,4   54,5   41,11   41,12   41,13   41,14   41,15   0,0
0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   13.0
****
UNIT 56 TYPE 47 Mixing of Building Zone 4 Return Flow
PARAMETERS 5
8,   8,   8,   5,   5
INPUT 12
54,11   54,12   54,13   54,14   54,15   52,7   52,8   52,9   52,10   52,11   57,1   52,14
0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
****
UNIT 57 TYPE 19 Chilled Water Mixing and Bypass at Secondary Side of the Second Stage HXs
INPUT 4

58,8   56,1   74,9   56,2

0.0   0.0   0.0   0.0

****

UNIT 58 TYPE 36 The Second Stage Heat Exchangers (HX-78-01 to 03) in Zone 4

PARAMETERS 5

20000,   2,   3707.5,   151,   151

INPUT 6

74,9   59,1   57,2   47,1   74,7   0,0

310   345   11.3   5.5   2.0   25.0

DERIVATIVES 6

25.0,   25.0,   25.0,   25.0,   25.0,   25.0

****

UNIT 59 TYPE 15 Water Flow Network of the Primary Side of the Second Stage HXs

PARAMETERS 3

0.0007,   0.0026,   0.001

INPUT 3

61,1   74,5   74,7

50.0   1.0   1.0

****

UNIT 60 TYPE 43 Temperature Controller for SHCWP-42-04 to 06

PARAMETERS 8

-0.5,   10.0,   0.0,   5.0,   50,   227,   9.0,   1.0

INPUT 3

58,8   0,0   0,0

0.0   7.1   1.0

****

UNIT 61 TYPE 43 Water Flow Controller for Pumps (SHCWP-42-04 to 06)

PARAMETERS 8

0.5,   15.0,   0.0,   5.0,   20,   50,   9.0,   1.0

INPUT 3

59,10   60,1   0,0

0.0   0.0   1.0

****

UNIT 62 TYPE 61 Mixing of Building Return Flow

INPUT 6

35,7   48,15   39,1   36,1   49,1   39,2

20.0   20.0   0.0   0.0   0.0   0.0

****

UNIT 63 TYPE 31 Chilled Water Return Pipe

PARAMETERS 6

0.25,   80.0,   1E-10,   1000.0,   4.187,   25.0

INPUT 3

62,1   62,2   0,0

0.0   0.0   25.0

****

UNIT 74 TYPE 39 Pump and HX Sequence Controllers
PARAMETERS 2
151, 149
INPUT 10
28,1 19,1 50,1 43,1 60,1 53,1 52,1 42,1 59,1 27,1
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
****
UNIT 64 TYPE 51 Totalization of Cooling Tower Fan Consumption
INPUT 11
3,19 3,20 3,21 3,22 3,23 3,24 4,16 4,17 4,18 4,19 4,20
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
****
UNIT 70 TYPE 52 Totalization of Pump Power Consumption
PARAMETERS 4
44.7, 36.1, 126, 202
INPUT 10
36,6 27,15 18,23 49,6 42,13 59,6 52,13 74,8 74,7 15,8
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
****
UNIT 65 TYPE 66 Totalization of Chiller Power Consumption
INPUT 7
15,8 8,7 9,7 10,7 11,7 12,7 13,7
0.0 0.0 0.0 0.0 0.0 0.0 0.0
****
UNIT 66 TYPE 25 Print Power Consumption of Cooling Towers
PARAMETERS 4
120, 0, 360000, 21
INPUTS 9
64,1 3,19 3,20 3,21 3,22 3,23 3,24 4,16 4,17
Pcttot PCTA1 PCTA2 PCTA3 PCTA4 PCTA5 PCTA6 PCTB1 PCTB2
****
UNIT 67 TYPE 25 Print Power Consumption of Pumps
PARAMETERS 4
120, 0, 360000, 22
INPUTS 9
70,1 70,2 70,3 36,6 27,15 18,23 49,6 42,13 59,6
Ptot Pvtot Pctot Pz1 Pz2 Pz3 Pz4 Pz5 Pz6
****
UNIT 68 TYPE 25 Print Power Consumption of Chillers
PARAMETERS 4
120, 0, 360000, 23
INPUTS 7
65,1 8,7 9,7 10,7 11,7 12,7 13,7
Pchtot Pch1 Pch2 Pch3 Pch4 Pch5 Pch6
****

```
UNIT 69 TYPE 25 Print Operating Number of Components
PARAMETERS 4
120,    0,    360000,    24
INPUTS 9
15,8    74,1    74,2    74,3     74,4    74,5    74,6     74,7    74,8
Nch    NP1    NP2     NP3    NP4     NP5    NP6    NP7    NP8
*******************************************************************************
END
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