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Publication Date
2019-09-01

DOI
10.1016/j.enbuild.2019.06.016

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Cooling load forecasting-based predictive optimisation for chiller plants

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A B S T R A C T

Extensive electric power is required to maintain indoor thermal comfort using heating, ventilation and air conditioning (HVAC) systems, of which, water-cooled chiller plants consume more than 50% of the total electric power. To improve energy efficiency, supervisory optimisation control can be adopted. The controlled variables are usually optimised according to instant building cooling load and ambient wet bulb air temperature at regular time intervals. In this way, the energy efficiency of chiller plants has been improved. However, with an inherent assumption that the instant building cooling load and ambient wet bulb temperature remain constant in the coming time interval, the energy efficiency potential has not been fully realised, especially when cooling loads vary suddenly and extremely. To solve this problem, a cooling load forecasting-based predictive optimisation method is proposed. Instead of minimising the instant system power according to the instant building cooling load and ambient wet bulb temperature, the controlled variables are derived to minimise the sum of the instant system power and one-time-step-ahead future system power according to both instant and forecasted future building cooling loads. With this method, the energy efficiency potential of a chiller plant can be further improved without shortening the operation time interval. 80% redundant energy consumption has been reduced for the sample chiller plant; energy can be saved for chiller plants that work for years. The evaluation on the effect of cooling load forecasting accuracy turns out that the more accurate the forecasts are, the more redundant energy consumption can be reduced.

1. Introduction

The energy consumption of buildings comprises 20–40% of total energy use in developed countries. The electric power required to maintain indoor thermal environments with heating and ventilation air conditioning (HVAC) systems accounts for almost half of that total [1]. Water-cooled chiller plants, which mainly refer to the condenser water loop of an HVAC system, are made up of chillers, cooling towers, and condenser water pumps; they comprise more than 50% of the total energy consumptions of HVAC systems [2]. The power used by a chiller plant can be reduced by understanding the interactions between its different components in the effort to meet the needs of time-varying building cooling loads.

For example, lowering the temperature of the condenser water supply temperature (T_{cws}) can reduce the power used by a chiller compressor by reducing the lift and increase the power requirement of a cooling tower fan. The contradictory effects of T_{cws} on a chiller and a cooling tower fan's power makes it important to find an optimum T_{cws} [3]. A lower condenser water mass flow rate (M_{cw}) can decrease the power used by the pump while increasing the temperature gap between the condenser water in and out of the chiller, which increases the chiller's power. The contradictory effects of M_{cw} on the energy efficiency of chillers and pumps also makes determining an optimum M_{cw} necessary [4].

The chiller plant system is typically controlled by a hierarchical control structure that combines local and supervisory controllers. The local controller maintains the basic setting of each system component with simple control techniques, such as proportional-integral-derivative (PID) control. The supervisory controller is a higher-level controller that releases commands, such as temperature or mass flow rate setpoints, to local controllers [5]. The set points of the local controllers can be kept constant or adjusted to accomplish some aim. For example, when the aim is to maximise system energy efficiency under time-varying building cooling loads and weather conditions, optimum settings are calculated using sophisticated optimisation algorithms; this is the so-called supervisory optimisation control.

Among different kinds of supervisory optimisation control methods, the model-based method is one of the most frequently

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Nomenclature

C_p	Specific heat of water cycled through the chiller plant (kJ/kg·K)
g	The gravity of earth (m/s^2)
h	Head of condenser water pumps (m)
η	The efficiency of condenser water pumps (%)
R_p	The control signal to the condenser water pumps (–)
T_{cws}	The temperature of condenser water supplied by the cooling tower to the chiller (°C)
T_{cwr}	The temperature of condenser water returning from the chiller to the cooling tower (°C)
T_{chs}	The temperature of chilled water supplied by the chiller to the air handling unit (°C)
T_{chr}	The temperature of chilled water returned from the air handling unit to the chiller (°C)
T_{wb}	Ambient wet bulb temperature (°C)
M_{cw}	The mass flow rate of the condenser water (Kg/s)
M_{ch}	The mass flow rate of the chilled water (Kg/s)
M_a	The mass flow rate of air in the cooling tower fan (Kg/s)
$h_{a,\,o}$	Enthalpy of the air outlet in the cooling tower fan (kJ/Kg)
$h_{a,\,i}$	Enthalpy of the air inlet in the cooling tower fan (kJ/Kg)
$\dot{P}$	The system power (W)
$\dot{P}_{st}$	The system power of none-predictive (static) optimisation (W)
$\dot{P}_{lb}$	Lower bound of system power (W)
$\dot{P}_{ch}$	Chiller power (W)
$\dot{P}_p$	Condenser water pump power (W)
P_{ct}	Cooling tower power (W)
$\dot{Q}_t$	Cooling load at current time t (W)
$\dot{Q}_{t+1\|t}$	Future cooling load at time step $t+1$, which is forecasted at current time t (W)
$\dot{P}(t)$	System power at the current time t (W)
$\dot{P}(t+1)$	System power at future time step $t+1$ (W)
$T_{wb,\,t}$	Ambient wet bulb temperature at the current time t (°C)
$T_{wb,t+1\|t}$	Future ambient wet bulb temperature at time step $t+1$, which is forecasted at current time t (°C)
W_{re}	Redundant energy consumption (kWh)

discussed in terms of optimising the energy efficiency of chiller plants [6]. This control method mainly comprises two parts: a mathematical model that reflects the behaviour of a chiller plant, or the so-called energy model, and an optimisation algorithm that calculates the optimum settings for controlled variables under time-dependent conditions.

In Chapter 42 of ASHRAE Handbook – HVAC Applications [7], the supervisory optimisation control is categorised into two types. The first is static optimisation, which addresses the optimisation problem at a given instant time. Typically, optimum variables are calculated according to instant building cooling and weather conditions at the current time. The second is dynamic optimisation, which highlights the control of a building system over time. It considers effects of future conditions, such as weather or utility prices, on the present optimal control decisions. The main difference between static and dynamic optimisation is the consideration of future conditions [8]. To stress the feature of whether allowing for future conditions or not, static optimisation is renamed as none-predictive optimisation and the dynamic optimisation is renamed as predictive optimisation in this paper.

Researchers have applied the idea of predictive optimisation control to different types of building systems [9], such as energy minimisation through thermal storage system management [10] and the determination of an optimal start time for heating [11]. Although studies have stressed the application of predictive optimisation to thermal storage systems, it has been less considered in the overall optimisation control of normal chiller plants without thermal storage, where none-predictive optimisation is often discussed. Given the assumption that building cooling loads and weather conditions remain constant until the next time step, the potential of energy efficiency has not been fully realised in none-predictive optimisation control [12]. To fill the gap in research on applying predictive optimisation to the overall control of chiller plants without thermal storage, this study considers cooling load forecasting-based predictive optimisation for chiller plants. By successfully integrating accurate dynamic cooling load forecasting into on-line supervisory optimisation control of chiller plants, the energy efficiency potential can be identified and further realised to save more energy than with commonly used none-predictive optimisation.

This paper is structured as follows. Section 2 defines and analyses the problem of the redundant energy consumption of none-predictive optimisation and outlines the research objectives. Section 3 reviews relevant studies on supervisory optimisation control. Section 4 thoroughly describes the proposed framework of cooling load forecasting-based predictive optimisation. Section 5 verifies the proposed cooling load forecasting-based predictive optimisation with a case study and comparison groups. Concluding remarks are presented in Section 6.

2. Statement on the redundant energy consumption problem

Fig. 1 illustrates a theoretical none-predictive optimisation process. In meeting the needs of time-varying cooling loads, the coefficient of performance (COP) of a chiller plant system may vary from around 3 (the worst scenario) to 7 (the best scenario) due to different settings of system parameters, such as T_{cws}, chilled water supplying temperature (T_{chs}), and M_{cw} [13]. The corresponding system power for each load scenario can be restrained within the upper and lower bounds as described in the grey coloured area in Fig. 1. Assuming the chiller plant system can react instantly, the system power can be minimised by carrying out optimisation at each time step: $t0$, $t1$, $t2$, $t3$, $t4$ and so on. As the optimum setting lasts until the optimisation at the next time step is carried out, the system power may not remain at the minimum level during the time interval, say between $t4$ and $t5$, due to the variation in building cooling load during the time interval. The fluctuation of the system power from the lower bound at the current time step to the upper bound at the next time step is a conceptual schematic diagram. It outlines an extreme condition that the system power will go to the upper bound until the optimisation at the next time step is carried out. However, in real cases, the system power does not necessarily to up to the upper bound, and it might go up the 1/4, 1/3, or half point between the upper and lower bound at the next time step according to the cooling load and weather conditions.

Simply put, Fig. 1 describes system power oscillation as a 'system power of none-predictive optimisation'. Compared with the system power of ideal optimisation, which closely approaches the lower bound of the system power, there is a redundant energy consumption during each time interval for the system power of the none-predictive optimisation.

The redundant energy consumption during each time interval can be defined as an integration of power difference between the system power of optimisation ($\dot{P}$) and the lower bound ($\dot{P}_{lb}$), as shown in Eq. (1). For chiller plants that have been working for

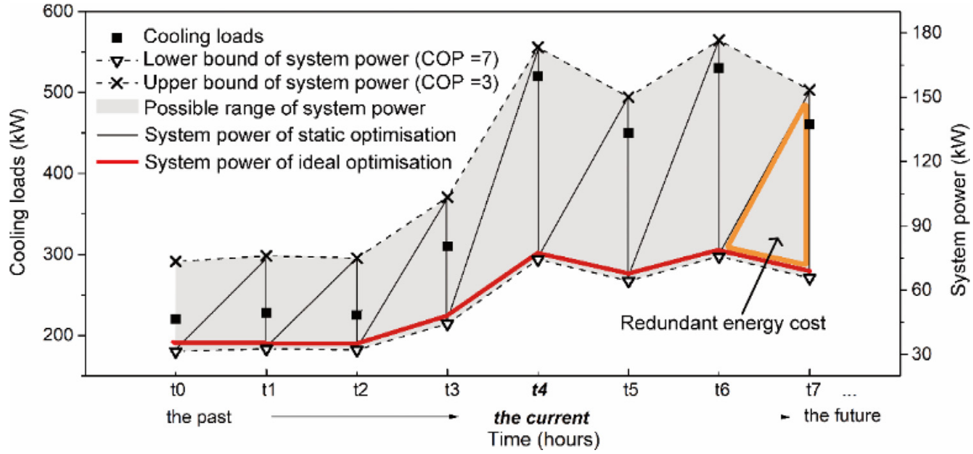


Fig. 1. Analysis of system power profile of different optimisation strategies.

years, the summation of redundant energy consumptions can be huge; it can be reduced by optimising the system with a higher frequency, namely a very short time interval. However, a highly frequent system resetting is less practical and may be harmful to system maintenance. Consequently, it is necessary to put forward an alternative solution to deal with the redundant energy consumption problem. Determining how the redundant energy consumption can be reduced as much as possible without shortening the optimisation time interval is the main problem discussed in this paper. This problem has been rarely discussed in previous studies, neither proposed nor settled. To identify this problem and propose a solution, the research objectives of this paper can be summarised as follows:

(1) Identify the problem of redundant energy consumptions via a case study;
(2) Obtain a general pattern of the redundant energy consumption behaviour; and
(3) Verify that the proposed optimisation method – cooling load forecasting-based predictive optimisation – can reduce the redundant energy consumptions without shortening the optimisation time interval.

$$W_{re} = \int (\dot{P} - \dot{P}_{lb}) dt \quad (1)$$

3. Previous work on supervisory optimisation control of chiller plants

Supervisory optimisation control of chiller plants, which has been extensively studied, can be reviewed from a perspective that whether future cooling load and weather conditions are considered; namely, a none-predictive optimisation control that considers only instant or instant and historic, and predictive optimisation control that allows for the future conditions into consideration.

None-predictive supervisory optimisation control methods have been studied by many researchers, by which the energy saving potential of supervisory optimisation control has been demonstrated. For example, with the activator of current building cooling loads, the genetic algorithm (GA) was adopted for the optimal control of an absorption chiller. Significant energy savings were achieved by optimising the mass flow rates of the condenser water and chilled water [14]. A model-based optimisation strategy for a condenser water loop was developed with a modified GA, showing that nearly 10% of the energy could be saved by optimising M_{cw} and the speed of the cooling tower fan during high load periods [15]. Temperature set points of the chilled and cooling water supplies were optimised with a hybrid optimisation algorithm that combined the particle swarm optimisation and Hooke-Jeeves algorithms, leading to 9.4% and 11.1% reductions in energy use in summer and winter, respectively [16]. A hybrid optimisation algorithm combining sequential quadratic programming with a modified branch and bound method was developed and produced a power savings of about 16.7% [17]. These studies not only demonstrate the benefits of supervisory optimisation control in reducing energy consumption, but also present the diversity in selecting optimised variables as well as optimisation algorithms.

Besides optimising the variables – M_{cw},T_{chs},T_{cws}, which have been mentioned in above literature, many other variables are also included in optimisation, such as the sequencing of chilled water pumps and chillers [18, 19], the pressure and temperature set point of supplying air to the building zone [20]. This inspires this paper to include more than one variable in optimising the chiller plant system. Evolutionary algorithms are popular in supervisory optimisation since their advantages in finding out the global extrema other than local extrema, which stimulates this paper in choosing GA as the optimisation algorithm.

Despite the great success of none-predictive supervisory optimisation control in reducing energy consumption, redundant energy consumptions are inevitable according to the theoretical analysis presented in Section 2. Predictive supervisory optimisation control can be an alternative solution to avoid redundant energy consumptions. Predictive supervisory control is not a brand-new concept in building automation and HVAC control area; it has been applied from 'a whole building level', 'a zone level' to 'a cooling system and component level' with a variable of objective functions [21].

On a whole building level, shading devices, the mechanical ventilation and on/off of air-conditioning systems, etc. are considered to be optimised with a predictive control. For example, a predictive control manner for hybrid night ventilation to precool thermally massive buildings and save energy is proposed according to the weather forecast [22].

On a zone level, the setpoint of supplying air temperature to the zone is often optimised with the aim of both saving energy and thermal comfort enhancement. For example, temperature setpoint of supplying air into the room is optimised with the cost function of minimising fan coil energy as well as ensuring thermal comfort [23]. Room temperature set points and on/off decisions of the HVAC units were optimised based on a prediction of indoor thermal comfort votes [24]. Room and hot/cold deck temperature setpoints were optimised by dynamic estimates, and zone loads and weather conditions were predicted while considering the constraints of providing thermal comfort [25]. The indoor heating setpoint is optimised to minimise energy consumption with 1 h and 24 h ahead data-driven indoor temperature and cooling energy consumption prediction [26].

On the cooling system and component level, most predictive control applications lie in the optimisation for charging periods of the thermal storage component of a cooling system [27]. For example, an optimal thermal storage charging strategy was derived using a predictive optimal controller at discrete time steps over a fixed look-ahead time window [10]. The potential of building thermal storage inventory, especially the combined use of active and passive inventory, to reduce electrical utility costs using common time-of-use rate differentials was investigated [28]. A model-based multi-variable controller was developed to optimise the charging schedule of a building thermal storage system with weather condition and building load predictions [29]. A new technique for solving a dynamic optimal chiller loading problem was presented for a cooling system with multiple chillers and a thermal storage tank. The load on each chiller and the charging period of the thermal energy storage system were optimised according to the total cooling load at each time step [8]. A model predictive control-based supervisory controller was designed to shift the peak load of a house to off-peak hours by optimising the buffer tank temperature setpoints [30].

Seldom efforts have been made in applying predictive optimisation control in a chiller plant without thermal storage; except for a study presented by Huang et al. [31], in which a model predictive control scheme was applied to optimise the condenser water setpoint. Targeting at legacy chiller plant system, how the optimisation starting points and frequency could be adjusted to produce faster computational speeds was also examined [31]. Huang et al. 's work has shown the predictive optimisation control lead to energy reduction in legacy chiller plant system, and it indicates that further improvements are possible when more variables are optimised simultaneously.

Numerous studies have demonstrated the energy reduction potential of supervisory optimisation control compared to traditional control strategies. With all kinds of controlled variables and optimisation algorithms, none-predictive supervisory control methods have been extensively studied. Predictive optimisation control methods have been studied in building automation from a whole building level to cooling system and component level, however, few attempts have been made to apply the predictive optimisation to chiller plants without thermal storage components. In the cooling system and component level, the predictive optimisation has been mainly studied in terms of optimising the charging period of thermal storage components and the air side of HVAC systems. What's more, the benefits of predictive optimisation of chiller plants have rarely been evaluated contrasting with a none-predictive optimisation control. These research gaps motivated this paper in proposing a framework of applying predictive optimisation control into chiller plants without thermal storage via optimising multiple control variables.

4. The framework of cooling load forecasting-based predictive optimisation

Computer-based simulation by MATLAB is adopted in this study, which contains three main parts as shown in Fig. 2, namely, the dynamic cooling load forecasting model, the supervisory optimisation control model and the 'real operated' chiller plant.

4.1. Dynamic cooling load forecasting model

The dynamic cooling load forecasting model is a predefined model that uses monitored historical building cooling loads, building information and ambient weather to forecast one-time-step-ahead building cooling loads [32].

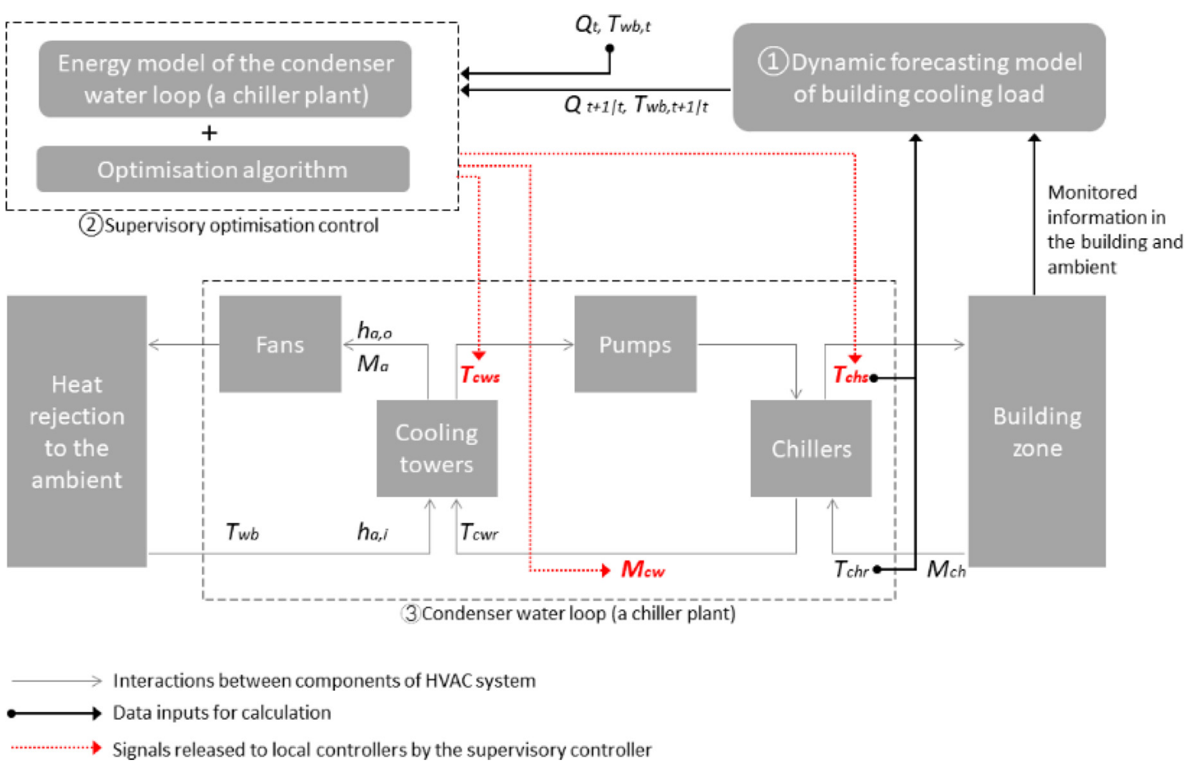


Fig. 2. Diagram of cooling load forecasting-based predictive optimisation.

Table 1
Description of cooling load forecasting models.

Name of forecasting models	Brief description
Unbiased Random Walk model	With an assumption that the load at the next time step is of equal probability either greater or less than the present load, the future cooling load is predicted to be equal to the present one, namely $\dot{Q}_{t+1\|t} = \dot{Q}_t$. This is a simple model that provides a base case against with more sophisticated forecasting models can be tested [10].
Artificial neural network (ANN) model	With 4 previous time step inputs, including cooling loads (kW), the ambient dry bulb temperature (°C), solar horizontal radiation(W/m^2) and room temperature setpoint (°C), a 3-layer ANN model is developed to forecast one time step ahead building cooling load(kW) [33].
Ensemble Approach model	Two sub-forecasting models are firstly built up with historic building cooling loads and the system conditions respectively; then, the forecasting results are combined by ensemble approach to draw the final forecasts [32].
Assumed ideal forecasting	The forecasted one-hour-ahead cooling load is assumed to be perfectly (100%) accurate. It reveals the maximum energy reduction potential that can be obtained by the proposed optimisation strategy.

Specifically, four forecasting models will be applied to the case study to verify the framework and evaluate the effect of the forecasting accuracy on redundant energy consumption reduction, as summarised in Table 1.

4.2. Supervisory optimisation control

The supervisory optimisation control is made up of an energy model and an optimisation algorithm. The energy model is described by a grey-box method, in which the chiller and cooling tower are modelled by an ANN algorithm as black-box modelling, while the pump and interaction between the components of the chiller plant are modelled by physics-based equations, namely white-box modelling. This grey-box method is adopted since white-box models are complicated by either look-up tables or iterations for chillers and cooling towers, while straightforward for the pump.

Using data-driven (black-box) model to simulate the chiller and cooling tower can simplified and speed up the modelling process and makes it convenient for real-time optimisation. For example, the white-box model of TRNSYS (Type 666) for modelling a chiller needs pre-defined look-up tables to determine the performance. To set up the model, the user must provide two text-based data files in the standard TRNSYS data file format. And it does not consider the effect of T_{cwr} on chillers' COP, which has been proved to affect the efficiency of a chiller plant [4]. The procedure in manipulating the chiller's performance data can be simplified by simulating the chiller by a data-driven (black-box) model, by which the procedure in developing the look up table is not necessary. And the effect of T_{cwr} can be included easily in the data-driven (black-box) model by including it as input to improve the model's accuracy.

The number of transfer unit (NTU) method, which contains assumptions and iterations, is one of the most frequently used physics-based models for cooling towers. The computational cost and the number of iterations associated with physics-based models is a challenge for real-time optimisation, which can be avoided by training data-driven models.

The combination of the black-box modelling, and white-box modelling generates the grey-box modelling of the whole chiller plant, as illustrated in Fig. 3. The blocks and arrows coloured in blue indicate the condenser water loop interaction between components in the chiller plant; the grey shadowed blocks and arrows show the modelling inputs and outputs of each component. The variables coloured in red are controlled variables which can be kept at their set points by local controllers. And their set points are derived by supervisory optimisation at each time step.

The energy model has been proposed by the authors' previous publication of [34], in which a chiller plant with one chiller, one condenser pump and one cooling tower were established and verified. As shown in Figs. 4 and 5, a 3-layer ANN(s) are set up to model the chiller and cooling tower; since the output of an ANN model with single hidden layer is in fact a superposition of numerous weighted sigmoid functions which has been proven to be universal function approximator [35]. The number of hidden neurons

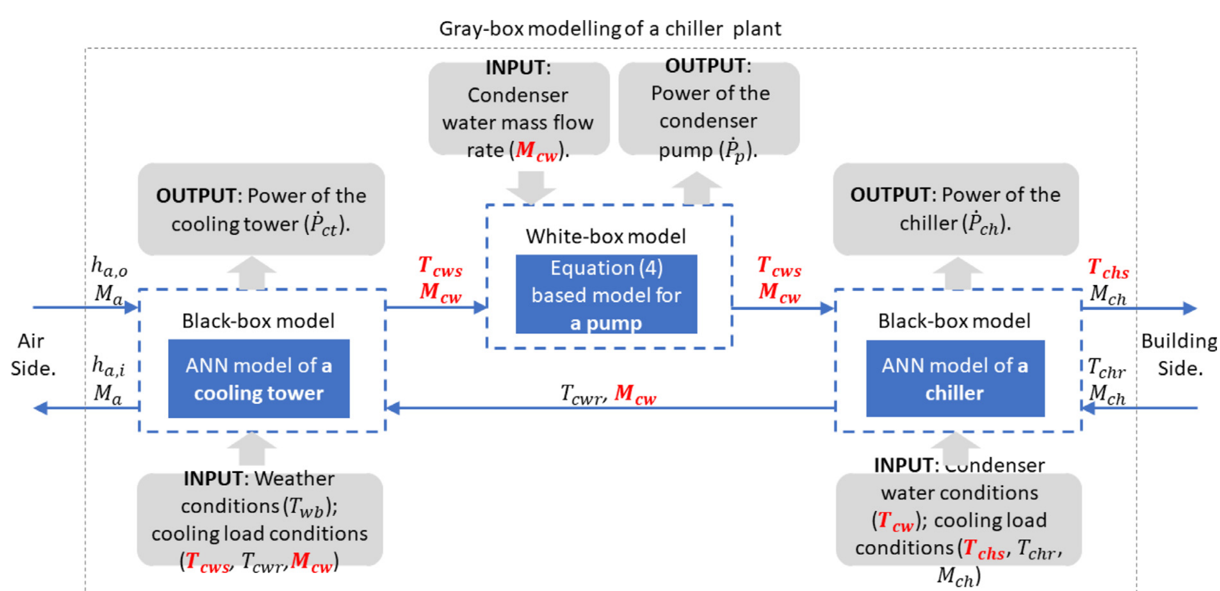


Fig. 3. Diagram of the energy model for a chiller plant.

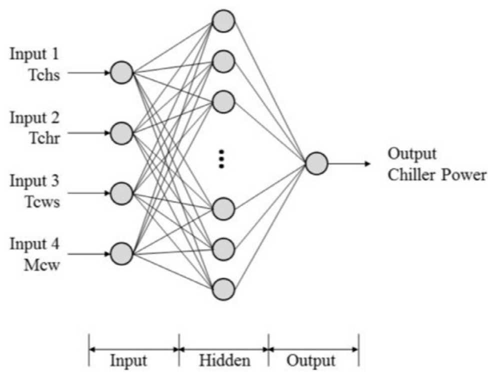


Fig. 4. Architecture of the ANN for modeling chillers.

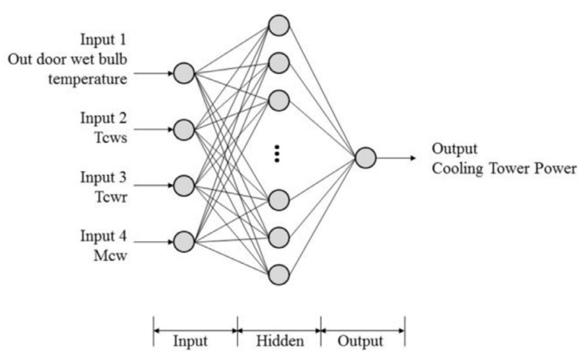


Fig. 5. Architecture of the ANN for modelling cooling towers.

is decided by a rule-of-thumb developed by Ward System Group [36]. T_{chs}, the temperature of chilled water returning to chillers (T_{chr}), T_{cws},M_{cw} are selected as the inputs of the ANN model for the chiller, which are the main parameters that affect the chiller efficiency. The ambient wet bulb temperature (T_{wb}),T_{cws}, the temperature of condenser water returning to the cooling tower (T_{cwr}) and M_{cw}, which affect the cooling tower efficiency, are the inputs of the ANN model for the cooling tower. Among the variables that affect both the efficiency of chillers and cooling towers, T_{chs}, T_{cws}, and M_{cw} are the variables that can be controlled by local controllers. T_{chr} is decided by T_{chs}, M_{ch} and instant cooling load, as shown in Eq. (2); T_{cwr} is decided by both instant cooling load and the heat released by the chiller, as shown in Eq. (3). The chilled water mass flow rate (M_{ch}) is considered as constant since the chilled water pumps are not included in the chiller plant (condenser water loop) system. The ANN(s) of the chiller and cooling tower of the case study are trained according to in-situ tested data and data generated by TRNSYS simulation respectively; details can be found out in [34].

$$\dot{Q} = M_{ch} * C_p * (T_{chs} - T_{chr}) \tag{2}$$

$$(T_{cwr} - T_{cws}) * M_{cw} * C_p = \dot{Q} + \dot{P}_{ch} \tag{3}$$

Simply put, the power of the chiller and the cooling tower can be summarised as the following Eqs. (4a) and (4b).

$$\dot{P}_{ch} = f(T_{chs}, T_{chr}, T_{cws}, M_{cw}) \tag{4a}$$

$$\dot{P}_{ct} = f(T_{wb}, T_{cws}, T_{cwr}, M_{cw}) \tag{4b}$$

The power of the condenser water pump is calculated by the following equations. The pumps are usually operated with a variable speed drive that ensures the mass flow rate varies according to the load. The mass flow rate of the variable speed water pump is decided by both a rated flow rate and a control signal R_p; the pump power is in direct proportion to the water mass flow rates and heads and inversely proportional to the efficiency η, as shown in Eq. (4c). The set points of T_{chs}, T_{cws} and M_{cw} are the optimised variables.

$$\begin{aligned} M_{cw} &= R_p * M_{cw,rated} \\ \dot{P}_p &= (M_{cw} * g * h)/\eta \end{aligned} \tag{4c}$$

The GA [37], which belongs to the large class of evolutionary algorithms, is selected as the optimisation algorithm. Inspired by the biological process of evolution, the evolutionary algorithm outperforms conventional gradient-based algorithms in finding global extrema rather than local extrema in a bounded parametric search space. However, it also takes more time than gradient-based methods when the searching space is large. The GA selected in this paper is one choice out of a bunch of evolutionary algorithms; other evolutionary algorithms, such as particle swarm optimisation can also be adopted in the supervisory optimisation control.

As for the fitness function, the main differences between the proposed cooling load forecasting-based predictive optimisation with the conventional none-predictive optimisation lie in the fitness function and the activators, as shown in Table 2. In the conventional none-predictive optimisation, the fitness function serves to determine the optimum variables that minimise the current instant total power according to the current instant cooling load and wet bulb temperature, as shown in Eq. (5). However, in the proposed cooling load forecasting-based predictive optimisation, the forecasted cooling load and ambient wet bulb temperature of the next time step $\dot{Q}_{t+1|t}$, $T_{wb,t+1|t}$ are included as activators to determine the optimum variables that minimise the summation of the current power $\dot{P}(t)$ and the future power on the next time step $\dot{P}(t+1)$, as shown in Eq. (6). Since the building cooling load is one

Table 2
Optimisation strategies description.

	Fitness function	Activator
None-predictive optimisation (baseline)	$\min_{Tchs,\,Tcws,\,Mcw} \{\dot{P}(t) = \dot{P}ch(t) + \dot{P}p(t) + \dot{P}ct(t)\}$ (5)	$\dot{Q}_t$, $T_{wb,\,t}$
Cooling load forecasting-based predictive optimisation	$\min_{Tchs,\,Tcws,\,Mcw} \{\dot{P}(t+1) + \dot{P}(t) = \dot{P}ch(t+1) + \dot{P}p(t+1) + \dot{P}ct(t+1) + \dot{P}ch(t) + \dot{P}ct(t) + \dot{P}ct(t)\}$ (6)	$\dot{Q}_t$ and $T_{wb,\,t}$ for $\dot{P}(t)$; $\dot{Q}_{t+1\|t}$ and $T_{wb,t+1\|t}$ for $\dot{P}(t+1)$

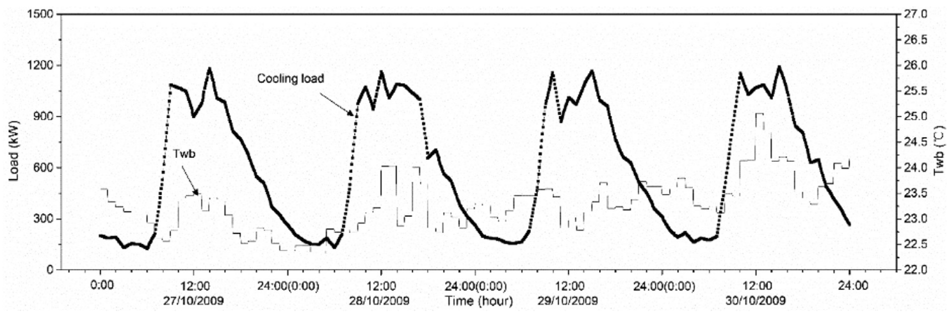


Fig. 6. Profile of cooling loads and wet bulb temperatures for the case study.

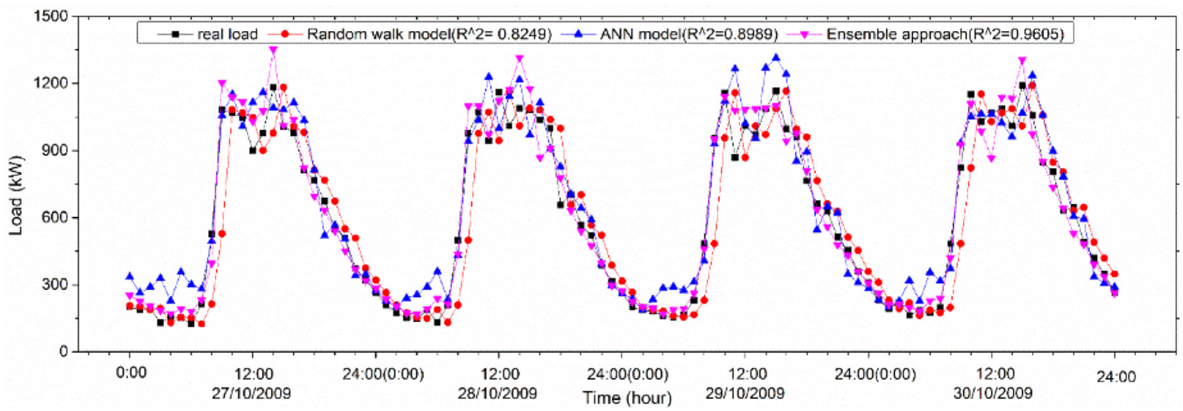


Fig. 7. Profile of hourly forecasted cooling loads with a look-ahead time of one hour.

of the most significant factors affecting the COP of a cooling system [38]and forecasting the ambient wet bulb temperature is beyond the scope of this paper, the future cooling load is addressed, and $T_{wb,t+1|t}$ is assumed to be equal to $T_{wb,\ t}$.

4.3. The 'real operated' chiller plant system

Allowing for the difficulties in applying the supervisory control to legacy chiller plants by experiments, a theoretical chiller plant system that receives supervisory control signals is adopted to represent a 'real operated' chiller plant system.

It can be modelled using simulation software, such as the Transient System Simulation Tool (TRNSYS), in which each component of the chiller plant is modelled by detailed physics-based equations [39]. For simplification, it can also be represented by the energy model.

In this paper, the 'real operated' chiller plant system is represented by the energy model introduced in Section 4.2 for simplicity.

5. Case study

In this section, the problem of redundant energy consumption is identified. Analysing the profile of redundant energy consumptions clarifies the general behaviour pattern of the redundant energy consumptions. The proposed optimisation method – cooling load forecasting-based predictive optimisation – can reduce the redundant energy consumptions without shortening the optimisation time interval; the more accurate the cooling load forecasts are, the more redundant energy consumption can be reduced.

5.1. Case description

The data of building cooling loads and weather conditions of this case study are derived from a real office building located in Hong Kong. Hourly cooling loads and ambient wet bulb temperatures were monitored and recorded during field research. Four typical working days (approximately from 27 to 30 October 2009) are selected in this paper. Fig. 6 shows the variation in building cooling loads and ambient wet bulb temperatures.

With the selected cooling load forecasting model introduced in Table 1, one-hour-ahead building cooling loads can be forecasted hourly, as shown in Fig. 7.

The coefficient of determination is taken to evaluate the accuracy of the dynamic forecasted load, as shown in Eq. (7). The $R^2$of the hourly dynamic forecasted load is 0.8249 by the Random Walk model, 0.8989 by the ANN model, 0.9605 by the Ensemble Approach model, as shown in Fig. 7.

The coefficient of determination is calculated as

$$R^2 = 1 - \frac{\sum \left(y_i - \hat{y}\right)^2}{\sum \left(y_i - \bar{y}\right)^2} \tag{7}$$

where y_i is the measured value, $\hat{y}$ is the modelled output and

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$$

5.2. Lower bound of the system power identification

To identify the redundant energy consumptions, ideally, the lower bound of the system power should first be determined using the Monte Carlo method. However, due to the heavy computational cost of Monte Carlo simulation, the GA is adopted to determine the lower bound instead of Monte Carlo simulation. To ensure the success of the algorithm, it is verified by the Monte Carlo method in the first place. After that, the lower bound of system power is calculated through frequent instant optimisations of the energy model by GA. The energy model has been described in Section 4.2.

Table 3
Clarification of operation strategies.

Name	Description	Comments
Opt. every 5 min	None-predictive optimisation with fitness function (5). The optimisation is carried out every 5 min.	It is regarded as an ideal optimisation that approximates the lower bound of the system power.
Hourly Opt. A	None-predictive optimisation with fitness function (5). The optimisation is carried out every hour. It is equally to a predictive optimisation with a Random Walk forecasting model.	It represents the commonly used none-predictive optimisation strategy.
Hourly Opt. B	Predictive optimisation with fitness function (6). The optimisation is carried out every hour. The forecasted one-hour-ahead cooling load is assumed to be perfectly (100%) accurate.	It reveals the maximum energy reduction potential that can be obtained by the proposed predictive optimisation strategy.
Hourly Opt. C	Predictive optimisation with fitness function (6). The optimisation is carried out every hour. The forecasted one-hour-ahead cooling loads are derived by the Ensemble Approach model (see Table 1), which are of practical achievable accuracy (see Fig. 7).	It is the energy reduction potential that can be practically obtained by the proposed predictive optimisation strategy.

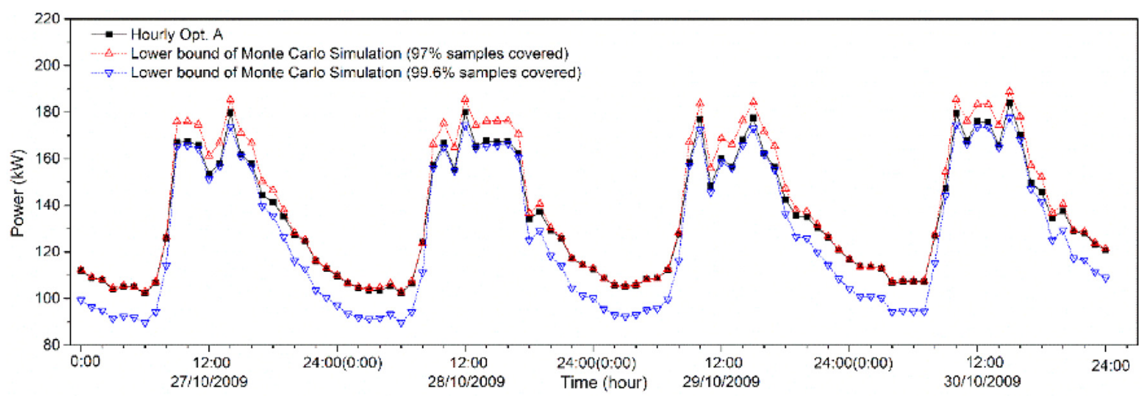


Fig. 8. Verification of GA optimisation by Monte Carlo method.

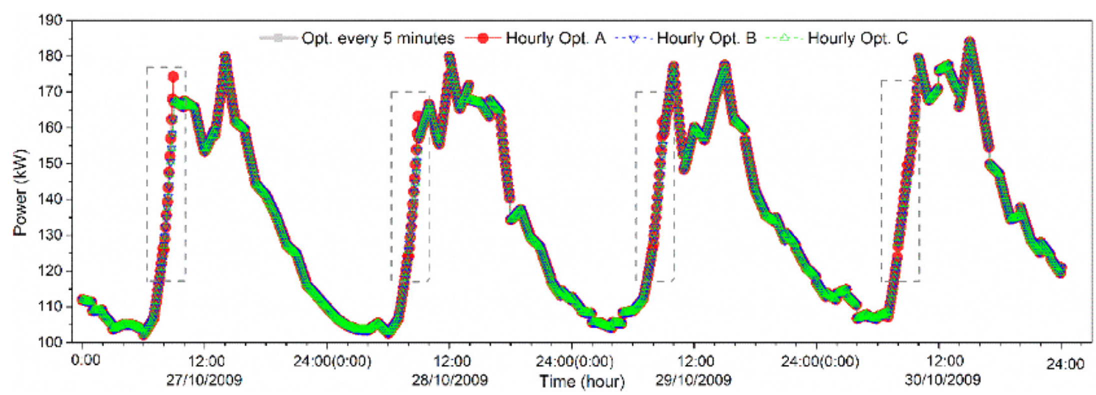


Fig. 9. Profile of system powers calculated by different operation strategies.

5.2.1. *Verifying genetic algorithm by Monte Carlo method*

The verification is carried out based on an hourly cooling load and T_{wb}. With each group of cooling load and T_{wb}, two methods are adopted to determine the minimum system power:

(1) Optimise the system hourly by the none-predictive optimisation (denoted as Hourly Opt. A, as described in Table 3 in Section 5.3.1) with the GA and
(2) Determine the power boundary at each hour using the Monte Carlo method; the controlled variables are randomly initialized 10,000 times in their domain of variation.

In this case study, the controlled variables are T_{chs}, T_{cws} and M_{cw}.

According to the available performance data pool, T_{chs} varies from 5.5 °C to 7.5 °C; M_{cw} varies from 95.5 to 100 Kg/s and T_{cws} varies from (T_{wb} +1) °C to 32 °C. 1 °C is taken as the minimum approach between T_{cws} and T_{wb} [40].

As shown in Fig. 8, the lower bounds of the Monte Carlo simulation are plotted out at each hour, with 97% and 99.6% of the samples covered, respectively. The hourly power optimised by Hourly Opt. A is located between the two lower bounds provided by the Monte Carlo simulations. This indicates that the GA successfully determines the minimum system power.

5.2.2. *Calculating the lower bound of system power*

Instead of Monte Carlo method, the GA has been adopted to find out the lowest system power since it has been verified in Section 5.2.1 to be capable of finding out the lowest system power.

Theoretically, the lower bound of the system power should be a curve on which each point represents the lowest power that the system can be obtained under time-varying cooling load profiles and weather conditions. Given the time-varying cooling load profile and weather conditions, which are introduced in Section 5.1, the lowest power can be calculated through instant

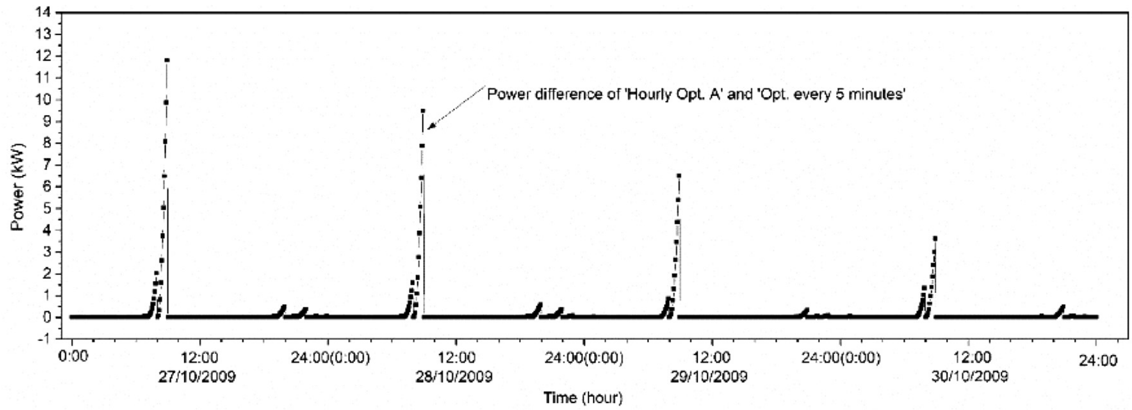
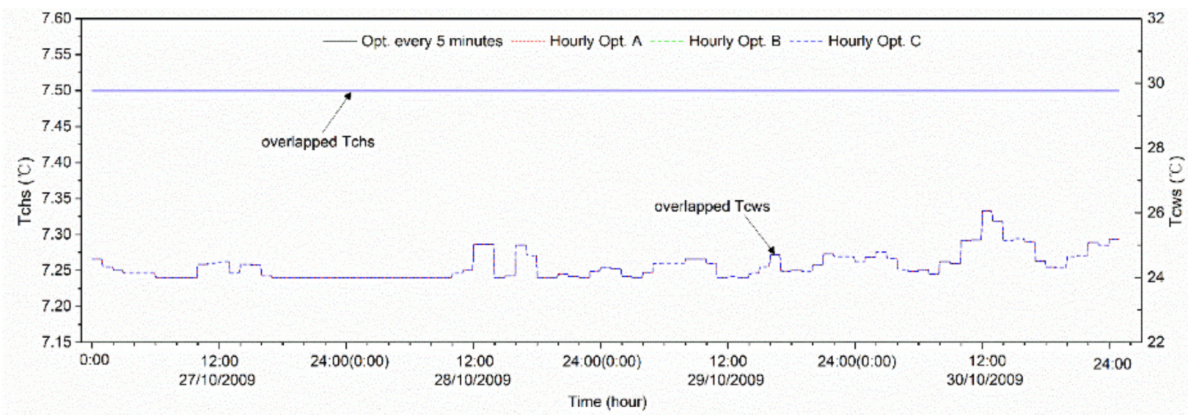
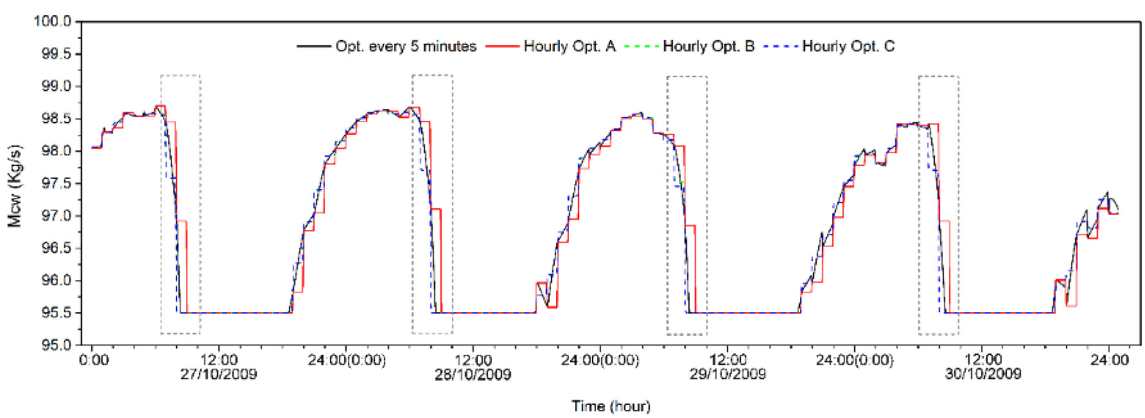


Fig. 10. Profile of power difference between the 'Hourly Opt. A' and 'Opt. every 5 minutes' operation strategies.



(a) Temperature set points of chilled supply water and condenser water



(b) Mass flow rate of condenser water

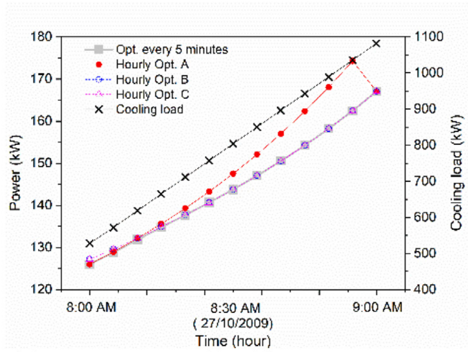
Fig. 11. Profile of controlled variables derived from different operation strategies.

optimisation by GA algorithm with a high frequency, say every 5 min, to closely approaching to the lowest system power profile. Five minutes time interval is chosen since the time-varying building cooling load profile and weather conditions are assumed to remain the same during that period according to engineering experience.

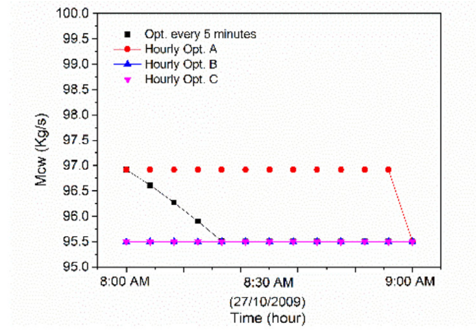
The calculations are carried out with the GA on the none-predictive optimisation fitness function, Eq. (5), the energy model introduced in Section 4.2, the controlled variables of T_{chs} that varies from 5.5 °C to 7.5 °C, M_{cw} that varies from 95.5 to 100 Kg/s and T_{cws} that varies from (T_{wb} +1) °C to 32 °C. The activators – instant cooling loads and weather data of every 5 min, are drawn from interpolations of the known hourly cooling load and weather data introduced in Section 5.1.

All in all, the power profile calculated through a frequent (every 5 min) none-predictive optimisation of the energy model is used to approximate the lower bound of the system power.

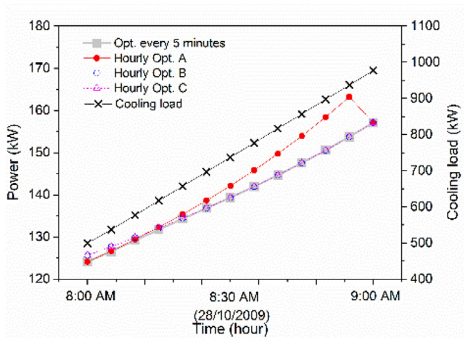
It should be noted that the very frequent optimisation (with 5 min time interval) is only adopted to approximate the lower bound of system power. In the optimisation process of the case study, the time interval of one hour is adopted, which is a reasonable and achievable time interval in the practical optimisation of a chiller plant allowing for the response time of system components [41].



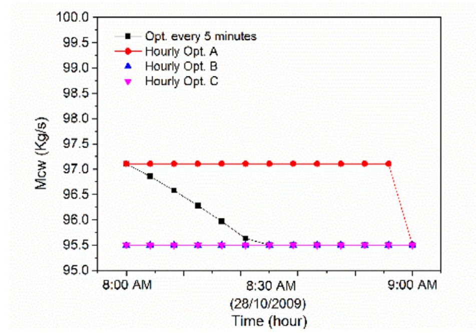
(a) System power and load from 8 AM to 9 AM Oct.27th



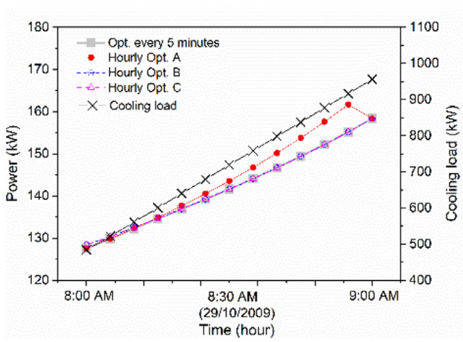
(b) Mass flow rate of condenser water from 8 AM to 9 AM Oct. 27th



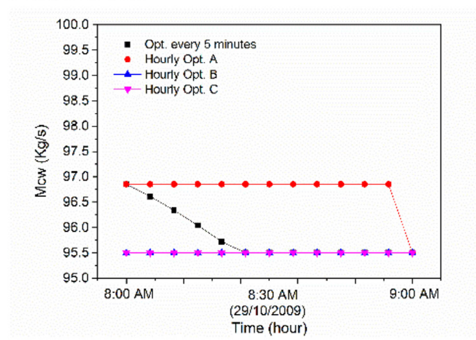
(c) System power and load from 8 AM to 9 AM Oct. 28 th



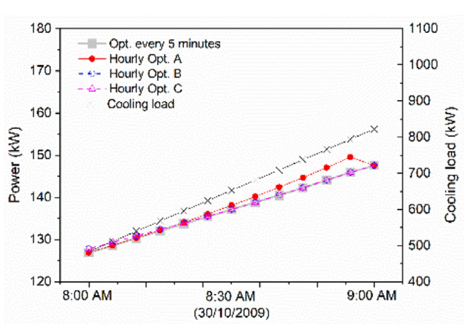
(d) Mass flow rate of condenser water from 8 AM to 9 AM Oct. 28th



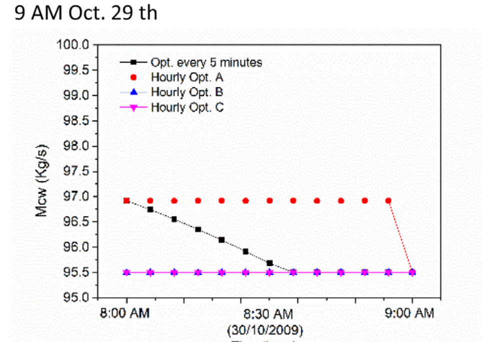
(e) System power and load from 8 AM to 9 AM Oct. 29 th



(f) Mass flow rate of condenser water from 8 AM to 9 AM Oct. 29 th



(g) System power and load from 8 AM to 9 AM Oct. 30 th



(h) Mass flow rate of condenser water from 8 AM to 9 AM Oct. 30 th

Fig. 12. Comparison of system power and corresponding operated condenser mass flow rate.

5.3. Redundant energy consumption identification

This section identifies the problem of redundant energy consumption of a chiller plant system. In Section 5.3.1, different operation strategies are designed to represent none-predictive and predictive control with a typical cooling load forecasting model – the Ensemble Approach model (described in Table 1). It is selected due to its high accuracy ($R^2 = 0.9605$) among the four forecasting models in Table 1. General patterns of the redundant energy consumption behaviour are obtained, and the proposed cooling load

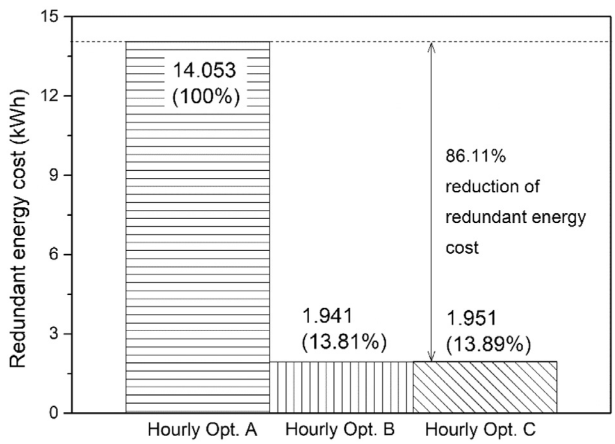


Fig. 13. Comparison of redundant energy consumptions.

forecasting-based predictive optimisation is verified to be capable of reducing redundant energy consumption without shortening the optimisation time interval. Section 5.3.2 analyses the effect of forecasting accuracy on the performance of predictive optimisation.

5.3.1. Redundant energy consumption depiction with a typical cooling load forecasting model

As summarised in Table 3, Hourly Opt. A, the none-predictive optimisation method currently used in overall chiller plant optimisation, is the baseline operation strategy adopted for comparison. Hourly Opt. B and Hourly Opt. C are the proposed predictive optimisation methods that integrate one-hour-ahead dynamic cooling load forecasting. Hourly Opt. B and Hourly Opt. C differ in that the former takes the real cooling load of the next hour as a forecast (assumed ideal forecasting), while the one-hour-ahead load forecasts of the latter are calculated from the available model—the Ensemble Approach model. The results of Hourly Opt. B reveal the maximum energy reduction potential that can be obtained by the proposed predictive optimisation method. The results of Hourly Opt. C reveal the energy reduction potential that can be practically obtained by the proposed optimisation method.

As shown in Fig. 9, system powers of different operation strategies overlap most of the time. However, when the cooling load climbs rapidly, differences in system powers of the different strategies become visible. System powers of the Hourly Opt. A are higher than those of the other operations. The differences are obvious during 8 to 9 o'clock on 27th, 28th, 29th, and 30th October 2009, as shown in Fig. 10. During these periods, the optimum M_{cw}(s) values derived from the various operation strategies are quite different from the other periods, as shown in Fig. 11(b). The optimum T_{chs} and T_{cws} values derived from different operation strategies overlap almost all the time, as shown in Fig. 11(a).

To further compare these operation strategies in detail, the results are truncated with plots of typical hours. As shown in Fig. 12, power values of Hourly Opt. B and Hourly Opt. C are approximately the same as those of the lower bound. Nevertheless, the power of Hourly Opt. A is higher than that of the lower bound. The triangle bound by the solid red line with solid circles and the overlapped line is the redundant energy consumption. Similar patterns emerge during four periods that are included in Fig. 12. Above results indicate the existence of redundant energy consumption when none-predictive control strategy – Hourly Opt. A is adopted. And the redundant energy consumption can be reduced a lot by predictive optimisation control strategies – Hourly Opt. B and Hourly Opt. C. The direct reasons can be found out by observing the variation of the M_{cw} during the optimisation process. It is easy to recognise that during these periods, cooling loads climb rapidly and correspondingly the optimum M_{cw} derived from the ideal optimisation (Opt. every 5 min) varies a lot. Compared with the none-predictive control strategy – Hourly Opt. A, the optimum M_{cw} (s)derived from the predictive optimisation control – Hourly Opt. B and C are more adjacent to those of the ideal optimisation. The optimised M_{cw} of Hourly Opt. A corresponds to only current cooling load, while the optimised M_{cw} of Hourly Opt. B and C corresponds to both current and future cooling loads. Since the optimum M_{cw} derived at the current time step actually controls the system in the coming time interval; the optimum M_{cw} derived by predictive optimisation control which includes the future cooling load into consideration would be more appropriate, especially when the cooling load varies rapidly, say with a steep growth trend.

The redundant energy consumptions are calculated using Eq. (1). As shown in Fig. 13, compared with that of Hourly Opt. A, the redundant energy consumption of Hourly Opt. C decreases as much as 86.11%. The performance of Hourly Opt. C is similar to that of Hourly Opt. B. With a practically achievable dynamic cooling load forecasting accuracy, the proposed optimisation strategy can be adopted to achieve satisfactory performances.

5.3.2. Effect of cooling load forecast accuracy

Accurate short-term cooling load forecasts are fundamental to the success of the proposed predictive control. Fig. 14 plots the forecasting error distribution of the first three models that have been introduced in Table 1, Section 4.1.

From the error scatter plots –Fig. 14(b), (d), (f), forecasted loads of Random Walk model deviate a lot from the real ones; however, most of the forecasted loads of ANN model and Ensemble Approach model are in accordance with the real ones.

From the error distribution plots—Fig. 14(a), (c), (e), 95% forecasting errors of Random Walk model cover the largest range, from −302.6 kW to 301.4 kW, while Ensemble Approach model the least, from −125.7 kW to 155.3 kW. Considering both errors scatter and the error distribution plots, the forecasting errors of Ensemble Approach are small and happen mostly when the real cooling loads are high; the forecasting errors of ANN model are medium, and appear averagely at low load or high load scenarios; the forecasting errors of Random Walk model are huge, and occur at all load scenarios.

With forecasts of the 3 models as well as the assumed ideal forecasts (100% accurate and R^2=1), the redundant energy consumption is calculated, and results are plotted in Fig. 15. The redundant energy consumption decreased a lot with the improvement of forecasting accuracy. Taking the redundant energy consumption of Random Walk model (forecasting $R^2 = 0.8249$) as 100%, nearly 75% of it can be reduced when the forecasting R^2 increases to 0.8989; about 85% when the forecasting R^2 increases to 0.9605; 87% when the forecasting R^2 increased to 1.

5.4. Discussion

According to the results presented in Section 5.2, redundant energy consumptions exist in the none-predictive optimisation (Hourly Opt. A), especially when building cooling load climbs rapidly. In the case studied in this paper, the deviation from optimum M_{cw} of ideal optimisation (Opt. every 5 min) results in the redundant energy consumptions. M_{cw} matters more than T_{chs} and T_{cws} might because an optimum M_{cw} is more sensitive than T_{chs} to the variation in building cooling loads, while the optimum T_{cws} is more related to T_{wb}.

Although redundant energy consumptions exist during the none-predictive optimisation (Hourly Opt. A), the absolute value is small in this case: about 14 kWh of electric power for the total 4 days' operation. It is highly possible because the M_{cw}, which is sensitive to the variation of building cooling loads, varies on a

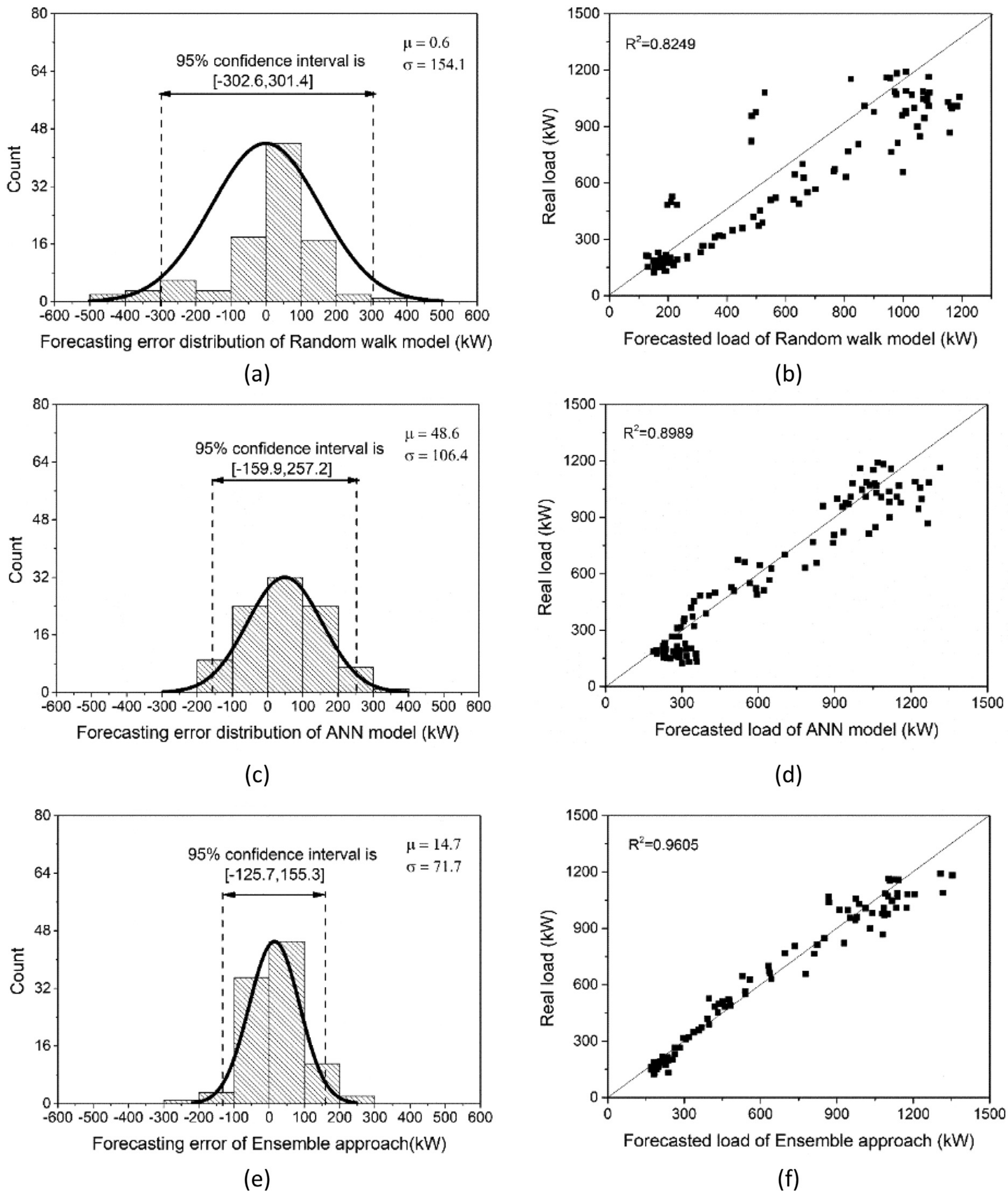


Fig. 14. Forecasting error of different models.

small scale, from 95.5 to 100 Kg/s, which is equal to that the M_{cw} is varying from 95.5% to 100% of its rated mass flow rate. This is a very small range compared with the ranges of 40–100% [42] or 50–100% [38] of its rated mass flow rate, which are reasonable ranges adopted in practical operations. However, due to the limitations of the available chiller plant system parameters, a chiller plant with M_{cw} values varying over a large range is not included in this paper. As the deviation of the optimum M_{cw} is the main reason for the redundant energy consumptions, it can be reasonably inferred that the redundant energy consumptions would be higher if the M_{cw} varies in a larger range.

Comparing redundant energy consumptions of the none-predictive optimisation (Hourly Opt. A) with those of the cooling load forecasting-based predictive optimisation (Hourly Opt. B), the percentage of reduction is huge. The none-predictive optimisation assumes that the cooling load remains constant in the coming time interval, while the cooling load forecasting-based predictive optimisation compromises the effects of sudden changes in the building cooling load.

For a system, in which M_{cw} can vary over a large range and the cooling load varies frequently and extremely, the proposed cooling load forecasting-based predictive optimisation can improve the system energy efficiency a lot without shortening the operation time interval.

The accuracy of forecasting model plays a key role in the performance of the predictive optimisation, the more accurate the

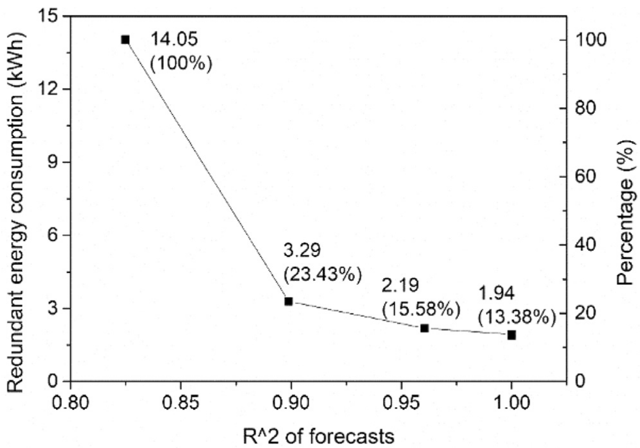


Fig. 15. Effect of cooling load forecast accuracy on redundant energy consumption.

forecasts are, the more redundant energy consumption can be reduced.

The engineering of building models and control designs in legacy systems has been the main challenge for predictive controller implementation [43]. Without shortening the operation time interval, the proposed cooling load forecasting based predictive optimisation can be applied in practice to legacy chiller plant systems in combination with existing local controllers with necessary information collected by sensors. With an operation time interval of one hour, it is totally practical to adjust the system manually with the optimised variables derived by a computer. Energy can be saved for systems that work for years.

6. Conclusions

This paper proposes a predictive optimisation framework for chiller plants without thermal storage systems. Advanced cooling load forecasting techniques are integrated into the instant optimisation algorithm to reduce the redundant energy consumptions, which exist when none-predictive optimisation is adopted in chiller plant optimisation with regular time intervals. The phenomenon of redundant energy consumption is more severe when the building cooling load climbs rapidly. Adopting cooling load forecasting-based predictive optimisation can reduce more than 80% of the redundant energy consumptions without shortening the optimisation time interval.

The amount of redundant energy reductions is related to the accuracy of cooling load forecasting. The predictive optimisation with a high forecasting accuracy performs similarly to that of ideal forecasting accuracy. The optimum condenser mass flow rate plays an important role in reducing redundant energy consumption given the variation in building cooling loads. The proposed cooling load forecasting-based method makes more sense for buildings with cooling load profiles that vary suddenly and extremely, and for chiller plant systems in which condenser mass flow rates can vary over a large range.

Compared with a control strategy without optimisation, none-predictive optimisation of the chiller plant system can greatly improve system energy efficiency, while cooling load forecasting-based predictive optimisation can improve it even more. It is a step forward from none-predictive optimisation to predictive optimisation by integrating advanced cooling load forecasting techniques into real-time optimisation. For chiller plant systems that work for years, energy can be saved by adopting cooling load forecasting-based optimisation.

In this paper, the application of the proposed predictive optimisation control framework is currently limited to a basic chiller plant system that excludes chilled water pumps. Extending the application of the proposed predictive optimisation control framework in the more complicated cooling systems with primary and secondary chilled water pumps would be important future work to the authors.

Declaration of Competing Interest

None competing interest exists.

Acknowledgments

This work described in this paper was fully supported by a grant from the Research Grant Council of the Hong Kong Special Administrative Region, China [Project No. CityU 11209518]. The U.S. authors recognize Berkeley Lab's support from DOE – The United States under Contract No. DE-AC02-05CH11231 and supports from the Energy Foundation and Shenzhen Institute of Building Research.

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