Model-based control optimization of air-conditioning for proactive building demand response

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ABSTRACT

Proactive building demand response has been proved to be a cost-effective approach for power system ancillary services. Air-conditioning systems are one of the significant and preferable demand response resources in large commercial buildings. Demand limiting control by shutting down part of operating chillers is fast enough to achieve load curtailment for providing valuable spinning reserve. However, it runs with the sacrifices of indoor thermal comfort due to the insufficient cooling supply during the demand limiting period. In this situation, the proper management of the limited cooling supply remains to be a challenge considering the trade-off between indoor air temperature and relative humidity affecting the indoor thermal comfort. Conventional building automation system fails to achieve rational use of determined power supply considering this trade-off when performing fast demand response after shutting down operating chillers. This paper therefore develops a model-based control optimization of supply air flow rates in the air-conditioning system to address this problem. A multi-objective problem is formulated to quantify this problem. Incremental building thermal balance models are employed to predict the indoor environment responses for optimization. Test results reveal that the proposed control strategy can determine the rational delivery of the cooling supply to the zones considering appropriate importance of objective for indoor air temperature and relative humidity.

1. INTRODUCTION

The global energy crisis and climate change are being exacerbated by the increasing global energy consumption. Projections indicate that electricity demand is growing at the fastest rate in over a decade (*Global Energy Review 2021*, 2021). To address this challenge, there is a significant push for integrating renewable energy sources into electricity generation. It is expected that renewable power capacity will expand by 50% between 2019 and 2024 (*Renewables 2019. Analysis and forecast to 2024*, 2019). However, the widespread adoption of renewables presents a challenge in maintaining a real-time power balance and ensuring reliable operation of the power system (Georgilakis, 2008; Karimi *et al.*, 2016). The building sector plays a critical role in global energy use, accounting for 30% of total energy consumption, with the situation being particularly acute in Hong Kong where buildings consume 90% of the electricity (*Hong Kong Energy End-use Data*, 2022). Grid-responsive buildings have the potential to reshape energy consumption patterns by adjusting their electricity usage in response to price signals, incentives, or instructions from grid operators. This process, known as demand response, has been identified as a key strategy (*Assessment of Demand Response and Advanced Metering*, 2011). Among the various energy-consuming systems in buildings, HVAC (Heating, Ventilation, and Air-Conditioning) systems are the largest consumers (Dai *et al.*, 2021). They can effectively facilitate demand response and enable the creation of grid-responsive buildings. In particular, fast demand response, which involves quickly adjusting electricity consumption, holds significant value for power grids. In commercial buildings, an effective method for fast demand response is to shut down some of the operating chillers in response to urgent power reduction requests from the grid. This approach has been proven successful (Tang *et al.*, 2016; Wang and Tang, 2017; Xue *et al.*, 2015).

The conventional feedback control is a widely adopted method for maintaining a comfortable indoor environment in buildings through air-conditioning systems. This control technique involves measuring temperature, humidity, and other environmental parameters, and adjusting the air-conditioning system accordingly. The feedback control loop typically comprises a sensor, controller, and actuator. The sensor measures environmental parameters, and the controller compares the measured values with a predefined setpoint. If there is a deviation, the controller sends a signal to the actuator to make adjustments. The PID (Proportional-Integral-Derivative) control algorithm is commonly used for feedback control in air-conditioning systems (Geng and Geary, 1993). This algorithm continuously monitors the system's performance and adjusts the output to meet the desired setpoint. The PID controller receives feedback from sensors that measure indoor temperature, humidity, and air quality. It compares this feedback to the setpoint and calculates the error. Based on the error, the controller adjusts the HVAC system's output. PID control has gained popularity in air-conditioning systems due to its effectiveness. However, under fast demand response scenarios for building grid-interaction, the conventional feedback control fails to effectively manage limited cooling supply. Previous studies mainly focus on the proper cooling distribution for the terminals (e.g., AHUs) during the demand limiting period. The control objectives mainly focus on the equal temperature thermal comfort sacrifices among different building zones when performing fast demand response. However, the cooling supply from each AHU to the corresponding building zone is not only determined by the chilled water from the chillers, but also the supply air flowrate. In addition, the indoor thermal comfort is not only determined by the temperature, the relative humidity also should be considered especially for the humid subtropical areas.

To address the above problems, this study develops a model-based optimization method for the supply air flowrate control considering the trade-off between indoor air temperature and relative humidity during the fast demand response period. A multi-objective problem is formulated for control optimization. Incremental building thermal balance models are employed to predict the indoor environment responses for optimization.

2. METHODOLOGY

2.1 Control framework

Figure 1 shows the framework of the proposed model-based control strategy. The supervisory control level is the high-level control layer of the model-based control strategy, responsible for determining the desired setpoint of the local control level. It employs a model-based optimizer to generate setpoints. The model-based optimizer consists of the dynamic building model and the optimization algorithm. By modeling and predicting the building environment, the supervisory level can assess the current environmental conditions and generate appropriate setpoints based on the prediction results. The local control level is the low-level control layer of the model-based control strategy, responsible for executing the actual control actions based on the instructions provided by the supervisory level. The process controller adjusts the control inputs based on real-time feedback signals to achieve the desired system response and performance. In this study, the controlled variable is the supply air flowrate of the AHUs in the central air-conditioning system. The control objective is to balance indoor air temperature and relative humidity sacrifice in the proactive demand response event.

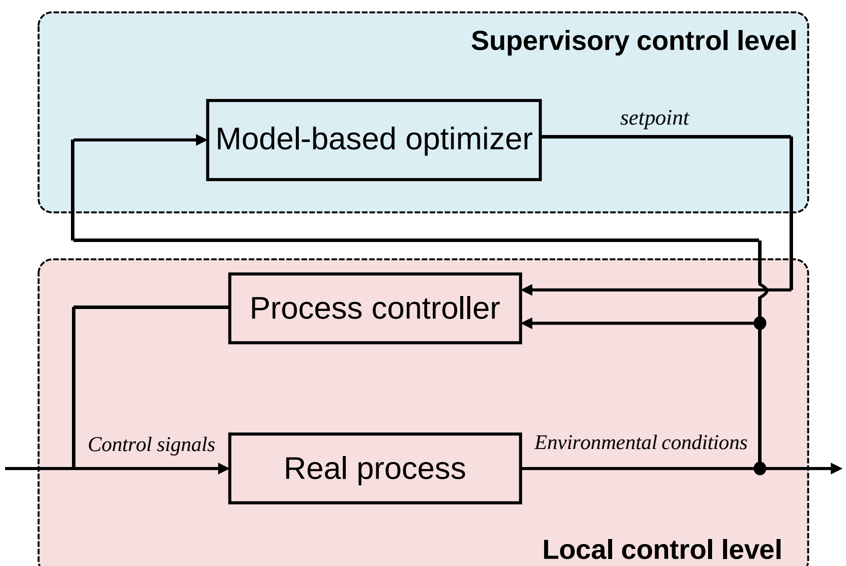

Figure 1: Framework of the proposed control strategy

2.2 Model description

Equation (1) and Equation (2) show the temperature and humidity of zone *i* with supply air from the air-conditioning system. Where, m_{air} is the supply air flowrate. M_i is the total mass of indoor air of zone *i*. c_p is the specific heat of air. $T_{sup,i}$ and $G_{sup,i}$ are the temperature and humidity of supply air. T_i and G_i are the indoor air temperature and humidity of zone *i*. $Q_{h,i}$ and D_i are indoor heat and humidity loads of zone *i*.

$$M_i c_p \frac{\partial T_i}{\partial t} = m_{air,i} c_p \left(T_{sup,i} - T_i\right) + Q_{h,i} \tag{1}$$

$$M_i \frac{\partial G_i}{\partial t} = m_{air,i} \left(G_{sup} - G_i\right) + D_i \tag{2}$$

Due to the slowly-varying nature of heat and humidity loads, it is assumed that they remain constant over a very short period of time. As a result, Equation (1) and Equation (2) can be approximated by replacing the derivative terms with finite difference terms. At sampling interval *k*, the prediction of indoor air temperature and humidity can be calculated using Equation (3) and Equation (4). Here, Δt_s represents the sampling time step. The heat load ($Q_{h,i}$) and humidity load (D_i) are considered to be constant during a sampling interval and can be estimated by Equation (5) and Equation (6).

$$T_i(k+1) = T_i(k) + [\frac{m_{air,i}(k)}{M_i(k)}(T_{sup,i}(k) - T_i(k)) + \frac{Q_{h,i}(k)}{M_i(k) c_p}]\Delta t_s \tag{3}$$

$$G_i(k+1) = G_i(k) + \left[\frac{m_{air,i}(k)}{M_i(k)}\left(G_{sup,i}(k) - G_i(k)\right) + \frac{D_i(k)}{M_i(k)}\right]\Delta t_s \tag{4}$$

$$Q_{h,i}(k) = M_i(k) c_p \frac{T_i(k) - T_i(k-1)}{\Delta t_s} - \frac{m_{air,i}(k-1) + m_{air,i}(k)}{2} c_p (T_{sup,i}(k-1) - T_i(k-1)) \tag{5}$$

$$D_i(k) = M_i(k) \frac{G_i(k) - G_i(k-1)}{\Delta t_s} - \frac{m_{air,i}(k-1) + m_{air,i}(k)}{2} (G_{sup,i}(k-1) - G_i(k-1)) \tag{6}$$

2.3 Optimization process

The multi-objective optimization model is developed as shown in Equation (7). f_T is the indoor air temperature and f_{RH} is the relative humidity. *a* is the user-defined weighting factor indicating the importance of the corresponding objective. The constrains of the optimized variable (i.e., supply air flowrate) ensure that the airflow remains within acceptable limits.

$$\min\left(a \cdot f_T\left(m_{air}(k) + (1-a) \cdot f_{RH}\left(m_{air}(k)\right)\right)\right) \tag{7}$$

$$constrains\colon m_{air}(k) \in [0.8V, 1.2V]$$

At each optimization interval, the two objectives in Equation (7) are normalized. The weighted normalized objective function is shown in Equation (8). *Obj1* represents the indoor air temperature (i.e., f_T in Equation (7)). *Obj2* represents the relative humidity (i.e., f_{RH} in Equation (7)). In this study, *Obj1min* is set to 24 and *Obj1max* is set to 34. *Obj2min* is set to 0.5 and *Obj1max* is set to 0.8. The supply air flowrate setpoint is determined by solving the multi-objective optimization function. By minimizing both objectives simultaneously, the optimization process seeks to achieve a balance between the two objectives.

$$Obj = a \cdot \frac{Obj1 - Obj1_{min}}{Obj1_{max} - Obj1_{min}} + (1-a) \cdot \frac{Obj2 - Obj2_{min}}{Obj2_{max} - Obj2_{min}} \tag{8}$$

3. VALIDATION TESTS AND RESULTS

3.1 Validation tests

Figure 2 shows the platform utilized to validate the proposed control strategy. The platform consists of a central air-conditioning system in a high-rise commercial building located in Hong Kong. The detailed physical models of building thermal behavior and air-conditioning system components (i.e., chillers, AHUs, pumps, hydraulic network etc.) are constructed in TRNSYS (Dai et al., 2023a, 2023b, 2023c, 2024). A two-hour demand respond event (i.e., 14:00-16:00) in a typical summer day (i.e., July 23th) in Hong Kong is selected for the validation tests. During the demand response event, three chillers are shut down, leaving one operational chiller.

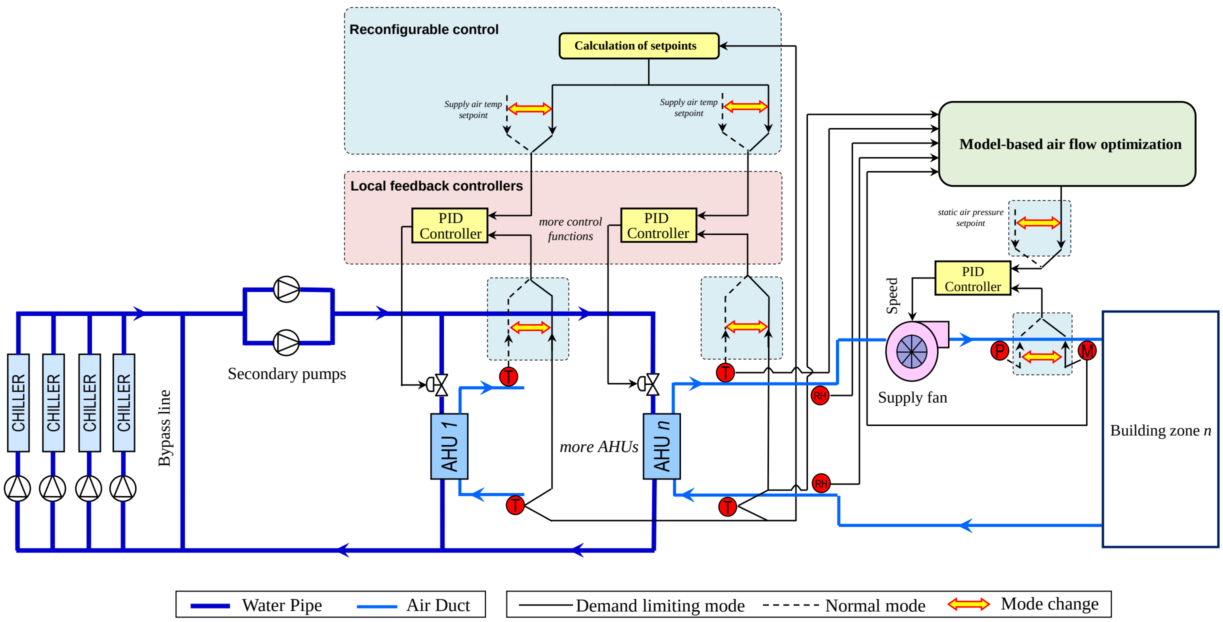

Figure 2: Test platform of the proposed control strategy

3.2 Test results

3.2.1 Supply air flowrates

Figure 3 shows the supply air flowrates profiles of two typical zones during the demand response event. It can be seen that the supply air flowrates of the building zones are controlled to be the maximum values using the conventional control. It is because the cooling supply is insufficient to maintain the indoor air temperature setpoints. In this situation, the conventional control is disordered since the beginning of the demand response event. It fails to consider the trade-off between temperature and relative humidity in the process of demand response, thus sacrificing thermal comfort. Besides, the conventional control leads to extra energy consumption due to the over-speeding of the AHU fans, which impacts the successful implementation of demand response. On the contrary, the proposed model-based control adjusts the air supply flowrates by solving the multi-objective function as illustrated in Section 2.3 in real-time to address these issues as shown in Figure 3.

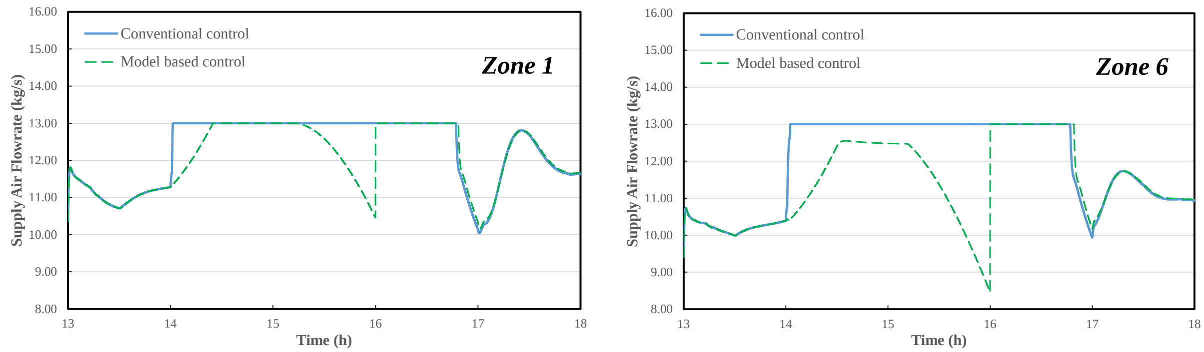

Figure 3: Supply air flowrates profiles of two typical zones

3.2.2 Indoor air temperature and relative humidity

Figure 4 and Figure 5 show the indoor air temperature profiles and relative humidity profiles of two typical zones correspondingly during the demand response event. It can be seen that the indoor air temperature profiles and relative humidity profiles of the zones start to increase since the beginning of the demand response event. It indicates the limited cooling supply is unable to maintain the comfortable setpoints. The indoor air temperature profiles using the conventional control are slightly higher than those using the proposed model-based control. However, the relative humidity sacrifice is relieved to some extent using the proposed control. It is because the proposed control strategy takes into account the trade-off between temperature and relative humidity in terms of thermal comfort sacrifice. Besides, more power reduction is achieved due to the adjustments of the suppl air flowrates. The weights for this multi-objective optimization can be adjusted in real application.

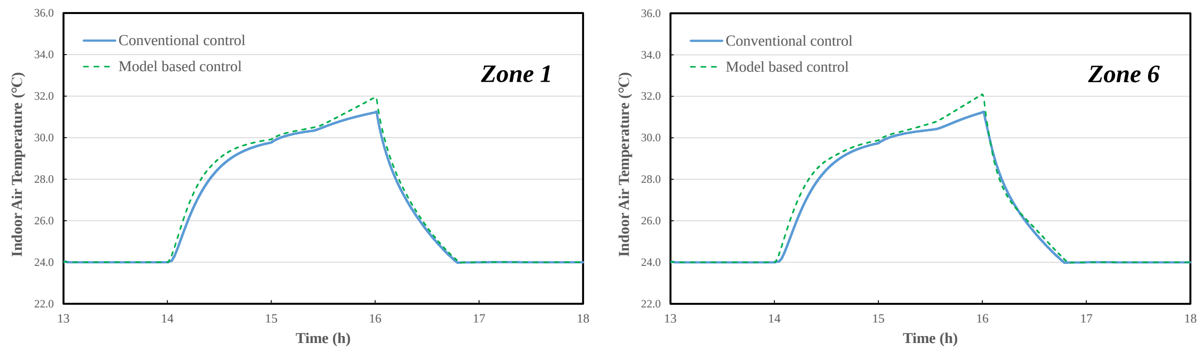

Figure 4: Indoor air temperature profiles of two typical zones

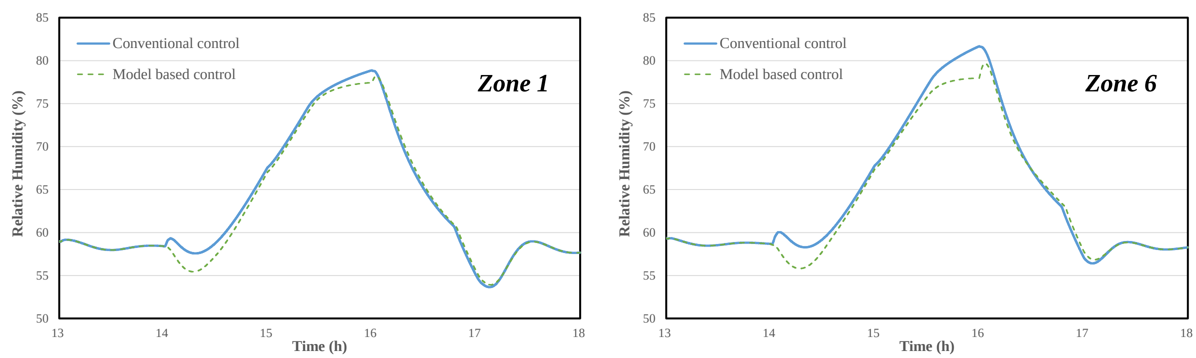

Figure 5: Relative humidity profiles of two typical zones

4. CONCLUSIONS

Air-conditioning systems possess significant potential for offering valuable building grid-interaction control. This study develops a model-based control optimization of supply air flow rates in the air-conditioning system considering the trade-off of different factors (i.e., indoor air temperature and relative humidity) affecting the indoor thermal comfort. Test results reveal that the proposed control strategy can determine the rational delivery of the cooling supply to the zones considering appropriate importance of objective for thermal comfort.

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