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A simulation-based inverse design of preset aircraft cabin environment

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ABSTRACT

The inverse design of preset aircraft cabin environment (ACE) is presented. Five design variables (inlet velocity, angle, temperature, position and outlet position) and three design objectives (PMV, DR and Air Age) are involved in the current inverse design. The Artificial Neural Network (ANN) and genetic algorithm (GA) are combined to design ACE based on the Computational Fluid Dynamics (CFD) analysis. To eliminate the uncertainty and risk of accumulative errors in the design process, both ANN and CFD are used to obtain the design objectives of new individuals generated by GA. To enhance the prediction accuracy of ANN, three single-output ANNs for each design objective are adopted instead of one mutiple-output ANN. The results obtained by GA alone and the proposed method are compared. Instead of applying GA, 57% of computational costs are reduced when the proposed method is used. Comparing the design results of different scales of CFD databases, it is found that the CFD database with 110 samples has the less computational cost, while that with 70 samples has better solutions.

1. Introduction

Many research activities have focused on the simulation-based design of building environment. The genetic algorithm (GA) is one of the most popular tools for this type of work [1]. GA is a global optimization method, and it has better chances to explore the entire design space and reach the global optimum [2]. Mossolly et al. [3] used the GA to design air condition system, and up to 30.4% energy savings was achieved while comfort and indoor air quality were satisfied. Sahu et al. [4] implemented GA to design the air-conditioned building in tropical climate, and the most energy efficient solution was obtained. Tuhus-Dubrow and Krarti [5] applied GA to design the building shape and envelope features. Different building shapes were investigated. The life-cycle cost was used to evaluate the performance of building. The rectangular and trapezoidal shaped buildings have the lowest life-cycle cost. So the rectangular and trapezoidal shaped buildings consistently have the best performance. Xue et al. [6] used GA to design indoor flow pattern and thermal comfort according to specific design goals. The results revealed that the accuracy of inverse prediction is affected by the error of CFD simulation, which need be controlled within 15%.

The major obstacle in the design of indoor environment with GA is expensive computational cost. Surrogate models are among the promising solutions to this problem. A surrogate model is an approximation model of the original simulation model. It typically mimics the behavior of the original model to produce the model responses at reduced computational cost [1]. The Artificial Neural Network (ANN) is the most popular surrogate model used widely in the design of indoor environment. It has been extensively used in building-related studies and can represent the response of the system over the entire design space [2]. Zhang and You [7] used ANN to identify the relationship between the thermal comfort and the inlet boundary condition of indoor environment, and high prediction accuracy was realized when Bayesian Regularization training algorithm was used. When GA and ANN are combined, the ANN is used to predict the design objectives of new individuals generated by GA. Zhang and You [8] coupled GA and ANN to design the cabin environment. Several groups of optimal air supply parameters were found with different trade-offs between the thermal comfort and energy consumption. Magnier and Haghighat [9] integrated ANN and GA to design the building environment. The results showed that energy consumption was significantly reduced as well as the thermal comfort was improved. Zhou and Haghighat [2,10] used the GA and ANN to enhance the thermal comfort and indoor air quality without sacrificing energy costs of ventilation. The results indicated great improvement in the design and operation of ventilation systems in an office environment was presented.

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Although the computational cost was reduced by ANN instead of an actual building model, the uncertainty and the risk of accumulative error increased in the whole design process [1]. For the cabin environment, when the multiple design variables and objectives are involved, the prediction accuracy is not satisfied with the limited scale of CFD database. High accumulative error is expected in the design process if there is no correction process.

This study is targeted at developing an inverse design approach to achieve preset aircraft cabin environment. A simulation-based design approach is developed with the ultimate goal of providing the values of design variables leading to the preset design objectives. The ANN combined with CFD analysis is used to identify the relationship between the design variables and objectives. The GA coupled with ANN and CFD is used to get the optimal design variables. Five design variables (velocity, angle, temperature, position of inlet, and outlet position) and three design objectives (PMV, DR and Air Age) are involved in the present inverse design. The efforts are taken to improve the prediction accuracy of ANN and eliminate the accumulative errors. Three single-output ANNs are adopted instead of one multiple-output ANN [2,9,10]. Both ANN and CFD are used to obtain the design objectives of new individuals generated by GA. The prediction accuracy and the design result with different scales of CFD database are compared.

2. Model and design parameters

2.1. Model

A simplified first-class cabin model of an MD-82 is shown in Fig. 1. The detailed model was studied by Liu et al. [11]. For simplification, half cabin with single row is considered as the cabin is symmetrical. The shape of inlet and outlet are simplified to rectangle. The area of inlet is equal to that of the original cabin model, which is described by Liu et al. [11]. The size of outlet is same with that of the inlet. The inlet and outlet are located at the sidewall of cabin. The area of the sidewall (except the window) is 40 times larger than that of the inlet. So there are 40 possible positions for both inlet and outlet. They are numbered by No.01~No.40 from above to below.

2.2. Design variables and design objectives

Five design variables (inlet velocity, angle, temperature, position and outlet position) are considered because they have important impacts on the indoor environment in cabin. Also they are easy to be controlled for cabin environment. The inlet angle is the one between the velocity vector and horizontal direction. Two ventilation styles are considered, i.e. mixing ventilation and displacement ventilation. When the position of inlet is above the window, the position of outlet is under the window (mixing ventilation). When the position of inlet is under the window, the position of outlet is above the window (displacement ventilation).

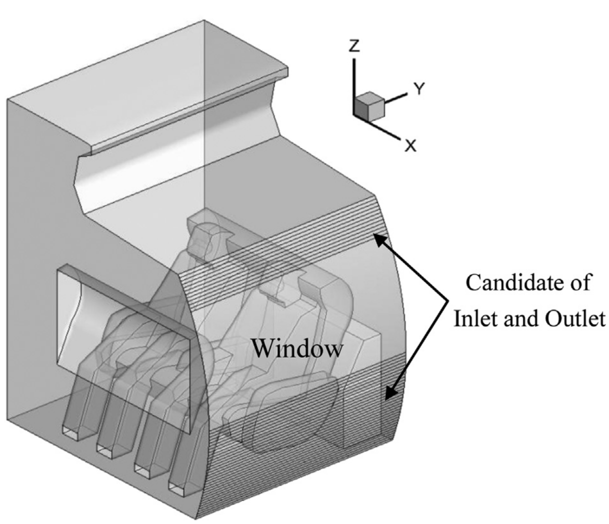

Fig. 1. Simplified first-class cabin model of MD-82.

Three design objectives (PMV, DR and Air Age) are involved in the present inverse design. The PMV (predicted mean vote) express warm and cold discomfort for the body as a whole [12]. It is used to describe the body's whole feeling of the environment. The design domain for PMV is the surface 10 cm away from the human body. The DR (draft rate) assesses the local discomfort for human. The design domain for DR is the surface 10 cm away from human head, shoulder and feet, because they are usually exposed to the environment directly. The Air Age assesses the indoor air quality in the breathing zones. The design domain for Air Age is the surface 5 cm away from human head. There is none standard to specify the design domain. The “10 cm” and “5 cm” are adopted according to other researches [13–15]. The design domains for different design objectives are shown in Fig. 2.

According to IOS 7730: 2005 and ASHRAE Standard 55-2004, the recommended value for PMV and DR are: $-0.5 < \text{PMV} < 0.5$, $\text{DR} < 20\%$. As no requirement for Air Age in the standard of indoor environment, the value 150 s of Air Age with the original model (Liu et al. [11]) is adopted as the basic standard. So the basic standards for the ACE are: $|\text{PMV}| < 0.5$, $\text{DR} < 20\%$, Air Age < 150 s. Three standards are proposed to obtain optimal ACE:

a $|\text{PMV}| < 0.3$, $\text{DR} < 20\%$, Air Age < 150 s
b $|\text{PMV}| < 0.5$, $\text{DR} < 5\%$, Air Age < 150 s
c $|\text{PMV}| < 0.5$, $\text{DR} < 20\%$, Air Age < 130 s

3. Methods

3.1. Artificial Neural Network

Artificial Neural Network (ANN) is highly sophisticated paradigm that borrows the features of human and animal brains to enable recognition of patterns within data. It has been learned to solve problems by developing a memory capable of associating a large number of input patterns with a resulting set of outputs or effects [16]. ANN realizes the mapping relationship from the input data to the output data. The basic unit of ANN is neuron. The output of the neuron t is generated by the following equation:

$$t = a\left(\sum_{i=1}^{n} w_i x_i - b\right) \tag{1}$$

Where, x_i and w_i represent the ith input and weight, respectively. b and a represent the bias and the transfer function, respectively. The relationship between the design variables and objectives is identified by ANN. The multilayered ANN consists of input layer, hidden layer and output layer. A three-layer ANN is shown in Fig. 3. V, T and A are the velocity, temperature and angle of inlet. P_{in} is the inlet position, and P_{out} is the outlet position, F_{ANN} is the predicted value of design objective (PMV, DR, or Air Age) or ANN result, and F_{CFD} is real value of design objective or CFD result, and E is the error function for training.

Different training algorithms were used to train the neural network. The Bayesian regularization (BR) algorithm was found to have perfect generalization capability [17,18]. A regularization term