Improving Indoor Multiphysics Prediction with Local Measurements Based on Data Assimilation

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Abstract. Accurately mastering the distribution of multi-physical field is an important prerequisite for rationally formulating building environment construction scheme. In practical engineering projects, sensor monitoring can obtain more accurate environmental state parameter values. However, due to the constraints of investment cost, spatial limitations and other factors, the number of on-site measured monitoring points is limited. On the contrary, CFD simulation can obtain global distribution information of the physical field, but the uncertainty of parameters such as boundary conditions seriously affects the reliability of simulation results. In view of the above problems, based on Ensemble Kalman Filter (EnKF), which is a sequential data assimilation algorithm, a technical framework for accurate indoor multiphysics simulation is established. We evaluated the performance of this method with reduced-scale model experiments, verifying that the simulation errors can be significantly reduced. The proposed method has a positive impetus for realizing the global monitoring of the physical field of the building space.

1 Introduction

With the rapid development of social and economic level and the continuous advancement of urbanization, building functions are gradually diversified to meet people's needs in all aspects of life and production. The indoor environment not only affects human health and comfort [1], but also plays a significant role in the maintenance, preservation and production of items. Therefore, it is extremely necessary to exactly grasp the spatial distribution information of indoor multiphysics.

Currently, sensors have always been playing an important monitoring role in building environmental control [2]. However, due to the constraints of economic cost and installation space, the number of sensors is always limited, and thus monitoring data cannot effectively reflect the global distribution of indoor environmental parameters. Nowadays, CFD has become one of the main methods for assessing environmental conditions [3]. The reliability of the simulation results depends on the accurate representation of the boundary conditions and important physical properties in the numerical model. As a matter of fact, the indoor environment is a multivariable and strongly coupled system, which is affected by many uncertainties, so using certain conditions to calculate the uncertain physics usually leads to a large difference between the simulation results and the truth.

In this paper, the data assimilation technology is introduced to modify the prediction model with the measured data to obtain more precise simulation results.

The main data assimilation methods can be divided into two categories: variational methods and statistical methods [4]. According to previous studies, variational methods rely on solving the adjoint equations of the prediction model, which leads to high computational cost [4]. It is reported that the ensemble Kalman filter (EnKF), which is a statistical data assimilation method proposed, is easy to implement and can solve high-dimensional nonlinear systems [5-8]. Previous studies on the use of EnKF have generally focused on meteorology, hydrology and fire dynamics [9, 10]. However, there is still a lack of research on the application of data assimilation in indoor environment simulation, especially in indoor multiphysics CFD simulation, which needs further exploration.

The current study extends the use of EnKF algorithm in multiphysics numerical simulation to infer boundary conditions, taking into account their variability, and thus reduce simulation errors. The method will be validated by reduced-scale model experiments.

2 Methodology

2.1 Ensemble Kalman filter

EnKF is a sequential data assimilation technology that can deal with the prediction of nonlinear dynamic models [11]. The EnKF algorithm consists of four steps: sampling, propagation, analysis and updating, and the
basic formulas of each step are described in detail as follows. In the first step, based on prior information, an initial ensemble of size $n$ is constructed to represent guesses of variables with uncertainty and is given by Eqs. (1)-(2):

$$E = \{s_1, s_2, \ldots, s_n\}$$

$$s_i = [v_{i1}^T, v_{i2}^T, \ldots, v_{im}^T]^T$$

where $s_i$ refers to the $i$-th ensemble member, $v$ represents condition variables, the subscript $m$ is the total number of variables, and the superscript $T$ denotes matrix transpose.

The next step is to substitute the samples in the above set into the forward model, and solve the calculation to obtain the state matrix $P$ after propagation. It is worth noting that the propagation process of each member in the set is independent of each other and can be executed in parallel. In the EnKF algorithm, the calculated Kalman gain operator $K$ determines the weight of each error in the difference between prediction and observation. which is expressed by Eqs. (3). Then, the ensemble member is updated by the Kalman filter formula as Eqs. (4), and the updated value will be used for the next iteration calculation.

$$K = C_{pp} M (MC_{pp} M^T + C_{pp})^{-1}$$

$$s_i = s_i + K (Y - M p_i)$$

where $C_{pp}$ represents the covariance matrix of the condition variables and the predicted state vectors, $C_{pp}$ denotes the prediction covariance matrix, $M$ is the observational operator that maps the model state space to the observation space, defined as the identity matrix in this study, $C_{ee}$ represents the known covariance matrix of the measurements, $p_i$ denotes to the $i$-th predicted state vector, $Y$ denotes the observation vector.

### 2.2 Multiphysics simulation coupled with EnKF

For optimized indoor multiphysics simulation results, a method of coupling CFD with EnKF for indoor multiphysics boundary conditions estimation and state prediction are presented. The objective of this method is to estimate the CFD equivalent boundary conditions that approximate the actual situation based on the EnKF algorithm, thereby reducing the deviation between indoor multiphysics numerical simulation results and field measurements.

During the preparation phase, it is necessary to sample the boundary condition parameters within their variation range and construct a case ensemble together with the design or initial condition to be corrected. Then, each case in the ensemble is substituted into the multiphysics CFD model for forward simulation, and the obtained results is subjected to covariance calculation. In the assimilation process, the measured data of the indoor environmental state parameters are used for Kalman filtering after pre-processing to reversely correct the boundary conditions of the CFD model. This process iterates continuously until the difference between the simulation results and the measured data reaches the convergence requirement.

### 3 Experimental and computational setup

#### 3.1 Reduced-scale model experiment schemes

The purpose of the experiments is to collect test data used to analyze the performance of the method proposed in Section 2.2. Experiments were carried out in a simplified model of an air-conditioned room. The inlet velocity, temperature and bottom heat flux were the main control parameters in experiments. It is known that the variation intervals of the boundary condition parameters with uncertainty in each case are shown in Table 1, and the actual operating parameters are a certain value in each range. During the experiments, it was necessary to ensure that there was enough time for the physical fields in the model to stabilize.

| Parameter                  | Variation Intervals |
|----------------------------|---------------------|
| Inlet velocity (m/s)       | [0.48, 1.12]        |
| Inlet temperature (℃)      | [16, 24]            |
| Floor heat flux (W/m²)     | [22, 38]            |

In this experiment, air was used as the working medium, and its temperature and flow velocity distribution were the main measurement contents that would be regarded as observations in data assimilation. The layout of measuring points ought to ensure that the number of measuring points was sufficient, therefore, a total of 30 temperature measuring points were distributed as Fig. 2 (a). Calibrated thermocouples with an accuracy of ±0.4% of the measured value were equipped to monitor the air temperature in all dimensions.

Moreover, the PIV technique was employed to visualize the velocity field inside the model, as illustrated in Fig. 2 (b). The PIV system is mainly composed of a double-pulse Nd: YAG laser with 150 mJ pulse intensity and 532 nm wavelength, a CCD camera with a resolution of 2048 × 2048 pixel, a synchronizer that triggers the laser and the camera simultaneously, and a computer for processing data. After the internal particle distribution was relatively uniform, the particle motion images were continuously captured through the view window, and the laser pulse interval time was determined according to the method in Ref. [12]. Besides, the images are processed by Davis software to obtain the velocity field data, and the measurement error is less than 12.8% [13-14].

![Temperature measurement points](image)
3.2 Computational setup

In this study, the numerical simulation of three-dimensional multiphysics is performed using the commercial CFD software ANSYS Fluent. The computational domain is divided by hexahedral meshes while the meshes are refined at the boundary layer and vents, and the grid independence is verified. Furthermore, selecting an appropriate turbulence model is critical to ensure the stability and accuracy of the simulation. In pre-simulations, the standard k-ε model showed better stability and convergence. As for the solver settings, the PISO algorithm is used as the usual pressure-velocity coupling method, and the governing equations are discretized by the second-order upwind scheme to ensure convergence accuracy and stability.

Table 2. The parameters of the assumed design conditions.

| Inlet velocity (m/s) | Inlet temperature (℃) | Floor heat flux (W/m²) |
|----------------------|-----------------------|------------------------|
| 0.7                  | 22                    | 32                     |

In terms of data assimilation calculation, the parameters of the assumed design conditions to be corrected are listed in Table 2. The convergence criteria of data assimilation are consistent in that the current prediction of the air state at all measurement points varied by less than 1‰ with respect to the prediction obtained in the previous assimilation step.

4 Results and discussion

We evaluate the ability of the CFD-EnKF framework to improve multiphysics predictions by comparing the experimental data with CFD simulation results before and after data assimilation. When simulating without considering observed data but only with design parameters, as we usually do, the results show very large errors. For instance, the simulated average temperature is about 6°C higher than the actual measurement. After inversely updating the input parameters of the CFD model according to several measurement data, the simulation accuracy of the temperature and velocity fields under each air distribution condition has been significantly improved, and the corrected results tend to be highly similar to the actual measurements.
5 Conclusions

The main goal of the current study is to solve the problem of large deviation between indoor multiphysics CFD simulation and reality caused by the uncertainty of system boundary conditions. Based on the EnKF data assimilation algorithm, a technical framework for calibrating multiphysics CFD simulations with limited monitoring data is constructed, so as to utilize the observation data to reversely correct the system boundary conditions such as internal load and air conditioning operating parameters to make the simulation results approach the observations. The effectiveness of the method is verified by scaled model experiments.

Overall, this study demonstrates that the CFD-EnKF framework improves multiphysics simulations significantly. Compared with original CFD simulations, the deviation of the assimilation results from the actual measurements is significantly reduced, among which the temperature and velocity simulation errors are decreased by more than 87% and 56%, respectively. Further research is needed to formulate specific schemes for optimizing performance by considering more detailed influencing factors such as measurement errors, and generalize the method to more applications.

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