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Model Predictive Control of Active Thermal Storage considering Indoor Environment for Building Proactive Demand Response in Smart Grids

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Abstract: Demand response (DR) can effectively manage electricity use to improve the efficiency and reliability of power grids. Shutting down part of operating chillers directly in central air-conditioning systems can meet the urgent power reduction needs of grids. But during the special events of fast DR, how to optimally control the active cold storage considering the indoor environment of buildings and the needs of grids at the same time is rarely addressed. A model predictive control (MPC) approach, with the features of shrunk prediction horizon, self-correction and simple parameter determination of embedded models, is therefore developed to optimize the operation of a central air-conditioning system integrated with cold storage during fast DR events. The chiller power demand and cooling discharging rate of the storage are optimized to maximize the building power reduction and meanwhile to ensure the acceptable indoor environment. Case studies are conducted to test and validate the proposed method. Results show that the proposed MPC approach can effectively handle the optimal controls of cold storage during DR events for required power reduction and acceptable indoor environment. Due to the feedback mechanism of MPC, the control performance is not negatively influenced by the simplified parameter identification of models, which will be convenient for real applications. While achieving the expected building power reduction for the power grid, the indoor environment is effectively improved in the DR events using the MPC and the maximum indoor temperature is reduced significantly without extra energy consumed.

Keywords: model predictive control (MPC); linear state-space model; air-conditioning system; building demand management; PCM tank; indoor thermal comfort.

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1. Introduction

The rapid growth of power demand and the greater integration of renewable energy generations, which depend heavily on weather conditions, impose enormous stress on the balance of power grids [1]. Any power imbalance will cause severe consequences in the reliability and quality of power supply (e.g., voltage fluctuations and even power outrages). Facing the challenges for power balance, smart grid is considered as a promising solution to incorporate advanced technologies to offer better flexibility, reliability and security in grid operation [2]. The efforts conducted from the demand side to satisfy the grid requests (e.g., dynamic price and reliability information) is known as demand response (DR) [3]. DR programs cannot only benefit the operation of power grids but also offer economic benefits to end-users. Among the demand-side users of power grids, buildings consuming over 73.6% of overall electricity in the United States [4] and over 90% in Hong Kong [5] play an important role in DR programs. Moreover, with the help of advanced technologies such as building automation systems and smart meters, DR control strategies could be implemented conveniently in buildings to realize a bidirectional operation mode between buildings and power grids [6, 7].

When pricing changes or grid requests are informed day ahead or hours ahead, demand shifting by rescheduling the system operation is a preferable alternative for building demand response. Demand shifting is the process of shifting on-peak loads to off-peak hours so as to take advantage of electricity rate difference in different periods. Since air-conditioning systems in commercial buildings are the largest energy consumer [8], particularly in cooling dominant regions, the demand shifting control of air-conditioning systems is preferably adopted for optimizing the building power demand. Building thermal mass (i.e., passive storage) and thermal storage system (i.e., active storage) are two typical candidates to be used for building demand shifting during DR events and many control strategies for optimizing their cooling charging/discharging processes have been developed as different requirements considered for buildings or power grids [9-13]. Global indoor temperature adjustment plus precooling and cooling system adjustment are commonly adopted for the demand shifting and management in buildings. Xu and Haves [14] developed a simple demand-limiting strategy by resetting the indoor air temperature to utilize the building thermal mass for peak demand reduction in an office building in California. Yin et al. [15] proposed a control strategy “pre-cooling with exponential temperature set-up” to optimize the cooling charging/discharging processes of building thermal mass for DR control.

By contrast, when facing urgent requests and incentives from the smart girds, an immediate power reduction cannot be achieved within a very short time interval (i.e., minutes) by rescheduling the system operation (e.g., resetting the indoor air temperature), resulting from the inherent and significant delay of charging/discharging control processes [16, 17]. In such a case, shutting down part of operating chillers directly in a central air-conditioning system is considered as an effective proactive demand response strategy to achieve immediate power reduction within a very short time. Due to the effectiveness of this fast demand response strategy for the urgent requests of smart grids, many studies have been conducted. The authors of this paper [18] pointed out that imbalanced chilled water distribution in a central air-conditioning system occurred after simply shutting down some of operating chillers. A cooling distributor based on adaptive utility function was developed to solve this problem. They [19] also proposed a control concept (i.e., supply-based feedback control strategy) for such fast DR events, instead of conventional control strategy commonly used for central air-conditioning systems, to effectively avoid the serious operation problems (e.g., imbalanced cooling distribution) and ensure the expected immediate power reduction after shutting down part of operating chillers.

Compared with building thermal mass (i.e., passive storage), thermal storage system (i.e., active storage) has a larger capacity and better controllability in peak demand reduction responding to the requests of smart grids while has a less negative impact on building indoor environment during DR events. It reduces building peak demand contributed by the cooling system through the production and storage of cold energy during off-peak periods and the usage of the stored energy for cooling during peak periods. The cold energy storage in the central air-conditioning system is usually stored in the form of ice, chilled water, phase change materials (PCMs) or eutectic solution [20, 21]. Compared with the studies conducted for the optimal control of cold thermal storage during DR events (i.e., day ahead or hours ahead), the studies for the fast DR events just started in recent years. Xue et al. [22] developed a building thermal model to predict the discharged cooling from the building thermal mass after shutting down part of operating chillers in the fast DR event. Cui et al. [23] developed a design method to optimize the capacity of cold storage during a fast DR event by a quantitative analysis on its life-cycle cost-saving potential concerning the operational cost, initial investment and space cost. Cui et al. [24] also proposed a control strategy to optimize the cooling discharging rate of cold storage during a DR event to achieve an immediately stepped power demand reduction after shutting down part of operating chillers.

In addition, although the primary objective of DR events is to satisfy the request of smart grids (i.e., power reduction), the indoor thermal comfort may be potentially sacrificed to unacceptable levels due to the power limiting control of central air-conditioning systems and hence would be taken into consideration. Zhang et al. [25] investigated 56 subjects' thermal comfort during DR events and pointed out that subjects' thermal comfort zone during DR events was wider than that predicted by Fanger's PMV/PPD model. Tang et al. [26] developed optimal and near-optimal control strategies to achieve a pre-determined power demand reduction and meanwhile ensure the indoor environment within the acceptable range in the DR events after shutting down part of operating chillers. In fact, during fast DR events, using active cold storage with proper control will be effective to increase the immediate power reduction for the power grid and meanwhile ensure the acceptable indoor environment. However, no study can be found in the literature in addressing the online optimal control issue for central air-conditioning systems integrated with active cold storages during fast DR events, considering the requirements at both supply and demand sides, i.e., power demand reduction (for smart grids) and indoor environment control (for buildings), simultaneously.

Model predictive control (MPC) is a simple yet effective approach for constrained control, which is able to predict the future behaviors of the controlled systems and to determine proper control actions by optimizing an objective function depending on the predictions over a given horizon subject to some constraints [27]. It uses a receding horizon (i.e., at each iteration, only the first step of the control strategy is implemented and then the control signal is calculated again) to enhance its robustness and control accuracy. MPC is now popularly adopted in the areas of built environment control and building demand management considering its obvious advantages [28, 29]. Due to the sudden changes caused by shutting down part of operating chillers at the start of the DR event, the control stability will be challenged and the control states in the air-conditioning system will experience a rather serious fluctuation before reaching a new control balance. Considering the advantage of MPC on the control robustness, this method would be preferable to be used for the optimal control issues of central air-conditioning systems during such fast DR events in the smart grids. Hence, it is necessary to use the MPC approach to address the optimal control problems of building fast DR.

In this study, the MPC approach is therefore adopted to optimize the control of a central air-conditioning system with active cold storage considering the expected building power reduction and the acceptable indoor environment during a fast DR event. The chiller power demand and the cooling discharging rate of cold storage are optimized online using the proposed MPC approach. The main contributions of this work include: (1) The online optimal control issue for the air-conditioning system with active cold storage during the fast DR event is effectively addressed, considering the requirements of power grid and building simultaneously. The power demand reduction is maximized as the expected profile pattern and meanwhile the indoor air temperature is maintained within a pre-determined acceptable range; (2) A linear state-space model together with a simple parameter identification method is developed for online prediction and optimization during the fast DR event, allowing the proposed control strategy computationally efficient; (3) The first-order exponential average method is used to handle the prediction errors caused by the model simplification and inaccuracy. Moreover, the MPC with shrunk prediction horizon, instead of a fixed width commonly used, is proposed to improve the control performance considering the characteristics of optimal control issues for fast DR events.

2. Schematic of proactive building demand response strategy for central air-conditioning systems with active cold storages during fast DR events

Generally, the total power demand in a commercial building can be classified into two parts: sheddable power demand and controllable power demand. The sheddable power demand, such as lighting, electrical equipment and lift, can be conveniently obtained based on the operation schedule. While the controllable power demand, such as air-conditioning systems, can be altered by power demand controls. The chillers always account for the largest power demand in a central air-conditioning system and therefore, in this study, the power demand reduction contributed by the chillers is concerned to meet the urgent requests of smart grids.

Once an urgent DR request is received from smart grids (e.g., a sudden power reduction request), a fast demand response strategy by shutting down part of operating chillers directly in a central air-conditioning system is activated. During the fast DR event, the schematic of proposed proactive demand response control strategy for chiller downstream PCM storage system is presented in Fig.1. Under the insufficient cooling supply caused by the limited number of operating chillers, the proposed control strategy will optimize the system operation to provide the expected power demand reduction for the smart grid and also to ensure the indoor environment. Three schemes are mainly involved in this proposed control strategy (i.e., power demand optimizer, storage load regulator and chiller load regulator) in order to optimize and control the cooling discharging rate of the cold storage and the chiller power demand. The focus of this study is to develop the scheme of power demand optimizer using the MPC approach. The studies on the schemes of storage load regulator and chiller load regular as well as the cooling distributor can be found in ref. [16, 19]. The detailed function of each scheme in the schematic is illustrated as follows:

Power demand optimizer: model predictive control is used in this scheme as a supervisory control to optimize the set-points of chiller power demand and cooling discharging rate of cold storage during the fast DR event.

Storage load regulator: this scheme controls the actual cooling discharging rate of cold storage as the set-point optimized by the scheme of power demand optimizer. Compared the actual cooling discharging rate of the storage with its optimized set-point, the chilled water flow through the storage is adjusted based on the PID algorithm for the opening control of the water valve.

Chiller load regulator: this scheme controls the actual chiller power demand as the set-point optimized by the scheme of power demand optimizer. Compared the actual chiller power demand with its set-point, the chilled water flow circulated in the secondary loop of the central air-conditioning system is adjusted based on the PID algorithm followed by an amplification factor (i.e., K). With adjusted total cooling supply represented by the chilled water flow in the secondary loop, the cooling distributor using an adaptive utility function is responsible to properly allocate the cooling supply among individual AHUs [18].

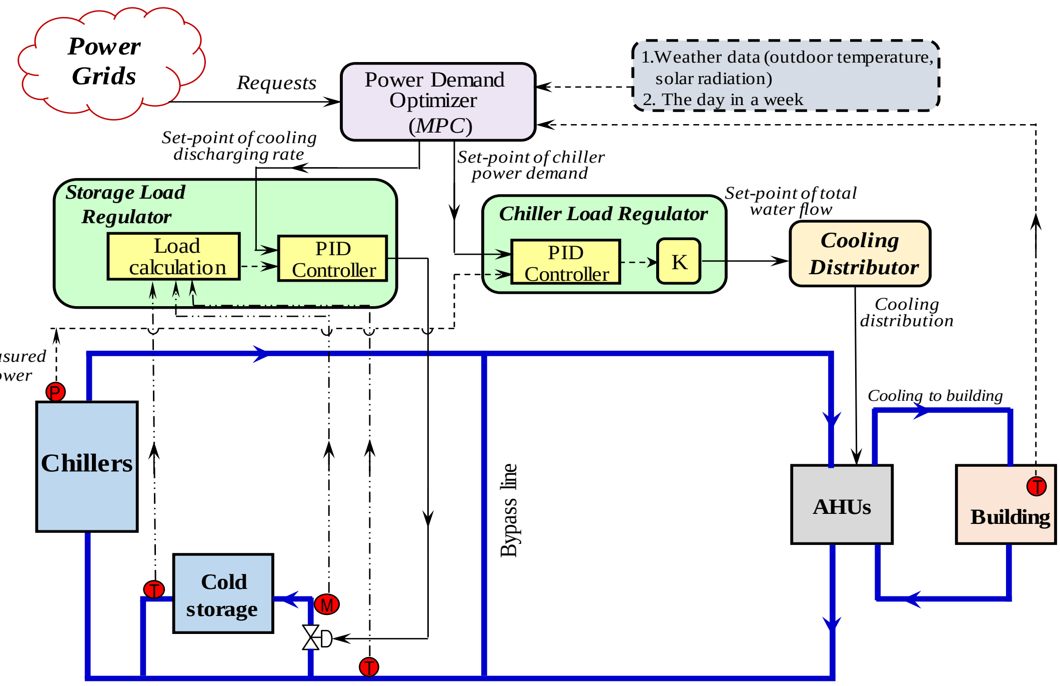

Fig.1 Schematic of proactive building demand response strategy for the central air-conditioning system with active cold storage during fast DR events

3. Power demand optimizer scheme using model predictive control

3.1 Mechanism of model predictive control

The basic mechanism of model predictive control (MPC) is to use a system model to predict the future evolution of the system performance using the predicted operating conditions over the prediction horizon. At each sampling interval, beginning at the current state, an optimization problem is formulated and solved over a finite horizon to achieve the expected system operation. The optimization result is a trajectory of future control signals into a system that satisfies the system dynamics and the corresponding constraints. But only the first control signal is adopted and implemented by the system at the next sampling time, whereas the rest of the sequence is discarded. Such a process is repeated at the following time step based on the updated current state over the next prediction horizon [30].

Fig.2 presents the schematic of model predictive control approach for the controls of active cold storage and chiller power demand during the fast DR events. In the structure of MPC, the dynamic model is responsible to achieve the online prediction of building evolutions (y') based on the required measurements and information (i.e., weather data and building use). According to the online prediction, the optimized control signals for the system (u) are determined by solving an optimization problem, subject to the objective function and constraints on the states. The optimized control signals in this study are the set-point of cooling discharging rate of cold storage and the set-point of chiller power demand. Considering the model prediction errors caused by the uncertainties and disturbances in the real system, the results predicted by the dynamic model is corrected (by 'e') at each sampling time based on the real measurements and predicted values.

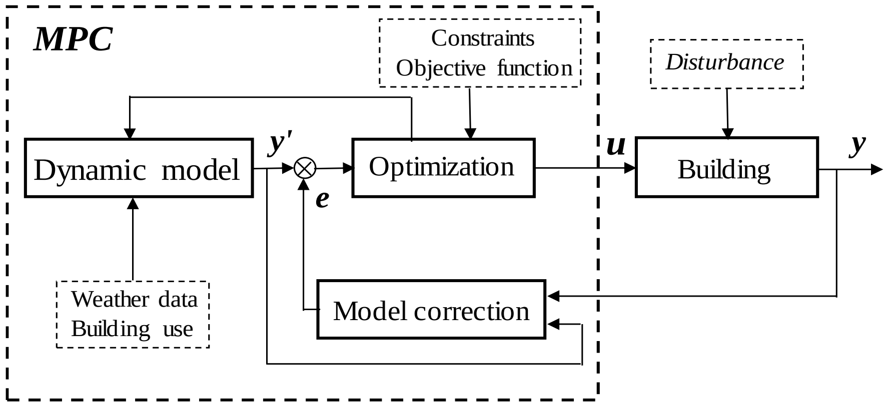

Fig.2 Schematic of model predictive control used for fast DR events

3.2 Description of models used in model predictive control

In order to establish the MPC controller, two models are needed, i.e., chiller power demand model (section 3.2.1) and dynamic building thermal model (3.2.2).

3.2.1 Chiller power demand model

The power demand of chillers ($P^k_{chiller}$) in a central air-conditioning system is determined by its cooling supply ($Q^k_{chiller}$) and *COP* (coefficient of performance), as shown in Eq.(1). During fast DR events, the chillers cooperate with the active cold storage to provide the cooling for the building. Thus, the cooling supply of chillers at each time step is determined by the building cooling demand (Q^k_{dem}) and the cooling discharged by the active cold storage ($Q^k_{storage}$), as shown in Eq.(2). Where subscript *k* represents the time step.

$$P^k_{chiller} = Q^k_{chiller}/cop^k \tag{1}$$

$$Q^k_{chiller} = Q^k_{dem} - Q^k_{storage} \tag{2}$$

3.2.2 Dynamic building thermal model

To predict the building response (i.e., indoor air temperature) under a given cooling supply (including two parts: cooling provided by the chillers and the active cold storage), a dynamic building thermal model is developed. The grey-box building thermal model used in this study integrates physical principles of thermal responses and data-driven optimization technique. Considering a complicated model would seriously increase the computing time particularly for the online control, the adopted building thermal model would be simple and generally grasp the key characteristics. The components in this model and the heat fluxes exchanged between them are shown in Fig.3. The model contains four parts, i.e., outdoor environment, building envelop, indoor air and internal thermal mass.

Two types of heat transfer on the external wall, including convective heat transfer with the outdoor air and radiative heat transfer with the sky, will occur. As for the solar radiation occurred on the window, a portion through the window is directly transmitted into the indoor air while the rest is absorbed by internal thermal mass (e.g., floor, ceiling. furniture). The building internal thermal mass, which is represented by 2R2C (consists of two resistances and two capacitances) [31], absorbs radiant heat from the window and that from the lighting, occupants and equipment etc., and then releases (or absorbs) the heat gradually to indoor air space. The energy balances for the external and internal wall surfaces, the indoor air and the internal thermal mass are presented as the following equations:

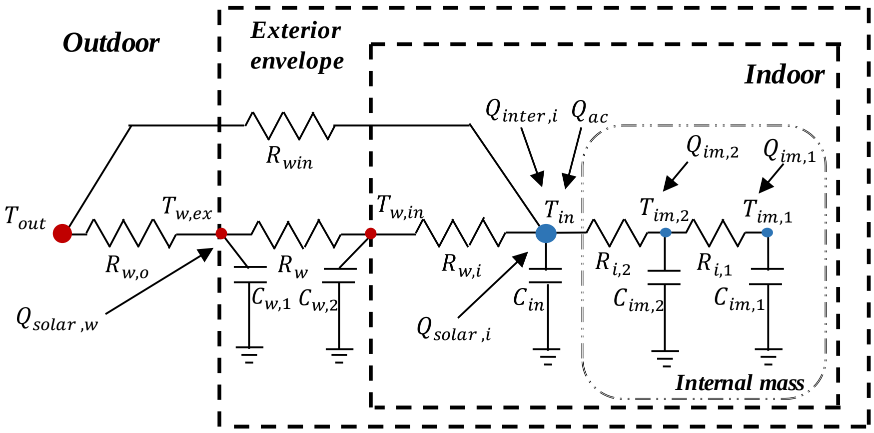

Fig.3 Schematic of RC grey-box building thermal model

$$C_{w,1}\frac{dT_{w,ex}}{dt}=\frac{T_{out}-T_{w,ex}}{R_{w,o}}-\frac{T_{w,ex}-T_{w,in}}{R_w}+Q_{solar,w} \tag{3}$$

$$C_{w,2}\frac{dT_{w,in}}{dt}=\frac{T_{w,ex}-T_{w,in}}{R_w}-\frac{T_{w,in}-T_{in}}{R_{w,i}} \tag{4}$$

$$C_{im,1}\frac{dT_{im,1}}{dt}=\frac{T_{im,2}-T_{im,1}}{R_{i,1}}+Q_{im,1} \tag{5}$$

$$C_{im,2}\frac{dT_{im,2}}{dt}=\frac{T_{im,1}-T_{im,2}}{R_{i,1}}-\frac{T_{im,2}-T_{in}}{R_{i,2}}+Q_{im,2} \tag{6}$$

$$C_{in}\frac{dT_{in}}{dt}=\frac{T_{im,2}-T_{in}}{R_{i,2}}+\frac{T_{w,in}-T_{in}}{R_{w,i}}+\frac{T_{out}-T_{in}}{R_{win}}+Q_{inter,i}-Q_{ac}+Q_{solar,i} \tag{7}$$

where, R and C represent the heat resistance and capacitance, which are free parameters and can be identified based on historical data using a data-driven method (i.e., genetic algorithm used in this study) [22]. T is the temperature. Subscripts i, out, w, in, ex, win and im denote indoor air, outdoor air, exterior wall, internal wall surface, external wall surface, window and internal mass, respectively. $Q_{solar,w}$ and $Q_{solar,i}$ are solar heat gains absorbed by external wall surface and indoor air. $Q_{inter,i}$ is internal heat gain. $Q_{im,1}$ *and* $Q_{im,2}$ are the radiation heat absorbed by nodes $C_{im,1}$ *and* $C_{im,2}$. Q_{ac} is the total cooling supply by chillers and active cold storage (removed heat, i.e., Q_{dem}).

The corresponding parameters in the building thermal model are determined based on Eqs.(8-12) [32]. Where, I_{solar} denotes global solar radiation. β, b and μ denote the radiative/convective split for heat gain, which are pre-determined and set as 0.5. α denotes the absorptance of surface of solar radiation and set as 0.8 in this study. *SHGC* denotes the solar heat gain coefficient, and set as 0.7 in this study.

$$Q_{solar,w}=aI_{solar} \tag{8}$$

$$Q_{solar,i}=\beta_i\cdot SHGC\cdot I_{solar} \tag{9}$$

$$Q_{im,1}=Q_{im,2}=b\cdot(Q_{solar,im}+Q_{inter,im}) \tag{10}$$

$$Q_{solar,im}=\beta_{im}\cdot SHGC\cdot I_{solar} \tag{11}$$

$$Q_{inter,im}=\mu\cdot Q_{inter} \tag{12}$$

It is worthy of note that the determination for corresponding parameters in the above two models (i.e., chiller power demand model (section 3.2.1) and dynamic building thermal model (3.2.2)) is simplified as follows: the outdoor temperature, solar radiation and internal gain can use the same values as those just before the DR event, while the coefficients including the radiative/convective split, absorptance of surface of solar radiation, solar heat gain coefficient and *cop* of chillers are set as constants. Such simplifications for the parameter identification of models are based on the special situation/characteristic of fast DR events. Normally, the dynamic building thermal model and chiller power demand model are used to make one or more day(s) ahead prediction and hence the parameters of the models will be changed over the prediction time. But the fast DR events usually last for a short duration within about one or two hours. The parameters of the models are likely to be without obvious changes in such a short time period and therefore are set as constants. Meanwhile, the MPC approach proposed in this study can be self-corrected at every time step to modify the prediction results so as to improve the control accuracy. Overall, with ensuring the prediction accuracy, such simplifications can be beneficial to make the online optimal control problem transforming into a linear problem (i.e., the establishment of the linear state-space model), which is convex and hence solved with an efficient computational speed in real applications compared with non-linear problems.

3.3 Establishment of state-space model for online MPC

3.3.1 Model Linearization

The system dynamic model for MPC is usually represented in the form of an impulse response model, a step response model, a transfer function model, or a state-space model. Considering the control problem of this study is multiple input multiple output (MIMO), the state-space model is selected to describe the system dynamics. Moreover, the state-space model can formulate a convex optimization problem that is easy to be solved. Therefore, the linearization of the model for MPC is conducted and then rewritten as a continuous-time state-space model to explicitly express the relationship between the inputs and outputs of the control system. The model linearization is to convert the dynamic building thermal model (i.e., Eqs.(3-7)) into a continuous-time state-space model, as shown in Eq.(13).

$$dx/dt = a \cdot x + b \cdot u + e \cdot d \tag{13}$$

where, the system state vector x = $[T_{w,ex} \;\; T_{w,in} \;\; T_{im,1} \;\; T_{im,2} \;\; T_{in}]^T$. Note that not all the system state variables are measureable in the real application. Only the indoor air temperature can be measured directly for the close-loop online control, while the other unmeasurable variables are optimally estimated by the Kalman filter [33, 34]. The control input vector $u = [Q_{chiller} \quad Q_{storage}]^T$. The disturbance vector $d = [\ I_{solar} \quad T_{out} \quad Q_{inter}\ ]^T$. The system matrix $a =$

$$\begin{pmatrix} \frac{-1}{C_{w,1}R_{w,o}}+\frac{-1}{C_{w,1}R_w} & \frac{1}{C_{w,1}R_w} & 0 & 0 & 0 \\ \frac{1}{C_{w,2}R_w} & \frac{-1}{C_{w,2}R_w}+\frac{-1}{C_{w,2}R_{w,i}} & 0 & 0 & \frac{1}{C_{w,2}R_{w,i}} \\ 0 & 0 & \frac{-1}{C_{im,1}R_{i,1}} & \frac{1}{C_{im,1}R_{i,1}} & 0 \\ 0 & 0 & \frac{1}{C_{im,2}R_{i,1}} & \frac{-1}{C_{im,2}R_{i,1}}+\frac{-1}{C_{im,2}R_{i,2}} & \frac{1}{C_{im,2}R_{i,2}} \\ 0 & \frac{1}{C_{in}R_{w,i}} & 0 & \frac{1}{C_{in}R_{i,2}} & \frac{-1}{C_{in}R_{i,2}}+\frac{-1}{C_{in}R_{w,i}}+\frac{-1}{C_{in}R_{win}} \end{pmatrix}_{5\times5}$$

. The input matrix $b =$

$$\begin{pmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ \frac{-1}{C_{in}} & \frac{-1}{C_{in}} \end{pmatrix}_{5\times2}$$

. The disturbance matrix $e =$

$$\begin{pmatrix} \frac{a}{C_{w,1}} & \frac{1}{C_{w,1}R_{w,o}} & 0 \\ 0 & 0 & 0 \\ \frac{b\beta_{im}SHGC}{C_{im,1}} & 0 & \frac{b\mu}{C_{im,1}} \\ \frac{b\beta_{im}SHGC}{C_{im,2}} & 0 & \frac{b\mu}{C_{im,2}} \\ \frac{\beta_i SHGC}{C_{in}} & \frac{1}{C_{in}R_{win}} & \frac{1-\mu}{C_{in}} \end{pmatrix}_{5\times3}$$

.

3.3.2 Model discretization

Model discretization is to convert the above continuous-time state-space building thermal model into the discrete-time state-space model based on the sampling time, prior to being applied for the online MPC controller. Combining the continuous-time state-space building thermal model shown in Eq.(13) with the chiller power demand model, the discrete-time state-space model can be given as the form of Eqs.(14-15), which is used for the online MPC optimal control strategy to predict the system evolutions.

$$X_{k+1} = A_d \cdot X_k + B_d \cdot u_k + E_d \cdot d_k \tag{14}$$

$$y_k = C_d \cdot X_k + \widehat{e_k} \tag{15}$$

where, the system state vector $X = [x^T \quad P_{chiller}]^T$. The system matrix $A_d = \begin{bmatrix} a_d & 0_{5\times1} \\ 0_{1\times5} & 0 \end{bmatrix}$. The input matrix $B_d = \begin{bmatrix} b_d \\ b' \end{bmatrix}$, where $b' = [cop\ 0]$. The disturbance matrix $E_d = \begin{bmatrix} e_d \\ 0_{1\times3} \end{bmatrix}$. a_d, b_d, c_d, and e_d are the corresponding matrixes of the discrete-time state-space building thermal model. y_k is the vector of prediction result including indoor air temperature and chiller power demand, i.e., $[T_{in}\ P_{chiller}]^T$. $\widehat{e_k}$ is the self-correction factor to modify the prediction result at every sampling time. A_d, B_d, C_d, and E_d are the corresponding state-space matrixes of the discrete-time state-space model that includes the building thermal model and chiller power demand model.

3.3.3 Self-correction of models

Exponential smoothing method is used to modify the prediction result in order to deal with the prediction error of the discrete-time state-space model. The first-order exponential smoothing method is selected in this study to modify the prediction results. The self-correction factor at *(k+1)th* time step (i.e., $\widehat{e_{k+1}}$ in Eq.(15)) is determined based on the prediction error at current time step (e_{k+1}) and the self-correction factor at last time step ($\widehat{e_k}$), as shown in Eq.(16). Where, θ is the weighting factor ($0 < \theta < 1$). e_k is the difference between the measured value and the predicted value at *kth* time step. $\widehat{e_k}$ is the self-correction factor at *kth* time step. The initial value of $\widehat{e_k}$ $(k = 1)$ is set to be zero at the start of the DR event.

$$\widehat{e_{k+1}} = \theta * e_{k+1} + (1 - \theta) * \widehat{e_k} \tag{16}$$

3.4 Formulation of the control problem

The formulation of MPC always includes four parts: an objective function, constraints, system dynamics, and current states. The system dynamics and current states are illustrated in section 3.3. The objective of the MPC controller is to achieve a maximum and stable power reduction during a fast DR event. There are many studies conducted for chiller power demand baseline prediction and this is not the focus of this study. Hence, the baseline of chiller power demand in this study is simplified and assumed to be the same as that just before the DR event. At each time step, the objective of MPC controller is therefore to achieve a stable and minimum chiller power demand over the prediction horizon N_p, as presented in the first and second parts of Eq.(17) respectively. *Note that* the prediction horizon of traditional MPC is usually a receding window with the fixed width. But, considering the fast DR event is a certain time period with a relatively short duration, the prediction horizon at each sampling time (N_p) in this study is shrunk over the entire DR event, as shown in Eq.(19). At each sampling time step, the prediction horizon (N_p) refers to the time duration from the next time step (i.e., $k+1$) to the end of the DR event. This can effectively grasp the changes of states to be controlled during the rest of DR period. Therefore, the vector of prediction result at *kth* time step is $\boldsymbol{y_k}= \begin{bmatrix} \boldsymbol{T_{in}^k} \\ \boldsymbol{P_{chiller}^k} \end{bmatrix} = \begin{bmatrix} T_{in}(k+1|k) & \cdots & T_{in}(k+N_p|k) \\ P_{chiller}(k+1|k) & \ldots & P_{chiller}(k+N_p|k) \end{bmatrix}$. Here, the argument $(k+N_p)|k$ indicates the prediction of the variables at $(k+N_p)th$ time step based on the measurements up to *kth* time step. Where, N is the maximum prediction horizon (i.e., that at the start of the DR event), which is determined by the time step (*step*) and time duration (D) of the fast DR event, as shown in Eq.(20). $\overline{P_{chiller}}$ is the average value of optimized chiller power demand over the prediction horizon (N_p) at *kth* time step. λ is a pre-determined weighting factor.

$$min \qquad J = \frac{1}{N_p}\left[(\boldsymbol{P_{chiller}^k} - \overline{P_{chiller}}) \cdot (\boldsymbol{P_{chiller}^k} - \overline{P_{chiller}})^T + \lambda \cdot \boldsymbol{P_{chiller}^k} \cdot \boldsymbol{P_{chiller}^k}^T\right] \tag{17}$$

$$\overline{P_{chiller}} = \frac{1}{N_p}\sum_{t=k+1}^{k+N_p} P_{chiller}(t|k) \tag{18}$$

$$N_p = N - k + 1 \tag{19}$$

$$N = D/step \tag{20}$$

The constraints for the MPC controller are shown in Eqs.(21-23), including the constraints for indoor air temperature, active cold storage and chiller power demand. The indoor air temperature should be kept within a pre-determined acceptable range during the entire DR period, as shown in Eq.(21). Where, T_{min} *and* T_{max} are the lower and upper limits of acceptable indoor air temperature. The control variables of chiller cooling supply and cooling discharging rate of cold storage should be maintained within their corresponding capacities, as shown in Eq.(22). Where, $Q_{chiller,min}$ and $Q_{chiller,max}$ are minimum and maximum cooling supply of retained chillers. $Q_{storage,min}$ *and* $Q_{storage,max}$ are the minimum and maximum cooling discharging rate of cold storage. The vector of control variables at *kth* time step $\boldsymbol{u_k}= \begin{bmatrix} \boldsymbol{Q_{chiller}^k} \\ \boldsymbol{Q_{storage}^k} \end{bmatrix} = \begin{bmatrix} Q_{chiller}(k+1|k) & \cdots & Q_{chiller}(k+N_p|k) \\ Q_{storage}(k+1|k) & \ldots & Q_{storage}(k+N_p|k) \end{bmatrix}$. *Note that* the control of active cold storage during the fast DR events is different with that of normal conditions. During the fast DR events, it is assumed that no charging process is conducted and the cooling stored in the storage should be discharged completely due to this special period with very limited cooling supply, as shown in Eq.(23). Where, Q_{total} is the total stored cooling in the cold storage just before the DR event. $Q_{dis,k}$ is the total cooling discharged up to *kth* time step. With the above objective function, inequality constraints and discrete-time state-space model, the MPC controller is built as a linear optimization problem, which is easy to be solved and hence convenient for online optimal control in real applications because of its high computational efficiency.

$$T_{min} \leq \boldsymbol{T_{in}^k} \leq T_{max} \tag{21}$$

$$[Q_{chiller,min} \quad Q_{storage,min}]^T \leq \boldsymbol{u_k} \leq [Q_{chiller,max} \quad Q_{storage,max}]^T \tag{22}$$

$$95\% \cdot (Q_{total} - Q_{dis,k}) \leq \sum_{t=k+1}^{k+N_p} Q_{storage}(t|k) \cdot step \leq Q_{total} - Q_{dis,k} \tag{23}$$

4. Test platform

In this study, a virtual test platform is built to test the proposed MPC for optimizing the operation of a central air-conditioning system integrated with an active cold storage during a fast DR event. The dynamic models are developed on TRNSYS [35]. The models used are validated by real data [36]. The TRNSYS multi-zone building model (type 56) is used to simulate the building thermal behavior. The detailed physical models, building envelop and major components (e.g. chillers [36], pumps [26], hydraulic network [37], air handling units [26], cold storage [23]) of a central air-conditioning system, are included in this dynamic platform. The central chiller plant simulated is a typical primary constant-secondary variable chilled water system, which is modified based on the air-conditioning system of a super-high-rise building in Hong Kong, and its schematic is presented in Fig.1. The central chiller plant consists of six identical chillers with a rated capacity of 4080 kW. Each chiller is associated with a primary chilled water pump of constant speed (172.5 L/s). The parameters of *R* and *C* in the dynamic building thermal model are trained using genetic algorithm (GA) based on the historical data. (The average return temperature is used as the uniform indoor air temperature of the building. The time interval of data for identification is 1min. The weather condition is determined by the data of typical meteorological year. The internal heat gain is determined by the on-site data [31].) The results are presented in Table 1. The PCM cold storage is equipped in the central air-conditioning system and the model used in this study is developed in ref. [23]. The PCM material E8 is selected due to its proper thermal dynamic properties. Its density, latent heat and unit storage capacity are 1469kg/m^3, 140kJ/kg and 57kWh/m^3, respectively. The cold capacity of the PCM storage is assigned with the value of 5300kWh just before the DR event.

Table 1 Parameters of dynamic building thermal model

Parameter	$R_{w,o}$ (m^2K/W)	R_w (m^2K/W)	$R_{w,in}$ (m^2K/W)	$R_{i,1}$ (m^2K/W)	$R_{i,2}$ (m^2K/W)
Value	0.0942	0.0892	0.0039	0.0024	0.0107
Parameter	R_{win} (m^2K/W)	$C_{w,1}$ ($J/(m^2K)$)	$C_{w,2}$ ($J/(m^2K)$)	$C_{im,1}$ ($J/(m^2K)$)	$C_{im,2}$ ($J/(m^2K)$)
Value	0.0105	9.229*10^8	9.997*10^8	8.811*10^7	9.725*10^7

The DR period is set as 2 hours between 14:00pm and 16:00pm. At the start of the DR event, two of four operating chillers are shut down and two chillers remain to operate accordingly. The outdoor weather data for the test is a typical summer day in Hong Kong, as shown in Fig.4. The original indoor air temperature set-point before the DR event is 24°C and the maximum acceptable indoor air temperature is 27°C. The optimization problem formulated in MPC controller is solved by the YALMIP optimization toolbox [38] with the Gurobi solver [39]. The proposed MPC optimizes and updates the set-points of chiller power demand and cooling discharging rate of the storage every 15min. The dynamic simulation time step is 1s. According to the sampling time, the determined values of matrix A_d, B_d, E_d, and C_d in the discrete-time state-space model for MPC are presented as follows:

$$A_d = \begin{pmatrix} 9.998\times10^{-1} & 1.093\times10^{-5} & 0 & 0 & 0 & 0 \\ 1.009\times10^{-5} & 9.989\times10^{-1} & 0 & 0 & 6.948\times10^{-7} & 0 \\ 0 & 0 & 9.958\times10^{-1} & 4.191\times10^{-3} & 0 & 0 \\ 0 & 0 & 3.796\times10^{-3} & 9.955\times10^{-1} & 2.571\times10^{-6} & 0 \\ 0 & 5.789\times10^{-1} & 0 & 2.084\times10^{-1} & 9.403\times10^{-7} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}_{6\times6}$$

$$B_d = \begin{pmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ -2.230 \times 10^{-3} & -2.230 \times 10^{-3} \\ 2.222 \times 10^{-1} & 0 \end{pmatrix}_{6\times 2}$$

$$E_d = \begin{pmatrix} 7.800 \times 10^{-7} & 1.034 \times 10^{-5} & 0 \\ 0 & 0 & 0 \\ 1.788 \times 10^{-6} & 0 & 2.555 \times 10^{-6} \\ 2.293 \times 10^{-6} & 0 & 3.276 \times 10^{-6} \\ 7.808 \times 10^{-4} & 2.119 \times 10^{-1} & 1.115 \times 10^{-3} \\ 0 & 0 & 0 \end{pmatrix}_{6\times 3}$$

$$C_d = \begin{pmatrix} 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

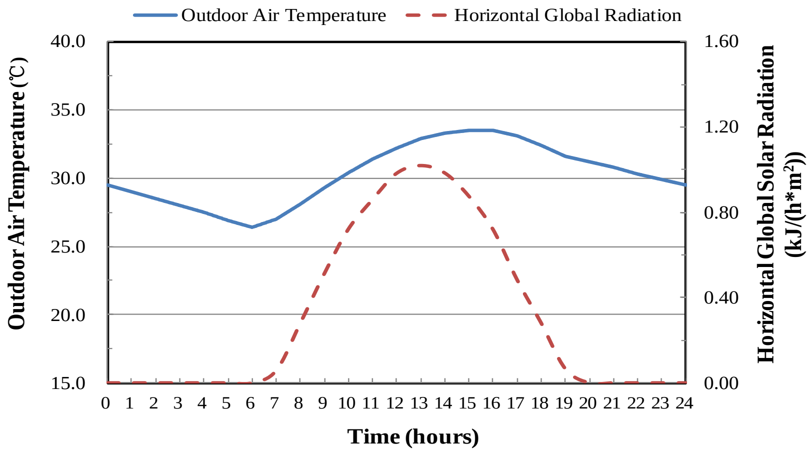

Fig.4 Outdoor temperature and solar radiation on the test day

Three cases are conducted in order to test the control performance of the proposed MPC approach and also to validate the need/importance of the optimal control of active cold storage on the expected power reduction and the acceptable indoor temperature during a fast DR event. In the two reference cases, the storage discharges all the stored cooling with a given discharging rate instead of optimized values in the DR event. The detailed information of the three cases are as follows:

- Reference case 1: the expected (i.e., the stable and minimum) chiller power demand control with constant cooling discharging rate of the active cold storage.
- Reference case 2: the acceptable indoor air temperature control (i.e., maintain the indoor air temperature at the upper limit of acceptable values) with constant cooling discharging rate of the

active cold storage.

- Optimized case using MPC: the MPC approach for the chiller power demand control and the cooling discharging rate control of the active cold storage.

5. Results and discussion

5.1 Validation of the dynamic building thermal model

The dynamic building thermal model was validated based on the simulation data, and the comparison between the predicted and actual indoor air temperatures is shown in Fig.5. In order to quantify the deviation of the predicted data from the actual data, three indices, i.e., mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE), were used to evaluate the prediction performance and the results are listed in Table 2. Undoubtedly, the accuracy of dynamic building thermal model was important for the online control performance. But the proposed MPC with the characteristics of self-correction and rolling optimization could effectively benefit the prediction accuracy and improve the control performance.

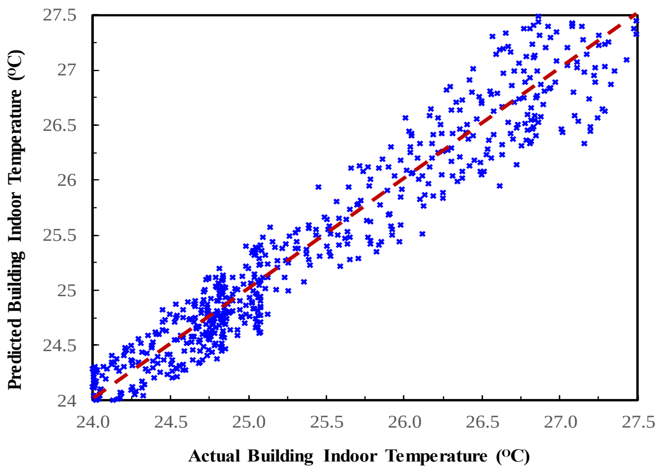

Fig.5 Comparison between the predicted and actual indoor air temperatures

Table 2 Accuracy indices of the dynamic building thermal model

	MAE (ºC)	MAPE (%)	RMSE (ºC)
Indoor air temperature	0.24	0.96	0.27

5.2 Control performance using different control strategies during fast DR events

The control performance of the central air-conditioning system during the fast DR event considered two aspects: the chiller power demand and indoor air temperature. A stable and minimum chiller power demand would be achieved and meanwhile the indoor air temperature would be maintained at its maximum acceptable value.

Reference case 1

Fig.6 presents the indoor air temperature and chiller power demand during the fast DR event in the reference case 1. In this case, the chiller power demand was controlled at a pre-determined set-point and the cooling discharging rate of active cold storage was set to be constant during the fast DR event. In order to achieve a comparison with the optimized case using MPC, the set-point of chiller power demand was set as the average value of set-points optimized by the MPC during the DR event. Although the control objective of chiller power demand could be satisfied (minimum and stable), the indoor air temperature kept increasing during the entire DR period and the maximum value significantly exceeded the acceptable range (27°C). It would be better that less cooling was provided for the first hour of the DR event, while more cooling for the second hour. This could optimize the indoor environment control by flatting the indoor air temperature profile of the DR event and hence to reduce its maximum value.

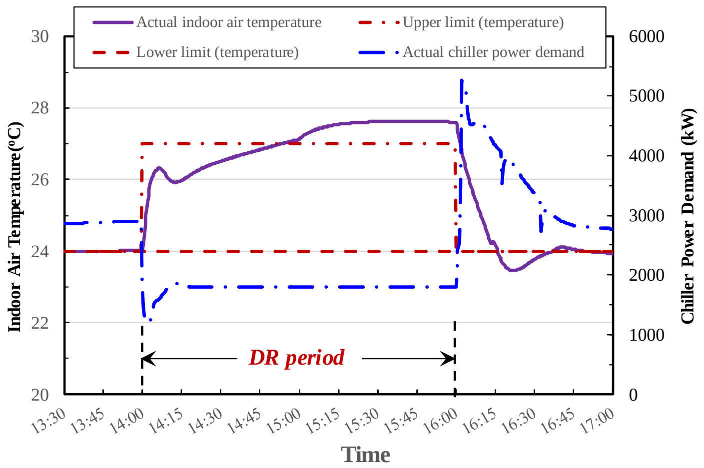

Fig.6 Indoor air temperature and chiller power demand during the fast DR event – reference case 1

<u>*Reference case 2*</u>

Fig.7 presents the indoor air temperature and chiller power demand during the fast DR event in the reference case 2. In this case, the indoor air temperature was reset as 27ºC, i.e., the maximum acceptable value, with the constant cooling discharging rate of the active cold storage during the fast DR event. The indoor air temperature was controlled at its maximum acceptable values in order to maximize the power demand reduction and hence minimize the chiller power demand. But the minimum and stable chiller power demand could not be obtained in this case to satisfy the requirements that the power grids expected. At the early stage of the DR event, the cooling discharging of building thermal mass caused by the indoor air temperature rise notably reduced the chiller power demand. As the cooling discharging of building thermal mass reduced, the chiller power demand increased and then almost followed the variation of building cooling demand. Meanwhile, due to the sudden change of central air-conditioning system (shutting down part of operating chillers directly), the indoor air temperature experienced a significant fluctuation (resulting in the indoor temperature beyond the acceptable range obviously) before reaching a new balance by PID control.

According to the above two reference cases, it was worthy of note that the chiller power demand and indoor environment controls could not be achieved as the expected profiles simultaneously without an optimal control strategy during the fast DR event.

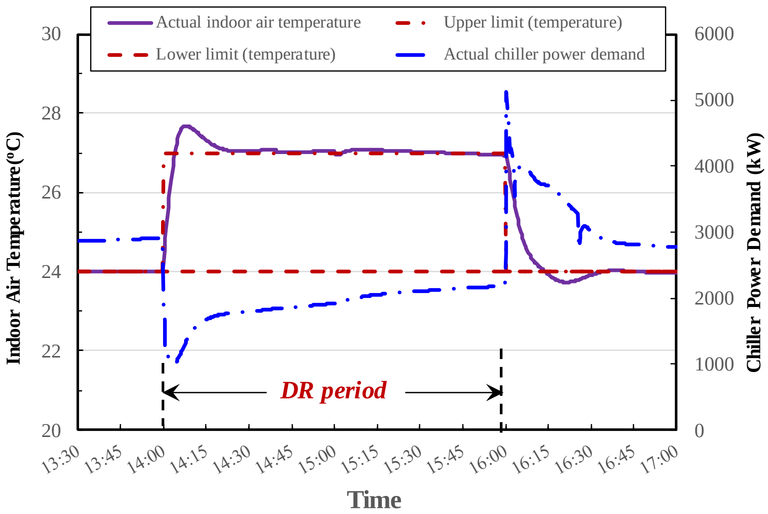

Fig.7 Indoor air temperature and chiller power demand during the fast DR event – reference case 2

Optimized case using MPC

Fig.8 presents the optimized cooling discharging rate of active cold storage during the fast DR event. Just after shutting down part of operating chillers, the indoor air temperature would increase and therefore the cooling would be discharged by the building thermal mass. At the beginning of the fast DR event, the discharged cooling of cold storage was low, particularly for the first 15min, so as to take full advantage of the cooling discharged by the building thermal mass. This could save the cooling in the storage, and then was used for the later stage of the DR event when the indoor air temperature was likely to exceed the acceptable range. As the discharged cooling of building thermal mass was reduced, the cold storage would discharge more cooling to ensure the indoor air temperature within the acceptable range. After the cooling stored in the building thermal mass was completely discharged, the cooling demand was the main factor considered for optimizing the cooling discharging of active cold storage. During the DR event, the cooling stored in the storage was almost discharged at the end of the event (i.e., nearly 5300kWh) in order to minimize the chiller power demand.

Fig.9 shows the optimized indoor air temperature profile when using the MPC approach to optimize the chiller power demand and the cooling discharging rate of active cold storage during the fast DR event. The indoor air temperature was not only maintained within the acceptable range (i.e., below 27^{o}C) but also almost kept at a stable level, which could effectively minimize the maximum indoor air temperature during the fast DR event. Meanwhile, although the simplifications were conducted when establishing the models for MPC and also the prediction error existed in the real system operation, the indoor air temperature was nearly controlled as the expected profile. This was because of the feedback self-correction ability and receding optimization of proposed MPC approach, and also the feature of the fast DR event that the building use would not have a significant change within two hours.

Fig.10 presents the optimized chiller power demand during the fast DR event using the MPC approach. The optimized set-points of chiller power demand during the DR event were almost kept at a constant level and a slight adjustment occurred to cooperate with the control of cold storage to maintain the indoor air temperature stable and within the acceptable range. Fig.11 presents the chilled water flows through the by-pass line and the cold storage during the fast DR event using the MPC approach. By adjusting the chilled water flow through the cold storage, the actual cooling discharging rate of the storage could well follow its optimized set-point using the MPC approach (in Fig.8), which demonstrated the effectiveness of the storage load regulator. Moreover, by adjusting the chilled water flow through the by-pass line and therefore the flow in the secondary loop of the system, the actual chiller power demand could well follow its optimized set-point (in Fig.9), which demonstrated the effectiveness of the chiller load regulator.

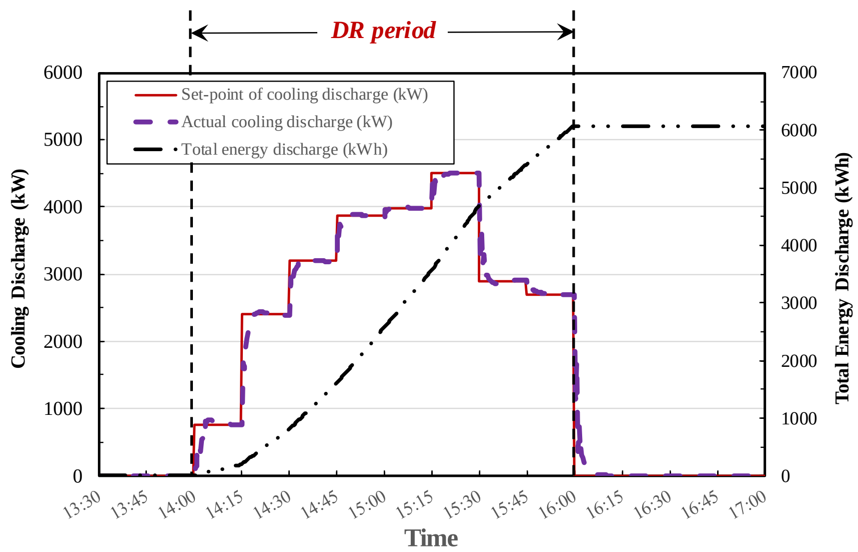

Fig.8 Optimized cooling discharging rate of active cold storage during the fast DR event – optimized case using MPC

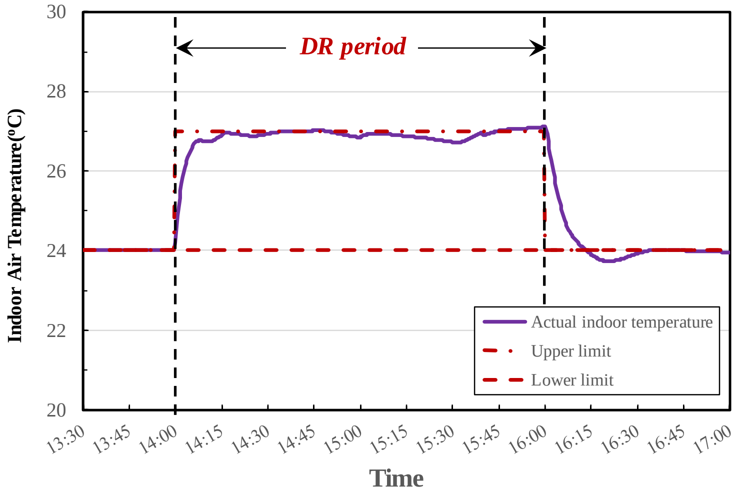

Fig.9 Optimized indoor air temperature during the fast DR event – optimized case using MPC

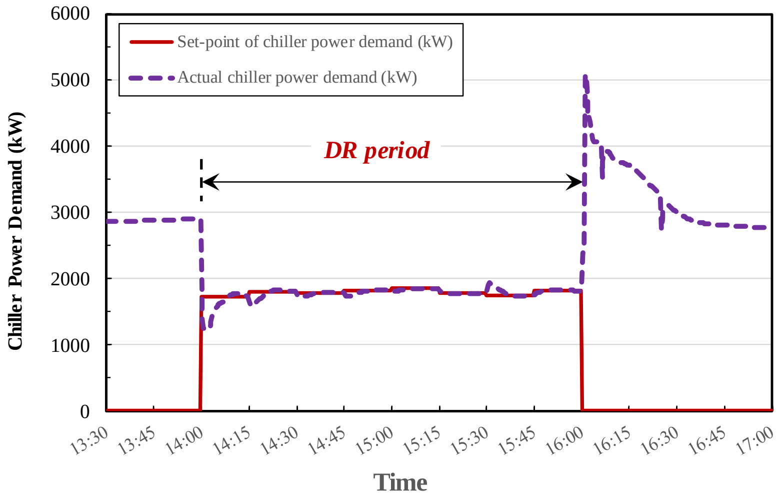

Fig.10 Optimized chiller power demand during the fast DR event – optimized case using MPC

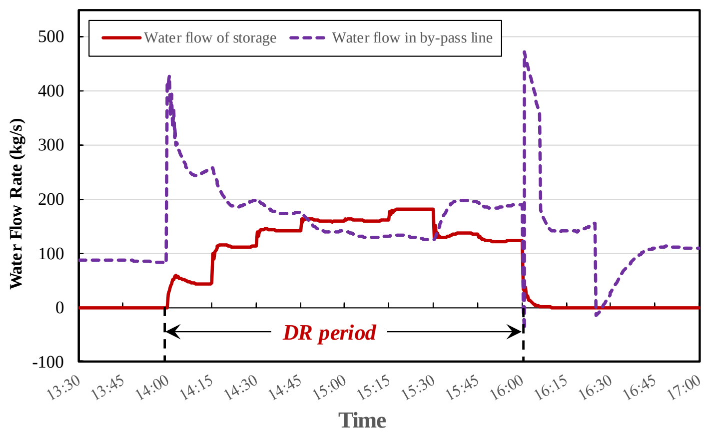

Fig.11 Chilled water flows through the storage and by-pass line during the fast DR event – optimized case using MPC

5.3 Control performance comparison of cases using different control strategies

Table 3 presents the control performance on the indoor air temperature and the chiller power demand using different control strategies during the fast DR event. Generally, in the two reference cases, the indoor air temperature and chiller power demand could not be controlled simultaneously as expected. In the reference case 1, the chiller power demand was stable but the maximum indoor air temperature during the DR event (i.e., 27.6ºC) significantly exceeded its acceptable limit. While in the reference case 2, the indoor air temperature was almost kept at the upper limit and the unsatisfied duration that the indoor air temperature exceeded the upper limit was reduced from 62min to 12min compared with the reference case 1. But the maximum value was not reduced in this case because a significant fluctuation occurred caused by the sudden change of system control (i.e., shutting down part of operating chillers directly). Moreover, the chiller power demand could not be kept at a stable level and the difference between the maximum and minimum chiller power demands during this DR event was nearly 1700kW. In contrast, using the proposed MPC approach, the maximum indoor air temperature was only 27.1ºC and the chiller power demand was stable and fluctuated slightly within the range of 342kW. In addition, the unsatisfied duration that the indoor air temperature exceeded the upper limit was almost diminished because of the better control performance of MPC approach to deal with the sudden change of the system [40].

Table 3 Comparison of the control performance among three cases during the fast DR event.

	Indoor air temperature			Chiller power demand	
	Max (ºC)	Unsatisfied duration (min)	Standard deviation (K)	Max-min (kW)	Standard deviation (kW)
Reference case 1	27.6	62	0.67	656.8	103.8
Reference case 2	27.6	12	0.33	1675.5	268.75
MPC case	27.1	0.2	0.30	342.6	50.2

*Max-min refers to the difference between the maximum and minimum chiller power demands during the fast DR event

6. Conclusions

Shutting down part of operating chillers in a commercial building is an effective means to achieve an immediate power demand reduction responding to urgent requests of smart grids. The active thermal storage is necessary to be used for a further power reduction and meanwhile for ensuring an acceptable indoor environment when this proactive demand response (DR) method is adopted. In this study, an optimal control strategy using model predictive control (MPC) is developed to optimize the operation of active cold storages during fast DR events. The chiller power demand and the cooling discharging rate of storage are optimized at the same time to achieve a maximum and stable power demand reduction as well as to maintain the indoor air temperature within a pre-determined acceptable range. In addition, simplifications are made for the parameter identification of models used in the MPC considering the characteristics of fast DR events. A linear discrete-time state-space model is developed to make the proposed online optimal control strategy computationally efficient in practical applications.

Test results show that the proposed optimal control strategy can effectively optimize the operation of the central air-conditioning system integrated with active cold storage, to achieve an expected power reduction for power grids and satisfy the indoor environment during the fast DR event. In the two reference cases without using the proposed optimal control strategy, the indoor air temperature and chiller power demand profiles could not be controlled as expected simultaneously during the fast DR event. Compared with the two reference cases, the MPC strategy significantly reduced the maximum indoor air temperature during the DR event, i.e., from 27.6°C to 27.1°C. The unsatisfied duration of indoor air temperature was almost diminished, only 0.2 minutes. Moreover, a stable and much more chiller power reduction was achieved. Furthermore, the model simplifications did not adversely affect the control performance due to the feedback self-correction and receding optimization of proposed MPC approach, which allows the applications simple and convenient.

This study effectively addresses the online control issue of cold thermal storage during a fast DR event considering the requests of both the power grids and the indoor thermal comfort. The proposed method can achieve online self-correction and hence present strong robustness facing the uncertainties of real conditions and the prediction errors of models. In this study, the indoor thermal comfort of buildings considers the uniform average return temperature. The different requirements of indoor thermal comfort among different zones/rooms in the building can be considered in the future studies.

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