Approach on prediction of indoor temperature distribution by combining POD, CRI and mobile sensors

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Abstract. In our previous study, a prediction method of indoor temperature distribution based on the Contribution Ratio of Indoor Climate (CRI) and finite air temperature collected by one mobile sensor has been proposed. However, the CRI fixed value hypothesis limits its application in practical situations. In this regard, this study proposes to introduce interpolation POD (proper orthogonal decomposition) method to obtain the dynamic distribution of CRI, so as to improve the prediction accuracy. As a case study, in a simplified CFD model with identified heat source conditions, based on the interpolation POD method, the reconstruction of each sub temperature field dominated by only one heat source under any air supply parameters was realized, and thus its CRI distribution could be calculated. Then, by combining the finite air temperature collected by the mobile sensor, the indoor temperature distribution was predicted. The results showed that the introduction of interpolation POD method is effective, which breaks the application limitations of CRI fixed value hypothesis on the proposed method, and further promotes its development potential in the direction of "real-time prediction and dynamic regulation" in practical application.

1 Introduction

With the proposal of low-carbon and energy-saving, the construction of non-uniform indoor thermal environment has gradually become an effective method to meet the relative balance of building energy efficiency and personalized thermal comfort. In this regard, it is essential to obtain the detailed temperature distribution quickly and accurately.

A method based on Contribution Ratio of Indoor Climate (CRI) and finite air temperature to quickly predicting the indoor temperature distribution has been proposed and improved [1-2]. However, The basic premise that CRI can be used to evaluate and predict the indoor temperature distribution is that in the steady airflow field, the CRI can be considered as a fixed value [3-4]. However, the indoor thermal boundary conditions are dynamic. When it changes significantly, the airflow field cannot be considered as steady. That is, the prediction error caused by CRI fixed value hypothesis cannot be ignored. Therefore, it is necessary to obtain the dynamic distribution of CRI according to the change of actual environment.

POD method is one of the most commonly used techniques in hydrodynamic model simplification. From a technical perspective, it greatly improves the computational efficiency by reducing the order of the physical field model. From an application perspective, the reduced-order model is more suitable for real-time control in practical situations. It has been widely used in many aspects, especially obtaining temperature distribution [5], and reverse design of indoor air supply parameters [6].

Therefore, this study proposes to introduce POD method to obtain the dynamic distribution of CRI under any air supply parameters. In a simplified CFD model with identified heat source conditions, the effectiveness of this method was verified. On this basis, the temperature distribution was predicted. And a detailed error analysis was carried out.

2 Methodology

2.1 Prediction algorithm based on CRI and mobile sensors

CRI extracted from CFD calculation results is an effective index to estimate the independent contribution of each heat source to indoor temperature distribution. In a forced convection airflow field, it is defined as the ratio of temperature rise or drop at a location caused by each heat source to the absolute value of uniform temperature rise or drop caused by the same heat source, as defined by Equation (1),

$$CRI_i(X_j) = \frac{\theta_i(X_j) - \theta_n}{(q_i/C_p\rho F)} \tag{1}$$

Where $\theta_i(X_j)[°C]$ is the air temperature at the location X_j caused by heat source i; $\theta_n[°C]$ is the air neutral temperature; $q_i[W]$ is the heat emission or absorption of heat source i; $C_p[J/(kg \cdot K)]$ is the specific heat of indoor air; $\rho[kg/m^3]$ is the air density; $F[m^3/s]$ is the

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volume of supply air. For more details, please refer to literature [7].

When the air supply speed and temperature are constant, the influence caused by the small-scale change of heat source intensity can be ignored, and the airflow field can be considered as steady-state. Under this condition, it can be considered that the heat transfer of each heat source in the space changes linearly with the heat source intensity, that is, the CRI of each heat source is a fixed value. Accordingly, a method based on CRI and finite air temperature collected by one mobile sensor to predict indoor temperature distribution has been proposed [2]. The temperature rise or drop from θ_n at the location X_j can be expressed by Equation (2),

$$\Delta\theta(X_j) = \begin{bmatrix} C_{j1} & C_{j2} & \cdots & C_{jm} \end{bmatrix}$$

$$\begin{bmatrix} C_{11} & C_{12} & \cdots & C_{1m} \\ C_{21} & C_{22} & \cdots & C_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ C_{1m} & C_{2m} & \cdots & C_{mm} \end{bmatrix}^{-1} \begin{bmatrix} \Delta\theta'_{s1} \\ \Delta\theta'_{s2} \\ M \\ \Delta\theta'_{sn} \end{bmatrix} \quad (2)$$

Where $\Delta\theta(X_j)$ is the temperature rise or drop from θ_n at the location X_j; C_{ji} is the CRI of heat source i to location X_j; $\Delta\theta'_{si}$ is the temperature rise or drop collected by mobile sensors from θ_n;

2.2 POD theory

The basic idea of POD method is that extracts a few representative modes in energy sense, which belongs to the category of projection methods. The detailed calculation procedure of POD is as follows:

1. Built the target parameter matrix based on a series of snapshots,

$$\mathbf{S} = \begin{pmatrix} \mathbf{s}^1 & \mathbf{s}^2 & \cdots & \mathbf{s}^N \end{pmatrix} \quad (3)$$

Where $\mathbf{s}^i$ is the distribution vector of physical field parameters in the ith snapshot; N is the number of snapshots.

2. Construct the auto covariance matrix of the target parameter matrix,

$$\mathbf{C} = \mathbf{S}^T\mathbf{S} \quad (4)$$

3. Solve the eigenvalues and eigenvectors of the auto covariance matrix,

$$\mathbf{CW} = \lambda\mathbf{W} \quad (5)$$

Where λ is the eigenvalues; $\mathbf{W}$ is the eigenvectors.

4. Arrange the calculated eigenvalues in order from large to small,

$$\lambda_1 > \lambda_2 > \ldots > \lambda_N = 0 \quad (6)$$

The proportion of each eigenvalue to the sum of all eigenvalues reflects the physical field energy captured by the corresponding eigenvector, which is generalized energy. Generally, the number of eigenvalues that can capture 99% of the energy of the physical field is sufficient. Therefore, the required number of eigenvalues can be determined according to Equation (7),

$$\frac{\sum_{i=1}^{P} \lambda_i}{\sum_{j=1}^{N} \lambda_j} \geq 99.99\% \quad (7)$$

5. Calculate the POD modes,

$$\boldsymbol{\varphi}^i = \frac{\sum_{n=1}^{P} \mathbf{A}_n^i \mathbf{s}^n}{\left\| \sum_{n=1}^{P} \mathbf{A}_n^i \mathbf{s}^n \right\|} \quad (8)$$

Where $\mathbf{A}_n^i$ is the ith order component of the eigenvector corresponding to the ith eigenvalue.

6. Calculate the mode coefficient corresponding to each POD mode,

$$\mathbf{a}^n = \begin{bmatrix} \boldsymbol{\varphi}^1 & \boldsymbol{\varphi}^2 & \cdots & \boldsymbol{\varphi}^n \end{bmatrix}^T \mathbf{s}^n \quad (9)$$

7. Reconstruct the physical field according to Equation (9).

2.3 Dynamic temperature prediction introducing interpolation POD approach

This study takes the air supply parameters as the design parameter and the air temperature as the design goal. Firstly, according to the adjustable range of air supply parameters, the calculation sample database is established. Based on this, the total temperature field dominated by all heat sources and each sub temperature field dominated by only one heat source under all sample conditions are calculated by CFD numerical simulation. Next, through POD analysis, the POD modes and corresponding modal coefficients in each sub temperature field can be obtained. On this basis, under any air supply parameters, the POD modal coefficients in each sub temperature field can be obtained by RBF interpolation. Subsequently, each sub temperature field can be reconstructed according to Equation (9), and the CRI distribution can be obtained by Equation (1). Finally, the mobile sensor is used to collect the air temperature at multiple locations, and is combined with the CRI reconstructed-based, according to Equation (2) to predict the temperature distribution.

3 Case study

3.1 Set-up description

A hypothetical model has been used in this study, which contains two heat sources inside (heat flux=50W/m²), with dimension of 1m × 1m × 1m, as shown in Fig. 1(a). Two air supply inlets (marked in blue) and two air exhaust outlets (marked in yellow) are located on the same side of the upper part of the room. The air supply direction is horizontal and the air exhaust direction is vertical. Set the two air supply inlets at the unified adjustment mode, with the temperature adjustment range of 20°C-24°C and the speed adjustment range of 0.1 m/s-1.0m/s. Besides, to simplify the calculation, the following assumption is also put forward: the ceiling, walls and floor are insulated, and the radiative heat transfer between surfaces is ignored. Also, the plane y=1.2m is selected as the target plane.

The neutral temperature is defined as 26℃. The numerical method used in this case is the same as the previous study, and its reliability has been verified [2]. No more details here. After the verification of grid independence, the number of grids is 318,3847 to balance the calculation accuracy and time.
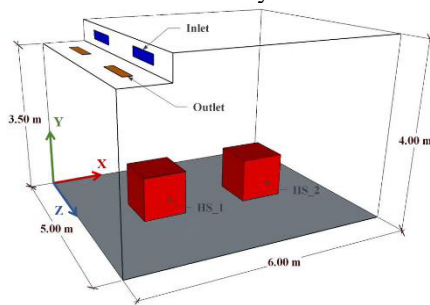

Fig. 1. CFD model.

3.2 Results analysis

Firstly, when the air supply parameters changes, it is worth discussing whether it is necessary to recalculate the representative airflow field to obtain the CRI of each heat source. It is assumed that when calculating the representative airflow field, the air supply temperature is 20 ℃ and the air supply speed is 0.5m/s. Besides, given the other four groups of air supply parameters (0.1 m/s_24℃, 0.3 m/s_22 ℃, 0.7 m/s_22 ℃, 0.9 m/s_24 ℃), taking heat source 1 as an example, the relative deviation between its actual CRI and the CRI under representative airflow field was calculated, as shown in Figure 2.
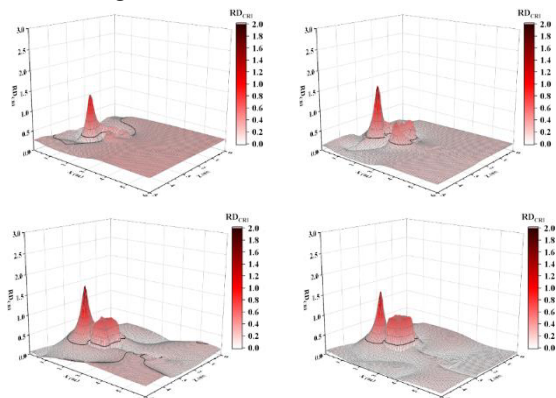

Fig. 2. Relative deviation of CRI.

Through the analysis and comparison, when the air supply parameter change, the variation of CRI distribution cannot be ignored. Therefore, it is necessary to break the limitation brought by CRI fixed value hypothesis to improve the prediction accuracy.

According to the adjustable range of air supply parameters, the interpolation interval of air supply speed and temperature was selected as 0.01m/s and 0.1℃ respectively. The established sample database includes 10 air supply speeds (0.1m/s, 0.2m/s, 0.3m/s, 0.4m/s, 0.5m/s, 0.6m/s, 0.7m/s, 0.8m/s, 0.9m/s and 1.0m/s). Each speed corresponds to 3 air supply temperatures (20℃, 22℃ and 24℃), that is, there are 30 air supply conditions.

In this study, for the total temperature field and each sub temperature field, the first 3, first 1 and first 1 POD modes were selected for the reconstruction, which can cover almost all the data characteristics of the whole temperature field.

Then, according to the current air supply parameter conditions (T=23℃, v=0.65m/s), the total temperature distribution and each sub temperature distribution at target plane y=1.2m were reconstructed, as shown in Fig. 3, Fig. 4 and Fig. 5 respectively. The detailed relative deviation analysis is shown in Fig. 6(a), 6(b) and 6(c). It can be seen that in most areas the relative deviation between the simulation results and reconstruction results is acceptable, except for the vicinity of the heat source.
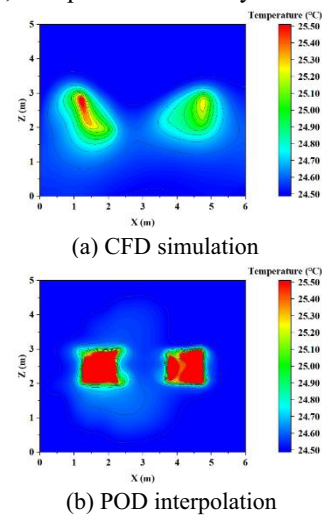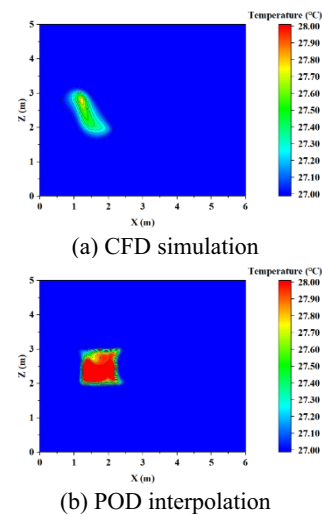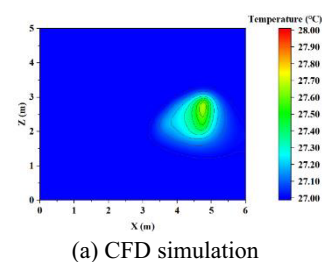

(a) CFD simulation

(b) POD interpolation

Fig. 3. Total temperature distribution.

(a) CFD simulation

(b) POD interpolation

Fig. 4. The first sub temperature distribution.

(a) CFD simulation
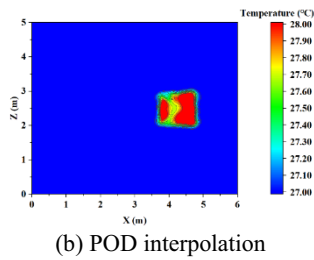
(b) POD interpolation

Fig. 5. The second sub temperature distribution.

After reconstructing each sub temperature field based on the interpolation POD method, the CRI distribution can be calculated according to the Equation (1). The reconstructed CRI is combined with the air temperature collected by the mobile sensor at three locations and substituted into the proposed prediction algorithm (Equation (2)) to predict the temperature distribution in the y=1.2m plane. The results are shown in Figure 7.
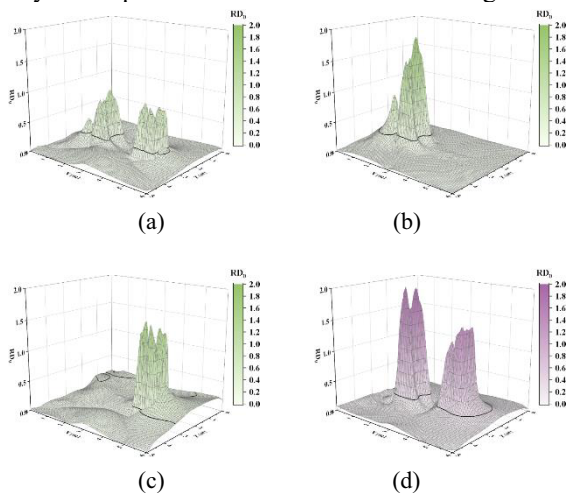

(a)

(b)

(c)

(d)

Fig. 6. Analysis of relative error on y = 1.0m plane under different conditions.

Comparing Fig. 7 and Fig. 3(a), it can be seen that the temperature prediction results in most areas are relatively accurate. The detailed relative deviation analysis is shown in Figure 6(d). From the figure, in most areas, the prediction results are satisfactory, while the larger deviation occurs near the heat source.
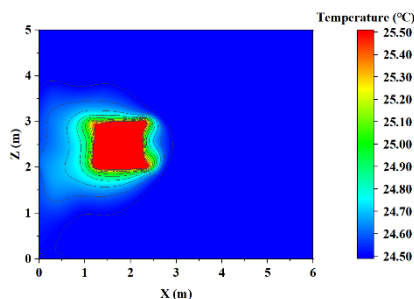

Fig. 7. Prediction results of temperature distribution based on CRI.

4 Conclusions

The main conclusions are summarized as follows:
(1) The influence of air supply parameters on CRI distribution cannot be ignored. It is necessary to put

forward improved methods to improve the calculation accuracy.
(2) It is effective to introduce the interpolation POD method to reconstruct the sub temperature field and further predict temperature distribution.
(3) In the area near the heat source, the relative error of pod reconstruction is relatively large, which is necessary to further optimize.

Acknowledgement

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