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An optimization framework for ventilation system operation in office environment using data interactive mechanism

Kangji Li[1], Wenping Xue[1] , Guohai Liu[1]

[1]*School of Electricity Information Engineering, Jiangsu University, Zhenjiang 212013, P.R.China*

likangji@ujs.edu.cn

Abstract

This paper is concerned with the development of an efficient and controls-friendly optimization scheme for ventilation system operation. The key part of this optimization framework is a kind of data interactive mechanism, which can couple any Matlab-based optimization algorithms into PDE-related simulation program that reads/writes its input/output from text files. Based on the proposed framework, lots of optimization algorithms are convenient to use. Differential evolution algorithm (DE) is employed for its simple structure and effective global optimization ability. A numerical optimization of ventilation system operation is conducted according to the established framework. Detailed analysis demonstrates the effectiveness of the proposed optimization approach.

Keywords - data interactive mechanism; optimization framework; TDVS; building environment; differential evolution algorithm;

1. Introduction

Various optimization methods have grown in popularity in air conditioning systems due to increasing concerns about the thermal comfort and indoor air quality (IAQ), as well as building energy consumption. Most of these methods generally assume that the indoor air are “perfectly mixed” and the spatial parameters, including temperature, CO_2 emission etc., are lumped at uniform values [1,2]. For some kind of ventilation systems, especially for thermal displacement ventilation systems (TDVS), detailed information about the indoor environment is necessary to be taken into consideration because of the fully stratified air distribution. Many researchers use parametric studies or data-driven methods to achieve better performance of such systems. However, the time-consuming problem and the generalization capabilities limit their applications [3-5]. The development of more controls-friendly building simulation tools is helpful. Genopt and its developments have been successfully applied for various complex optimization problems [6,7]. Genopt’s algorithm interface only allows adding new optimization algorithms that are programmed in JAVA code. In addition, if the model file of the simulation program is considerably large, Genopt will become inefficient to some extent.

A kind of general optimization framework, which can couple Matlab-based optimization algorithm into any text-based building simulation program, is established in this study. The key part of this optimization framework is the data interactive mechanism, which is realized by C++ language. The interface module passes the independent variables from optimization algorithms to simulation programs at the beginning of each iteration, and passes the related simulation results back to optimization algorithm for cost function evaluation. This data interactive mechanism is similar to Genopt while the algorithm library is linked to Matlab. Based on the proposed framework, a plenty of optimization algorithms are convenient to use. To test the proposed optimization scheme, a validated model of an office room equipped with a TDVS is constructed in this paper. Differential evolution algorithm (DE) is adopted to improve occupied zones' thermal comfort, IAQ and energy cost in a balanced way. Performance investigations will prove the effectiveness of the proposed optimization approach.

2. Optimization framework

2.1 Problem description

Many commercial optimization tools, such as GenOpt, BeOpt, Opt-E-Plus etc., have been widely used for building energy and operation cost optimization. However, Researchers who are more familiar with the standard simulation tools and Matlab based algorithms may wish to use them for optimization studies directly. In addition, researchers will often prefer to use CFD based simulation programs (Fluent, Airpak, etc.) that most commercial optimization tools may not provide a perfect interface with. To this end, we aim to provide a kind of Matlab based optimization framework that facilitate researchers to use their familiar modelling software for indoor environment optimizations.

Consider an optimization problem of the form

$$P_c : \min_{x \in X} f(x) \tag{1}$$

where $f : \mathbb{R}^n \to \mathbb{R}$, X is a user-specified constraint set. We here discuss problem P_c for the situation where the cost function f can not be evaluated directly, but can be approximated numerically by approximating cost functions $f^* : \mathbb{R}_+^p \times \mathbb{R}$, where the first argument is the precision parameter of the numerical solvers. This is typically the case when the cost function is solved by a CFD-related simulation program, such as Fluent, Airpak, Comsol, etc.. In general, one can not obtain an exact solution, but can obtain an approximate numerical solution. Hence, the cost function $f(x)$ can only be approximated by an approximating cost function $f^*(\varepsilon, x)$, where

$\varepsilon \in \mathbb{R}_{+}^{p}$ is a vector that contains precision parameters of the numerical solvers. Consequently, the optimization algorithm can only be applied to $f^{*}(\varepsilon, x)$.

For the proposed optimization framework, the simulation program must satisfy two requirements: i) The simulation program read its input from one or more text files, and write its output to one or more text files; ii) The simulation program can be called by the command line and terminated automatically.

2.2 Optimization framework

Within the optimization framework, the problem is divided into three modules. The first module consists of the simulation software that is used for the on-line model; The second module is the optimization module, which runs one of many possible algorithms to solve the optimization problem; The third one is a data interactive module, which interfaces with both the simulation software and optimization module.

The data interactive mechanism is the key part of this optimization frame. It passes the independent variables from optimization module to building simulation program at the beginning of each iteration, and passes the related simulation results back to Matlab for cost function evaluation. A general optimization problem using the proposed data interactive mechanism will be set up in four steps:

S1. Construct a building model using simulation program;

S2. Design an optimization algorithm using Matlab;

S3. Set all the Input/Output files of the interactive module;

S4. Run the searching procedure until the optimized control variables are obtained.

The basic structure of the optimization framework is shown in Fig.1, along with how it passes information by text files. A plenty of Matlab based algorithms are convenient to use for the proposed optimization scheme.

2.3 Differential evolution algorithm

Differential Evolution (DE) algorithm was proposed by Price and Storn in 1995 [8]. DE algorithm aims at evolving a population of NP D-dimensional parameter vectors, so-called individuals, which encode the candidate solutions, i.e., $X_{i,G} = \{x_{i,G}^{1}, ..., x_{i,G}^{D}\}$, $i = 1, ..., NP$ towards the global optimum. During the optimization procedure, three steps, i.e., mutation operation, crossover operation and selection operation are repeated generation after generation until some specific termination criteria are satisfied. DE is an effective, robust, and simple global optimization algorithm which only has a few control parameters. According to frequently reported studies, DE has been shown to be an efficient evolutionary algorithm for many optimization problems in real world applications.

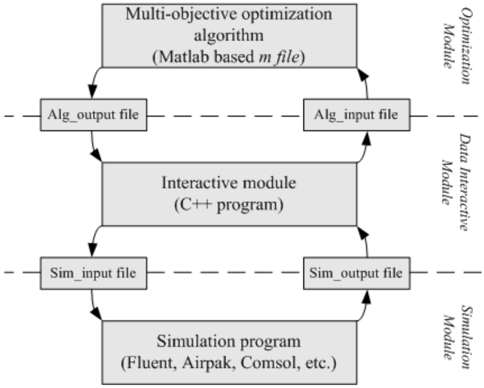

Fig.1 The basic optimization frame

3. Application: an office room equipped with TDVS

3.1 Model description

A small office layout is shown in Fig.2. The 5.16m×3.65m×2.44m room is occupied by two simulated sitting persons and equipped with two tables, two heated computers, two file cabinets and six overhead lights. A 3.65m×1.04m window is mounted on the west wall and the displacement ventilation system provides air from a diffuser that is situated on the opposite wall of the window. The simulated pollutant, CO_2 in this paper, is discharged at both occupants' head level. The sizes, locations and heat released can be found in [9].

3.2 Assessment indices

(1) Thermal discomfort index

The PMV-PPD (Predicted Mean Vote-Predicted Percentage of people Dissatisfied) model [10] is the most frequently used and best understood model for quantitative thermal comfort analysis. PMV reflects the mean thermal sensation vote on a standard scale for a large group of occupants. In this study, the index PPD is preferred to PMV because it provides an objective function to minimize, which is fundamental for running the optimization algorithm. PPD reflects the percentage of thermally dissatisfied persons among a large group of occupants. It can be evaluated by the formula below,

$$PPD = 100 - 95 \times \exp(-0.03352 \times PMV^4 - 0.2179 \times PMV^2) \qquad (2)$$

According to ISO7730 and ASHRAE 55-2004, the proper value of the index PMV is between ±0.5 (PPD <10%).

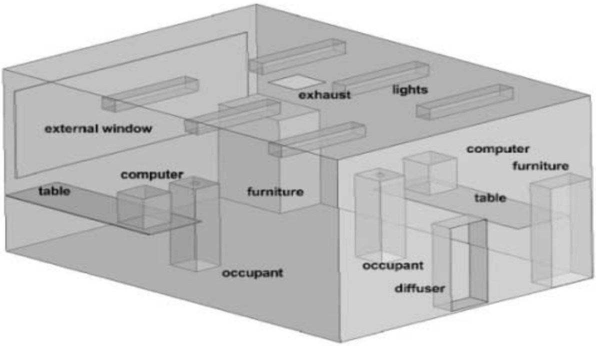

Fig. 2 The 3D office layout

(2) CO_2 based ventilation effectiveness

Supplying fresh outdoor air and removing air pollutants is necessary for maintaining acceptable IAQ levels. However, ventilation rates inside buildings must be seriously reduced in order to optimize the cooling or thermal load in an improved manner and save the energy load.

To access the effect of airborne contaminants removal, CO_2 is injected into the space as airborne contaminants and the index ventilation effectiveness [11] is used for IAQ assessment, which is formulated as,

$$\varepsilon_v = \frac{C_{return} - C_{supply}}{C_{br} - C_{supply}} \tag{3}$$

where C_{return} is the CO_2 concentration in the return air (mass fraction), $C_{suppply}$ is the CO_2 concentration in the supply air, and C_{br} is the CO_2 concentration at breathing level near the occupant.

(3) Energy consumption

For simplicity, we divide the energy usage of the ventilation system into two parts: fan power input and cooling energy consumption [12]. Fan power input (W) can be determined using the following expression:

$$E_{fan} = \frac{\Delta P \times \dot{V}_{air}}{1000\eta_{fan}} \tag{4}$$

where ΔP is the pressure rise through the supply fan (Pa), $\dot{V}_{air}$ is the overall volumetric flow rate of supply air (L/s), and η_{fan} is the fan efficiency. The pressure rise and fan efficiency are assumed to be 562.5 Pa and 0.75 respectively.

The cooling energy requirement is subdivided into two portions: the sensible heat load produced within the conditioned space and the cooling load due to the fresh air treatment, which is shown below,

$$E_{cooling} = \dot{m}_{air} c_p (T_{return} - T_{supply}) + \dot{m}_{fresh} (h_{out} - h_{return}) \quad (5)$$

where $\dot{m}_{air}$ is the total mass flow rate of supply air (kg/s), c_p is the specific heat of air (J/kg*k), T_{return} and T_{supply} are the temperature of return air and supply air (K), and $\dot{m}_{fresh}$ is the mass flow rate of outdoor fresh air (kg/s). h_{out} and h_{return} are the specific enthalpy of the outdoor air and return air (J/kg).

(4) Weighted objective functoin

Accordingly, the objective function for optimization is prescribed by aggregating and weighting the above indices into one equation:

$$J = min\left\{ \omega_{PPD} \left(\frac{1}{n \times PPD_{max}} \sum^{n} PPD_i \right) + \omega_{iaq} \left(\frac{\varepsilon_{vmax}}{\varepsilon_v} \right) + \omega_E \left(\frac{E_{fan} + E_{cooling}}{E_{max}} \right) \right\} \quad (6)$$

where ω represent the weighting factors. Subscript i denotes the number of occupant. Subscripts max denote the maximum values of corresponding objective variables, which are used to ensure no specific factor is dominant over the others.

4. Results

4.1 Validation of CFD simulation

For this study, the main configurations of CFD simulation are set as follows: RNG $k-\varepsilon$ model for turbulence, standard wall functions for near-wall treatment, buoyancy effects under consideration using boussinesq's approximation and no viscous heating. The inner surface temperature is set as 24.65℃ and CO_2 emission rate is 0.87 L/min. To validate the CFD model, the supply air temperature and velocity are set at 17℃ and 0.09m/s as [9]. The corresponding prediction solved the 3D mass, momentum, energy and concentration equations on the computing domain containing non-uniform 72282 nodes.

To compare the simulation results with measured data, three poles are set in the mid vertical plane: Pole A (x:1.75m, z:1.825m), Pole B (x:2.65m, z:1.825m) and Pole C (x:3.55m, z:1.825m). The simulated temperature and velocity at the three poles are extracted and compared with the measurements reported in [9]. Fig. 3 shows the temperature comparisons between the CFD results and experimental data at the poles. The agreement between the computed results and measured data demonstrate the availability of the CFD model.

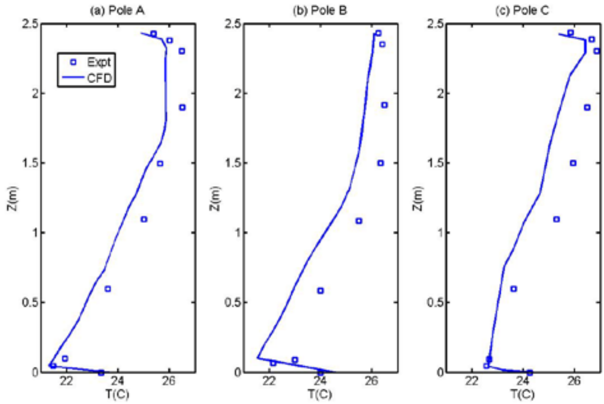

Fig. 3 Temperature Comparisons between the CFD results and experimental data at Pole A, B, C

4.2 Construction of the optimization case

Based on the framework described in Section 2, DE is realized using Matlab m files for optimal solution search. For this study, indoor temperature and velocity of inlet airflow are set as decision variables. According to the literature analysis and to meet a trade-off with available computational capacity, the population size and maximum number of generations are both chosen as 25. The variation range of the controlled variables and DE's main configuration are both listed in Table. 1. In order to record environmental parameters during the optimization procedure, three virtual points are set in the computing domain. Two of them are near the top of two simulated occupants. The third point is set at the exhaust of the room. The optimization framework of the office case is shown in Fig. 4. Firstly, an office model is constructed by Airpak. Make sure that three points' resulting values (including steady temperature, air speed and CO_2 concentration) are saved automatically to report files (Airpak*.out), and the decision variables (inlet temperature and air speed) are read automatically from the file Airpak*.cas. A cost function of DE is defined according to Section 3's discussion. For the cost function evaluation, ω_{PMV} , ω_{IAQ} , and ω_E should be set appropriately according to the emphasis on the optimization target.

The computer used to run the simulation is an Intel Core E3(4 cores, 3.2 GHz) with 8 GB of RAM and the whole optimization procedure requires about 70 hours to obtain the optimal solution.

4.3 Results and analysis

To investigate the performance improvements via such optimization framework, we set up a baseline case for comparison (inlet temperature: 17℃, inlet velocity: 0.1m/s). Via the proposed optimization framework, optimal solution of the control variables can be found, which will improve thermal comfort, IAQ and energy cost in a balanced way. In the objective function, the relative magnitude of each weighting factor reflects occupants' preference. When the relative magnitude of a weighting factor is increased, thus the objective function places more emphasis on the corresponding target term.

Table 1. Design parameters of the optimization approach

Category	Parameter	Design range
CFD	Velocity of inlet airflow	0.01-1.5 m/s
	Temperature of inlet air	17-25℃
	Inner surface temperature	24.65℃
	CO_2 emission rate	0.87 L/min
	Number of iterations	250
DE	Number of generations	25
	Population size	25
	Crossover probability	0.8
	Number of elites produced	2

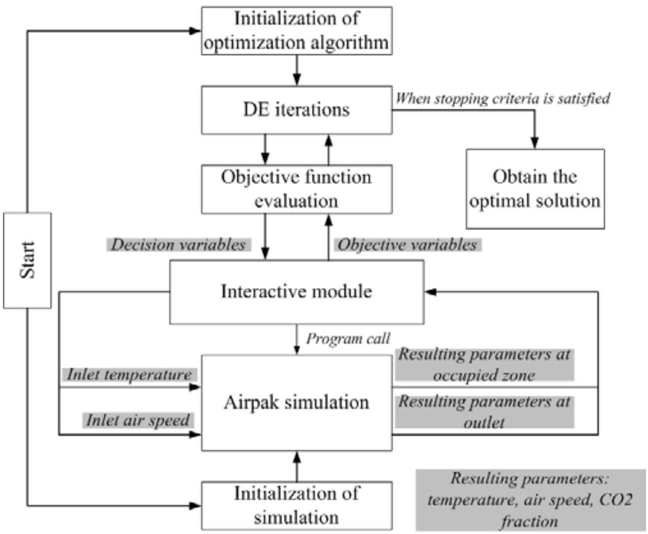

Fig. 4 The optimization framework of the office case

Fig. 5 records improvement of indoor ventilation effectiveness compared with the baseline case. Fig. 6 records improvement of indoor thermal comfort (PMV). According to the standard of ASHRAE, as PMV is approaching zero, a higher percentage of occupants will feel comfortable. In this case, the weights [ω_{PMV} , ω_{IAQ} , ω_E] = [2,1,1]. It is noted that indicators' weights are very sensitive to the optimization result, which should be selected carefully. Using the proposed framework, various of optimization problems can be easily performed by Matlab based optimization regardless of the difficulty of cost function evaluation for complex PDE systems.

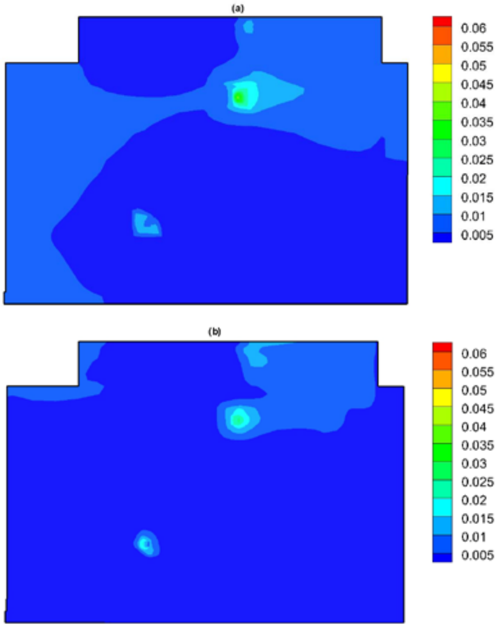

Fig.5 Comparison of CO_2 fraction distributions: (a) baseline case, (b) the optimal case

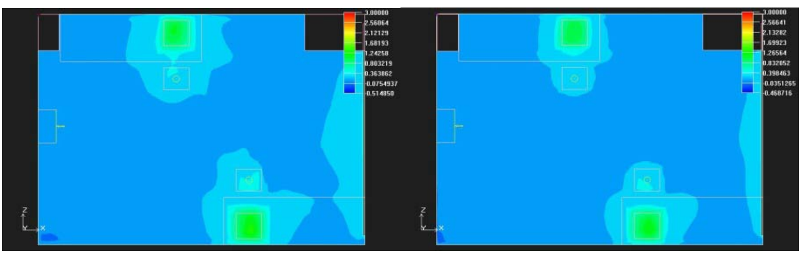

Fig.6 Comparison of PMV Contours: baseline case (left) and the optimal case

5. Conclusions

This study presents a high-resolution and effective optimization scheme of ventilation system operation, which can improve the quality of indoor occupied zones' environment, as well as energy cost of heating and cooling simultaneously. This framework can couple Matlab-based optimization algorithms into any PDE related simulation program that reads/writes its input/output from text files. A kind of data interactive mechanism plays a key role in the optimization framework. A numerical optimization of the ventilation system operation is conducted. Detailed results illustrate the effectiveness of the proposed optimization framework.

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