Fast prediction for multi-parameters (concentration, temperature and humidity) of indoor environment towards the online control of HVAC system

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Abstract

Heating, ventilation and air conditioning (HVAC) systems are the most energy-consuming building implements for the improvement of indoor environmental quality (IEQ). We have developed the optimal control strategies for HVAC system to respectively achieve the optimal selections of ventilation rate and supplied air temperature with consideration of energy conservation, through the fast prediction methods by using low-dimensional linear ventilation model (LLVM) based artificial neural network (ANN) and low-dimensional linear temperature model (LLTM) based contribution ratio of indoor climate ($CRI_{(T)}$). To be continued for integrated control of multi-parameters, we further developed the fast prediction model for indoor humidity by using low-dimensional linear humidity model (LLHM) and contribution ratio of indoor humidity ($CRI_{(H)}$), and thermal sensation index (TS) for assessment. CFD was used to construct the prediction database for CO_2 , temperature and humidity. Low-dimensional linear models (LLM), including LLVM, LLTM and LLHM, were adopted to expand database for the sake of data storage reduction. Then, coupling with ANN, $CRI_{(T)}$ and $CRI_{(H)}$, the distributions of indoor CO_2 concentration, temperature, and humidity were rapidly predicted on the basis of LLVM-based ANN, LLTM-based $CRI_{(T)}$ and LLHM-based $CRI_{(H)}$, respectively. Finally, according to the self-defined indices (i.e., E_v , E_t , E_h), the optimal balancing between IEQ (indicated by CO_2 concentration, PMV and TS) and energy consumption (indicated by ventilation rate, supplied air temperature and humidity) were synthetically evaluated. The total HVAC energy consumption could be reduced by 35% on the strength of current control strategies. This work can further contribute to development of the intelligent online control for HVAC systems.

Keywords

HVAC system,
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1 Introduction

HVAC (Heating, ventilation and air conditioning) systems play an important role in improving air quality (Chen et al. 2018) and thermal comfort (Bluyssen et al. 2011; Lai et al. 2020) of building environment. In the region with hot summer and cold winter, HVAC systems are always designed with larger loads to ensure the comfort of occupants and indoor air quality, while it can also cause significant energy consumption, especially in summer (Pérez-Lombard et al.

2008; Kim and Yu 2018). A recent study shows that building energy consumption accounts for 40% of global final energy use (Yuan et al. 2020). Among the large building energy consumption, HVAC systems account for more than 50% of the total building energy consumption (Zhuang and Wang 2020; Tian et al. 2020), especially in non-residential buildings (e.g., commercial and office buildings), where the share of energy consumption is as high as 60% (Grosskopf et al. 2008). However, the traditional operation of HVAC systems cannot be self-adjusted according to the real time

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characteristics of dynamic changes and non-uniform distribution of indoor environment, which can easily cause the comfort instability and energy waste (Ren and Cao 2019a). From the perspectives of the dynamic demands of the indoor environment and the energy efficiency, it seems that the traditional HVAC control methods are no longer stable and reliable (Wang et al. 2020). Therefore, it is of great significance to propose and develop new HVAC control methods following real-time demand with the consideration of dynamic changes and non-uniform distributions of indoor environment.

The HVAC systems are used to regulate indoor ventilation rate (to mitigate pollutant concentration), temperature and humidity to meet the requirements of indoor air quality and thermal comfort (Anand et al. 2020). Different control strategies for HVAC systems in actual operation can result in different parameters of air supply into the room (ASHRAE 2009), which can affect the energy consumption of the HVAC system and the health of indoor personnel. Therefore, researchers have carried out a large number of studies on control methods from multiple aspects, such as HVAC equipment control, online monitoring control, model predictive control (MPC) and building energy management system control (MBC), etc. Ganchev et al. (2019) saved energy consumption of HVAC systems by improving the efficiency of the cooling equipment and optimizing the operating rate of the equipment. Monitoring of indoor ventilation parameters (CO_2) can be conducted in buildings for the diagnostic control of HVAC systems to save energy (Li et al. 2018). Moroşan et al. (2010) improved regional comfort and energy savings by using decentralized, centralized, and distributed MPCs for simulation of regional temperature regulation. Gul and Patidar (2015) proposed an integrated building energy management system (BMS) to manage and control the HVAC system to save building energy consumption through research and learning on building energy consumption habits. However, these control methods didn't consider the non-uniform distribution of indoor environment parameters along with dynamic changes, and they are not able to quickly respond to instant variation of the indoor environment through the fast prediction of the non-uniform distribution of the indoor environment, thus failing to ensure the actual demand of the indoor air quality and thermal comfort.

For this, a fast-predictive intelligent control for HVAC system based on real-time environmental response (e.g., dynamic sources of pollutants, heat) was proposed to achieve a balanced and coordinated indoor environmental distribution and energy consumption, which is consisted of three key steps: monitoring, prediction and control (Ren and Cao 2020). Monitoring is the use of limited sensors to monitor changes in regulated environmental parameters

(e.g., pollutant concentration, temperature), automatically recording monitoring data as input. Based on monitoring data of targeted environment parameters, it is able to make rapid predictions for the non-uniform distributions of indoor environment parameters by using faster-than-real-time prediction models, whose prediction time is much less than the actual diffusion time of indoor environmental parameters, thus making indoor environmental conditioning more safer and reliable (Cao and Ren 2018; Cao 2019). Finally, the predicted indoor environments will be assessed by environmental evaluation indicators, to minimize the energy consumption within acceptable environmental requirements to realize the dynamic control of intelligent HVAC systems. This is also named as intelligent ventilation online control strategy (to largely mitigate indoor air pollution with the maximize ventilation efficiency) (Cao and Ren 2018), where the fast prediction was realized by a combination of low-dimensional linear ventilation model and artificial neural network (i.e., LLVM-based ANN). On the basis of Cao and Ren (2018), Ren and Cao (2019a) further proposed a low-dimensional linear temperature model for the fast prediction of indoor temperature based on $\text{CRI}_{(T)}$ (Zhang et al. 2013) (i.e., LLTM-based $\text{CRI}_{(T)}$). Custom evaluation indices for ventilation and temperature were respectively defined, i.e., E_V and E_T , further to well regulate the HVAC system (Ren and Cao 2019a).

However, previous studies integrated online control of contaminant concentrations and temperature but without considering the indoor humidity factors on indoor thermal comfort and HVAC energy consumption. Unlike the effect of ventilation rate and temperature, humidity not only affects a person's heat sensation, but also has more of an effect on a person's physical health. For example, low humidity can lead to the symptoms of dry skin, mouth and throat (Hashiguchi et al. 2005), and also induce mucous membrane, eye sensation, bronchitis, asthma, influenza (Sato et al. 2003; Jaakkola et al. 2014), and static electricity (Paasi et al. 2001; Egawa et al. 2002). The high humidity environment can cause dust mites and moulds on building walls, which in turn can lead to poorer indoor conditions, respiratory discomfort and allergic reactions among indoor workers (Fisk et al. 2007). Humidity also has a significant impact on the energy consumption of the HVAC system. It has been shown that in an effective ventilation system, reducing the indoor relative humidity (RH) setting from 60% to 50% increases total energy consumption by a maximum of 22.4% (Fang et al. 2011; Shehadi 2018). Considering that humidity is important for both indoor environment and energy conservation, in this study we aim to incorporate humidity into fast prediction and online control of environmental parameters along with temperature and pollutant concentration.

In previous work, we have achieved rapid prediction of indoor pollutant concentration and temperature, similarly, for rapid prediction and control of indoor humidity, the establishment of a rapid prediction model is a main focus of achieving online control of indoor humidity. CFD simulation can be effective for indoor humidity, but it will consume a lot of time (Huang et al. 2011). Based on the uniformity of indoor humidity distribution, a low-dimensional humidity model (LLHM) combined with a $CRI_{(H)}$ prediction (Huang et al. 2011) method (i.e., LLHM-based $CRI_{(H)}$) is proposed to realize rapid prediction of indoor humidity distribution while ensuring the prediction accuracy within the acceptable range. Therefore, for the rapid control of humidity, in order to balance the thermal comfort of the indoor body and energy consumption, the indoor humidity evaluation index (E_H) has been defined, so that the indoor humidity distribution is evaluated for rapid feedback and control. Up to this point, we propose an online control strategy for the integrated regulation of HVAC systems in terms of ventilation rate, temperature and humidity, potentially based on the adjustment of fan voltage or compressor input voltage. In this work, we use independent control of air conditioning system to regulate temperature and humidity, which can better satisfy indoor environment requirements and effectively save energy consumption (Zhang et al. 2014). The non-uniform distribution of the indoor environment was considered to ensure that the HVAC system control is more accurate and feasible for engineering application. The present work can contribute to HVAC online control with a full consideration of multiple environmental parameters (i.e., ventilation, temperature and humidity) from perspectives of indoor health and energy conservation.

2 Method

In this work, integrated HVAC control for indoor environmental parameters was mainly achieved through the three regulation steps of air change rate per hour (ACH), supplied air temperature and humidity, in order to rationally evaluate and optimize the balance between air-conditioning energy consumption and indoor environmental quality (IEQ). Firstly, the ACH was mainly controlled. The CFD simulations of indoor pollutant concentrations were performed based on different input variables (e.g., source intensity and air supply parameters) to establish the initial CFD database. The initial CFD database was expanded through low-dimensional linear ventilation model (LLVM) and the dimension of expansion database was decreased (to reduce the size of the data in the database, e.g., a data storage reduction from 200MB to 20KB). The low-dimensional pollution data were then combined with the self-defined

index E_V to evaluate the indoor pollution distribution status and derive the optimal control strategy for ACH. Secondly, based on the optimal ACH, the inlet temperature was controlled. Different cases with different supply air temperatures can be simulated by CFD in order to establish the temperature distribution database, and the contribution ratio of indoor temperature ($CRI_{(T)}$) was derived from the simulation results. Both the low-dimensional linear temperature model (LLTM) and the $CRI_{(T)}$ model can rapidly predict the data of indoor temperature, and LLTM can also reduce the amount of database. The low-dimensional temperature data were then combined with the self-defined index E_T to evaluate the indoor temperature distribution status and derive the optimal control strategy for air supply temperature. Thirdly, based on the optimal ACH and supply air temperature, the supply air humidity was regulated. CFD simulations were used to establish the database of indoor humidity distributions under different supply air humidity. And the contribution ratio of indoor humidity ($CRI_{(H)}$) was derived from the simulation results. Both the low-dimensional linear humidity model (LLHM) and the $CRI_{(H)}$ model can rapidly predict the data of indoor humidity, and the LLHM can reduce the amount of database. The low-dimensional humidity data were then combined with self-defined index E_H to evaluate the indoor humidity distribution status and derive the optimal control strategy for air supply humidity. Finally, the online control of integrated HVAC system was achieved through the regulation of above three environmental factors (this paper focuses on the control strategy for central air conditioning systems in non-residential buildings). See Figure 1 (flowchart) for details.

2.1 Methods used for Step 1

2.1.1 LLVM used for superposition of pollutant concentration fields resulting from multiple pollutant sources

Based on CFD simulation results, linear ventilation model (LVM) was used to predict the distributions of indoor pollutant (e.g., CO_2) concentration by using the linear superposition method, which has presumed that indoor pollutant had negligible influence on indoor air motion, and the pollutant concentration field was approximated to be linear (Cao and Ren 2018). Specifically, the pollutant concentration fields produced by multiple pollutant sources were equivalent to the superposition of concentration fields produced by each single source. On the basis of LVM model, low-dimensional linear ventilation model (LLVM) was further proposed to largely reduce the data storage about pollutant concentration fields (Cao and Ren 2018). Figure 2 showed the schematic diagram of low-dimensional discretization process.

Fig. 1 The flow chart of this work (PMV: predicted mean vote; TS: thermal sensation index)

Fig. 2 The schematic diagram of low-dimensional discretization process (Ren and Cao 2019a; reprinted with permission ©2019 Elsevier)

2.1.2 LLVM-based ANN used for fast prediction of pollutant concentration

On the basis of LLVM, we continued to adopt artificial neural network (ANN) for autonomous learning and rapid prediction of indoor pollutant concentration based on low-dimensional database of concentration fields (Cao and Ren 2018). As one part of machine learning method, ANN was able to rapidly map the relationships between inputs (e.g., position and strength of pollutant source) and outputs (e.g., pollutant concentration). From the above, the method of LLVM-based ANN could be well developed to greatly save the prediction time with the acceptable accuracy for engineering application.

2.1.3 Evaluation index of E_v for optimal ventilation control

In our previous work, by using the coefficient of variation

(CV) (definitions are found in the Electronic Supplementary Material (ESM) of the online version of this paper), the weightings of ACH (i.e., ventilation energy consumption) and indoor CO_2 concentration (indicated by the averaging CO_2 concentration of the breathing region, C_{mean}) were respectively calculated (Cao and Ren 2018). The equation of assessment index E_v was shown as follows:

$$E_v = W_{v1} \frac{\text{ACH}}{\text{Max}(\text{ACH})} + W_{v2} \frac{C_{\text{mean}}}{\text{Max}(C_{\text{mean}})} \quad (1)$$

where, W_{v1} and W_{v2} are the weights for ACH and C_{mean} respectively. On the basis of index E_v , The ACH in the minimum E_v value corresponds to the optimal ACH. Thus, the optimal selections of ACH can be determined under different conditions of different CO_2 source strength and positions.

2.2 Methods used for Step 2

2.2.1 LTM and LLTM-based $CRI_{(T)}$ used for fast prediction of temperature fields

Similar to LVM model, Ren and Cao (2019a) also proposed linear temperature model (LTM). The premise of LTM was that if the buoyancy resulting from indoor temperature variation had negligible effect on the indoor airflow, the temperature field can be approximately considered to be linear (Zhang et al. 2013), i.e., the temperature fields caused by multiple heat sources were equal to the superposition of temperature fields caused by these single sources. On the basis of LTM and low-dimensional discretization process, low-dimensional linear temperature model (LLTM) was also proposed.

Regarding $CRI_{(T)}$ (contribution ratio of indoor climate) model, the definition was the ratio of indoor temperature increase (or decrease) at any position produced by the heat source to the absolute value of indoor temperature increase (or decrease) produced by the same heat source with the increasing (or decreasing) heat quantity diffused uniformly (Zhang et al. 2013). The specific $CRI_{(T)}$ of the heat source was defined as shown in the ESM of the online version of this paper (Zhang et al. 2013; Ren and Cao 2019a). According to the well-performed $CRI_{(T)}$ and LLTM, LLTM-based $CRI_{(T)}$ model was further proposed for fast and efficient prediction of indoor temperature fields, similar to the idea of LLVM-based ANN model for fast prediction of indoor air pollution (Ren and Cao 2019a).

2.2.2 Evaluation index of E_T for optimal temperature control

Based on the optimal ACH selection, the index E_T mainly focused on the balancing of supply air temperature (i.e., cooling loads) and PMV (calculate by average temperature of the room) values. With the corresponding weighting coefficients calculated by CV method, the equation of E_T was defined as follows (Ren and Cao 2019a).

$$E_T = W_{T1} \frac{|PMV|}{\text{Max}(|PMV|)} + W_{T2} \frac{T}{\text{Max}(T)} \quad (2)$$

where, W_{T1} and W_{T2} are the weightings for PMV (absolute value) and supply air temperature, respectively. Besides, PMV is calculated by the average room air velocity (V_R) and temperature (T_R) (Deng et al. 2018), as shown below:

$$PMV = -\frac{7}{83}T_R V_R + \frac{28}{75}T_R - \frac{689}{74} \quad (3)$$

On the basis of index E_T , the supply air temperature (T) in the minimum E_T value corresponds to the optimal supply air temperature. Thus, the optimal choice of supply air

temperature is obtained for conditions of varying intensity and heat source location.

2.3 Methods used for Step 3

2.3.1 LHM used for superposition of humidity field

Indoor humidity environments can be resulted from different sources of moisture, e.g., human body, equipment, building envelope, and outdoor air. Ventilation airflow pattern can affect the distribution of indoor humidity. In the current study, we assumed that the inlet ACH was constant (continued with the previous steps), and the airflow field was considered to be fixed. Thus, the influence of indoor airflow on humidity fields was not focused in this work. According to the study of Huang et al. (2011), with the indoor moisture assumed to be passively scalar, if the humidity distributions caused by each moisture source were obtained individually, indoor humidity values would be the linear summation of the rises (or falls) in humidity caused by each moisture source. Therefore, we can firstly calculate the humidity fields caused by each humidity source independently, and then obtain the distributions of indoor humidity fields resulting from multiple humidity sources through linear superposition method as LVM and LTM, namely as linear humidity model (LHM).

2.3.2 LLHM-based $CRI_{(H)}$ for fast prediction of humidity field

The contribution rate of indoor climate for humidity $CRI_{(H)}$ was utilized to judge the influence of various moisture sources on indoor humidity distribution. According to Huang et al. (2011), $CRI_{(H)}$ indicated the ratio of the rise (or fall) in humidity at a point from an individual moisture source to the rise (or fall) in humidity with the perfect mixing conditions for the same moisture source. The equation of $CRI_{(H)}$ can be defined as follows:

$$CRI_{(H)}(x,n) = \frac{\delta X(x,n)}{X_n}, \quad X_n = \frac{q_n}{\rho \cdot Q} \quad (4)$$

where, $\delta X(x,n)$ is the rise (or fall) in humidity value from standard status at a point x due to the n th moisture source [kg/kg^3]; X_n is the rise (or fall) in humidity value under the perfect mixing conditions due to the n th moisture source [kg/kg^3]; q_n is the moisture flux generated by the n th moisture source [kg/s]; ρ is the air density [kg/m^3]; and Q is the air flow rate [m^3/s] (Huang et al. 2011). Similar to LLTM-based $CRI_{(T)}$, low-dimensional humidity model (LLHM)-based $CRI_{(H)}$ was proposed in this paper with the combinations of LHM, low-dimensional discretization process and $CRI_{(H)}$.

2.3.3 Transferring absolute humidity to relative humidity

Since that the prediction results from LLHM-based $CRI_{(H)}$ were absolute humidity which cannot be directly controlled, the transformation from absolute humidity to relative humidity should be carried out, according to the following formulas:

$$h_a = 1.006t_a + w(2501 + 1.86t_a) \quad (5)$$

$$w = 0.622 \frac{\varphi P_{sw}}{P_b - \varphi P_{sw}} \quad (6)$$

$$\ln P_{sw} = C_1 / T_a + C_2 + C_3 T_a + C_4 T_a^2 + C_5 T_a^3 + C_6 \ln T_a \quad (7)$$

where, t_a is the air dry-bulb temperature ($^{\circ}\text{C}$); w is the moisture content (kg/kg for dry air); φ is the relative humidity; P_{sw} is the saturation vapor pressure over liquid water (Pa); P_b is the atmosphere pressure (Pa); C_1 to C_6 were the regression coefficients indicated in Table 1; and T_a is the absolute air temperature (K) (ASHRAE 2009; Jia and Lee 2015; Feng et al. 2018).

2.3.4 Evaluation index of E_H for optimal relative humidity control

On the basis of optimal evaluations of ACH and supplied air temperature, this work further defined the evaluation index E_H to assess the balancing between indoor personal perception of humidity values and air-conditioning energy consumption (i.e., humidity loads), so as to obtain the optimal supplied air humidity. The supply air relative humidity (H) in the minimum E_H value corresponds to the optimal supply air humidity. Combined with weighting coefficients from CV method, the equation of E_H was shown as follows (the value of TS was calculated by the average relative humidity of the room):

$$E_H = W_{H1} \frac{TS}{\text{Max}(TS)} + W_{H2} \frac{H}{\text{Max}(H)} \quad (8)$$

where, W_{H1} and W_{H2} are the weightings for thermal sensation (TS) and supply air relative humidity (H), respectively. The expression of index TS is presented as below (de Paula Xavier and Roberto 2000):

$$TS = 0.219T_0 + 0.012RH - 0.547V_a - 5.83 \quad (9)$$

where, T_0 is the temperature ($^{\circ}\text{C}$); RH is the relative humidity (%); and V_a is the air velocity (m/s). The scales of thermal sensation (TS) were indicated in Table 2.

Table 1 The coefficients C_1 to C_6 in Eq. (7)

Coefficient	C_1	C_2	C_3	C_4	C_5	C_6
Constant	-5.8e+03	1.391	-4.864e-02	4.176e-05	-1.445e-08	6.546

Table 2 Assessment scales of thermal sensation (TS)

TS sensations scale						
Cold	Cool	Slightly cool	Neutral	Slight warm	Warm	Hot
-3	-2	-1	0	1	2	3

To sum up, on the strength of the rapid prediction of indoor pollutant concentration, temperature as well as humidity fields respectively from LLVM-based ANN, LLTM-based $CRI_{(T)}$ and LLHM-based $CRI_{(H)}$, online control of HVAC system (aiming for the optimal selections of supplied loads) can be well proceeded with the assistance of three evaluation indices E_V , E_T and E_H .

2.4 Descriptions of simulations for three steps

The full-scale experiment chamber used in this study was described in Figure 3(a), which was also used for previous work (Cao and Ren 2018; Ren and Cao 2019a). CFD simulations were corresponding to the chamber set up. The full size of this chamber is 3.5 m (length) $\times$ 3.4 m (width) $\times$ 2.5 m (height). Multiple diffusers were installed along the wall and ceiling to achieve the adjustment of different ventilation modes. In this study, we only considered the ventilation mode with side supply and side return grilles. Of this mode, inlet-1 and inlet-2 were both located on the side wall with the size of 18 cm (length) $\times$ 18 cm (width). The outlet was located on the same side wall with the size of 18 cm (length) $\times$ 18 cm (width). Besides, the mesh grids for CFD simulations were with the grid number of 2123820. Turbulence models were selected for simulations with re-normalization group (RNG) k - ϵ model for pollutant concentration and temperature (Ren and Cao 2019a) and low Reynolds number k - ϵ model for humidity simulation (Huang et al. 2011). In previous studies, numerous experiments using this chamber were carried out for the validation of simulation results about pollutant concentration and temperature with the maximum errors below 20%, thus CFD simulations have shown good performance and reliability for this study.

2.4.1 Settings of input variables in Step 1 for pollutant concentration simulation

In this work, we set four locations of pollution sources respectively corresponding to A (0.875, 2.55, 1.1) m, B (2.625, 2.55, 1.1) m, C (0.875, 0.85, 1.1) m and D (2.625, 0.85, 1.1) m, as shown in Figure 3(b). For a single pollutant source, the release rate was set as 5×10^{-6} kg/s and the background concentration value (molar fraction) was initialized to 5×10^{-4} (500 ppm) (Chow 2002). The ACH values of 2, 4, 6, 8 and 10 were considered as the initial conditions for the construction of CFD database. The ACH values were

Fig. 3 (a) Ventilation mode and (b) location coordinates of four CO₂ sources, i.e., A, B, C and D

calculated by the supply air volume at the ventilation inlets, and the optimal ACH selection was realized based on the above model in Section 2.1.

2.4.2 Settings of input variables in Step 2 for temperature simulation

Corresponding to the locations of pollutant sources (ref., Figure 3), four heating sources were set in this work with the same size of 0.2 m (length) $\times$ 0.2 m (width) $\times$ 1.1 m (height). One single heating source can stand for the combination of one human body and one personal computer. The intensity settings of heating sources were shown in Table 3 (Zhang et al. 2013; Zhang et al. 2019), and all heat sources were defined by user-defined function (UDF). Besides, another heat source standing for the heat dissipation of window was set on the east wall (with the wall thickness equal to 0.2 m) of the chamber, and the size of window was 1.5 m (length) $\times$ 1.0 m (width) $\times$ 0.01 m (height) (Ren and Cao 2019a). In this work, the outdoor temperature (i.e., surface temperature of window) was set as 30.7 °C (303.7 K). Since that inlet-1 was responsible for indoor temperature control in this study, the adjustment ranges of supplied air temperature for inlet-1 were set as 16–22 °C (289–295 K). Different from inlet-1, the supplied air temperature of inlet-2 (used for humidity control) was set as 26 °C. Studies have showed that 26 °C was used as the standard indoor temperature, with a small difference in thermal comfort and perceived air quality under the high and moderate humidity conditions (GB50019-2003 2004; He et al. 2017). It should also be noticed that the above adjustments of supplied air temperature were all based on the optimal ACH selection results.

Table 3 Thermal parameters of heating sources including human body, personal computer and window

	Heat source (human body)				Window	Personal computer
	A	B	C	D		
Source intensity	85 W	85 W	85 W	85 W	6.17 W/(m ² ·K)	50 W

2.4.3 Settings of input variables in Step 3 for humidity simulation

According to ASHRAE Standard, 30%–60% of relative humidity (RH) was required in the office buildings for acceptable thermal comfort (ASHRAE 2009). Moreover, a correlational study suggested that RH values ranging around 45% may cause neglected influence to people's subjective feeling (Razjouyan et al. 2020). Therefore, in this work, the constant relative humidity value of inlet-1 was set as 45%, and the ranges of supplied air relative humidity for inlet-2 were set as 30%–60%, based on the optimal selections of supplied air temperature. Besides, four humidity sources with the size of 0.45 m (length) $\times$ 0.33 m (width) $\times$ 0.88 m (height) (Huang et al. 2011) were designed with the locations respectively corresponding to pollutant sources A, B, C and D (ref., Figure 3). One single humidity source can stand for one human body and one object (e.g., kettle as moisture generator) with the moisture released. Although a certain amount of moisture could transfer through the wall in the actual situation, we mainly focused on the humidity variations of indoor personnel, object and inlet in this work. Thus, the walls with small moisture release were not considered as the separate humidity source.

Regarding the strength of humidity source, the total moisture generation rate (respiration and transpiration) for one occupant was suggested as 60g/h, which corresponded to the metabolic rate of an average adult performing typical office work (Popescu-Croitoru 2011). Moreover, the moisture generation rate of kettles around indoor workers is close to 40 g/h (Huang et al. 2011). We continued to use UDF method to define the humidity sources for CFD simulation. More details of simulation conditions were shown in Table 4.

3 Results

In this section, we mainly adopted fast prediction models to predict indoor environmental fields (i.e., pollutant concentration, temperature and humidity fields). Then, three corresponding self-defined evaluation indices (E_V , E_T , E_H)

Table 4 Conditions and settings for humidity simulation.

CFD model	Low Reynolds number $k-\epsilon$ model
Mesh	2123820
Differencing scheme	Convection term: Second order upwind
Air inlet	Velocity: based on the optimal ACH value Humidity: inlet-1: 45% relative humidity. Inlet-2: 30%–60% relative humidity
Moisture generation	Moisture(human): 60g/h; Moisture(kettle): 40g/h
Wall	Material: no moisture generation, Others: no-slip

were applied to obtain the optimal control solutions of HVAC system. The control processes were divided into three parts: (i) In Step 1, the accuracy of LLVM-based ANN model was verified, followed by the comprehensive evaluation of indoor pollutant concentrations and energy consumption based on E_V to determine the optimal ventilation rate (ACHs); (ii) In Step 2, on the basis of optimal ACHs, the accuracy of LLTM-based $CRI_{(T)}$ model was verified followed by the evaluation of indoor thermal comfort (expressed as predicted mean vote, PMV) and air-conditioning cooling load with E_T to determine the optimal inlet-1's supply air temperature; (iii) In Step 3, on the basis of optimal ACH and supply air temperature, we further verified the accuracy of LLHM-based $CRI_{(H)}$ model. According to the index E_H , the balance between indoor thermal comfort and humidity load was well evaluated, with the optimal inlet-2's relative humidity (RH) obtained. Combined with the above steps, the optimal control of HVAC system was achieved through the comprehensive and sequential regulation of ACHs, temperature and humidity.

3.1 Step 1: selection of the optimal ACH for indoor air pollution (CO_2) control by using LLVM-based ANN methods

The method of LLVM-based ANN was mainly employed to rapidly predict indoor CO_2 concentration fields. According

to the method part, we utilized LLVM to rapidly extend the database, and the validation results between LLVM and CFD were shown in Figure 4. The mean deviation error of the CO_2 concentrations between LLVM and CFD was less than 13%. With pollutant source locations as inputs, LLVM-based ANN model was able to largely improve the prediction efficiency of CO_2 concentrations. As shown in Figure 4, the depiction of CO_2 concentration from LLVM-based ANN was in good agreement with CFD simulation along with the mean error less than 15% (when ACH is 8, it is a training set containing more than 2 million grid points of data, and the test set ACH is 4, the output is more than 2 million grid points of data, within the acceptable margin of error for engineering application).

High ventilation rates can mitigate the concentration of indoor pollutants (such as CO_2 in the current study). However, holding up to the high ACH value can also result in the large amount of ventilation energy consumption (Cao et al. 2016). Therefore, with the assistance of fast prediction results of indoor CO_2 concentration and self-defined evaluation index E_V (shown in Eq. (1)), we comprehensively assessed the balance between indoor CO_2 concentration levels and energy consumption (ventilation rate) by calculating the E_V values, as shown in Table 5. The lowest E_V value corresponded to the optimal selection of the targeted ACH value, i.e., 4 in the current work.

3.2 Step 2: optimization of cooling load for indoor temperature regulation using LLTM-based $CRI_{(T)}$ method based on optimal ACH

Based on the optimal ACH values, we came to the optimization of cooling load (supply air temperature) of HVAC systems. By comparing the prediction results from LTM (low-dimension temperature model) and CFD, Ren and Cao (2019a) demonstrated that the prediction accuracy of LTM was below 20% to meet the demands of engineering

Fig. 4 Comparisons of CO_2 concentrations (ppm) between CFD, LLVM and LLVM-based ANN when ACH equal to 4

Table 5 The calculated results of E_v index for different inlet ACHs

ACH	2	4	6	8	10
E_v	0.54	0.51	0.62	0.74	0.80

application. Then, we further employed the CFD simulation to verify LLTM (low-dimensional linear temperature) model. As shown in Figure 5, the LLTM method was adopted to obtain low-dimensional discrete data of indoor temperature fields with the inlet-1's supply air temperature equal to 17 °C and 20 °C, respectively. The maximal temperature deviation between CFD and low-dimensional data from LLTM was less than 2 K. Thus, well-behaved LLTM method can be further employed for the rapid prediction of indoor temperature fields by combing $CRI_{(T)}$ model.

According to $CRI_{(T)}$ equation in Eq. (S1), the distributions of $CRI_{(T)}$ were calculated with the inlet-1's temperature equal to 16 °C (as shown in the ESM of the online version of this paper). With the combination of LLTM and $CRI_{(T)}$, LLTM-based $CRI_{(T)}$ model was able to improve the rapid prediction efficiency of indoor temperature distributions. Figure 6 showed the comparisons of the temperature fields respectively obtained from LLTM-based $CRI_{(T)}$ and CFD simulations (with inlet-1's temperature set as 20 °C). It was found that the temperature distribution results from LLTM-based $CRI_{(T)}$ were well consistent with CFD results, with the maximum error less than 2%. Hence, it was

considered that LLTM-based $CRI_{(T)}$ model can be more efficient for the fast prediction of temperature distributions with less data storage.

On the basis of prediction results about indoor temperature, evaluation index E_T (shown in Eq. (2)) was used to evaluate the balance between indoor thermal comfort (indicated by PMV) and energy consumption (i.e., supply air temperature). With the E_T values for different inlet temperature conditions, the minimum E_T value corresponded to the optimal selection of supply air temperature for inlet-1. Considering that the adjusting range of supplied air temperature was 16–22 °C (with the summer condition), we obtained the optimal supplied air temperature of 21 °C in this study. In order to show the control effects with the optimal temperature, Table 6 listed the absolute PMV values corresponding to different supplied air temperatures. From the table, PMV was closest to the desired value of optimal thermal comfort (i.e., $PMV = 0$) when the inlet-1's temperature equal to 21 °C. Moreover, studies have shown that when the average indoor temperature or the supplied air temperature of air-conditioning system was reduced by 1 °C, the energy consumption of HVAC system could be increased by about 8% (Cao and Deng 2019). Thus, through the optimal control strategy of inlet temperature, the HVAC system can potentially reduce the energy consumption for cooling loads by about 32% in this work.

Fig. 5 Comparisons of temperature distribution between CFD and LLTM with two different inlet-1 temperatures of 17 °C and 20 °C

Fig. 6 Comparisons of temperature distributions from CFD and LLTM-based $CRI_{(T)}$ prediction with inlet-1 temperature set as 20 °C

Table 6 The calculated results of PMV for different inlet-1's temperatures

	16 °C	17 °C	18 °C	19 °C	20 °C	21 °C	22 °C
PMV	0.821	0.682	0.421	0.302	0.218	0.0102	0.015

3.3 Step 3: selections of optimal relative humidity using LLHM based- $CRI_{(H)}$ based on optimal ACH and cooling load

3.3.1 Validation of humidity prediction with LHM and LLHM by using CFD simulations

The LHM model was firstly validated by CFD simulation. The absolute humidity results from CFD and LHM model were respectively shown in Figures 7(a) and (b). The maximum error for CFD and LHM is 13% (around 1.2 g/kg) under condition of 40% relative humidity at inlet-2. Moreover, Figure 7(c) quantitatively compared the absolute humidity results obtained from LHM and CFD methods at the four positions of A (0.875, 2.55, 1.1) m, B (2.625, 2.55, 1.1) m, C (0.875, 0.85, 1.1) m and D (2.625, 0.85, 1.1) m (along vertical direction). For these four positions, the maximum error of absolute humidity between CFD and LHM was less than 11% (around 1 g/kg), which appeared at the height of 0.5 m. Generally speaking, the accuracy of LHM could be sufficiently fine for the engineering applications with the

acceptable error within 20%.

Then, we further compared the relative humidity results from CFD simulation and LLHM with the conditions of humidity (at inlet-2) equal to 25% and 30%. As shown in Figure 8, with the amount of CFD data largely decreased, the mean error between CFD and LLHM results were below 4%, which indicated that LLHM method had great performance in the improvement of humidity prediction.

3.3.2 Validation of humidity prediction with $CRI_{(H)}$ and LLHM based- $CRI_{(H)}$ method by using CFD simulations

Based on Eq. (4), we calculated the $CRI_{(H)}$ values with the following conditions that inlet-1's supplied air temperature and relative humidity were respectively equal to 21 °C and 45%, and inlet-2's supplied air temperature and relative humidity were respectively equal to 26 °C and 25%. Figure 9 declared the distributions of $CRI_{(H)}$ at the stereogram perspective and planes of $x = 1.75$ m, $y = 1.7$ m and $z = 1.1$ m. The calculated results of $CRI_{(H)}$ near the inlet-2 were smaller than the values near the regions of inlet-1, which

Fig. 7 Comparisons of humidity distributions using CFD and LHM model with 40% relative humidity of inlet-2: (a) CFD results; (b) LHM model; (c) the absolute humidity results at position A, B, C, D from CFD simulation and LHM model

Fig. 8 Comparisons of relative humidity distributions between CFD and LLHM methods with inlet-2 humidity equal to 25% and 30%

Fig. 9 Calculation results of contribution ratio of indoor humidity ($CRI_{(H)}$): (a) stereogram; (b) plane of $x = 1.75$ m; (c) plane of $y = 1.7$ m; (d) plane of $z = 1.1$ m

was due to the fact that larger source strength could lead to the greater $CRI_{(H)}$ values. Then, the $CRI_{(H)}$ values would be employed to predict indoor humidity distributions. Figure 10 indicated the comparison results of absolute humidity distributions from CFD and $CRI_{(H)}$ model with inlet-2 relative humidity equal to 30%, 40% and 47%. According to Figure 10, the prediction errors were larger when the relative humidity (at inlet-2) reached up to 40% and 47%, since the inlet-2's relative humidity differences between initial value (used in the calculation of $CRI_{(H)}$, equal to 25%) and increased values (especially for 40% and 47%) were growing synchronously. Nevertheless, the maximum errors between $CRI_{(H)}$ prediction and CFD simulation were all within the acceptable limits (i.e., no more than 8%).

Combined with well-behaved $CRI_{(H)}$ and LLHM, LLHM-based $CRI_{(H)}$ model could be utilized to further improve the prediction efficiency of indoor humidity distributions. Figure 11 showed the comparison results of relative humidity between CFD and LLHM-based $CRI_{(H)}$ with the inlet-2's supplied relative humidity of air equal to 40% and 47% respectively. It can be seen that the results of LLHM-based $CRI_{(H)}$ were well acceptable with the maximum error of 9% (around 4% relative humidity) when compared to CFD results. Thus, LLHM-based $CRI_{(H)}$ model could also

contribute to the rapid prediction and implementation of optimal control for indoor humidity.

3.3.3 Application of LLHM-based $CRI_{(H)}$ for the control strategy to balance indoor thermal comfort and energy consumption

In Step 3, we combined the thermal comfort indicator TS with HVAC system energy consumption (indicated by relative humidity of inlet-2) in the evaluation index E_H to assess the humidity environment for obtaining of the optimal supplied air relative humidity (corresponding to the minimum value of E_H). Regarding the TS indicator, when the value of TS was close to zero, the comfortable state of indoor personnel should be ideal. For the HVAC energy consumption considered in Step 3, it was analyzed by the co-effects of temperature and humidity on the total energy consumption of integrated HVAC system, which could be more closely matching the real energy consumption of HVAC system during daily regulation. According to Eq. (5), the enthalpy required for the control process is calculated from the outdoor air parameters before control and the indoor air parameters after control as a reference to the energy calculation. In standard GB50736-2012 (2012), it can be obtained that the temperature and humidity parameters for outdoor calculation (taking Guangzhou city as example)

Fig. 10 Comparisons of absolute humidity distribution between CFD and CRI(H) model with various inlet-2 relative humidity equal to 30%, 40% and 47%

are respectively corresponding to 30.7 °C and 68%. Besides, the temperature and humidity parameters at the inlet processed by the traditional HVAC system are corresponding to 16 °C and 50%. On these bases, the selections of inlet-2's supplied air relative humidity for the optimal control solutions were shown in Table 7, by considering five different conditions of humidity sources (including human body and kettle), and the relative humidity control ranges of inlet-2 were from 30% to 60% (with the optimal inlet-1's supplied air temperature equal to 21 °C). It can be seen that the optimal supplied relative humidity of air at inlet-2 varied between 30% and 40%. Table 7 also listed the TS values in the occupied areas and energy savings of HVAC system corresponding to the optimal strategies. According to Eq. (5), the enthalpy value required for the operation of air-conditioning system could be rapidly calculated, in order to further obtain the energy saving results. Based on the optimal selections of supplied air relative humidity, the total energy consumption of HVAC system (considering cooling and humidity loads) could be maximally decreased by 35% (with inlet-2's relative humidity and supplied air temperature corresponding to 40% and 26 °C).

4 Discussion

The control of HVAC systems has been a complex issue mainly due to the diversity and dynamic demands of indoor environmental parameters along with a large amount of energy consumption for operation. In this circumstance, the intelligent HVAC control system based on real-time environmental responses was appreciated to achieve the optimal coordination of indoor environmental distributions and energy consumption, including three steps of "monitoring", "prediction" and "control" (Ren and Cao 2020). Of these steps, this work proposed a comprehensive control strategy for the HVAC system corresponding to the third step of intelligent control system. Specifically, by synthesizing our previous studies on the optimal control of ventilation rates (ACHs) (Cao and Ren 2018) and supplied air temperatures (Ren and Cao 2019a), the rapid prediction of multiple indoor parameters (i.e., pollutant concentration, temperature and humidity) and the optimal regulation of supply air parameters (i.e., ACH, temperature and humidity) for integrated HVAC system control were well implemented, on the basis of the coupling prediction models with low-

Fig. 11 Comparisons of relative humidity distribution between CFD and LLHM-based $CRI_{(H)}$ with the inlet-2's supplied air relative humidity equal to 40% and 47%

Table 7 Selection results of supplied air relative humidity for the optimal control strategy with corresponding TS values in the occupied areas and energy savings of HVAC system (considering different humidity conditions of humidity source including human body and kettle)

Indoor humidity conditions (g/h)				Control strategies corresponding to the minimum E_H (control range of relative humidity at inlet-2: 30%–60%)		
A	B	C	D	Optimal humidity	TS	Energy saving
60	60	60	60	40%	−0.008	35%
100	60	60	60	30%	−0.05	24%
100	100	60	60	35%	−0.009	29%
100	100	100	60	35%	0.003	29%
100	100	100	100	30%	0.007	24%

dimensional linear models and two rapid prediction models (i.e., LLVM-based ANN, LLTM-based $CRI_{(T)}$, LLHM-based $CRI_{(H)}$). Besides, three evaluation indicators (E_V , E_T , E_H) were also adopted to realize the efficient evaluations of supply air parameters and energy consumption to contribute to the optimal and synthetically control strategies of HVAC system.

However, in order to improve the applicability of above-

mentioned intelligent HVAC control system, “monitoring” part and real-life control system combined with the optimal control strategies needed to be focused on as well. Regarding the monitoring step of HVAC control system, we should apply the monitoring technology to obtain the real-time data of indoor environmental parameters, so that the HVAC control system is able to quickly respond to the real demand of indoor environment with the online monitoring data as

inputs. Considering that more monitoring sensors may call for larger expense and installing space towards actual building environment, Ren and Cao (2019b) used limited number of sensors to monitor the concentration of indoor pollutants. From the findings, it was concluded that the prediction of environmental fields showed the satisfying performance as the sensor numbers equal to 5, regardless of sensor locations. Nevertheless, when using 3 or 4 sensors, there was an occasional error appearing in the prediction results, which had a great relationship to the sensor layout. Then, in order to achieve the optimal layout strategies with fewer sensors (e.g., 3 sensors), Cao et al. (2020) investigated the systematic sensor deployment method by using clustering model of fuzzy C-means (FCM) algorithm for the efficient prediction of indoor environments. From the above, the well-behaved limited monitoring technology could be promising for the development of intelligent HVAC control system, which should be further incorporated into the comprehensive control strategies presented in this work.

In addition, there are some limitations of this work, as follows. (1) This work used a full fresh air system for case study and simulation. To achieve the purposes of economic and energy saving, the return air conditioning system should be focused on in our future work. (2) The method proposed in this work was mainly based on the linear principle to achieve the step-by-step control of HVAC system. In our future work, we will consider the interactions among different environmental factors to achieve comprehensive control of HVAC system. (3) The design of the actual control system for temperature and humidity has not been implemented in this work. According to our previous work, the ventilation rate was adjusted corresponding to the variation of fan voltage (Zhu et al. 2020; Ren and Cao 2020). Thus, we can also adjust the compressor speed (i.e., compressor input voltage) of HVAC system to obtain different inlet temperature and humidity, in order to achieve the effective regulation of integrate air conditioning system (Zhong et al. 2017). To sum up, the future work will focus on improving the applicability of actual HVAC control system for the real-life building environment.

5 Conclusion

The purpose of this work was to provide fast prediction models for indoor environmental parameters (i.e., air pollutant concentration, temperature and humidity), with a final goal to realize on line control of HVAC systems through the sequential regulations of optimal ACH, supplied air temperature and humidity. This work will further contribute to the balancing between air-conditioning energy consumption (including ventilation, cooling and humidity loads) and indoor environmental quality. Of this study, indoor

environmental distributions (i.e., CO₂ concentration, temperature and humidity fields) can be rapidly predicted based on the coupling models with low-dimensional linear models (LLM), artificial neural network (ANN) and contribution ratio of indoor climate (CRI), i.e., LLVM-based ANN, LLTM-based CRI_(T) and LLHM-based CRI_(H) models. The optimal control strategies for ACH, supplied air temperature and relative humidity were respectively implemented with the three self-defined evaluation indices (E_V , E_T and E_H). The main conclusions are summarized as follows.

- (1) The deviation errors between the prediction results of linear humidity model (LHM) and CFD results were less than 15%. Considering the well-behaved linear models (i.e., LVM's error less than 13% and LTM's error less than 20%) proposed in our previous work (Cao and Ren 2018; Ren and Cao 2019a; Zhu et al. 2020), the adoption of linear models could show favorable performance in the rapid prediction of indoor environmental fields.
- (2) The well-behaved CRI_(H) model was utilized to rapidly predict indoor humidity, and the maximum prediction error compared to CFD results was less than 15%.
- (3) Through using LLVM-based ANN, LLTM-based CRI_(T) and LLHM-based CRI_(H), low-dimensional indoor environmental fields (i.e., CO₂, temperature and humidity fields) could be effectively predicted with the maximum error less than 15%. On account of evaluation indices (E_V , E_T , E_H), the integrated HVAC system can be effectively regulated to save the maximum energy consumption by 35% and ensure acceptable indoor thermal comfort environment (i.e., TS $\approx$ 0).

From the above, the integrated HVAC control strategy proposed in the current work could be beneficial to the management of HVAC control system in the perspectives of energy saving and human health. However, several limitations should also be noticed in this work, such as ignoring the applicability of control strategies to the actual air-conditioning system for the complex building environments. Moreover, the current study of HVAC system control was carried out based on CFD simulation, without taking the real-time responses of indoor environment into account. The future work will further develop and implement the real-life and intelligent HVAC control system for the actual various building environments.

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