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Prompt design of the air-supply opening size for a commercial airplane based on the proper orthogonal decomposition of flows

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A B S T R A C T

Air supply is crucial for creating an acceptable air distribution inside aircraft cabins. To determine proper air-supply parameters, a conventional design has to solve many cases to obtain the flow patterns for each air-supply parameter, which is time-consuming. This study proposed a proper orthogonal decomposition (POD) of the flows to accelerate the design. A few original thermo-flow data samples are obtained using a full CFD simulation, and then the orthogonal spatial modes and their coefficients are extracted from these data samples. A trial and data sample increase scheme is used to determine whether the CFD-provided data samples are sufficient. A shape-preserving interpolation is applied to estimate the coefficients of the spatial modes between two neighboring data samples. With a quick map of the thermo-flow fields, the proper air-supply parameters can be rapidly determined based on the specific design criteria. The proposed method was applied to determine the size of an air-supply opening in a three-dimensional aircraft cabin, with the percentage of dissatisfied (PD), the predicted mean vote (PMV) and the mean age of air as the design criteria. The results show that the POD-based design is able to construct the field data with generally good accuracy. The inversely determined air-supply opening sizes between the proposed method and the full CFD simulation are quite similar. Future research may explore a better coordination between the original data sample preparation using the full CFD simulation and the interpolation of the coefficients of the spatial modes to further reduce the computing time.

1. Introduction

Proper air distribution is crucial for maintaining a comfortable thermal environment and good air quality in enclosed spaces. To design an appropriate air distribution, a cause-effect relationship must be established between the air-supply parameters and the resulting environmental performance. This cause-effect relationship is governed by the Navier–Stokes (N–S) equations. Because of the nonlinearity in the N–S equations, mapping the cause-effect from a design parameter to the interior environmental performance is not straightforward. It is challenging to determine the exact air-supply parameters that can create the target performance of thermal comfort and interior air quality. The current design would require a lengthy iterative trial-and-error procedure, by enumerating every possible air-supply parameter to find an optimal solution. An inverse design is able to provide a faster approach for fulfilling the task by setting the design targets first and then inversely solving for the required causal boundary parameters. This approach forms the framework of inverse modeling, i.e., determining causal information from certain expected consequences.

Current inverse modeling in indoor environments is primarily constrained to pollutant source identification, such as the determination of pollutant source locations [1–5], quantifying temporal pollutant release rates [6], and judging pollutant release times [7]. These methods may not be applicable to the inverse design of enclosed environments [8]. When identifying pollutant sources in a fixed flow context, an inversion of the passive scalar transport equation is sufficient. However, the inverse design of enclosed environments would require an inversion of the thermo-flow equations, which include a velocity vector, pressure scalar, and temperature scalar; occasionally, all of the above variables are coupled together.

There are only a few studies addressing the inverse design of enclosed environments. Xue et al. [9] developed a CFD-based genetic algorithm to optimize and predict flows in confined spaces. Zhai et al. [10] imposed constraints on a multi-objective genetic

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Nomenclature

$\mathbf{a}$	coefficient vector of dummy variables or eigenvector
a	element of the coefficient vector $\mathbf{a}$
c	coefficient of the POD mode
E	error between the interpolated fields and the CFD simulated fields
$\mathbf{f}$	dummy vector for the velocity, temperature, etc., at all grid points that constitute a vector
f	dummy variable for the velocity, temperature, etc., at a grid point
n	number of eigenvalues for which the general energy exceeds 99.99%
N	number of grid points
P	number of data samples
$\mathbf{s}$	averaged autocorrelation matrix of the fields
s	elements in the averaged autocorrelation matrix
$\mathbf{x}$,$\mathbf{x}'$	position vector

Greek variable

$\boldsymbol{\varphi}$	orthogonal basis or spatial mode or POD mode
λ	Lagrangian multiplier or eigenvalue of $\mathbf{s}$
$\boldsymbol{\Omega}$	domain over which $\mathbf{f}(\mathbf{x})$ is defined

Superscript

i, j	index of a data sample
k	index of a spatial mode

Subscript

i, j	index of an eigenvector
k	index of coefficient of a POD mode
m	index of a grid point

algorithm to design ventilation systems for an aircraft cabin. Zhang and You [11] applied a neural network to optimize air-supply speed and temperature for a commercial aircraft cabin. Currently, no study has inversely determined the sizes of air-supply openings for an enclosed space. In addition, the computing efficiency for both the CFD-based genetic algorithm and the neural network is quite low due to the large number of forward CFD simulations involved.

To accelerate the forward thermo-flow solution, a POD technique was developed. The POD method was proposed by Lumley [12] nearly a half century ago to analyze inhomogeneous turbulent flows. The POD technique provides a basis for the modal decomposition of an ensemble of data, such as the thermo-flow fields obtained from numerical simulations or experiments. The coherent structures of these data that contain the basic features of the fields are extracted. The most important benefit of the POD analysis is its efficiency in capturing the dominant features with only a few modes [13]. Early applications of the POD method consisted of a few near-wall and jet-induced mixing flows [14–16]. Later, the snapshot method [17] was proposed to minimize the dimensions of the POD eigenvalue system. Snapshots are the data samples used for extracting the POD modes, which reduce the dimensions of the eigenvalue system from the number of grid points to the number of snapshots. Generally, the number of snapshots is far less than the number of spatial grid points, and thus a significant amount of computing costs can be saved.

In enclosed environments, the POD is primarily used for the rapid prediction of indoor thermo-flow and pollutant concentrations, optimization of air-supply parameters, and development of controllers for dynamic ventilation control. Elhadidi and Khalifa [18] applied a POD analysis to efficiently predict the indoor velocity and temperature distributions inside an empty office. Ding et al. [19] proposed a POD-based data interpolation to predict the thermo-flow fields for natural and forced convection flows. Sempey et al. [20] performed a POD-based prediction of the temperature distribution in air-conditioned rooms in a fixed-flow context. Allery et al. [21] tracked the particle motion in a two-dimensional ventilated cavity with airflow provided by a POD construction. Li et al. [22] integrated a genetic algorithm into the POD prediction of thermo-flow to efficiently optimize the air-supply velocity and temperature. Ahuja et al. [23] developed POD-based controllers to eliminate the heat disturbance in an indoor environment. Tallet et al. [24] used a POD analysis to dynamically control the window opening for optimizing the indoor environment comfort and quality. Li et al. [25] proposed a POD-based temperature prediction model for the dynamic control of room temperature.

The above review reveals that the current inverse design suffers from a high computing cost. The POD has provided a quick method for obtaining the thermo-flow fields based on a limited number of full CFD simulations. It is viable to use the POD analysis to accelerate the inverse design. This study demonstrates how a POD based model was utilized to promptly determine the size of an air-supply opening in an aircraft cabin. The solution accuracy and the computing costs were compared between the full CFD simulation and our proposed POD approach.

2. Methodologies

In this section, the basic principles of the POD are first outlined, followed by criteria for determining whether the original data samples provided by the full CFD simulation are sufficient. Then the solution procedure for the POD-based prompt design is presented.

2.1. Basic principles of POD analysis

The POD method originates from the decomposition of turbulent flow fields. However, the method can be applied to decompose any data ensemble based on the statistical theory. This investigation has applied the POD to analyze the field data of air velocity, temperature and mean age of air when the air-supply opening sizes are varied. Then a quick map from the air-supply opening size to the velocity, temperature and mean age of air is established. Let $\mathbf{f}$ represent a dummy vector for velocity, temperature and mean age of air at all grid points that constitute a vector. Suppose that we have an ensemble $\{\mathbf{f}^i\}$, each as a function of the spatial coordinates, i.e., $\mathbf{f} = \mathbf{f}(\mathbf{x})$, where $\mathbf{x}$ represents a position vector. We can define an orthogonal basis (or spatial mode, or POD mode) $\boldsymbol{\varphi}$ that captures more information on a variable than any other mode, which is maximized with the projection of $\mathbf{f}$ onto $\boldsymbol{\varphi}$ [13] as follows:

$$\max \frac{\left\langle |(\mathbf{f}, \boldsymbol{\varphi})|^2 \right\rangle}{\|\boldsymbol{\varphi}\|^2}, \tag{1}$$

where (,) represents the inner product, $|\cdot|$denotes the modulus, $\langle\cdot\rangle$ is an averaging operation, and $\|\cdot\|$ is the L^2-norm. Eq. (1) can be recast into the following Euler–Lagrange integral equation [26] as:

$$\int_{\Omega} \left\langle \mathbf{f}(\mathbf{x})\mathbf{f}^*(\mathbf{x}') \right\rangle \boldsymbol{\varphi}(\mathbf{x}')d\mathbf{x}' = \lambda \boldsymbol{\varphi}(\mathbf{x}), \tag{2}$$

where * denotes the complex conjugation, λ is a Lagrangian multiplier, and Ω is the domain over which $\mathbf{f}(\mathbf{x})$ is defined. Writing