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An MPC-Based Optimal Control Strategy of Active Thermal Storage in Commercial Buildings during Fast Demand Response Events in Smart Grids

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Abstract

Demand response (DR) is a set of demand-side activities to reduce or shift electricity use to improve the electric grid efficiency and reliability. Shutting down part of operating chillers directly in central air-conditioning systems of buildings to meet the urgent demand reduction needs of power grids has received increasing attention recently. A model predictive control strategy is developed for optimizing the operation of a central air-conditioning system integrated with an active cold storage during such fast demand response events. The primary objective of the proposed control strategy is to maximize the power reduction with a profile pattern preferred by power grids as well as to maintain the indoor air temperature within an acceptable level during fast DR period. The MPC controller determines the control outputs of chiller power demand and active storage discharge rate based on the discrete-time state space building thermal response model. Test results show that expected profile pattern (i.e., maximum and stable) of power reduction was achieved by the proposed MPC strategy during fast DR events. Meanwhile, the indoor air temperature was maintained within the acceptable range.

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Keywords: model predictive control; active thermal storage; central air-conditioning system; fast demand response; smart grid

1. Introduction

1.1. Background

The power balance between the supply side and the demand side of a power grid is a critical issue in the grid real-

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time operation [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 from the power imbalance, smart grid is considered as a promising solution to incorporate advanced technologies to offer better flexibility, reliability, and security in grid operation. The control conducted at the consumer side in response to grid requests (e.g., dynamic price and reliability information) is known as demand response (DR). Considering buildings are the major energy consumer in the demand side of power grids and the air-conditioning system always accounts for a large part of building energy use, building demand response contributed by air conditioning systems attracts increasing attention recently [2].

When an urgent request or incentive from smart grids, shutting down part of operating chillers is considered as an effective way to achieve immediate power reduction within a very short time [3, 4]. Meanwhile, active cold storage is an effective device for fast DR event to provide more immediate power reduction without worsening indoor thermal comfort. But no study focuses on the optimal control for the operation of active thermal storage during fast DR events.

Model predictive control (MPC) is a simple yet effective approach for constrained control, which is able to predict the future behaviors of the controlled system and to determine control actions by optimizing an objective function depending on the predictions over a given horizon subject to some constraints [5]. It uses receding horizon (i.e., at each iteration, only the first step of the control strategy is implemented and then control signal is calculated again) to enhance its robustness and control accuracy.

1.2. Problem illustration on the optimal control of active cold storage during fast DR events

During fast DR events, part of operating chillers is shut down to provide immediate power reduction. Then, the active thermal storage and retained chillers in the central air-conditioning system will together benefit the indoor thermal comfort and further adjustment of power reduction. Compared with conventional DR events, the main differences in the control of active cold storage during fast DR events is no charging process and all the stored cooling discharged for such urgent periods. The discharge rate of cooling stored in cold storage would be optimized to achieve an expected profile pattern of power reduction during such events, such as a maximum and stable reduction as shown in Fig.1. At the same time, the indoor thermal comfort should be considered and the maximum indoor air temperature during this period would be minimized and restricted within the acceptable range. The cooling provided by retained chillers and active cold storage would make indoor temperature preferably as shown in Fig.1 instead of increase all the time. But no literature has been conducted for the optimal control of the cooing provided by active cold storage effectively considering indoor air temperature and power reduction during fast DR events.

In this study, therefore, MPC is used to optimize the controls of cold storage and power demand of retained chillers during fast DR period for a maximum and stable power reduction as well as maintaining the acceptable indoor air temperature.

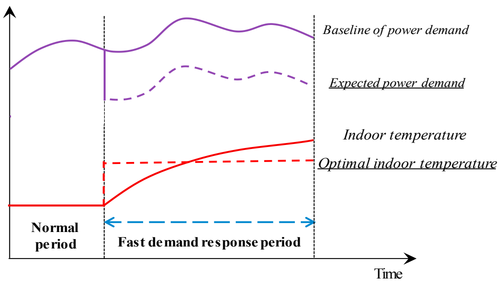

Fig. 1. Problem illustration on the control of active cold storage during fast DR period

2. Model predictive control for the operation of active cold storage during fast DR events

The model predictive control (MPC) is applied as a supervisory control to optimize the operation of active thermal storage during fast DR period. The optimized variables by MPC strategy are the discharge rate of active cold storage and the power demand of retained chillers. Then, the optimal cooling discharge rate is achieved by adjusting the chilled water flow through the storage before back to the chillers, while the optimal power demand of retained chillers is achieved by adjusting the chilled water flow in the secondary loop of the central air-conditioning system.

2.1. Model description for MPC

To predict the building response given an optimized chiller power demand and cooling supplied by the storage, a dynamic building thermal model is developed. The components in this model and the heat fluxes exchanged between them are shown in Fig.2. The grey-box building thermal model proposed 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 developed building thermal model would be simple and generally grasp the key characteristics. Although the simplification would reduce the prediction accuracy, MPC proposed in this study is self-corrected every time step. The model mainly includes four parts: outdoor environment, building envelop, indoor air, and internal thermal mass. The detailed calculation process is shown in Eqs.(1-8).

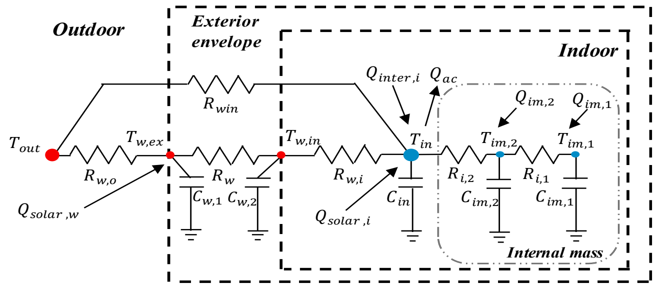

Fig. 2. Schematic of dynamic building R-C model

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

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

$$C_{im,1}\frac{dT_{im,1}}{dt}=\frac{T_{im,2}-T_{im,1}}{R_{i,1}}+Q_{im,1} \tag{3}$$

$$C_{im,2}\frac{dT_{im,2}}{dt}=\frac{T_{im,1}-T_{im,2}}{R_{i,1}}-\frac{T_{im,2}-T_{in}}{R_{i,2}}+Q_{im,2} \tag{4}$$

$$C_{in}\frac{dT_{in}}{dt}=\frac{T_{im,2}-T_{in}}{R_{i,2}}+\frac{T_{w,in}-T_{in}}{R_{w,i}}+\frac{T_{out}-T_{in}}{R_{win}}+Q_{inter,i}-Q_{ac}+Q_{solar,i} \tag{5}$$

where, R and C represent the heat resistance and capacitance, respectively; 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* $Q_{im,2}$ absorbed by nodes $C_{im,1}$ *and* $C_{im,2}$ are the radiation heat; Q_{ac} is the total cooling supplied by chiller and cold storage.

The corresponding parameters in the building thermal model are determined based on Eqs.(6-12) [6]. Where, I_{solar} denotes global solar radiation; β, *b* and μ denotes the radiative/convective split for heat gain; α denotes absorptance of surface of solar radiation; *SHGC* denotes solar heat gain coefficient; $Q_{storage}$ and $Q_{chiller}$ are the cooling provided by the active storage and retained chillers, respectively; $P_{chiller}$ and *cop* are the power demand and efficiency of retained chillers.

$$Q_{solar,w}=aI_{solar} \tag{6}$$

$$Q_{solar,i}=\beta_i\cdot SHGC\cdot I_{solar} \tag{7}$$

$$Q_{im,1} = Q_{im,2} = b \cdot (Q_{solar,im} + Q_{inter,im}) \tag{8}$$

$$Q_{solar,im} = \beta_{im} \cdot SHGC \cdot I_{solar} \tag{9}$$

$$Q_{inter,im} = \mu \cdot Q_{inter} \tag{10}$$

$$Q_{ac} = Q_{storage} + Q_{chiller} \tag{11}$$

$$Q_{chiller} = P_{chiller} \cdot cop \tag{12}$$

2.2. Control formulation

The objective of MPC is to achieve a maximum and stable power reduction during a fast DR event as well as ensuring the acceptable indoor air temperature. In this study, the baseline of chiller power demand is assumed to be the same as that just before the DR events because many studies have been conducted on such prediction and this is not the focus of this study. Thus, the objective of MPC is to achieve a stable and minimum (i.e., first and second parts of Eq.(13)) power demand as well as meeting the constraint of indoor air temperature and discharging nearly all the stored cooling of cold storage during fast DR period, as shown in Eqs.(13a-13c).

$$min \quad J = \frac{1}{N_p}\sum_{k=1}^{N_p}[(P^k - \bar{P})^2 + \lambda \cdot {P^k}^2] \tag{13}$$

$$\text{s.t.} \quad T_{min} \le T^k \le T_{max} \tag{13a}$$

$$[P_{chiller,min} \quad Q_{storage,min}]^T \le [P_{chiller}^k \quad Q_{storage}^k]^T \le [P_{chiller,max} \quad Q_{storage,max}]^T \tag{13b}$$

$$95\% \cdot Q_{total} \le \sum_{k=1}^{N} Q_{storage}^k \cdot t \le Q_{total} \tag{13c}$$

where, T_{min} *and* T_{max} are the lower and upper constraints of indoor air temperature; $P_{chiller,min}$ and $P_{chiller,max}$ are minimum and maximum power demand of retained chillers; $Q_{storage,min}$ *and* $Q_{storage,max}$ are the minimum and maximum cooling discharge rate of storage; Q_{total} is the total stored cooling of storage just before the DR event; N_p is the prediction horizon of MPC controller; subscript k denotes the k^{th} time step; t is the time duration of a step.

The dynamic building model developed in session 2.1 should be discretized and linearized prior to being applied for MPC. The discrete-time state-space model of building thermal response can be given as the form of Eqs.(14-15), which is embedded in the MPC controller to predict the system evolutions.

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

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

where, the states of system $x = [T_{w,ex} \;\; T_{w,in} \;\; T_{im,1} \; T_{im,2} \; T_{in}]^T$, the control variable vector $u = [P_{chiller} \; Q_{storage}]^T$, the disturbance $d = [I_{solar} \; T_{out} \;\; Q_{inter}]^T$; y is the indoor air temperature; e is the self-correction factor of the prediction; A_d, B_d, E_d, and C_d are the corresponding state-space matrices of the discrete-time state-space model which depend on the sampling time.

3. Results and discussion

3.1. Set-up of test platform

In this study, a virtual test platform is built to test the proposed MPC strategy for optimizing the operation of active cold storage and power demand of retained chillers during fast DR events. The dynamic models are developed on TRNSYS [7]. A central air-conditioning system integrated with a cold storage is considered and its schematic is presented in Fig.3. The weather data adopted is a typical summer day in Hong Kong, as shown in Fig.4. The original indoor air temperature set-point before DR event is 24°C. The DR period is between 14:00 pm and 16:00 pm. The simulated central chiller plant is a typical primary constant-secondary variable chilled water system. It 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). At the start of the DR event, two of four operating chillers are shut down and two chillers remain to operate accordingly. The MPC updates the set-points of chiller power demand and discharge rate of storage every 15min and the simulation time step is 1s.

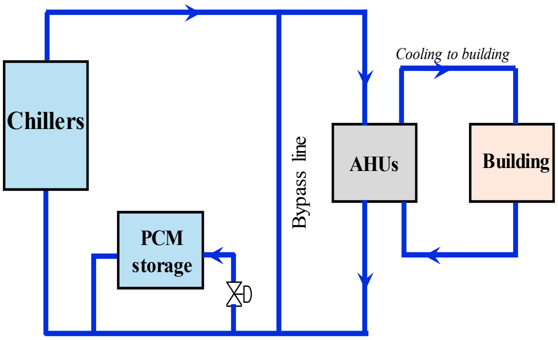

Fig. 3. Schematic of cold storage discharging process

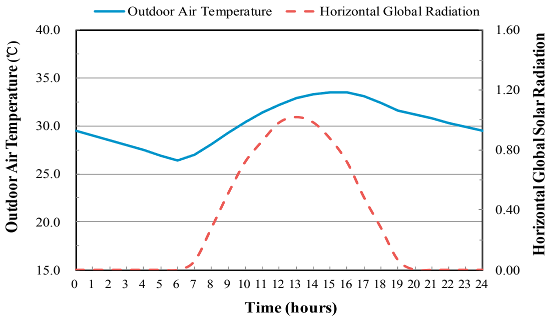

Fig. 4. Outdoor temperature and solar radiation in the test day

3.2. Results of the case study

The parameters of *R* and *C* in the dynamic building thermal model are trained using genetic algorithm (GA) based on the historical data. Although there are uncertainties in real cases and the prediction exists inevitable errors, the proposed MPC strategy can effectively self-corrected based on the feedback information to enhance the control performance and accuracy.

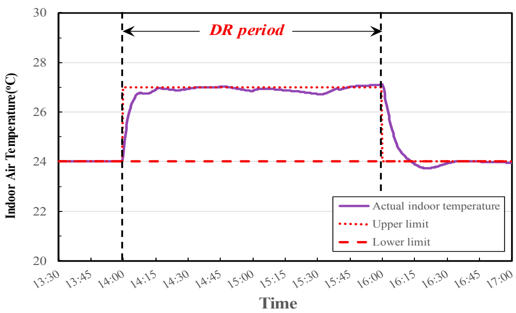

Fig. 5. Indoor air temperature using the proposed MPC strategy during fast DR period

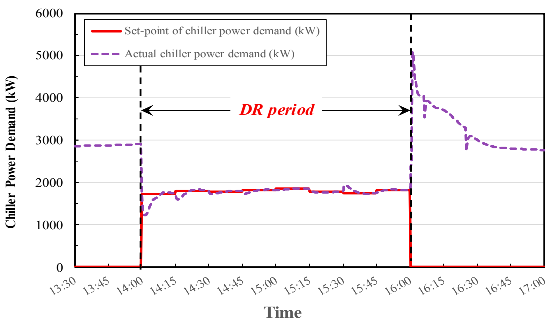

Fig. 6. Chiller power demand using the proposed MPC strategy during fast DR period

In Fig.5, using the MPC strategy, the indoor air temperature profile of the building is not only maintained within the acceptable range (i.e., below 27°C) but also almost at a similar sacrifice level, which can effectively minimize the maximum indoor air temperature during the fast DR event. Due to the optimal control of chiller power demand and cooling discharge of storage using the proposed MPC strategy, the indoor temperature during the entire DR event would effectively avoid increasing all the time and hence was maintained at the upper limit to achieve a maximum power reduction.

Fig.6 and Fig.7 present the control performances of chiller power demand and cold storage discharging process optimized by the MPC during the fast DR period. The baseline profile of chiller power demand was assumed to be the same as that just before the DR event. In such a case, to realize a constant power reduction was to maintain the power demand at a stable level. The MPC strategy optimized the set-points of chiller power demand and cooling discharge rate every 15min to achieve the stable and maximum power reduction during the fast DR event. It was worth of noticing that nearly all the cooling stored in the storage was discharged for this urgent period to benefit the smart grids. In Fig.6, compared with the baseline, about 40% of chiller power demand, nearly 1200kW, was reduced averagely.

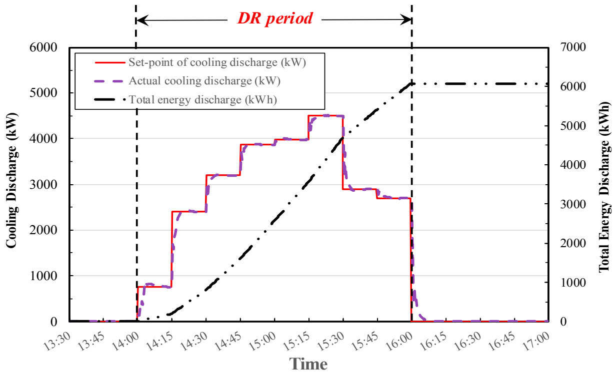

Fig. 7. Cooling discharge of active cold storage using the proposed MPC strategy during fast DR period

4. Conclusion

In this study, model predictive control was used to optimize the operation of active thermal storage during fast demand response period facing an urgent request/incentive of smart grids. Considering the characteristics of such fast DR event, the chiller power demand and cooling discharge of storage were optimized for a maximum and stable power reduction as well as maintaining the acceptable indoor air temperature. A linear state-space model (i.e., building thermal model) was developed and embedded into the MPC strategy.

Test results showed that the proposed MPC strategy effectively minimized the maximum indoor temperature and kept it within an acceptable range. Also, a constant and maximum power reduction could be achieved because the active storage and chiller demand were controlled optimally during the fast DR event.

Acknowledgments

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