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INDOOR CO_2 CONCENTRATION CONTROL IN MULTI-ZONE ACB AIR-CONDITIONING SYSTEMS

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Abstract. *Indoor Air Quality (IAQ) along with the call for energy-saving has become a hot research topic in recent years. Low ventilation rate consumes less energy but may result in poor air quality, causing health issues for occupants in the long run. Conventional ventilation strategies often result in imbalance in multiple zones served by one HVAC system considering different number of occupants in each zone. This paper presents a model-based control of CO_2 concentration for multi-zone ACB air-conditioning systems aiming at achieving a high IAQ level. A multi-zone CO_2 concentration model is established which takes account of the coupling between neighbour zones. Genetic Algorithm (GA) and Least Squares Method (LSM) are used for parameter identification of the CO_2 model. A control strategy is proposed for the intake airflow rate so that the desired level of the CO_2 concentration can be achieved in the presence of varying number of occupants. Simulations are given to validate the proposed control design.*

Keywords: IAQ, Multi-zone room, CO_2 concentration, Model-based control, Intake airflow rate

1. **Introduction.** Heating, Ventilation and Air Conditioning (HVAC) system plays an important part in buildings and provides a comfortable and healthy environment to people. The HVAC consumes more than 50% of the total building energy consumption. Many studies have been performed aiming to save the energy usage of the HVAC systems since the world energy crisis in the 1970s [1, 2, 3]. With many of the steps having been taken to reduce power consumption, the level of human comfort decreased significantly. And with the term sick building syndrome used to describe people experiencing acute health problems related to indoor poor air quality being introduced, researchers started to pay attention to the IAQ [4]. The outdoor air ventilation rate affects both IAQ and the energy consumption [5]. Low ventilation rate can directly decrease the energy consumption but may also bring about poor indoor quality since air pollutant cannot be discharged promptly. Hence the research of ventilation efficiency is important in order to achieve a desirable IAQ while minimizing energy cost.

There are many existing works using CO_2 concentration for evaluating the IAQ and ventilation. Škrjanc and Šubic [6] proposed an internal model control system with an internal loop, which constantly checks indoor CO_2 concentration, and adjusts the air flow accordingly to achieve the desired CO_2 concentration. Compared with the PI controller, the internal model control results in a better CO_2 concentration. Lu et al. [7] apply the Maximum Likelihood Estimation to estimate space air change rates and further predict transient CO_2 generation rates for an individual space in a great confidence in commercial buildings. In order to be easily adopted for some complex ventilation systems, a novel coupled-method is presented to estimate CO_2 generation rates. Xu et al. [8] also use the

CO_2 as a direct parameter for demand-controlled ventilation since CO_2 is a contaminant of concern in rooms, and present a model-based optimal ventilation control strategy for multi-zone VAV air-conditioning systems aiming at optimizing the intake air flow rate and keeping the IAQ level high with low energy consumption. The number of detected occupants in each zone is used to correct the air flow rate of over-ventilation zones. Model predictive control strategies are used to save energy for HVAC systems.

Considering a multi-zone ACB based air-conditioning system, the requirement of airflow rate of each zone may differ greatly due to the different number of occupants. If we only adjust the intake airflow rate based on the total number of occupants, it may easily result in over-ventilation in some zones while under-ventilation in other zones [9]. In this paper, occupant numbers in different zones are considered when adjusting the intake airflow rate for each zone. Note that the CO_2 concentration in a zone can be affected by those of its neighbouring zones. It is well known that indoor temperature also depends heavily on the intake airflow rate in conventional air-conditioning system such as VAV all-air HVAC systems. So if we try to adjust the ventilation rate to control the CO_2 concentration, it may affect indoor temperature. In this regard, we design a CO_2 concentration controller for HVAC systems with ACB terminals where the indoor temperature can be controlled by both air and water, which means we can control the indoor CO_2 concentration by adjusting the intake airflow rate while controlling the water flow rate to achieve thermal comfort in case when the intake airflow rate cannot meet the requirement of temperature.

In the paper, we firstly present an indoor CO_2 concentration model for multi-zone ACB air-conditioning systems in Section 2. In Section 3, we try to estimate the model parameters by using the GA [10] and LSM, where the optimal values computed by GA will be used as the initial values for the LSM algorithm. We design a controller for the developed bilinear model in Section 4. We introduce the experimental data acquisition process and identification results in Section 5. Some simulations are provided to validate the designed controller in Section 6. Finally, some concluding remarks are shown in Section 7. Compared with [11], this paper adds some experiment results and enriches the corresponding content.

2. **System Model.**

As occupancy of rooms is time-varying, a ventilation system with fixed airflow rate cannot react to the change of the number of the occupants. This paper aims at keeping the CO_2 concentration at a desired level by the regulation of intake airflow [12]. The model describes the change of CO_2 concentration in dependence of the airflow from the ventilation system, the influence of neighbour zones and the amount of CO_2 concentration generated per person in the room [13]. The CO_2 concentration dynamics can be given by

$$v_i \frac{dC_i(t)}{dt} = Q_{oi}(C_0(t) - C_i(t)) + \sum_{j=1}^{N} Q_{ij}(C_j(t) - C_i(t)) + G(t) \tag{1}$$

where v_i is the volume of zone i, $C_0(t)$ is defined as the supply CO_2 concentration, which is usually viewed as a constant C_0; $C_i(t)$ denotes the CO_2 concentration of zone i at time t, $C_j(t)$ is the CO_2 concentration of zone j at time t, N is the number of neighbouring zones of zone i. Q_{oi} is the volumetric airflow rate into zone i, Q_{ij} is the volumetric airflow rate from zone j into (and out of) zone i, and $G(t)$ denotes the CO_2 generation rate in zone i at time t, namely CO_2 concentration exhaled by occupants in zone i.

$G(t)$ can be expressed as

$$G(t) = S * N(t) \tag{2}$$

where S denotes the average CO_2 generation rate of an occupant, $N(t)$ is the number of occupants in each zone at time t.

When CO_2 generation rate $G(t)$ equals zero, Equation (1) can be expressed as:

$$v_i \frac{dC_i(t)}{dt} = Q_{oi}(C_0(t) - C_i(t)) + \sum_{j=1}^{N} Q_{ij}(C_j(t) - C_i(t)) \quad (3)$$

To accurately predict the dynamic responses of process over the period $[kT, (k+1)T)$, $k \geq 0$, the sampling period T is divided into m simulation steps of the time step Δt_{sim}. During a small simulation time step, supply air flow rate outside CO_2 concentration and air flow rate between neighbors are assumed to be constant. Therefore, Equation (3) can be expressed approximately as below by replacing the derivative terms approximately with finite difference terms,

$$v_i \frac{C_i(k+1) - C_i(k)}{\Delta t_{sim}} = Q_{oi}(C_0 - C_i(k)) + \sum_{j=1}^{N} Q_{ij}(C_j(k) - C_i(k)) \quad (4)$$

The obtained Equation (4) can be used to estimate the airflow rate from outside and neighbour zones in this study.

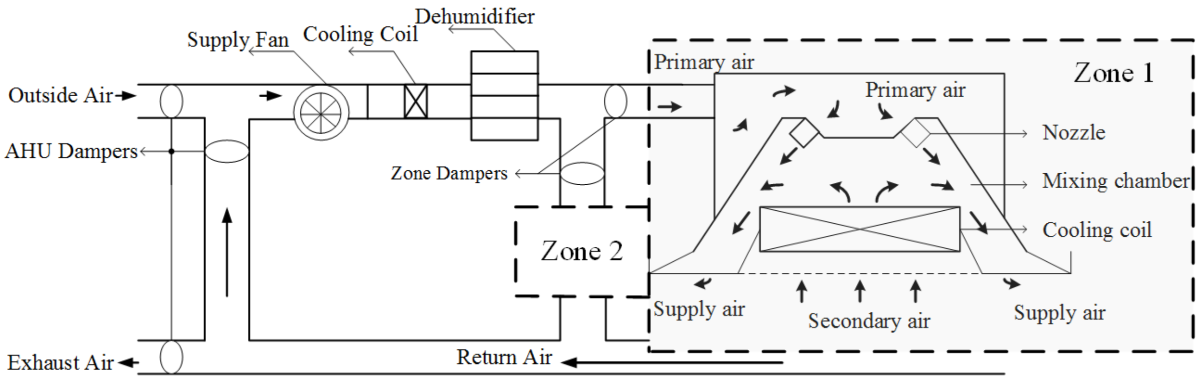

Figure 1. Schematic diagram of HVAC system with ACB terminals

3. Parameter Identification of Dynamic Zone Model.

Having derived a CO_2 concentration model for a zone, we try to find optimal parameters that best fit with the experimental data. In this paper, optimal parameters are found by using GA and LSM. According to Equation (1), the parameters are Q_{oi} and $Q_{ij}(j = 1, \ldots, N)$, and S in Equation (2). GA is a search method by using natural selection and survival of the fit test in the biological word. The objective function o of Equation (4) employs sum square errors.

$$o(Q_{oi}, Q_{ij}(j = 1, \ldots, N)) = \sum_{k=1}^{m} \left(C'_{ik}(t) - C_{ik}(t)\right)^2$$

where m is the sample data numbers, C_{ik} and C'_{ik} are the fitted and measured zone CO_2 concentration respectively, and all the sample data are added together. We introduce a fitness function f as follows, which is the reciprocal of the objective function.

$$f(Q_{oi}, Q_{ij}(j = 1, \ldots, N)) = \frac{1}{o(Q_{oi}, Q_{ij}(j = 1, \ldots, N))}$$

The fitness function is responsible for performing this evaluation and returning a positive integer number, or fitness value. The value is then used in a process of natural selection to choose which potential solutions will continue on to the next generation, and which will die out, reflecting how optimal the solution is: the higher the number, the better the solution. The optimal parameters computed by GA are then used as the initial values of LSM, which not only reduces the computation, but also makes the model better fit with the measured data. For the CO_2 concentration model, Q_{oi} and $Q_{ij} (j = 1, \dots, N)$, can be firstly identified according to Equation (4), which can be expressed as follows,

$$C_i(k+1) = C_i(k) + \frac{\Delta t_{sim}}{v_i}((C_0 - C_i(k))Q_{oi} + \sum_{j=1}^{N}(C_j(k) - C_i(k))Q_{ij}) + n_k$$

where n_k denotes the kth measurement noise. Observe that

$$\begin{aligned} C_i(k) - C_i(k-1) = & \frac{\Delta t_{sim}}{v_i}((C_0 - C_i(k-1))Q_{oi} \\ & + \sum_{j=1}^{N}(C_j(k-1) - C_i(k-1))Q_{ij}) + n_{k-1} \ (k > 1) \end{aligned}$$

We adopt the notation $\mathbf{X} = [C_i(2) - C_i(1), C_i(3) - C_i(2), \dots, C_i(k) - C_i(k-1)]^T$ as the $(k-1) \times 1$ observed vector, $\mathbf{H} = [H_1^T, H_2^T, \dots, H_{k-1}^T]^T$ as the $(k-1) \times (N+1)$ observed matrix, where $H_m = [C_0 - C_i(m),\ C_1(m) - C_i(m), \dots, C_N(m) - C_i(m)]$ $(m = 1, \dots, k-1)$, $\mathbf{Q} = [Q_{oi}, Q_{i1}, \dots, Q_{iN}]^T$ as the $(N+1) \times 1$ estimated vector, $\mathbf{n} = [n_1,\ n_2, \dots, n_{k-1}]^T$ as the $(k-1) \times 1$ observed noise vector. Then the model can be expressed in matrix equation as

$$\mathbf{X} = \mathbf{HQ} + \mathbf{n}$$

The estimated $\hat{\mathbf{Q}}$ minimizes the performance function

$$J\left(\hat{\mathbf{Q}}\right) = \left(\mathbf{X} - \mathbf{H}\hat{\mathbf{Q}}\right)^{\mathbf{T}} \left(\mathbf{X} - \mathbf{H}\hat{\mathbf{Q}}\right) \tag{5}$$

Because the room has no occupant at night after 1:00am, $G(t)$ can be considered as zero. Then Q_{oi} and $Q_{ij} (j = 1, \dots, N)$ can be obtained by using the data at that time. After Q_{oi} and $Q_{ij} (j = 1, \dots, N)$ have been estimated, we try to estimate parameter S in Equation (2) and further to obtain G in every sampling period by using the discretized Equation (1). $N(t)$ can be obtained by using the WiFi detection system [14]. We estimate S to improve fitting precision.

4. **Controller Design.** According to the bilinear Equation (1), the change of CO_2 concentration can be controlled by Q_{oi}. This means Q_{oi} is the input and $C_i(t)$ is the controlled variable [15]. $G(t)$ can be derived from the detected occupants number, so we can define Q'_{oi} as,

$$Q'_{oi} = Q_{oi} + \frac{G(t)}{C_0 - C_i(t)} \tag{6}$$

As $\frac{G(t)}{C_0 - C_i(t)}$ can be known at every time t, then Q'_{oi} can be viewed as system input which has the same meaning with Q_{oi}. Then Equation (1) can be rewritten as,

$$v_i \frac{dC_i(t)}{dt} = Q'_{oi}(C_0 - C_i(t)) + \sum_{j=1}^{N} Q_{ij}(C_j(t) - C_i(t)) \tag{7}$$

Here we introduce $x_i(t) = C_i(t) - C^*$, C^* denotes the expected CO_2 concentration in the room, where $x_i(t)$ means the difference between the reference value and the observed CO_2 value at time t. Then Equation (7) can be rewritten as

$$\begin{aligned} v_i \frac{dx_i(t)}{dt} &= Q'_{oi}(C_0 - C^* + C^* - C_i(t)) + \sum_{j=1}^{N} Q_{ij}(C_j(t) - C^* + C^* - C_i(t)) \\ &= Q'_{oi}(C_0 - C^* - x_i(t)) + \sum_{j=1}^{N} Q_{ij}(x_j(t) - x_i(t)) \end{aligned} \tag{8}$$

In this system, indoor CO_2 concentration is always greater than outdoor CO_2 concentration because of exhaling of indoor occupants. So the initial condition can be given as $C_i(0) > C_0$. In fact, when $C_i(0) \leq C_0$, we do not need to use controller to control indoor CO_2 concentration any more. However, owing to the indoor occupants, $\exists t_0$, $C_i(t_0) > C_0$, then we can view t_0 as the virtual initial time.

Theorem 4.1. *Consider the system in bilinear Equation (1), let the controller be given by*

$$Q_{oi} = C_i(t) - C^* - \frac{G(t)}{C_0 - C_i(t)} \tag{9}$$

Then all the states asymptotically converge to zero.

Proof: Firstly as $x_i(0) > C_0 - C^*$, for any i, once $x_i(t)$ approaches $C_0 - C^*$, which can be viewed as the smallest state, namely $x_j(t) \geq \cdots \geq x_i(t)$; so $\sum_{j=1}^{N} Q_{ij}(x_j(t) - x_i(t)) \geq 0$, then from Equation (8), $\frac{dx_i(t)}{dt} \geq 0$. So $x_i(t) \geq x_i(0)$. That is to say, $x_i(t)$ will never reach $C_0 - C^*$ in finite time.

We set $X = [x_1, \ldots, x_n]^T$. Then the following Lyapunov functional candidate is defined to assess the convergence to the origin:

$$V(t) = \| X \|_\infty$$

$V(t)$ can be written as $V(t) = \max\{|x_1|, \ldots, |x_n|\}$. In the following, we will prove that the derivative of $V(t)$ as $\dot{V}(t)$ is negative when $t \geq 0$. Firstly, we assume $\| X \|_\infty = |x_i|$, then $|x_i| \geq \cdots \geq |x_j| \geq 0$. We denote $sign[.]$ the signum function. According to Equation (8), we see that

$$\begin{aligned} \dot{V}(t) &= \frac{d|x_i(t)|}{dt} = sign[x_i(t)]\frac{dx_i(t)}{dt} \\ &= \frac{1}{v_i} sign[x_i(t)] \left[x_i(t)(C_0 - C^* - x_i(t)) + \sum_{j=1}^{N} Q_{ij}(x_j(t) - x_i(t)) \right] \end{aligned}$$

It is noted that $x_i(t) > C_0 - C^*$, and $sign[x_i(t)]x_i(t) = |x_i|$. So $\frac{1}{v_i}|x_i|(C_0 - C^* - x_i(t)) \leq 0$.

As $|x_i(t)| \geq \cdots \geq |x_j(t)| \geq 0$, when $x_i(t) < 0$, $\sum_{j=1}^{N} Q_{ij}(x_j(t) - x_i(t)) \geq 0$, Then it follows that $\dot{V}(t) < 0$; when $x_i(t) \geq 0$, $\sum_{j=1}^{N} Q_{ij}(x_j(t) - x_i(t)) \leq 0$, we can also get that $\dot{V}(t) \leq 0$. $\dot{V}(t) = 0$; therefore, the states will converge to the region where, i.e.,

$$0 = x_i(t)(C_0 - C^* - x_i(t)) + \sum_{j=1}^{N} Q_{ij}(x_j(t) - x_i(t))$$

As $|x_i(t)| \geq \cdots \geq |x_j(t)| \geq 0$, $x_j(t) - x_i(t) \leq 0$. So $x_i(t) \leq 0$, and combining with $x_i(t) \geq 0$, we obtain $x_i(t) = 0$.

It is concluded that $\dot{V}(t) < 0$ almost everywhere, that is $\dot{V}(t) = 0$ happens only if $x_i(t) = 0$. Hence, the system is of asymptotic convergence. □

In this study, we use this controller into multi-zone ACB air-conditioning systems, occupant numbers in different zones are considered when adjusting the intake airflow rate for each zone, and CO_2 concentration in a zone affected by those of its neighbouring zones are also considered, which can effectively improve IAQ when the rapid acceleration of indoor persons and realize energy conservation to some extent.

5. **The Experimental Data Acquisition.** The multi-zone ACB air-conditioning system is illustrated in Figure 2. The lab was divided into four zones corresponding to four ACB terminals. CO_2 sensors were put at the places indicated by circle as shown in Figure 2 and fixed on stands with height of 1.5m.

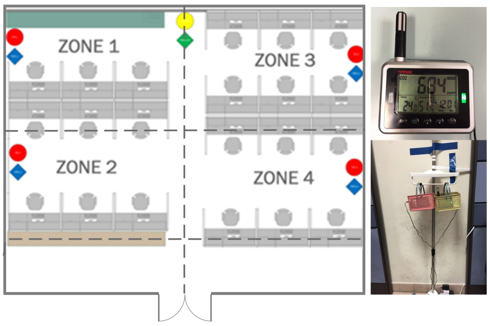

FIGURE 2. Test site and sensor layout of multiple zones

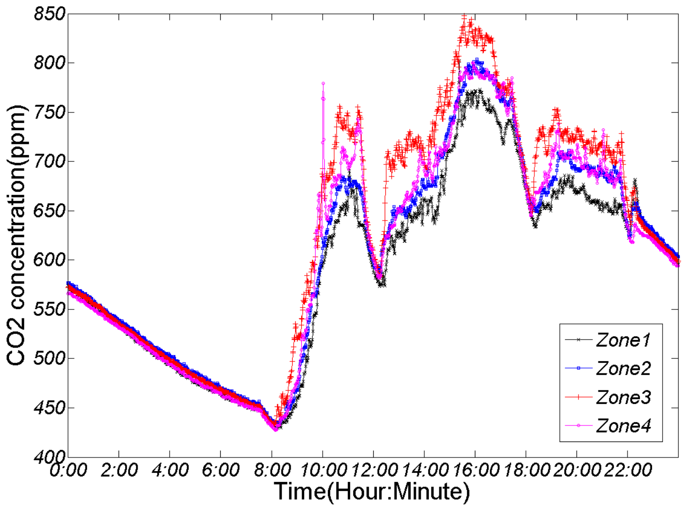

FIGURE 3. CO_2 concentrations in each zone

Refer to ASHRAE standard, and CO_2 at very high concentration levels can pose a health risk. CO_2 concentration almost never reaches these levels in most buildings, however, is generally greater than outdoor air CO_2 concentrations because of exhaling CO_2 of occupants. Outdoor air CO_2 typically ranges from 300ppm to 500ppm. In this paper, we measure outdoor CO_2 concentration as 470ppm which can be used as supply CO_2 concentration. We can see from Figure 3 that indoor CO_2 concentration in any zone is greater than outdoor CO_2 concentration due to the presence of human beings. From Figure 4 we know that the numbers of occupants vary in four zones. Occupants start to come around 8:30am and the CO_2 concentration in each zone tracks this trend well. We also notice that during lunch time around 12:00am and off duty 5:00pm, sharp transitions happen, where CO_2 concentrations decrease accordingly. There is no occupant in the lab during night time so CO_2 concentration trends are relatively more stable than that of daytime.

After acquiring the experimental data, we carry out parameter identification of zone 1 and zone 2, and the fitting results are shown in the following figures. Figure 5 shows the fitting result of Q'_{o1}, Q'_{o2} and Q_{12}. The data after 1:00am are chosen and Equation (4) is used as fitting function. Then we use the discretized form of Equation (1), Equation (2) and the obtained values of Q'_{o1}, Q'_{o2} and Q_{12} to estimate S. The occupant numbers from 8:30am to 3:45pm are collected every 15 minutes. We can see from Figure 6 that the CO_2 concentration of zone 1 changes according to the occupants number. By using the proposed identification method, the estimated value of S is obtained. Now we try to predict the CO_2 concentration of zone 1 by using the obtained parameter values to demonstrate

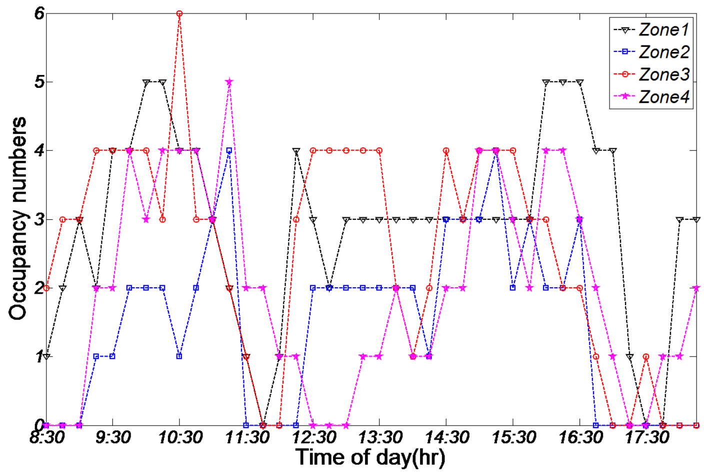

FIGURE 4. Occupants number in each zone

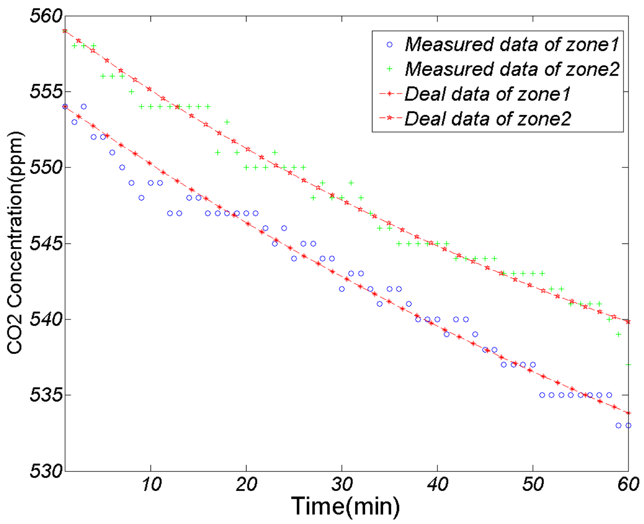

FIGURE 5. The fitting result of Q'_{o1}, Q'_{o2} and Q_{12}

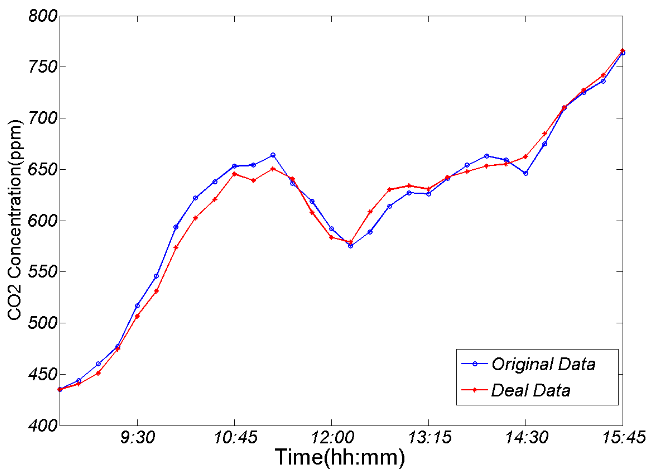

FIGURE 6. The fitting result of S

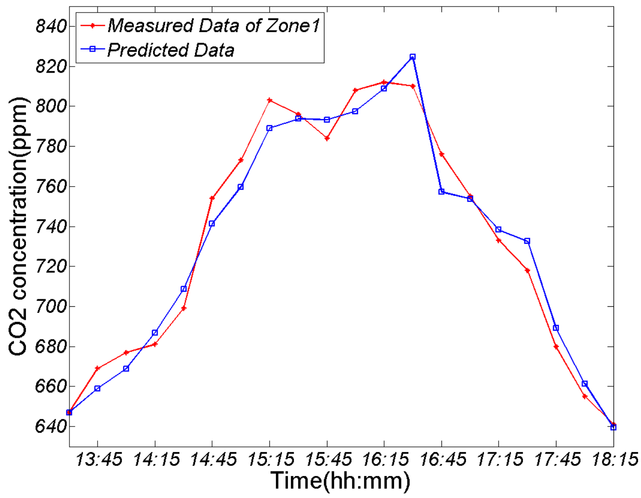

FIGURE 7. Prediction of CO_2 concentration by using the identified parameters

the effectiveness of the estimated model. The occupants number and measured CO_2 concentration of zone 1 on another day are collected. The comparison between the predicted concentration and the measured one can be seen from Figure 7. The model can fit the real CO_2 concentration well as shown in the figure, which also reflects the change of CO_2 concentration according to the occupants number accurately. So the identified parameters can be used in our experiments, the estimated Q_{12} and S can be used in simulations, Q'_{o1}, Q'_{o2} are viewed as system input and we adjust them to keep CO_2 to the expected value.

6. **Simulations.** According to IAQ guidelines in EU standard, CO_2 concentration between 485ppm and 875ppm is the lowest threshold which may make 5.8% of people feeling unwell. So we set the desired indoor CO_2 concentration as 500ppm, namely $C^* = 500$ppm. We can see there is a passage between zone 1 and zone 3, zone 2 and zone 4 from Figure 2. We just consider zone 1 and zone 2 in this simulation, and zone 2 is the neighbour of zone 1. So the system can be expressed as

$$v_1 \frac{dx_1(t)}{dt} = -Q'_{o1}(30 + x_1(t)) + Q_{12}(x_2(t) - x_1(t)) \tag{10}$$

$$v_2 \frac{dx_2(t)}{dt} = -Q'_{o2}(30 + x_2(t)) + Q_{21}(x_1(t) - x_2(t)) \tag{11}$$

where $Q = \left[Q'_{o1}, Q'_{o2}\right]^T$ is the system input, $X = [x_1, x_2]^T$ is the system state, $x_1 = C_1 - C^*$, $x_2 = C_2 - C^*$. And the parameter values have been obtained from the last section. Then the initial values of states X are chosen as $X(0) = [147, 78]^T$. Using the controller in Equation (9), namely $Q = [x_1, x_2]^T$, a simulation is conducted for one sampling period. The evolutions of the states in Equation (10) and Equation (11) are shown in Figure 8 respectively. It can be seen that each state reaches zero, that is to say, CO_2 concentrations of zone 1 and zone 2 reach the desired values asymptotically.

Now we try to adjust the actual intake airflow rate when indoor occupant numbers changed, and the real numbers can be obtained by using the WIFI localization system. We assume that the occupant numbers of zone 1 and zone 2 can be detected every one minute and the numbers are as shown in Figure 9. According to Equation (2) and Equation (5), Q_{o1} and Q_{o2} can be obtained. Since the zone occupants number is taken into consideration, the situation of over-ventilation in some zones while under-ventilation in other zones will not happen. In Figure 10 the effect of the designed control is presented. We firstly use the estimated parameters to predict the CO_2 concentration versus the number of occupants

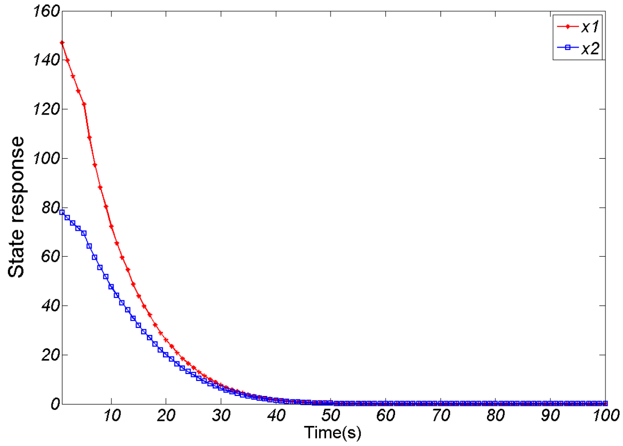

FIGURE 8. Evolution of state for each zone

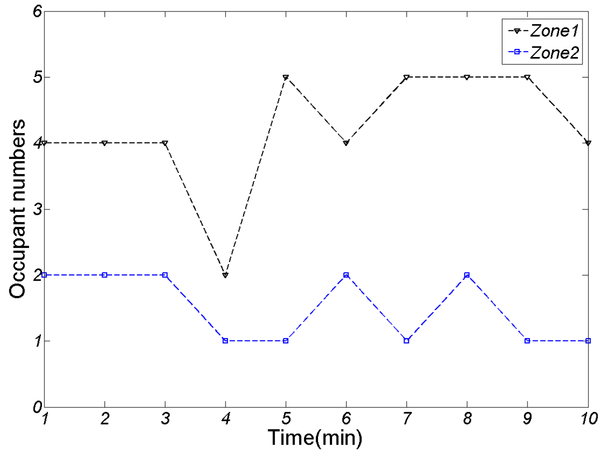

FIGURE 9. Occupant numbers of each Zone

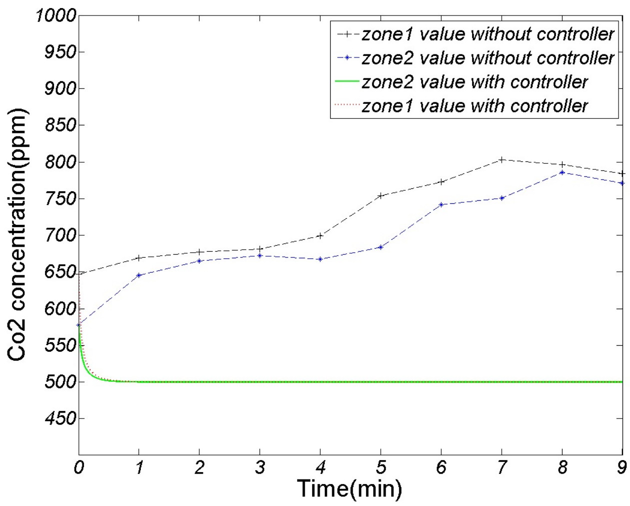

FIGURE 10. CO_2 concentrations with or without controller

as shown in Figure 10. The CO_2 concentration changes with different occupants number and is always greater than the desired value. The occupancy level changes every one minute, and zone 1 CO_2 concentration is higher than that of zone 2 because of its higher number of occupants as shown in Figure 9. However, with the designed controller, the CO_2 concentration can reach the desired value less than one minute in the simulation. That is to say, when the occupancy level changes, the input also changes accordingly, so the CO_2 concentration can be regulated within a relative short period of time.

7. **Conclusions.** In this paper, a model-based control of CO_2 concentration in multi-zone ACB air-conditioning systems has been proposed to keep the IAQ at a suitable level. The number of occupants in each zone was taken into consideration to avoid over-ventilation in some zones while under-ventilation in other zones, which in a sense reduced energy consumption. A simple first order model with couplings from neighbours has been used to estimate the CO_2 concentration in the room. GA and LSM were adopted for parameter identification. The model was experimentally verified in the test lab, and the fitting and predicting results have been shown to be promising. A simple controller was proposed to regulate the intake airflow rate so as to achieve the desired CO_2 concentration and a Lyapunov function approach was introduced to prove the stability of the system. Simulations showed that the controller can effectively achieve the desired indoor CO_2 concentration regardless of the number of occupants.

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