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Optimal design of an indoor environment by the CFD-based adjoint method with area-constrained topology and cluster analysis

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ABSTRACT

An indoor environment should be designed to provide occupants with a desirable level of thermal comfort and air quality. The optimal design of an indoor environment can be achieved by using the computational fluid dynamics (CFD)-based adjoint method to determine the size, locations, and shape of air supply inlets, and the air supply parameters (i.e., velocity, temperature, and angle). However, the optimal design may involve a large number of air supply inlets, which would be impractical to implement. This investigation developed an area-constrained topology and cluster analysis to consolidate multiple air supply inlets into a limited number and to determine their size and locations. The desired indoor environment can be maintained by further optimizing the air supply inlet shape and parameters. This investigation demonstrated the method's capability by applying it to a two-person office and a single-aisle, fully-occupied aircraft cabin. The optimal thermal comfort conditions around the occupants can be achieved with a limited number of air supply inlets at appropriate locations.

1. Introduction

In a survey of human activity patterns, Klepeis et al. [1] found that people in the United States spent an average of 87% of their time inside buildings. It is therefore very important to create a comfortable, healthy, energy-efficient, and productive indoor environment. Such an indoor environment is usually created by heating, ventilating and air-conditioning (HVAC) systems. In the United States, heating of building spaces accounts for 37% of the total building energy consumption, and cooling of spaces accounts for 10%; in turn, the total energy use in buildings accounts for 41% of the country's primary energy consumption [2]. Even with such high energy usage, the indoor environments created were found to be unsatisfactory in nearly a quarter of U.S. residences [3]. Thus, it is crucial to design an HVAC system with optimal air supply conditions that provides a desirable indoor environment.

Conventional design of an indoor environment uses a trial-and-error process [4]. The process requires tens of trials to adjust the HVAC system parameters for creation of a better environment. Even with such a dedicated effort, the final design may not be optimal. Recently, many researchers have attempted to use optimization methods such as the genetic algorithm (GA) method [5], artificial neural network (ANN) method [6], proper orthogonal decomposition (POD) [7], and adjoint method [8]. For design of an indoor environment, all the above methods would require the use of computational fluid dynamics (CFD) for determining the air distributions. This is because CFD is the most accurate and informative tool for predicting indoor air distributions [9]. Thus, most recent optimizations have been CFD-based, as summarized by Chen et al. [10].

Chen et al. [10] compared different CFD-based optimization methods and found that the CFD-based GA method could find the globally optimal solution with high accuracy, but its computing time was equivalent to 20 times that of the adjoint method, and its computing time was proportional to the number of design variables [11]. The CFD-based ANN method performs CFD simulations of multiple representative cases to train the ANN. With a well-trained ANN, the design objectives can be obtained without using any CFD simulations in the design procedure, and thus this method can be highly efficient. However, the prediction error of the ANN may reduce the accuracy of design results [12]. The CFD-based POD method establishes cause-effect maps between the design variables and the design objectives using a number of CFD simulations as samples. With this mapping relationship, the POD method can directly provide a design objective for a given design variable, thus speeding up the calculation. However, the accuracy of the POD method also depends on the number of samples used [13]. The CFD-based adjoint method is a gradient-based optimization method that computes the gradient of the objective function over

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the design variables to provide the search direction. Thus, the CFD-based adjoint method can quickly find the optimal value, and the computing time does not change with the number of design variables, although it may fall into local optima [4]. By means of the above comparison, this study identified the CFD-based adjoint method as a suitable approach for designing an indoor environment.

Liu et al. [14,15] used the CFD-based adjoint method to identify the air supply inlet size and location and air supply parameters for a ventilated cavity and an aircraft cabin. They fixed the number of air supply inlets and assumed the inlet shape to be rectangular during the design process. For an optimal indoor environment, the number of air supply inlets may be unknown in advance, and the air supply inlet can take any shape. Therefore, the present investigation further developed the CFD-based adjoint method to determine the number, size, locations, and shape of the air supply inlets and the corresponding air supply parameters.

2. Methods

Using the CFD-based adjoint method to design an indoor environment, this study first needed to construct an objective function for the design objectives. There are multiple design objectives for an indoor environment, such as thermal comfort, air quality, and energy efficiency, etc. For the purpose of demonstration, this study used thermal comfort as the design objective. The thermal comfort level in an indoor environment can be quantitatively defined by the predicted mean vote (PMV) [16] and the predicted dissatisfied percentage (PD) due to draft [17]. The closer to zero the PMV and PD are, the better the thermal environment is. Therefore, this study normalized each criterion and constructed a single objective function by using weighting factors as shown in Eq. (1):

$$J(\xi) = w_1 \frac{\int_\Theta \frac{PMV^2}{9} d\Theta}{\int_\Theta d\Theta} + w_2 \frac{\int_\Theta \frac{PD}{100} d\Theta}{\int_\Theta d\Theta} \tag{1}$$

where J is the objective function; $\boldsymbol{\xi}$ a vector that denotes the design variables, such as air supply velocity, $\mathbf{V}_{inlet}$, air supply temperature, T_{inlet}, and number, size, locations, and shape of the air supply inlets; Θ the design domain of the indoor environment; and w_1 and w_2 the weighting factors. This investigation used values for w_1 and w_2 from Ncube and Riffat [18], who conducted a questionnaire survey in offices and found $w_1 = 0.455$ and $w_2 = 0.545$. The goal of the inverse design in this study was to identify the optimal $\boldsymbol{\xi}$ that ensured a minimal objective function J.

2.1. CFD-based adjoint method

To minimize the objective function, the CFD-based adjoint method started with initialized design variables and conducts CFD simulations to check whether or not the objective function was sufficiently small. If not, the method calculated the gradient of the objective function over the design variables. Since the design variables were not explicitly included in the objective function, it was impossible to find the relationship between the objective function and the design variables directly. To obtain the gradient, the adjoint method introduced an augmented objective function L as shown in Eq. (2).

$$L = J + \int_\Omega (P_a, \mathbf{V_a}, T_a)\mathbf{N} d\Omega \tag{2}$$

where Ω was the computational domain; P_a, $\mathbf{V}_a$, and T_a the adjoint pressure, adjoint velocity, and adjoint temperature, respectively; and $\mathbf{N}$ the incompressible Navier-Stokes equations in vector form.

The gradient of the augmented objective function over the design variables could be expressed as Eq. (3). Direct calculation of the gradient of the augmented objective function over the air velocity V, air temperature T, and pressure P was very difficult. Therefore, the adjoint method set the last three terms of Eq. (3) to zero, as expressed by Eq. (4). From Eq. (4), this study derived the adjoint equations as shown in Eqs. (5)–(7). By numerically solving the Navier-Stokes equations and the adjoint equations alternatively, we could calculate the gradient of the objective function over the design variables using Eq. (8).

$$\frac{dL}{d\xi} = \frac{\partial L}{\partial \xi} + \frac{\partial L}{\partial P}\frac{\partial P}{\partial \xi} + \frac{\partial L}{\partial \mathbf{V}}\frac{\partial \mathbf{V}}{\partial \xi} + \frac{\partial L}{\partial T}\frac{\partial T}{\partial \xi} \tag{3}$$

$$\frac{\partial L}{\partial P}\frac{\partial P}{\partial \xi} + \frac{\partial L}{\partial \mathbf{V}}\frac{\partial \mathbf{V}}{\partial \xi} + \frac{\partial L}{\partial T}\frac{\partial T}{\partial \xi} = 0 \tag{4}$$

$$-\nabla\cdot\mathbf{V}_a = 0 \tag{5}$$

$$-\nabla\mathbf{V}_a\cdot\mathbf{V} - (\mathbf{V}\cdot\nabla)\mathbf{V}_a - \nabla\cdot(2\nu D(\mathbf{V}_a)) + \nabla P_a + T_a\nabla T + \mathbf{A} = 0 \tag{6}$$

$$-(\mathbf{V}\cdot\nabla)T_a + \nabla\cdot(\kappa\nabla T_a) - \gamma(\mathbf{V}_a\cdot\mathbf{g}) + B = 0 \tag{7}$$

$$\frac{dL}{d\xi} = \frac{\partial J}{\partial \xi} + \int_\Omega (P_a, \mathbf{V_a}, T_a)\frac{\partial \mathbf{N}}{\partial \xi} d\Omega \tag{8}$$

$$\xi_{k+1} = \xi_k - \lambda_k \frac{dL}{d\xi_k} \tag{9}$$

where ν is the effective viscosity; κ the effective thermal conductivity, $\mathbf{g}$ the gravity vector; γ the thermal expansion coefficient of air; $\mathbf{A}$ and B the source items in the adjoint momentum equations; λ the adaptive step size [19]; and k a positive integer. Next, we update the design variables for each initial air supply inlet cell using the steepest descent method [20] as shown in Eq. (9). This process was repeated until the objective function was sufficiently small.

The adjoint method could determine the movement of each cell individually within the air supply inlet. If the number of air supply inlets is fixed [14,15], the movements of all the cells within the air supply inlet needed to be averaged. Then, the adjoint method changes only the size and location of the air supply inlet as shown in Fig. 1 (red dashed line). However, the optimal air supply inlet number may be variable, and the air supply inlets could take any shape. If we let each cell within the air supply inlet move individually, the design would lead to many small air supply inlets as shown in Fig. 1 (black regions), which is not realistic in an engineering application. Determination of the optimal and reasonable number, location, and shape of air supply inlets requires further investigation.

2.2. Determination of number, location, and shape of air supply inlets

To determine the optimal and reasonable number, location, and shape of air supply inlets, this study investigated an area-constrained topology optimization method [21]. The method was originally used to identify the optimal solid material distribution in a given space. The

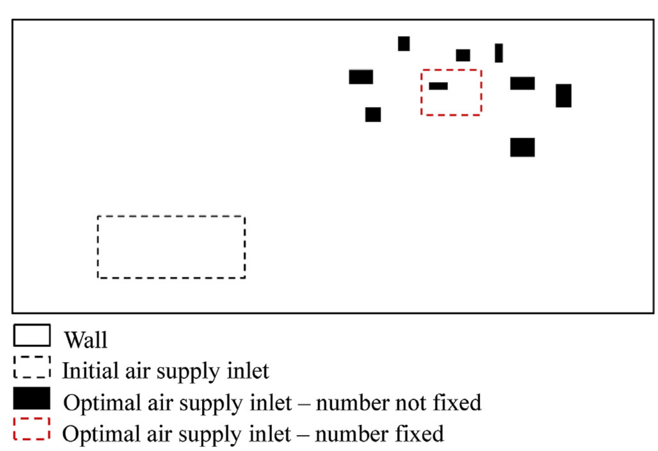

Fig. 1. Inverse design of air supply inlets by the CFD-based adjoint method.