Air conditioning system online control by incorporating low-dimensional linear models and intelligent predictions

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Abstract. Development of control techniques for heating, ventilation and air conditioning (HVAC) systems to provide occupancy driven energy and comfort management has been an active area. In this study, we carried out the work on the balance between indoor environmental quality (IEQ) and energy consumption with low-dimensional linear models (LLM), artificial neural network (ANN) and contribution ratio of indoor climate (CRI) to provide support for HVAC control. In general, ventilation (pollutant) and temperature factors were both considered in the CFD simulation. Linear ventilation model (LVM) and linear temperature model (LTM) were employed to expand the CFD database. Then, combined with ANN, CRI and LLM, LLVM (low-dimensional linear ventilation model)-based ANN and LLTM (low-dimensional linear temperature model)-based CRI could rapidly predict the indoor environmental parameters. The evaluation indices were also defined to provide weightings between indoor environment and energy consumption. On this basis, the HVAC energy consumption caused by ventilation and air conditioning loads could be decreased by 50% and 16% respectively. This study will promote an intelligent HVAC control strategy for user comfort and HVAC energy conservation.

1. Introduction

As the largest energy consuming sector, the worldwide energy consumption of buildings has increased from 102 to 120 EJ between 2000 and 2012 [1]. With regard to this severe issue, the public buildings have occupied the dominant position of energy consumption [2]. For such buildings with large space and people flow, the growth in building energy consumption is due to flexible indoor environment quality (IEQ) which covers indoor air quality (IAQ) and indoor thermal comfort (ITC) [3, 4]. In order to have more comforting indoor environment, higher amounts of energy will be consumed. Thus, it is important for the buildings to synthetically manage the indoor environment and energy consumption. Heating ventilation and air conditioning (HVAC) system has been widely utilized for better IEQ, and lessening HVAC energy is sought without conceding to IEQ. In this circumstance, one control strategy based on real indoor environmental responses will be a reasonable proposal for HVAC energy management by comprehensively and separately assessing the indoor environmental parameters.

In this work, the originalities were listed as follows. (i) The ventilation (pollutant) and temperature factors were synthetically considered. (ii) Nonuniform and nonlinear indoor environment have been studied. (iii) The real indoor environmental responses were studied by using artificial neural network (ANN) and contribution ratio of indoor climate (CRI) to combine with computational fluid dynamics (CFD). Besides, low-dimensional linear model (LLM) was used to improve the prediction efficiency.

2. Methodology and model development

On the basis of self-defined evaluation indices, this study was to comprehensively assess the indoor environmental parameters and energy consumption for HVAC control in two steps, including: (i) the balance between pollutant concentration (IAQ) and ACH; (ii) the balance between indoor temperature
(ITC) and air condition load (or supply air temperature). In this study, the full-scale size of indoor chamber was 3.5m (length) × 3.4m (width) × 2.5m (height), and only the ventilation mode with the top air supply and return grilles was considered.

2.1. Low-dimensional models (LM)

The LM was used by one discrete method to reduce the amount of grid data. First of all, the CFD grid with the volume Ω was divided into numerous cubes (i) with the volume Ωₐ(i) (i << grid number). Then, the coordinates of cube (i) were allocated into group (i) with the corresponding data. Next, the volume average value of cube (i) was calculated in the group (i) to realize the low-dimensional representation.

2.2. Linear ventilation models (LVM) and linear temperature models (LTM)

If there were several pollutant sources in the room, LVM could be used to reconstruct the pollutant concentration fields, i.e., the concentration field caused by multiple pollution sources was equal to the superposition result from total single pollution sources [5]. Similarly, if the buoyancy caused by temperature had petite effect on the airflow, it could be supposed that the temperature field was linear [6]. Further, low-dimensional linear models (LLM) would be well combined with LVM and LTM.

2.3. Artificial neural network (ANN) and contribution ratio of indoor climate (CRI)

ANN was a method which was capable of associating a large number of input and output quantities. In this work, ACH as well as pollutant sources were inputs and CO₂ level was output. Then, based on LTM, contribution ratio of indoor climate (CRI) was used to judge the effect of each single heat source on indoor temperature distribution [6]. The CRI of the heat source m at the location xᵢ was defined as:

\[ CRI_m(x_i) = \frac{\Delta T_m(x_i)}{\Delta T_{m,0}} = \frac{T_m(x_i) - T_n}{T_{m,0} - T_n} = \frac{Q_m}{C_p \rho V} \]

(1)

The xᵢ is the spatial coordinates (i = 1, 2, 3 for x, y, z); Qₘ is the convective heat transfer from source m; Cₚ is the specific heat of indoor air; ρ is the air density; V is the volume of supply air; Tₙ is the neutral temperature; Tₘ₀ is the temperature of the room when the heat transfer Qₘ from heat source m is diffused uniformly; Tₘ₀(xᵢ) is the temperature at position xᵢ caused by heat source m.

2.4. Optimal strategies for HVAC system control

The next step was to apply some evaluation indices to realize HVAC control by the optimal selections of ACH and supply air temperature. In this study, the minimum value of Eᵥ and Eₜ corresponded to the optimal control strategy. The evaluation indices Eᵥ and Eₜ were defined as follows:

\[ E_v = w_{v1} \frac{ACH}{Max(ACH)} + w_{v2} \frac{C_{mean}}{Max(C_{mean})} \]

(2)

\[ E_T = w_{T1} \frac{T_s}{Max(T_s)} + w_{T2} \frac{|PMV|}{Max(|PMV|)} \]

(3)

The wᵥ1 and wᵥ2 are the weights for ACH and C_mean; and wₜ1 and wₜ2 are the weights for Tₛ (supply air temperature) and PMV (absolute value). Hereinto, we adopted the coefficient of variation (CV) to calculate the weights in this work [7], and PMV was calculated according to the ASHRAE 55-2013.

3. Results

3.1. Step one: optimal ACH to control indoor air quality (IAQ) and energy consumption

3.1.1. Case setup. In this case, the effect of the positions of pollutant sources (CO₂) on IAQ was considered in the cooperation of different ACHs. There were a total of four indoor CO₂ sources A, B, C and D, of which the coordinates were respectively (0.875, 2.55, 1.1), (2.625, 2.55, 1.1), (0.875, 0.85, 1.1) and (2.625, 0.85, 1.1) m. Furthermore, five different ACHs (4, 6, 8, 10 and 12) were considered.

3.1.2. Validation of CO₂ concentration by using LVM and ANN. Figure 1 (a) showed the CO₂ concentration fields respectively from CFD simulation and LVM. The results revealed that the CO₂
concentration acquired by CFD and LVM were almost the same except for the location of pollutant source. Figure 1 (b) showed the CO₂ distributions between CFD and ANN methods, and the concentrations obtained from ANN agreed well with the direct CFD.

Figure 1. (a) Comparisons of CO₂ concentrations (ppm) respectively from CFD and LVM with two pollutant sources (A and B) and ACH equal to 8 at the plane of z = 1.1m; (b) comparisons of CO₂ concentrations (ppm) between CFD and ANN methods when ACH equal to 7 and pollutant source located at position A at the plane of z = 1.1m.

3.1.3. Validation of CO₂ concentration by using LLVM (low-dimensional linear ventilation model)-based ANN. As ACH equal to 7 and the pollutant sources located at the positions A and B, we compared the prediction results obtained from LLVM-based ANN with the CFD simulation, as displayed in Figure 2. Clearly, the depiction of LLVM-based ANN was in good agreement with the CFD outcome (the mean error was less than 10%) excluding around the source locations.

3.1.4. Application of LLVM-based ANN for a control strategy to balance IAQ and ACH. In view of four pollutant sources, Table 1 showed the selections of the optimal ACH and the corresponding effects after control. In Table 1, the optimum ACH with four pollutant sources was equal to 8. Besides, this optimal ACH could be efficient in reducing the ventilation energy consumption by 33.3%.

Table 1. ACH selection results for the optimal strategy and corresponding energy saving benefits after control considering four pollutant sources.

| Positions of pollutant sources | After control |
|-------------------------------|--------------|
| A                             | B            | C             | D             | ACH | Energy saving |
| √                             | √            | √             | √             | 8   | 33.3%         |

Figure 2. Comparisons of CO₂ concentrations (ppm) between CFD and LLVM-based ANN with A and B source positions and ACH equal to 7.
3.2. Step two: optimal cooling load to control indoor thermal comfort (ITC) and energy consumption based on optimal ACH

3.2.1. Case setup. The thermal model with multiple heat sources was used. The HVAC system has been installed with the varying supply air temperature (289-295K). Four heating bodies (including 85W human body and 50W personal computer) with the size of 0.2m (length) × 0.2m (width) × 1.1m (height) were added corresponding to four pollutant sources. Besides, one window was set on the east wall (outdoor temperature: 298-306K) with the size of 1.5m (length) × 1.0m (width) × 0.01m (height).

3.2.2. Validation of temperature distribution by using linear temperature model (LTM). When we looked at Figure 3, it could be concluded that the errors between the CFD result and the temperature field obtained by LTM would not exceed 1.50K except for few zones. Generally speaking, it was appreciated the accuracy of LTM could be sufficiently fine in the engineering applications.

3.2.3. Validation of temperature prediction by using contribution ratio of indoor climate (CRI). Figure 4 indicated the indoor temperature distributions between CRI and CFD results. It was not difficult to find that the CRI could make accurate prediction of temperature fields with the temperature errors kept around ±1K. Hence, the CRI prediction would be feasible in engineering applications.

![Figure 3](image1.png)

**Figure 3.** Comparisons of temperature (K) between CFD and LTM with one thermal condition: heating body (85W) and window (outdoor temperature: 298K).

![Figure 4](image2.png)

**Figure 4.** Comparisons of temperature (K) obtained by CFD and CRI with one thermal condition: supply air (292K), heating body (85W) and window (outdoor temperature: 298K).

3.2.4. Validation of temperature distribution by using LLTM (low-dimensional linear temperature model)-based CRI. Figure 5 depicted the temperature comparisons between LLTM-based CRI and CFD. It was clear that the temperature representation of LLTM-based CRI agreed well with CFD (maximum less than 1%) and LLTM could efficiently predict the temperature distribution.
3.2.5. Application of LLTM-based CRI for a control strategy to balance indoor thermal comfort and cooling load. Table 2 showed one result of optimal supply air temperature after control. The PMV value was very close to zero, which has proved the effectiveness of this control strategy for HVAC. By this time, the energy consumption of air conditioning terminal could be decreased again to a great extent (with the maximum up to 16%) on the basis of optimal ACH.

Table 2. The selection result of supply air temperature for the optimal strategy and corresponding PMV values after control considering one parameter of heating body.

| Outdoor temperature: 298K (25°C) | After control |
|----------------------------------|---------------|
| Parameters of heating body (W)   | Supply air temperature | PMV  |
| 135                              | 135           | 135  |
|                                  | 291K (18°C)   | ≈0.00|

4. Conclusions

In this work, we aimed to create a healthy and energy-efficient indoor environment through the step-by-step HVAC control strategy both considering IAQ and ITC. The conclusions were as follows.

(1) LVM and LTM were both consistent with CFD for prediction of indoor environmental parameters.
(2) ANN and CRI showed good performance in the indoor environmental prediction with the maximum error less than 10%. Furthermore, LLVM-based ANN and LLTM-based CRI could make more effective predictions about indoor environment.
(3) This control strategy could significantly decrease the energy consumption caused by ACH and air conditioning loads with the maximum percentages up to 50% and 16%, respectively.

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