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Optimization of air supply parameters for stratum ventilation based on proper orthogonal decomposition

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A R T I C L E   I N F O

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A B S T R A C T

Under the current COVID-19 epidemic conditions, stratum ventilation can provide treated fresh air directly into the human breathing zone, improving the air quality for inhalation. However, in the design of air supply parameters for stratum ventilation, the traditional trial-and-error and experimental methods are inefficient and time consuming, and they cannot be used to identify the optimal air supply parameters from a large number of parameters. Therefore, in this paper, the inverse design method based on proper orthogonal decomposition (POD) was applied to the design of ventilation parameters for a room with stratum ventilation. Predicted mean vote (PMV), predicted percentage dissatisfied (PPD) and droplet nuclei concentration in the human breathing zone were selected as design objectives to optimize air supply parameters. The transmission of COVID-19 was controlled by reducing the concentration of droplet nuclei in the respiratory area. The results show that, compared with the trial-and-error method, the inverse design method based on POD is more than 90% faster. POD method can greatly expand the sample size. Considering the dispersion of exhaled droplet nuclei in the room, the appropriate stratum ventilation parameters can reduce the concentration of fine droplet nuclei by more than 20% compared with the traditional design parameters.

1. Introduction

Nowadays, COVID-19 is a big problem for humanity’s health and economy according to the negative impact of the virus on people’s quality of life, leading to acute respiratory diseases, death, and financial crises worldwide (Rahmani & Mirmahaleh, 2021). There are many modes of COVID-19 transmission, of which droplet transmission is considered the most important (Novel coronavirus pneumonia diagnosis and treatment plan (trial version 7), 2020). Morawska and Cao (2020) have found that aerosol propagation of COVID-19 is possible. The particle size of viruses is between 0.01 and 0.5 μm, and the particle size of the COVID-19 virus is between 0.08 and 0.16 μm (Li, Wu, Niu, & Gao, 2020). Lindsley et al. (2010) found that the virus content of small particles was greater than that of large particles. Meanwhile, Jan, Euan, Mary-Louise, and D (2011) summarized the size of droplets produced by the human body under normal respiration. The results showed that the droplet size produced under normal breathing conditions was less than 5 μm. The small particle droplet nuclei produced in respiration cannot be ignored in the course of disease transmission. Air cleaning is an effective and reliable method in indoor airborne COVID-19 control (Feng, Cao, & Haghighat, 2021). For most infectious diseases, ventilation can effectively reduce the probability of infection (Qian, Zheng, & Zhang, 2012). Therefore, it is of great importance to study ventilation parameters and droplet nuclei propagation for small particles. To cope with this pandemic, professionals in architecture, urban planning sectors, and design agencies have already switched their focus to visualize the post-pandemic era (Megahed & Ghoneim, 2020). The choice of ventilation method has become very important.

In the stratum ventilation method, fresh air is sent directly to the breathing zone of the human body, and the indoor air is fresher. Tian, Lin, Wang, and Liu (2009) and Lin, Wang, Yao, and Chow (2012) studied the diffusion of indoor particulate matter under stratum ventilation and displacement ventilation by numerical simulation. According to their results, the particle concentrations in the room overall and in the breathing zone under stratum ventilation were lower than those under displacement ventilation; as a result, the risk of particulate matter inhalation, and thus of pathogen inhalation, is lower under stratum ventilation. Tian et al. (2019) studied the ventilation characteristics of stratum ventilation, displacement ventilation and mixed ventilation. They found that stratum ventilation can ensure good air quality for...
indoor occupants, with better contamination exclusion than that provided by mixed ventilation or displacement ventilation. This effective contamination exclusion gives stratum ventilation a clear advantage during an epidemic, particularly in multi-row classrooms where students gather after returning to school. Therefore, this paper will optimize the air supply parameters of stratum ventilation from the perspective of controlling airborne diseases and thermal comfort. Considering the effective contamination exclusion and energy saving characteristics of stratum ventilation, this work will be of great importance for sustainable development of the post-pandemic era.

Many people have studied the optimization of the supply air parameters of the stratum ventilation. Table 1 shows a summary of the studies on optimization of air supply parameters of stratum ventilation. The usual methods are experimental or numerical simulation. However, the experimental method is time-consuming, expensive and the study sample size is relatively small. The sample size of the numerical simulation method is larger than that of the experimental method, but it still takes a long time to obtain a large number of data. Therefore, the inverse design method based on proper orthogonal decomposition (POD) was applied to the design of ventilation parameters for a room with stratum ventilation.

In recent years, inverse design methods have been widely used in the design of indoor air supply parameters. These methods, which include the computational fluid dynamics (CFD)-based adjoint method, CFD-based genetic algorithm method, and the proper orthogonal decomposition (POD) method, show promise in the inverse design of airflow and heat transfer in an enclosed environment (Liu et al., 2015). POD is an effective method for reducing CFD simulation effort (Feng, Yu, & Cao, 2018). In the continuous development and evolution of inverse design methods, Wei et al. (2019) integrated the POD method with other inverse design methods that can provide the optimal design for each design objective. In the design process, they demonstrated the efficiency of the POD method. Therefore, the POD method is adopted in this paper to optimize the supply air parameters of the stratum ventilation.

To date, there is no relevant literature that applies the inverse design method based on POD to the design of air supply parameters for a room with stratum ventilation. The thermal comfort and air quality under stratum ventilation could be further improved with optimized air supply parameters. Since the traditional trial-and-error method and experimental methods are inefficient and time-consuming, they are not suitable for the analysis and optimization of the flow field under a large number of air supply parameters. Therefore, this study combined the use of the POD inverse design method to optimize the design of ventilation parameters in a stratum-ventilated room, and the goals of environmental thermal comfort and a reduction in the indoor droplet nuclei concentration.

2. Method

2.1. Description of the environmental chamber geometry

City University of Hong Kong has built an environmental chamber room for investigation of various ventilation methods. Numerous experiments and studies on stratum ventilation have been carried out in this chamber (Lin, 2011; Yao & Lin, 2014a). It provides a useful reference value for the numerical simulation of stratum ventilation, as well as a large amount of experimental data to verify the accuracy of a numerical model. As described in this paper, we have optimized the air supply parameters of the environmental chamber and verified the numerical model with the experimental data provided in Yao and Lin (2014b).

The chamber is laid out as a classroom, and the layout and geometric model are shown in Fig. 1 and Fig. 2, respectively. The size of the classroom is 8.8 m (length) × 5.75 m (width) × 2.4 m (height). There are 16 seats arranged in two rows. In the simulation, the human body is represented by a rectangle with dimensions of 0.4 m (length) × 0.3 m (width) × 1.2 m (height). Each occupant’s mouth is represented by an opening at a height of 1.0 m on the human body model. To simulate the mouth during breathing, the opening size is 0.01 m (width) × 0.02 m (length), and position 3 was set as the sources of droplet nuclei. There are 17 human body models in the classroom, and they are numbered as shown in Fig. 1.

2.2. Numerical method

2.2.1. CFD model

In this study, STAR-CCM+ software was used for simulation calculations. Xu and Chen (2000) used the K-epsilon two-layer turbulence model to predict mixed convection by displacement ventilation in an office. The computed results agreed well with the corresponding airflow pattern and the distributions of air temperature, air velocity, air velocity fluctuation, and tracer-gas concentration. Therefore, the K-epsilon two-layer turbulence model was selected in this study. This model can be applied accurately to either low-Reynolds number type meshes of y* close to 1 or wall-function type meshes of y* greater than 30 (Rodi, 1991).

Because of the indoor heat source, we turned on the radiation model. For the simulation of droplet nuclei diffusion, Ai, Mak, Gao, and Niu (2020) demonstrated that a tracer gas is a suitable substitute for studying the air propagation of droplet nuclei in a building environment. It is found that under some indoor scenarios, the coronaviruses present in the respiratory droplets become active due to size reduction that occurs both in sessile and airborne droplet nuclei causing an increase in the spread (V. R., & Haghighat, 2020). An extensive literature search in Ai et al. (2020) indicated that tracer gas simulation is sufficiently accurate for study of the particle size of particles not larger than 3–5 µm. This size range represents the dominant portion of human expiratory...
droplet nuclei in terms of quantity. The passive scalar method is typically used to simulate the tracer gas and was therefore used to simulate the droplet nuclei from human expiratory in this study.

To generate the mesh for this model, we used a trimmed cell mesher. Because the classroom model was more regular after simplification, it was appropriate to use a hexahedral mesh. The mesh at the inlet and at the source of droplet nuclei, i.e., the oral cavity of the human body, was encrypted.

The simulated velocities of the validation case (in Section 3.1) at 20 positions uniformly distributed in two lines, i.e., Line 1 \((X = 3.0 \text{ m}, Y = 2.875 \text{ m})\) and Line 2 \((X = 6.6 \text{ m}, Y = 2.875 \text{ m})\), were monitored and compared for three types of grid number, as shown in Fig. 3. The velocities between 530,000 grids and 1,004,000 grids were close to each other, whereas large discrepancies existed at several positions between 219,000 grids and the other two types of grid number. Therefore, 530,000 grids were adopted with consideration of both accuracy and time cost.

2.2.2. POD method

Inverse design concept uses the desired enclosed environment as the design objective and inversely determines the systems required to achieve the objective (Liu et al., 2015). POD method shows the promise in the inverse design of airflow and heat transfer in an enclosed environment. POD technology provides a linear approximation of a set of functions, which makes it easier to describe complex raw input data as the sum of weighted basis functions. This method is also called principal component analysis, and it can be used to extract the main feature components of data; it is often used to reduce the dimension of high-dimensional data. For the flow field, the coherent structure of the data can be extracted through analysis, and several linearly independent orthogonal bases are constructed. Thus, the physical field under any design parameters can be expressed as a linear combination of the orthogonal basis functions and its corresponding coefficients, so as to realize the dimensionality reduction and fast acquisition of the physical field. The mathematical process of POD is described in reference Chen, Reuss, and Sick (2012). This paper only briefly introduces the necessary
components.

The data selected in this paper are the predicted mean vote (PMV) and predicted percentage dissatisfied (PPD) value near the human body and the average concentration of droplet nuclei in the human breathing zone, calculated by CFD simulation cases. The POD method is used to decompose the scalar field $S^{(k)}_i = (S^{(1)}_i)^T$ (called snapshots; $i$ is the index of the grid points in the scalar quantity distributions, and $k$ is the snapshot index) into a linear combination of $M$ spatial basis functions (POD modes, $\varphi_m$) and the corresponding coefficients $c_m^{(k)}$. The index of the grid points is arbitrary (e.g., they needn’t correspond to the nodes of a mesh), but they must be the same order for all $K$ snapshots. The scalar field composed of PMV, PPD and concentration data was reordered into a row in the same order. The average value of the data in the scalar field is removed. Then rearranged the data into the matrix (1) according to the sequence of snapshot.

$$S = \begin{bmatrix} S^{(1)}_i \\ S^{(2)}_i \\ \vdots \\ S^{(K)}_i \end{bmatrix} = \begin{bmatrix} c_{1}^{(1)} & c_{2}^{(1)} & \cdots & c_{M}^{(1)} \\ c_{1}^{(2)} & c_{2}^{(2)} & \cdots & c_{M}^{(2)} \\ \vdots & \vdots & \ddots & \vdots \\ c_{1}^{(K)} & c_{2}^{(K)} & \cdots & c_{M}^{(K)} \end{bmatrix}$$ (1)

Here, ‘$I$’ is the number of grid points of the selected scalar field, and ‘$K$’ is the number of snapshots. The spatial correlation matrix of the scalar field is defined as $C = \frac{1}{K}SS^T$. The eigenvectors and eigenvalues of the matrix $C$ are solved.

$$C\beta_m = \lambda_m \beta_m \tag{2}$$

The basis functions (POD modes, $\varphi_m$) are obtained by projecting $S$ onto the eigenvector $\beta_m$ ($m = 1, 2, \ldots, M$), with subsequent normalization (the sum of squares is 1). The number of POD modes is equal to the number of snapshots. In addition, the modes are orthogonal to each other. Then $S$ is projected onto the calculated basis functions $\varphi_m$, and the coefficients of each mode are calculated, and the coefficient matrix $c_m^{(k)}$ is obtained.

The actual energy coefficients of each mode are contained in the matrix $c_m^{(k)}$, and each mode of each snapshot has a coefficient. There is a certain relationship between the coefficient and the air supply parameters. For example, in the analysis of PMV scalar field, the relationship between supply air velocity and coefficient $c_m^{(k)}$ is linear, so linear interpolation is used. In the analysis of coefficient field, polynomial interpolation is used between supply air temperature and coefficient $c_m^{(k)}$. $\lambda_m$ represents the energy contributed by the $m$th mode. The energy fraction of the $m$th mode is expressed by Chen et al. (2012)

$$r_m = \frac{\lambda_m}{\sum_{n=1}^{M} \lambda_n} \tag{3}$$

The scalar field can be reconstructed by the following formula:

$$S^{(k)} = \sum_{n=1}^{M} c_n^{(k)} \varphi_n \tag{4}$$

The first few orthogonal basis functions with large energy contributions can be selected to reduce the dimension of the original data field. The energy contained in the orthogonal basis function plays a key role in the number of orthogonal basis functions used in scalar field reconstruction. In general, if the cumulative energy of the selected orthonormal basis functions is greater than 90%, the scalar field can be reconstructed by interpolation. Compared with CFD simulation, the POD method is very simple and efficient.

In this study, multi-parameter and multi-objective optimization of the stratum-ventilated classroom was carried out, and the optimization strategy is shown in Fig. 4. The whole process is divided into two parts. First, the data set is obtained through numerical simulation, and then the POD is used to expand it. Finally, the target parameters are obtained by filtering the data obtained through POD interpolation. The parameters to be optimized in this study are air supply temperature and air supply velocity. The optimization objectives were selected in accordance with the design requirements, and three POD optimization objectives were identified: $\{\text{PMV}_{\text{ave}}, \text{PPD}, \text{and the average concentration of droplet nuclei}\}$ in the breathing zone of the human body.

2.3. Case setup

During the normalized phase of COVID-19, droplets or aerosol particles produced by infected personnel are considered as the potential source of infection with uncertain exposure risk (Ren et al., 2021). In this study, the occupant of seat 3 was the potential source of infection. The dimensionless concentration ($C_d$) of droplet nuclei at the mouth opening of the occupant (seat 3) was set as 1, and the human respiratory volume was set as 6.6 L/min Liu et al. (2014). The cooling loads of the occupants, lighting and workstall were $7 \times 70$ W, 1176 W and 300 W, respectively (Cheng & Lin, 2015). This study optimized the supply air temperature and velocity, and the optimal range of the supply air temperature was 17–26 °C (Shao, Wang, Li, & Lin, 2018). In the study of Cheng and Lin (2015), it is pointed out that when the air change per hour exceeds 15, it will cause greater draft risk, so the selection of maximum air change per hour should be less than 15. Therefore, the range of air supply velocity selected in this paper was 1.6–3.2 m/s (7.2–14.4 ACH) (Zhang, Cheng, Fang, Huan, & Lin, 2017). In the calculation of PMV and PPD, we assumed that the classroom occupants were sedentary and wearing summertime clothing; thus, the clothing thermal resistance was 0.57 clo, and the human metabolic rate was 1.0 met (Shao et al., 2018). The relative humidity in the room was set at 50%.
The setup of the cases is detailed in Table 2, with different air supply temperatures and velocities for 20 cases. In the analysis of droplet nuclei concentration, taking each occupant’s mouth as the center, the volume of the breathing zone was 0.4 m × 0.3 m × 0.2 m, and the average concentration in each occupant’s breathing area was taken as the optimization object. The inhalation fraction (IF) index of respiratory zone could be used as the evaluation index of the optimized concentration results (Kong et al., 2021).

\[
IF = \frac{\int Q_{inh}c_{inh}dt}{\int Q_{exh}c_{exh}dt}
\]  

Table 2

Parameter setup for different cases.

| Case | Supply air temperature (°C) | Supply air velocity (m/s) |
|------|----------------------------|--------------------------|
| 1–5  | 17                         | 1.6, 2, 2.4, 2.8, 3.2    |
| 6–10 | 20                         | 1.6, 2, 2.4, 2.8, 3.2    |
| 11–15| 23                         | 1.6, 2, 2.4, 2.8, 3.2    |
| 16–20| 26                         | 1.6, 2, 2.4, 2.8, 3.2    |

In the POD interpolation process, the step size for velocity interpolation was 0.05 m/s, and the step size for temperature interpolation was 0.25 °C. Information for a total of 1221 flow fields was obtained by interpolation. In the process of POD orthogonal basis extraction, more than 95% of the "energy" was extracted in the flow field reconstruction.

3. Results and discussion

3.1. Validation of numerical method

For validation of the environmental model shown in Fig. 1, the simulation accuracy of STAR-CCM+ and the selection of the physical model were verified. The flow field and temperature field of the classroom model were simulated and compared with the experimental results of Yao and Lin (2014b). In the validation case, the ventilation rate of the room was 10 ACH, and the supply air temperature was 20.6 °C. The indoor heat sources were mannequins, workstations and lamps. The heat source intensity levels were 17 × 70 W, 17 × 300 W and 21 × 56 W, respectively. The velocity and temperature at a height of 1.1 m at six positions (L1–L6) in Fig. 1 were compared with the simulation results. The comparison between the simulated and measured results is shown in Fig. 5. For details of the experiment, see reference (Yao & Lin, 2014b).

The simulation results were similar to the experimental results, with the exception of position 1. The reason may be that this location was close to the air supply outlet, where the simulation error was relatively large. The simulation results show that this numerical simulation model can be used to calculate the indoor flow field.

Because the experimental data of the environmental model shown in Fig. 1 was not found, the experimental data of a classic office model (Yuan et al., 1999) was chosen for the passive scalar method verification. The geometric model of the experiment is shown in Fig. 6. The simulation results for SF6 concentration obtained by CFD simulation under the same boundary conditions on three lines in the figure were compared with the experimental data of Yuan et al. to verify the correctness of model selection and parameter settings in the passive scalar method.

The comparison between the experimental and simulation results is shown in Fig. 7, which indicates that the concentration distribution was essentially consistent with the experimentally measured results. Generally speaking, the simulation results for the chamber were in good agreement with the experimental data. Passive scalar method can be used to simulate indoor concentration field.

3.2. Analysis of optimization results

3.2.1. Analysis of optimization results for PMV and PPD

The interpolation results for the PMV and PPD field are shown in Fig. 8. The optimal air supply parameters for |PMV|ave and PPD as the optimization objective were an air supply temperature of 19 °C and an air supply speed of 2.45 m/s. The PMV and PPD results obtained through POD interpolation were relatively smooth with the variation of each parameter. In this study, the influence of temperature on thermal comfort was greater than that of air supply velocity. The variation trend...
Fig. 7. Comparison of the SF6 concentration along three lines in an office ($C = C_i/C_s - C_s = 0$ ppm, $C_v = 0.42$ ppm, $Z = z/h$, $h = 2.43$ m. Symbols: measurement; lines: simulation).

Fig. 8. $|\text{PMV}|_{\text{ave}}$ and PPD with different ventilation parameters: (a) $|\text{PMV}|_{\text{ave}}$, (b) PPD.

Fig. 9. Temperature and velocity field in the horizontal sections at $Z = 1.1$ m. (Air supply parameters: $19^\circ$C, 2.45 m/s): (a) Temperature, (b) Velocity.
of PPD results was similar to PMV results.

The temperature field and velocity field at the height of the inlet under the optimal air supply parameters calculated by CFD are shown in Fig. 9, and the temperature on the air supply path was lower than in other areas. The air velocity was higher and the temperature was lower near the front row of the classroom than near the back row under stratum ventilation. The flow field and temperature field at this height were not uniform. Therefore, the thermal comfort of occupants in different positions was affected differently by the changes in air supply parameters. The PMV values of occupants in the front row were more sensitive to the variation in air supply parameters than was the PMV values of back-row occupants. The PMV under optimized air supply parameters of the occupant at each location is shown in Fig. 10. Because the front row was close to the inlet, the PMV of the first row of occupants in the room was lower than for those in the second row. The PMV values at the 17 positions all represent a relatively comfortable thermal environment under the optimized air supply parameters. The $|\text{PMV}_{\text{ave}}|$ and $\text{PPD}_{\text{ave}}$ (average PPD of 17 occupants) under the optimal air supply parameters calculated by POD interpolation was 0.17 and 4.6%. The $|\text{PMV}_{\text{ave}}|$ calculated by CFD was 0.18, and the error was only 2.42% compared with the POD result.

### 3.2.2. Analysis of optimization results for droplet nuclei diffusion

After the concentration data under 1221 sets of air supply parameters were obtained by the POD interpolation method, the average scalar value of the droplet nuclei in the 17 occupants’ breathing zones in each case was calculated. The average relative concentration ($C/C_d$) results are shown in Fig. 11. On the whole, the average relative concentration of droplet nuclei in the human breathing zone decreased with the increase in air supply volume. The optimal air supply parameters under the optimization target were 26 °C and 3.15 m/s.

In a previous paper (Lin et al., 2012), Lin Zhang et al. compared the large particle droplet diffusion in a classroom with stratum ventilation and with displacement ventilation under an air supply temperature of 20 °C and air supply speed of 2.48 m/s. They found that the droplet concentration in the human breathing zone under stratum ventilation was far lower than that under displacement ventilation. In the present study, we compared the $IF$ values under the air supply parameters in Zhang et al.’s study (Lin et al., 2012) with the $IF$ values under our optimized air supply parameters. The $IF$ values are shown in Fig. 12. The average $IF$ value under the optimized air supply parameters was lower by 22.1%. At most of the locations, the $IF$ values were lower under the optimized air supply parameters than under the parameters of Zhang et al. (Lin et al., 2012) Since position 3 was the source of the droplets, the $IF$ value was the 100% at this location, with a large impact on the adjacent seats and the teacher’s seat. It can be seen that an improvement in the air supply parameters can further enhance contamination exclusion in a stratum-ventilated room and thus reduce the infection risk of airborne diseases like COVID-19.

Fig. 13 presents the relative concentrations ($C/C_d$) for the planes of $X = 3.2$ m, $Y = 2.1$ m and $Z = 1.0$ m. Compared with the concentration field under the air supply parameters in Lin et al. (2012), the pollutant diffusion influence range is smaller and the concentration is lower. From the viewpoint of engineering controls, ventilation can help dilute contaminants and reduce infection risk (Agarwal et al., 2021).

The $C/C_d$ with different temperature is compared for different zones in Fig. 14, where the sixteen seats have been divided into four zones (i.e., zones 1–4) of four seats each as shown in Fig. 1. At different air supply temperatures, the concentration ratio of each region is roughly the same. It can be seen from Fig. 14 that temperature has little influence on the concentration distribution in each region.

### 3.2.3. Comprehensive analysis to determine the optimal ranges of air supply parameters

The results for the three optimization objectives were sorted, the comprehensive score was calculated to evaluate the optimization results under each air supply parameter, and then the appropriate air supply parameters were obtained. The proportions of different optimization objectives can be adjusted in accordance with the actual scenario. In the current epidemic situation, the proportion of thermal comfort can be reduced, and more attention can be paid to the freshness of indoor air and the effects of contamination exclusion. The health of occupants in confined spaces should be of utmost priority (Agarwal et al., 2021). As an example, we set the weight of the concentration field optimization goal to 70% and the total weight of the PMV and PPD optimization goal to 30%. Scoring function $F_{\text{POD}}$ can then be defined as

$$F_{\text{POD}} = 15 \times \left(2 - \frac{|\text{PMV}| - |\text{PMV}_{\text{ave}}|}{|\text{PMV}_{\text{ave}}|} - \frac{\text{PPD} - \text{PPD}_{\text{ave}}}{\text{PPD}_{\text{ave}} - \text{PPD}_{\text{ave}}} + 70 \times \left(1 - \frac{c_{\text{ave}} - c_{\text{ave}}}{c_{\text{ave}} - c_{\text{ave}}} \right) \right)$$

The $F_{\text{POD}}$ results are shown in Fig. 15, and the air supply parameters can be selected accordingly. According to this scoring function, the object of the classroom scenario in this study has a higher $F_{\text{POD}}$ value under the conditions of stratum ventilation, low air supply temperature and high air supply velocity. Therefore, it is recommended that lower air supply temperature and higher air supply speed be selected. Under this scoring function, the final optimized air supply parameter is 19.75 °C and 3.1 m/s. CFD calculation was carried out for the flow field and concentration field under the optimized air supply parameters. $|\text{PMV}_{\text{ave}}|$ and $\text{PPD}_{\text{ave}}$ are 0.18 and 6.07%, respectively. The $|\text{PMV}_{\text{ave}}|$ and $\text{PPD}_{\text{ave}}$ calculated under the supply air parameters of (Lin et al., 2012) are 0.32 and 8.12%. The optimized $|\text{PMV}_{\text{ave}}|$ and $\text{PPD}_{\text{ave}}$ were reduced by 43.9% and 25.3% respectively.

Compared with the concentration field under the air supply parameter in Lin et al. (2012), the average $IF$ value under the optimized air...
supply parameters was lower by 25.4%. It can be seen that the optimized air supply parameters can meet the needs of different optimization objectives.

In this study, a 24-core CPU was used to conduct the CFD simulation. Each case was calculated for more than 1000 iterations. Each case took about one hour, and thus the calculation of 20 cases required about 24 h. Meanwhile, the POD analysis and interpolation process required even less time. Two hours would be sufficient when the designers are familiar with the relevant program code. By comparison, it would take at least 1200 h to calculate 1221 cases with the traditional trial-and-error method. The POD method can expand the sample space of research and reduce the calculation time by more than 90%, greatly improving the design efficiency.

Fig. 12. *IF* values for each occupant.

Fig. 13. Comparison of relative concentrations at $Z = 1.0 \, \text{m}$, $Y = 2.06 \, \text{m}$, $X = 3.2 \, \text{m}$.

Fig. 14. $C/C_d$ in different regions under different air supply parameters.
4. Discussion

In general, POD interpolation must ensure that the selected basis function contains more than 90% of the total "energy", which in turn will ensure good interpolation and reconstruction of the flow field information under other parameters. "Energy" can be understood as the amount of information extracted. The energy ratios of the orthogonal basis functions extracted by the POD method are shown in Fig. 16. Cumulative contribution of orthogonal basis function to total energy is shown in Fig. 17. It can be seen that in the extraction of orthogonal basis functions, the energy proportion of mode 1 is above 60%, and the accumulated energy proportion of the first two modes is above 95%. When the PMV, PPD and concentration field results are extracted and reconstructed by orthogonal basis functions, two orthogonal basis functions can be used to reconstruct more than 95% of the cumulative energy.

The PMV and PPD calculated by CFD for the other 20 cases were compared with the interpolation result from the POD method, and the error percentage is $R_{\text{pmv}}$ and $R_{\text{ppd}}$:

$$R_{\text{pmv}} = \frac{|\text{PMV}_{\text{ave}} - \text{PMV}_{\text{ave}}^{\text{POD}}|}{\text{PMV}_{\text{ave}}} \times 100\%$$  \hspace{1cm} (6a)  

$$R_{\text{ppd}} = \frac{|\text{PPD}_{\text{ave}} - \text{PPD}_{\text{ave}}^{\text{POD}}|}{\text{PPD}_{\text{ave}}} \times 100\%$$  \hspace{1cm} (7)

Here $|\text{PMV}_{\text{ave}}^{\text{Cfd}}|$, and $|\text{PPD}_{\text{ave}}^{\text{Cfd}}|$, represents the result of CFD calculation, and $|\text{PMV}_{\text{ave}}^{\text{POD}}|$, and $|\text{PPD}_{\text{ave}}^{\text{POD}}|$, represents the result of POD interpolation. The errors in the PMV and PPD results obtained by POD interpolation are shown in Tables 3 and 4, and the total average error was only 2.58% and 1.12%. Similarly, the percentage error for POD interpolation of concentration is $R_{C}$:

$$R_{C} = \frac{|C_{\text{ave}}^{\text{Cfd}} - C_{\text{ave}}^{\text{POD}}|}{C_{\text{ave}}^{\text{Cfd}}} \times 100\%$$  \hspace{1cm} (8)

Here $C_{\text{ave}}^{\text{Cfd}}$ represents the result of CFD calculation, while $C_{\text{ave}}^{\text{POD}}$ represents the result of POD interpolation. The errors in the POD interpolation results are shown in Table 5, and the total average error was 3.89%.

5. Conclusions

In this study, through numerical simulation, the inverse design method based on POD was applied for the first time to the design of ventilation parameters for a stratum-ventilated room. The numerical model was verified, and the accuracy and feasibility of the method were confirmed by comparison with experimental data. Taking PMV, PPD and concentration as the evaluation indexes, the optimal design scheme provides references for the design of ventilation parameters for stratum-ventilated rooms.
the concentration of droplet nuclei in breathing zone as the optimization objective, the optimized air supply parameters were obtained. The transmission of COVID-19 was controlled by reducing the concentration of droplet nuclei in the respiratory area. The main conclusions are summarized as follows.

1. Compared with the traditional trial-and-error method, the inverse design method based on POD can reduce the calculation time by more than 90%. POD method can greatly expand the study sample size. In this study, through the flow field and concentration data of 20 CFD cases, 1221 sets of data were obtained by interpolation after POD analysis.

2. In the current COVID-19 epidemic situation, where the indoor transmission of small droplet nuclei is a significant problem, the IP value can be reduced by more than 20% under the appropriate stratum ventilation parameters compared with the traditional design parameters.

3. The proportions of different optimization objectives can be adjusted in accordance with the actual scenario. In this work, the scoring function is set according to the optimization target of thermal comfort accounting for 30% and the optimization target of concentration accounting for 70%. The optimized PMV\textsubscript{ave} value decreased by 43.9%, 25.3% and 25.4% respectively.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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