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A Systematic Optimization and Operation of Central Chilling Systems for Energy Efficiency and Sustainability

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Abstract: This paper presents an optimization strategy for optimal control and operation of building central chilling systems in order to minimize their energy consumption and provide improved control performance. The strategy is formulated using a systematic approach, in which the characteristics and interactions among the components and subsystems in the central chilling system are considered. The simplified models of major components are used in the strategy as the performance predictors to estimate the system energy performance and responses to the changes of control settings and working conditions. To ensure the models to provide reliable estimates when the working condition changes, the model parameters are updated online using the recursive least squares (RLS) estimation technique. A genetic algorithm (GA) is used to solve the optimization problem and search for globally optimal control settings on the basis of a cost function estimator defined. The performance of this strategy was tested and evaluated in a simulated virtual system representing the complex central chilling system in a super high-rise building under various working conditions. The model parameter identification and performance validation as well as the performance evaluation of the optimization strategy are presented.

Keywords: *Optimization strategy, systematic approach, central chilling system, performance model, parameter identification, energy saving*

1. Introduction

Building central chilling systems as major function of air-conditioning system often consumed about twenty-five to fifty percent of annual energy budgets in most air-conditioned commercial buildings [1]. Many studies have showed that well monitored and controlled central chilling systems have great potentials to help reduce the global energy consumption in buildings and improve the overall operational reliability [1-6].

In the last two decades, many efforts have been made on developing and applying optimal control strategies for building central chilling systems with an aim to enhance their operational performance [2-6]. For instance, a physical model-based supervisory control strategy for a direct-fired LiBr absorption chiller system was developed by Koeppel et al. [3]. Gibson [4] used artificial neural networks (ANNs) and genetic algorithms (GAs) to formulate an optimal control strategy for central chilling systems for energy efficiency. Ahn and Mitchell [5] presented an optimal control strategy for a cooling plant. The optimal control strategy was formulated using a quadratic regression equation. The results obtained from these studies showed that substantial amount of energy in central chilling systems can be saved when optimal control strategies are used. It is worthy noticing that most existing optimal control strategies for central chilling systems were developed using a model-based approach [2,3,5,6], in which different types of models were used to estimate system energy performance and response to the changes of control settings. When models are used in control systems, their prediction accuracy becomes essential. Since the working conditions of the models used in HVAC systems have no noticeable changes in finite time step or working range, the models (parameters of models) are only required to be accurate in limited working range. Therefore, the models can be reasonable simple and online learning and estimation approaches can be used to identify and update the model parameters to ensure the model accuracy when the working condition changes. The models using online learning and estimation approaches for parameters estimations are

often called self-tuning models. Since new operation data are continuously used to estimate and update the model parameters, the prediction uncertainty of models can be reduced greatly.

In the HVAC field, the importance of using self-tuning models in optimal control has been addressed in Ref. [7,8]. A number of model-based optimal control strategies combined the online parameter estimation techniques were also developed [6,9,10]. Farris and McDonald [9] presented an algorithm for applying advanced control concepts in HVAC systems. In order to utilize the optimal control approach and obtain closed-loop control equations, a linearized system representation was used and the sequential least squares were developed for the parameter estimation. The user-adaptable comfort control for HVAC systems was described by Federspiel and Asada [10], in which the controller learns to predict the actual thermal sensation of the specific occupant by tuning parameters of the model of the occupant's thermal sensation and the model parameters were estimated using the RLS method. In the optimal control strategy for VAV air-conditioning systems developed by Wang and Jin [6], the adaptive finite-time incremental models of major components were used for performance prediction and the model parameters were updated using the RLS estimation with exponential forgetting. The results from above studies demonstrated that model-based optimal control strategies using online parameter estimation techniques taking into account the system dynamics can provide more reliable control and better energy performance.

This paper presents an online adaptive optimal control strategy for centralized chilling systems. The optimal control strategy is formulated using a model-based approach, in which simplified physical models are used as the performance predictors and the model parameters are online continuously updated by using the RLS estimation with exponential forgetting. The optimization problem is solved by using a GA. The performance of this strategy is tested and evaluated in a simulated virtual environment representing the actual central chilling system in a super high-rise building.

2. Description of the Central Chilling System

The central chilling system concerned in this study is a complex system in a super high-rise building in Hong Kong. Figure 1 presents the schematic of this central chilling system, in which six identical high voltage centrifugal chillers with the capacity of 7230 kW each at the design condition are used to supply the cooling energy for buildings. Each chiller is interlocked with a constant condenser water pump and a constant primary chilled water pump. A total of eleven cooling towers are used for heat rejection proposes. All cooling towers are an in house type and equipped with variable speed axial fans.

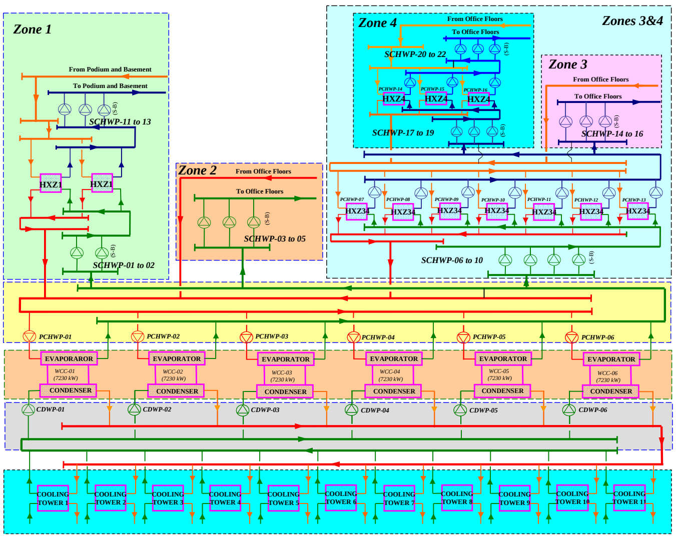

Figure 1 Schematic of the centralized chilling system.

The secondary chilled water system is divided into four zones to avoid the chilled water pipelines and terminal units from suffering extremely high pressure. Only Zone 2 is supplied with the secondary chilled water directly. For the other three zones, the heat exchangers are used to transfer the cooling energy from low zones to high zones to avoid the high water static pressure. Zone 1 is supplied with the secondary chilled water through the heat exchangers located on the sixth floor. Zone 3 and Zone 4 are supplied with the secondary chilled water through the first stage heat exchangers (HXZ34)

located on the 42nd floor. Some of the chilled water after the first stage heat exchangers is delivered to Zone 3 and some water is delivered to the second stage heat exchangers (HXZ4) located on the 78th floor. All pumps in the secondary water system are equipped with variable frequency drivers for energy efficiency except that the primary chilled water pumps dedicated to the heat exchangers in Zones 3&4 are constant speed pumps.

3. Formulation of the Optimal Control Strategy

3.1 Outline of the optimal control strategy

Since Zone 1 of the building covers all possible control issues in the secondary chilled water system, the optimal control strategy presented in the following is only focused on Zone 1 in order to reduce the complexity of the control system. Figure 2 illustrates the overall optimization process of the optimal control strategy. It mainly consists of a rule-based supervisor, a GA optimizer, a cost function estimator, performance predictors (i.e., performance models) and model parameter estimators as well as system operating constraints. The control settings optimized include the condenser supply water temperature set-point ($T_{w,cd,set}$), chiller (chilled) supply water temperature set-point ($T_{w,ch,set}$) and heat exchanger supply water temperature set-point ($T_{w,hx,set}$). Here, the heat exchanger supply water temperature refers to the outlet water temperature at the secondary side of heat exchangers. The models used include a simplified chiller model, a heat exchanger model, a fictitious global AHU coil model and a cooling tower model. The model parameter estimators adopting the RLS estimation technique with exponential forgetting are used to identify and update the parameters required by these models using the online measurements. A GA optimizer is used to solve the optimization problem and seek the most energy efficient control settings on the basis of the cost function estimator and performance predictors. The operating constraints give the upper and lower limits of the control settings to be optimized. The rule-based supervisor is used to provide the final control settings for the real process based on the compromise of the control stability and energy savings, according to a set of rules defined. When cost saving is significant, the optimal control settings identified by the GA optimizer will be used to update the current settings. Otherwise, the control settings remain unchanged. It is worthy noticing that the operating number of the heat exchangers and variable speed pumps in the secondary side of heat exchangers in Zone 1 are optimized simultaneously during the model prediction process in each GA trial computation. This is because they are controlled based on the water flow rate in the secondary side of heat exchangers in this study.

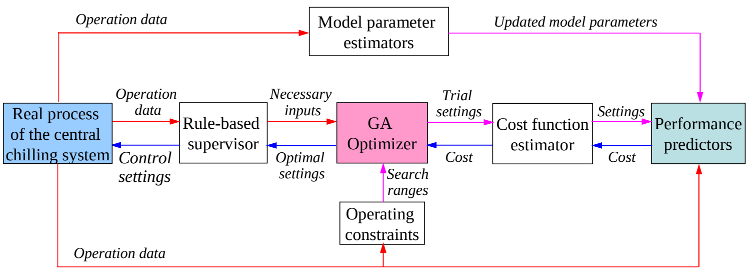

Figure 2 Optimization process of the optimal control strategy.

The objective function for the system under investigation (only Zone 1 is considered in this study) is illustrated in Equation (1). Since the GA used in this study [11] intends to search for maximum values while the optimization problem is to seek the minimum energy consumption, the GA fitness function is therefore defined as Equation (2).

$$J(T_{w,set,i}) = \min W_{tot} = \min(W_{ch,tot} + W_{ct,tot} + W_{pu,tot}) \quad (1)$$

$$f\left(T_{w,\sup,i}\right) = \frac{1}{J\left(T_{w,set,i}\right)} \quad (2)$$

where, J is the cost function, f is the fitness function, T is the temperature, W is the power consumption, and subscripts w, *ct*, *pu, ch, set* and *tot* represent water, cooling tower, pump, chiller, set-point and total, respectively.

To ensure the system to operate properly, a set of system operating constraints are considered. The input frequencies of variable speed pumps and cooling tower fans are constrained between 20 Hz and 50 Hz. To avoid low chiller (chilled) supply water temperature set-point causing the problems of ice in evaporators and the low efficiency of chillers, and high chiller supply water temperature set-point

resulting in the problems of the humidity control for the air-conditioned spaces and inadequate cooling load provided, the chiller supply water temperature set-point is constrained between 5.0°C and 9.5°C. Taking into account the actual heat transfer performance of heat exchangers, the heat exchanger supply water temperature set-point is constrained between 5.5°C and 10.0°C. To avoid low condenser supply water temperature set-point causing low pressure problems in chillers, a low limit of 18.0°C is constrained as well.

3.2 Description of the performance models

To ensure robust and reliable control performance, a series of semi-physical models are used in this study. The parameters in these models are considered to be slowly-varying, and be constant within a limited working range. All models used are linear in the parameters directly or linear in the parameters after through the logarithm transformation. The RLS estimation technique with exponential forgetting can be used to online identify and update the parameters required by the models to ensure the models to provide reliable estimates when the working condition changes. The details of the models used are presented as follows.

3.2.1 The fictitious global AHU coil model

A fictitious global AHU coil is assumed to represent all AHU coils in the entire zone (Zone 1) of the central chilling system under study. Given the air inlet and outlet temperatures, humidity, water inlet temperature and air flow rate, the global AHU coil model is used to predict the required chilled water flow rate in the entire zone and the chilled water outlet temperature from the AHU coil. The total heat transfer rates on the water side and air side are computed by using Equations (3) and (4), respectively. The heat transfer coefficients at the water side and air side are assumed to be related with the water flow rate and air flow rate only and computed by using Equations (5) and (6), respectively. To identify the model parameters of γ_w, γ_a, β_w and β_a, both heat transfer coefficients in the water side and air side need to be calculated based on the inlet and outlet air and water states of the coil. Using the heat transfer coefficients calculated at the current and former sampling instants, the RLS estimation is used to estimate and update the parameters of the coil model.

$$Q_{tot} = UA_w(T_b - T_{w,in}) \tag{3}$$

$$Q_{tot} = UA_a(h_{a,in} - h_b) \tag{4}$$

$$UA_w = \gamma_w (m_w)^{\beta_w} \tag{5}$$

$$UA_a = \gamma_a (m_a)^{\beta_a} \tag{6}$$

Where *UA* is the heat transfer coefficient, *Q* is the heat transfer rate, T_b is the equivalent coil surface temperature, h_b is the saturated air enthalpy at the temperature T_b, γ and β are the model parameters to be identified, and subscript *in* represents inlet.

3.2.2 Heat exchanger model

In this study, the performance of the water-to-water heat exchanger with counter flow is modeled using classical *ε-NTU* method. The actual heat transfer in the heat exchanger is computed using Equation (7). The overall heat transfer coefficient is computed by Equation (8), which is considered as a function of the water flow rate in the secondary side of heat exchangers. There are three parameters (b_0-b_2) in this model. To identify these parameters, the heat transfer coefficient needs to be calculated based on the inlet and outlet water temperatures and the water flow rates in both sides of heat exchangers. Using the coefficients calculated at the current and former two sampling instants, the RLS estimation is then used to estimate and update the parameters in the heat exchanger model.

$$Q = \varepsilon \cdot C_{\min} \cdot (T_{w,s,in} - T_{w,p,in}) \tag{7}$$

$$UA = b_0 + b_1 M_{w,s} + b_2 M_{w,s}^2 \tag{8}$$

Where *C* is the capacity flow rate, *ε* is the heat transfer effectiveness, and subscripts *s* and *p* represent secondary side of heat exchangers and primary side of heat exchangers, respectively.

3.2.3 Chiller model

The chiller model used in this study is a simplified physical model developed previously [12]. In this model, a fictitious refrigeration cycle, as shown in Figure 3, is assumed to simplify the complicated thermodynamic processes occurred in the refrigeration systems. The overall heat transfer coefficients of the evaporator and condenser (UA_{ev}, UA_{cd}) are represented empirically as in Equations (9) and (10), respectively. The actual chiller power consumption (W_{com}) is computed based on a fictitious power

consumption (W_{fic}), as in Equation (11). There are nine parameters (C_1-C_9) that need to be identified in this model.

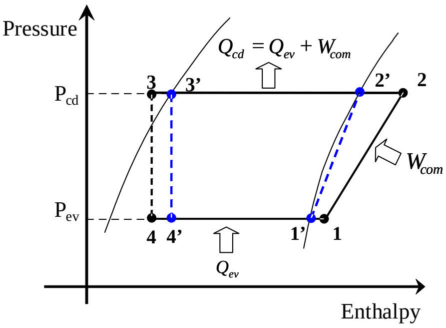

Figure 3 Illustration of the fictitious refrigeration cycle (Actual cycle: 1-2-3-4; fictitious cycle: 1'-2'-3'-4').

To identify the parameters of C_1-C_6, the overall heat transfer coefficients of the evaporator and condenser need to be calculated based on the evaporator cooling energy and measured compressor power consumption together with the calculated evaporator and condenser logarithm mean temperature differences. To identify the parameters of C_7-C_9, the fictitious power consumption (W_{fic}) needs to be calculated based on the condensing temperature and evaporating temperature by using the fictitious refrigeration cycle. Using the heat transfer coefficients and fictitious power consumptions calculated at the current and former two sampling instants, the RLS estimation technique is used to estimate and update the parameters of the chiller model.

$$C_1 M_{w,ev}{}^{-0.8} + C_2 Q_{ev}{}^{-0.745} + C_3 = \frac{1}{UA_{ev}} \tag{9}$$

$$C_4 M_{w,cd}{}^{-0.8} + C_5 (Q_{ev} + W_{com})^{1/3} + C_6 = \frac{1}{UA_{cd}} \tag{10}$$

$$W_{com} = C_7 + C_8 W_{fic} + C_9 W_{fic}^2 \tag{11}$$

3.2.4 Cooling tower model

In this study, a simplified model developed by Lebrun et al. was used [13]. In this model, the cooling tower was treated as an equivalent heat exchanger and modeled using classical ε-*NTU* method. The heat transfer coefficient of the cooling tower is simulated using Equation (12), where $c_{p,a}$ is the air specific heat and $c_{p,af}$ is the fictitious air specific heat which is computed by using Equation (13). Through the logarithm transformation, Equation (12) can be linear in the parameters. To identify the model parameters of D_o, m and n, the heat transfer coefficient of the cooling tower needs to be calculated based on the inlet and outlet air and water states and calculated heat rejection capacity. Using the heat transfer coefficients calculated at the current and former two sampling instants, the RLS estimation technique is used to identify and update the model parameters.

$$UA = D_0 \left(\frac{M_w}{M_{w,des}}\right)^m \times \left(\frac{M_a}{M_{a,des}}\right)^n \times \frac{c_{p,af}}{c_{p,a}} \tag{12}$$

$$c_{p,af} = \frac{h_{a,out} - h_{a,in}}{T_{wb,out} - T_{wb,in}} \tag{13}$$

3.2.5 Pump and fan models

The power inputs of the cooling tower fan and secondary water pump are modeled to be approximately proportional to their flow rates cubed as in Equation (14) when the changes of the flow rates are small in a finite step or working range. Since the power consumption (W) and flow rate (M) are measured, the parameter (λ) can be learnt and estimated directly by using Equation (15) and updated at each sampling instant.

$$W = \lambda M^3 \tag{14}$$

$$\lambda^k = \frac{W^k}{(M^k)^3} \tag{15}$$

4. Performance Tests and Results Analysis

4.1 Test platform and test conditions

A simulated virtual system representing the actual central chilling system under study was used as the test platform of the optimal control strategy. This simulated virtual system was constructed based on a transient simulation program TRNSYS. The local control strategies used in the simulated virtual system are as follows. The chillers were sequenced based on their design cooling capacities considering one constant primary chilled water pump and one constant condenser water pump dedicated to one chiller in this system. The operating number of the cooling towers was controlled based on the operating number of the chillers. The operating speeds of variable speed pumps at the secondary side of heat exchangers are controlled by maintaining the pressure difference of the critical loop at a predetermined constant value. A cascade controller, as illustrated in Figure 4, was used to control the operating speeds of the variable speed pumps at the primary side of heat exchangers by maintaining the outlet water temperature at the secondary side of heat exchangers at its set-point.

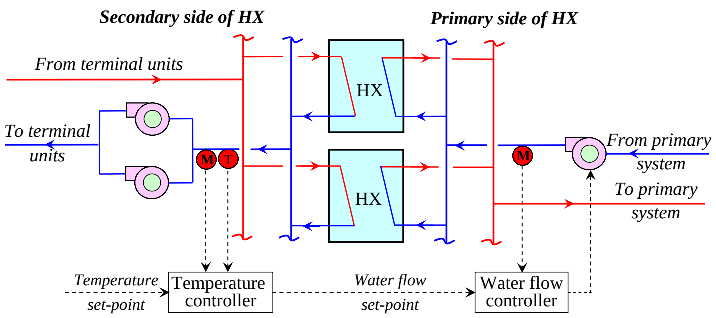

Figure 4 The speed control of variable speed pumps at the primary side of heat exchangers.

4.2 Performance test and validation of the performance models

Since the accuracy of the performance models directly affects the performance of the optimal control strategy, the performance of major component models is validated firstly. In order to save the page size, only the validation results of the chiller model are presented.

Figure 5 and Figure 6 show the comparisons between the model estimated and online 'measured' instantaneous power consumptions of the chiller when using different forgetting factors to update the model parameters. It can be observed that large deviations between the estimated and 'measured' values were existed when the forgetting factor used is 0.9998. However, good agreements between the two set of values can be found when the forgetting factor is changed to 0.993. Therefore, the selection of the forgetting factor is important for online parameter identification. The response of the RLS estimator to the change of the system characteristics can be accelerated by reducing the value of the forgetting factor, but a too low value might cause unstable estimation of the coefficients. The above test results showed that the chiller model combined with the RLS estimation technique with exponential forgetting can provide satisfactory performance prediction and are reliable for online control applications.

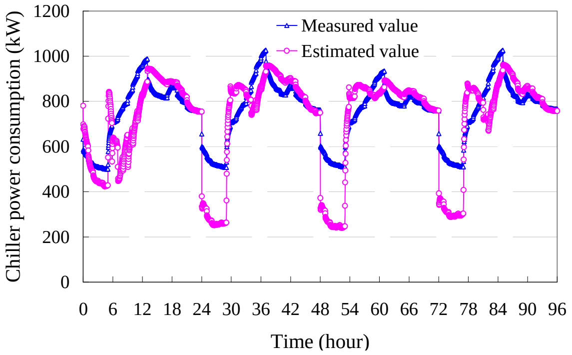

Figure 5 Comparison between the estimated and 'measured' power consumptions of the chiller (Forgetting factor: 0.9998).

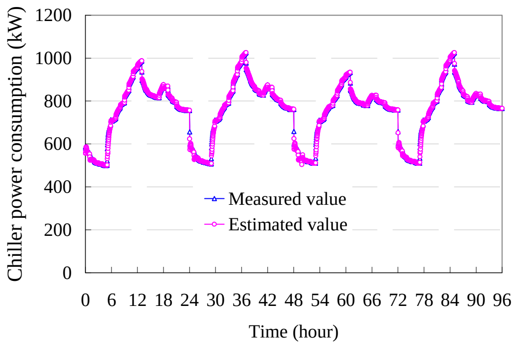

Figure 6 Comparison between the estimated and 'measured' power consumptions of the chiller (Forgetting factor: 0.993)

4.3 Performance test and validation of the optimal control strategy

The performance of the proposed control strategy is tested and evaluated by comparing with that of a conventional control strategy. In the conventional strategy, the chiller and heat exchanger supply water temperature set-points were set to be constant, and the design temperature set-points of 5.5°C and 6.3°C were used, respectively. The condenser supply water temperature set-point was set using the fixed approach control method. In this study, the design approach of 5.0°C was used. During the tests, the sampling interval and prediction period used in the proposed strategy were 60s and 300s respectively, and the simulation time step of the virtual system simulation was 60s.

Figure 7 present the profiles of the optimal temperature set-points searched by the proposed strategy for the typical mild-summer day. It can be found that all three temperature set-points searched were not constant but varied significantly during the day, and the differences between the chiller supply water temperature set-point and the heat exchanger supply water temperature set-point were varied significantly as well instead of maintaining at a constant value. It is also noted that the optimal chiller and heat exchanger supply water temperature set-points reduced greatly around 5:00am. This was caused by increasing an additional heat exchanger and an additional variable speed pump after heat exchangers in operation in that period. In the meantime, it is interesting to notice that the searched condenser supply water temperature set-points were increased greatly around 5:00am although the operating of heat exchangers and secondary water pumps has no direct impacts on the cooling tower system. The above results further demonstrated that the subsystems in central chilling systems are highly interactive and the systematic optimization rather than local optimization can help to minimize the overall system running cost.

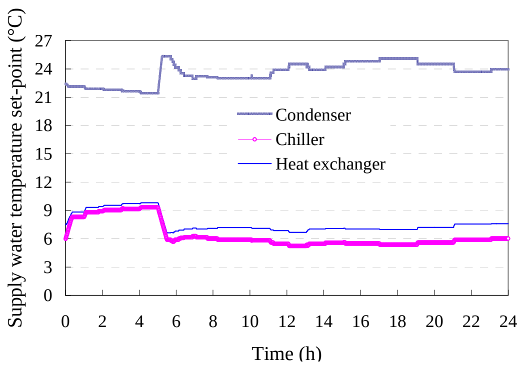

Figure 7 Profiles of the optimal temperature set-points in the typical mild-summer day.

Table 1 summarizes the energy consumptions of the central chilling system (only Zone 1 is considered in this study) in the typical mild-summer day by using the settings provided by the two control strategies. Since the constant condenser water pumps and constant primary chilled water pumps consumed relatively constant power consumptions, their energy consumptions were not included. Compared with the conventional strategy using traditional settings, the proposed strategy using optimal settings saved 390.7 *kWh* (1.35%) energy in the typical mild-summer test day. This part of energy saving was achieved through applying the optimal control algorithm only and without adding any additional cost.

Table 1 Energy consumptions of the central chilling system when using different strategies

Control strategies		Conventional	Proposed
Energy consumption of cooling towers (kWh)		3639.5	3141.7
Energy consumption of chillers (kWh)		21597.3	21421.8
Energy consumption of pumps (kWh)		3602.9	3885.5
Total energy consumption (kWh)		28839.7	28449.0
Energy saving of cooling towers		-	497.8
Energy saving of chillers		-	175.5
Energy saving of pumps		-	-282.6
Total saving	(kWh)	-	390.7
	(%)	-	1.35

Based on the above results, it can be found that the proposed optimal strategy, which considers the characteristics and interactions among and within the subsystems in central chilling systems, is more energy efficient and cost effective, as compared with the control strategy using traditional settings.

5. Conclusions

A model-based optimal control strategy for centralized chilling systems is presented. This strategy is formulated by using the simplified performance models and a GA optimizer. To ensure the model accuracy, the RLS estimation with exponential forgetting was used to estimate and update the parameters required by the models using online measurements. The performances of the performance models and the optimal control strategy were tested and evaluated on a simulated virtual system representing the actual central chilling system in a super high-rise building. The results showed that the performance models combined with the RLS estimators can provide good performance in prediction. The test of the optimal control strategy showed that this strategy is capable of optimizing the overall system performance. Compared with a conventional strategy using traditional settings, this optimal strategy can save about 1.35% daily energy of the central chilling system.

Acknowledgement

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Nomenclature

Symbols

b_0-b_2	coefficients
C_1-C_9	coefficients
D_0	coefficient
C	mass flow rate capacity, *kW/K*
$c_{p,a}$	the air specific heat, *kJ/(kg·K)*
$c_{p,af}$	the fictitious air specific heat, *kJ/(kg·K)*
f	fitness function
h	enthalpy, *kJ/kg*
h_b	the saturated air enthalpy at the temperature T_b, *kJ/kg*
J	cost function
M	flow rate, *kg/s*
m, n	coefficients
Q	heat transfer rate, *kW*
T	temperature, *°C*
T_b	the equivalent coil surface temperature, *°C*
UA	overall heat transfer coefficient, *kW/K*
W	power consumption, *kW*

Greek symbols

λ, γ, β	coefficients
ε	heat transfer effectiveness

Subscripts

a	air
cd	condenser
ch	chiller
com	compressor
ct	cooling tower
ev	evaporator
fic	fictitious
hx	heat exchanger
in	inlet
p	primary side of heat exchangers
pu	pump
s	secondary side of heat exchangers
set	set-point
tot	total
w	water

References

[1] Wang S.W. *Intelligent buildings and building automation*. Taylor & Francis, UK, 2009.

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

[3] Koeppel E.A., Klein S.A., Mitchell J.W. and Flake BA. *Optimal supervisory control of an absorption chiller system*. HVAC&R Research 1995;1(4), pp.325-342.

[4] Gibson G.L. *A supervisory controller for optimization of building central cooling systems*. ASHRAE Transactions 1997;103(1), pp.486-493.

[5] Ahn B.C. and Mitchell J.M. *Optimal control development for chilled water plants using a quadratic representation*. Energy and Buildings 2001;33(4), pp.371-378.

[6] Wang S.W. and Jin X.Q. *Model-based optimal control of VAV air-conditioning system using genetic algorithm.* Building and Environment 2000;35(6), pp.471-487.

[7] Åström K.J. and Wittenmark B. *Adaptive control (Second edition)*. Addison-Wesley Publishing Company, Inc. New York, 1995.

[8] Nassif N., Moujaes S. and Zaheer-uddin M. *Self-tuning dynamic models of HVAC system components*. Energy and Buildings 2008;40(9), pp.1709-1720.

[9] Farris D.R. and McDonald T.E. *Adaptive Optimal Control – An algorithm for direct digital control*. ASHRAE Transactions 1980;86(1), pp.880-893.

[10] Federspiel C.C. and Asada H. *User-Adaptable Comfort Control for HVAC Systems*. Transactions of the ASME, Journal of Dynamic Systems, Measurement, and Control 1994;116(3), pp.474-86.

[11] Carroll DL. *FORTRAN genetic algorithm (GA) driver*. Version 1.7a. Available from: http://cuaerospace.com/carroll/ga.html, 2001.

[12] Ma Z.J., Wang S.W., Xu X.H. and Xiao F. *A supervisory control strategy for building cooling water systems for practical and real time applications*. Energy Conversion and Management 2008;49(8), pp.:2324-2336.

[13] Lebrun J., Silva C.A., Trebilcock F. and Winandy E. *Simplified models for direct and indirect contact cooling towers and evaporative condensers*. Building Services Engineering Research and Technology 2004;25(1), pp.25-31.