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DEVELOPMENT OF A MULTI-OBJECTIVE DESIGN OPTIMIZATION PLATFORM USING NSM-PSO AND CFD FOR HEATING AND VENTILATION APPLICATIONS

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ABSTRACT

A healthy indoor air environment is essential to maintain the comfort, health and productivity of the occupants. Governed by the law and regulations, building owners and operators are obligated to provide a safe workplace environment for employees, tenants, and visitors. Nevertheless, with the soaring energy price over decades, the operation cost of heating and ventilation systems is becoming more and more expensive. It has become a huge challenge for engineers to design an optimal system maintaining the desired thermal comfort with minimum cost. Aiming to resolve the problem, a number of numerical and experimental works have been carried out to develop a design optimization methodology. Most of the previous studies concentrated mainly on single objective optimization which aggregated all design indices using artificial weighting factors. The optimal solution, however, is sensitive to the value of weighing factors. This paper reports some preliminary results of the development of a multi-objective design optimization platform for heating and ventilation applications. The algorithm is developed based on the Nondominated Sorting-based Multi-objective Particle Swarm Optimization (NSM-PSO) technique where optimization is carried based on validated CFD predictions. NSM-PSO is an expansion of the basic PSO to achieve more effective nondominated comparisons through a better use of particle's personal best and its offspring. The supply air temperature and velocity are the design parameters selected to optimize against the predicted mean vote (PMV), CO2 concentration and energy consumption as objective functions. The results show that the optimal design temperature ranges from 290.15K to 294.15K, and the velocity ranges between 0.15m/s and 0.44m/s where a Pareto-optimal front is given within this range. Based on the given Pareto-optimal front, designers could then choose the optimal design that is well-balanced between thermal comfort, air quality and energy consumption, according to their professional judgments or end-user preferences.

NOMENCLATURE

T temperature
P air pressure
m mass
c_p specific heat capacity
h specific enthalpy

INTRODUCTION

In recent years, benefit from the rapid development of computational technology, numerical methods (such as Finite Volume Method and Finite Element Method) have attracted significant attention in literature. Computational Fluid Dynamics (CFD), as a kind of Finite Volume Analysis Method, has been widely used among researchers and engineers working on heating, ventilation and air-conditioning (HVAC) system (Stavrakakis et al. 2010, Fong et al. 2006, Stavrakakis et al. 2011, Fong et al. 2009, Chen et al. 2010). Lately, some researchers proposed to use a validated CFD model as a reliable tool to predict the performance (such as air temperature, air velocity, air flow pattern, etc.) of the HVAC system. The CFD predictions are then coupled with some evolutionary algorithms (EA) to search for the optimal design parameters (Fong et al. 2006, Zhai et al. 2014, Zhou and Haghighat 2009a, Li et al. 2013, Zhou and Haghighat 2009b). This kind of methodology is often referred as the CFD-EA coupling approach.

In general, the HVAC system design is a multi-objective optimization problem, where the objectives are generally conflictive with each other and there exist multiple trade-off solutions. In most of the previous research works, the multiple design indices were blended into a single objective problem using artificial aggregating or weighting factors given by the generic form:

$$\min f(\mathrm{x}) = \omega_1 f_1(\mathrm{x}) + \omega_2 f_2(\mathrm{x}) + \cdots + \omega_n f_n(\mathrm{x}) \qquad (1)$$

where $\omega_{1\ldots n}$ are the aggregating/weighting factors. This is an easy implement and high efficient optimization structure, however, the optimal design could be critically sensitive to the weighting factors. The designer must have sufficient professional knowledge deciding the weighting factors to make sure the result is the expected one. Moreover, this method of handling multi-objective gives only one of all the trade-off solutions dominated by the weighting factors, which means there is no alternative solution to be provided to the designer. In attempting to overcome the aforementioned shortcoming, in this study, we propose the use of a nondominated sorting-based multi-objective particle swarm optimization (NSM-PSO) algorithm to achieve multi-objective optimization without any weighting factors. This population-based algorithm, as an improved technique of the basic particle swarm optimization (PSO), can give a group of nondominated (i.e. non-biased) solutions, providing the engineers multiple options from which they can select the most appropriate design according to professional judgment or end-user preference (Carrese et al. 2011).

This paper presents some preliminary results on the development of a multi-objective optimization algorithm which could be integrated into generic CFD packages. In this paper, a three-dimensional domain of a typical office room was built to simulate a HVAC system. The temperature and velocity of the supply air (the two critical design variables) were selected for assessment and optimization. The system performance will be evaluated against in terms of thermal comfort, indoor air quality (IAQ) and energy consumption. The predicted mean vote (PMV), CO_2 concentration and energy consumption are therefore selected as objective functions. The NSM-PSO is performed to handle the multi-objective optimal design problem. Compared to the traditional weighting method where only one point can be located on the Pareto Front, the NSM-PSO is capable of finding a host of points which are well distributed on the Pareto Front, and providing designers more flexibility of choosing their favorite solutions.

CFD-EA COUPLING TECHNIQUES

In the literature, the CFD-EA coupling technique has been adopted as a feasible method in engineering optimization problem (Carrese et al. 2012, Zhou and Haghighat 2009a, Li et al. 2013, Zhou and Haghighat 2009b). The procedure of this kind of method is described as the following. Firstly, a validated CFD model is needed to predict the output (i.e. objectives) regarding to different input parameters. Secondly, after collecting sufficient dada from CFD, some interpolation methods (such as Kriging Interpolation, Artificial Neural Network and Linear Interpolation) are used to get a response surface in a continuous space. Finally, evolutionary algorithms like genetic algorithm (GA) and PSO can be used to search for best design corresponding to the selected objectives. Compared to conventional design cycle, this numerical simulation-based methods offer a faster and more economical way for engineers to assess or predict the design performance and its relationship to different design parameters.

A schematic of the overall methodology is depicted in Figure 1. In this paper, a generic CFD framework (ANSYS CFX V14.5) has been adopted as a reliable predictive tool to construct the input-output data space and predictions of the CFD model were validated against full-scale experimental data by Yuan et al. (1999). After validation, simulations with different controlled variables (i.e. inlet temperature and velocity) were performed to obtain the corresponding system performance for the output space (i.e. PMV, CO2 concentration, energy consumption). The output space was then passed into the NSM-PSO to perform iterative optimization processes for searching the Pareto Front (i.e. optimal trade-off solutions). Multi-dimensional interpolation is applied to calculate fitness value of particles. A brief descriptions of the adopted NSM-PSO is presented in the following.

Basic PSO

Firstly introduced by (Kennedy 2001), the particle swarm optimization (PSO) has been widely adopted as a population-based stochastic optimization method. The basic PSO is inspired by observing social behaviors of ants which include learning from the previous experience and communicating with successful individuals. In the PSO algorithm, each particle has its own position and velocity, which are represented by x_i and v_i, respectively and they are updated according to the following equations:

$$\begin{aligned} v_i(\mathrm{t}+1) &= \omega v_i(\mathrm{t}) + c_1\varphi_1(p_i - x_i(\mathrm{t})) + c_2\varphi_2(p_g - x_i(\mathrm{t})) \\ x_i(\mathrm{t}+1) &= x_i(\mathrm{t}) + v_i(\mathrm{t}+1) \end{aligned} \tag{2}$$

where p_i and p_g represent the personal best position and global best position, respectively, and c_1 and c_2 are two uniform random numbers within the range [0, 1]. The φ_1 and φ_2 are two constants which are set to 2. The parameter ω decreases with the increasing iteration number while within the range [1.2, 0.4]. Unfortunately, the original architecture of the PSO is only capable to solve single-objective optimization problem.

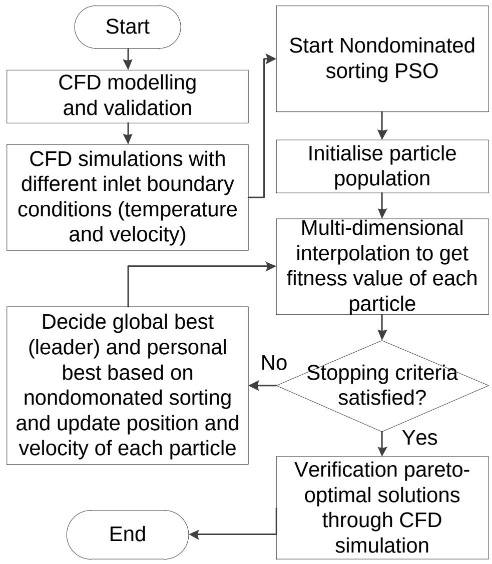

Figure 1: System framework of CFD-EA coupling technique.

Nondominated Sorting-based PSO

In order to enable the basic PSO to solve multi-objective optimization problem, Li (Li 2003) applied a Nondominated Sorting Method (NSM) to the original PSO inspired by (Deb et al. 2002). In NSM-PSO, the updating equations for particle position and velocity do not change, but the selection methods of personal best and global best are different. Nondominated comparison between particles' personal bests and their offspring is used to decide the new personal bests. Nondominated sorting is carried out in a temporary population which consists of N particles' personal bests and N their offspring (therefore $2N$ individuals) to decide the nondomination rank of each individual. Then the global best is selected from the group which has top nondomination rank and in order to avoid local optimal aggregation, crowding distance is calculated and sorted. Therefore, the global best must meet both the following requirements: top nondomination rank and largest crowding distance. Throughout the iteration process, the particles are moving towards the Pareto-optimal Front guided by the leader (global best) and are well distributed because of population diversity maintenance (crowding distance).

MODEL DESCRIPTION

In order to study the aforementioned HVAC system design optimization, a three-dimensional computational domain representing a typical office room was constructed. Figure 2 shows the geometry layout of the computational domain and Figure 3 gives the mesh distribution of the computational model. A total of 2,849,852 elements and 1,043,811 nodes were generated throughout the whole domain. The conditioned air flows from the supply air unit at the right and leaves the room from the exhaust at the center of the roof. Details of the boundary conditions are listed in Table 1. Table 2 gives the geometry dimensions of the objects in the room. It should be noted that the temperature and velocity of the inlet are controlled variables and other boundary conditions are fixed for all simulations.

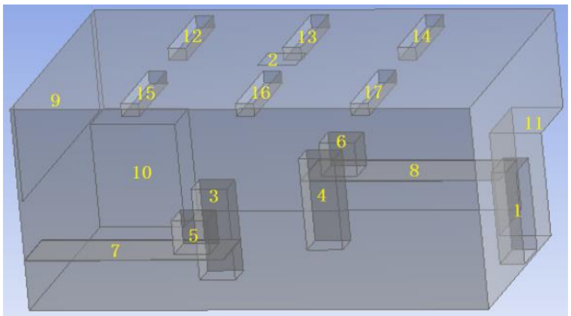

Figure 2: The geometry layout of the typical office room.

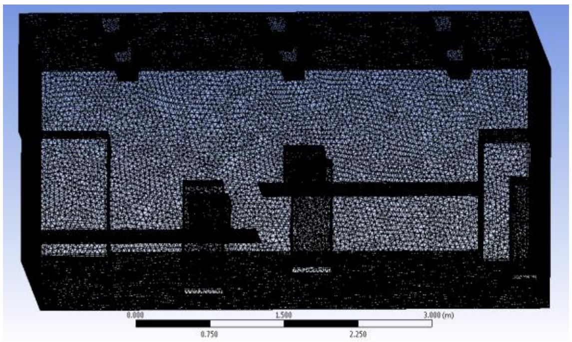

Figure 3: Mesh distribution of the CFD model.

Number	Name	Boundary details	Comments
1	Supply air unit	Normal speed & Static temperature	Controlled variables
2	Exhaust	Average static pressure	0[Pa]
3,4	Occupant	Temperature	37[C]
5,6	Desktop	Heat flux	108.5[W/m^2]
7,8	Table	Adiabatic	-------
9	Partition	Heat transfer coefficient	3.7[W/(m^{2}K)]
10,11	Furniture	Adiabatic	-------
12-17	Light	Heat flux	34[W/m^2]
	Room wall	Heat transfer coefficient	0.19[W/(m^{2}K)]

Table 1: The boundary conditions.

CFD MODEL VALIDATION

To ensure the validity of the CFD simulation, predictions of the CFD model were first validated against the full-scale experimental data reported by (Yuan et al. 1999). Figure 4 shows the comparisons between the measured and predicted air temperature and velocity along a vertical line at the center of the office room under the inlet condition (17[*C*], 0.09[*m/s*]). The blue lines are the results extracted from the CFD simulation and the red dots are the experimental data report by (Yuan et al. 1999). As depicted, the predicted temperature and velocity are in satisfactory agreement with the experimental measurements; showing that the CFD predictions are reliable for design optimization.

Number	Name	Length(m)	Width(m)	Height(m)
1	Supply air unit	0.28	0.53	1.11
2	Exhaust	0.43	0.43	-----
3,4	Occupant	0.4	0.35	1.1
5,6	Desktop	0.4	0.4	0.4
7,8	Table	2.23	0.75	0.01
9	Partition	-----	3.35	1.16
10,11	Furniture	0.95	0.58	1.24
12-17	Light	0.2	1.2	0.15
	Room	5.16	3.65	2.43

Table 2: The geometry dimensions of CFD model.

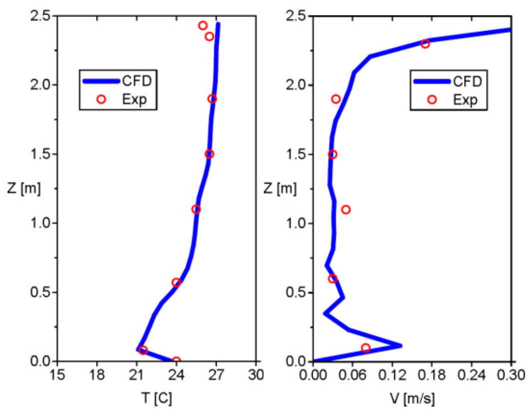

Figure 4: Comparisons between the CFD results and experimental data.

ASSESSMENT INDICES

PMV for thermal comfort assessment

The predicted mean vote (PMV) is a thermal comfort evaluation index which was firstly introduced by (Fanger 1972). This value represents the subjective mean satisfaction with the indoor thermal environment with a number between -3 (cold) and +3 (hot). Zero is defined as the ideal value representing thermal neutrality and our objective is to make |PMV| as small as possible. Fanger's equations are used to calculate the PMV with a particular combination of air temperature, mean radiant temperature, relative humidity, air speed, metabolic rate, and clothing insulation (Fanger 1972). In this paper, we evaluated the average PMV based on the predicted field information obtained from CFD simulations.

$$\begin{aligned} PMV = {} & [0.303*e^{-0.036M}+0.028]\{M-W \\ & -3.05*10^{-3}[5733-6.99(M-W)-P_a]-0.42 \\ & [(M-W)-58.15]-1.7*10^{-5}M(5867-P_a) \\ & -0.0014M(34-t_a)-3.96*10^{-8}f_{cl}.[(t_{cl}+273)^4 \\ & -(\bar{t}_s+273)^4]-f_{cl}h_c(t_{cl}-t_a)\} \end{aligned} \tag{3}$$

CO_2 Concentration for IAQ assessment

To assess the air quality within the space, the concentration of CO_2 emitted by occupants throughout the office room was also resolved in the CFD simulation. In the simulation, the CO_2 is emitted from the occupants with the velocity and concentration of 0.018m/s and 4.0ppm respectively. Similar to the average PMV, the average CO_2 concentration was extracted from the predicted CFD field information.

Energy Consumption for ventilation

The energy costs of air-conditioning can be divided into two parts: ventilation fan power and cooling/heating energy consumption (Li et al. 2013). These two parts and total energy costs can be determined by the following equations:

$$
\begin{aligned}
E_{fan} &= \frac{P \cdot V_{air}}{\eta_{fan}} \\
E_{cooling/heating} &= m_{supply} c_p (T_{return} - T_{supply}) \\
&\quad + m_{outdoor} (h_{outdoor} - h_{return})
\end{aligned}
\tag{3}
$$

where P is air pressure difference of the fan and V is volume flow rate of supply air (m^3/s), m represents the mass flow rate of the air (kg/s), c_p is the specific heat capacity of air, T represents temperature, h is the specific enthalpy of air (J/kg) which is related to air temperature and relative humidity. Similarly, we can get energy costs from the CFD-Post package.

SIMULATION RESULTS AND ANALYSIS

CFD simulation results

To obtain sufficient sample data, a total 25 simulations with different combinations of controlled variables (temperature and velocity of inlet) were carried out (see Figure 5). In this study, the commercial CFD package – ANSYS CFX 14.5 was adopted to simulate air flow and heat transfer within the typical office room. Figure 6 and 7 show the temperature contour and velocity vector, respectively, on the middle plane under the inlet condition (17[C], 0.1[m/s]). Afterwards, the validated CFD model was then applied to predict the response surface of the system performance (i.e. PMV, CO_2 and energy) with respect to different design parameters (i.e. supply air temperature and velocity). The corresponding response surfaces are shown in Figure 8.

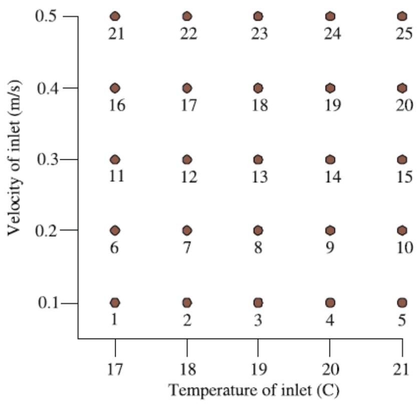

Figure 5: Definition of controlled-variable combinations for CFD simulaitons.

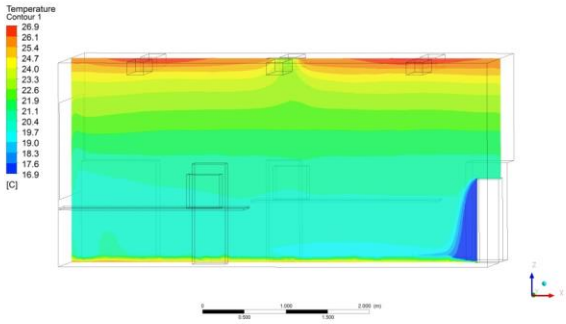

Figure 6: Temperature contour on the middle plane at (17C, 0.1m/s)..

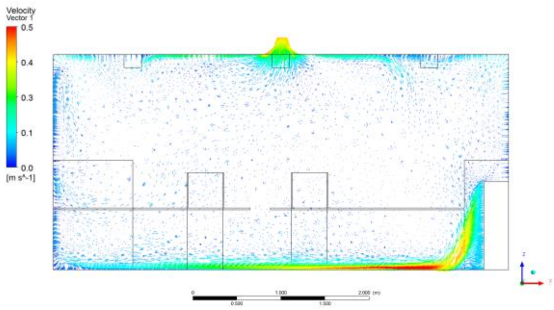

Figure 7: Velocity vector on the middle plane at (17C, 0.1m/s).

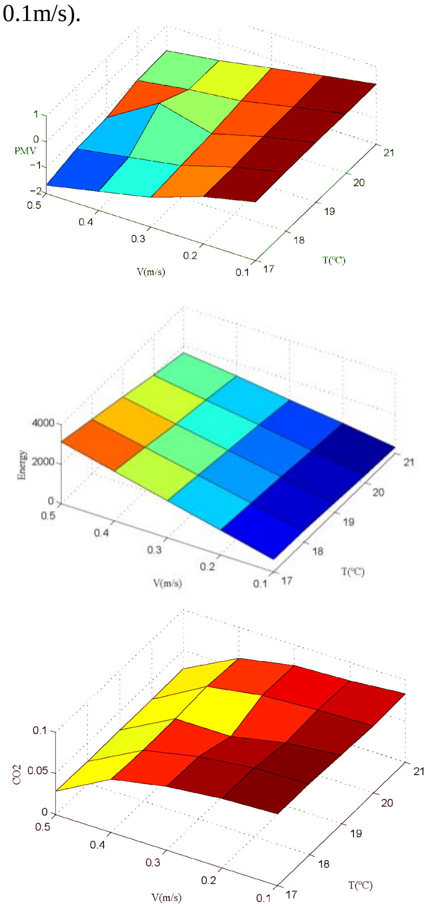

Figure 8: Response surfaces of the three objectives (PMV, energy, CO2).

Optimization results

For comparison, two methods of optimization were used in the present study. Method one adopts similar approach from previous literature using weighting factors to construct a single objective function. Method two adopts the proposed NSM-PSO to find multiple equally good and well-distributed solutions.

(a) Weighting method

In this optimization process, two objectives (i.e. PMV and energy consumption) are selected to construct the objective function, given by:

$$f = \omega_1 f_{PMV} + \omega_2 f_{Energy} \qquad (4)$$

where ω_1 and ω_2 are the weighting parameters which decide the optimization results. Table 3 shows the impact of weighting factors on the optimal results and Figure 9 shows a comparison of PMV contour between the Baseline case (17[C], 0.1[m/s]) and the improved Case 2 (20.6[C], 0.17[m/s]).

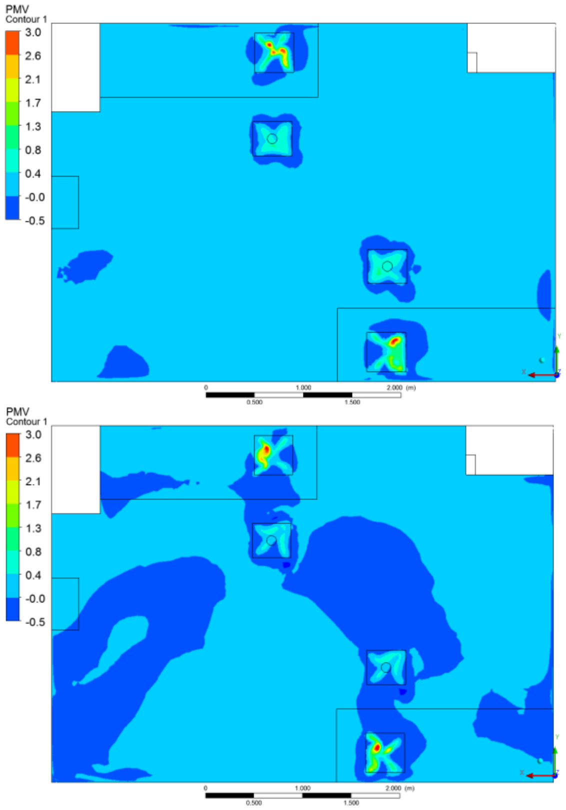

Figure 9: Comparisons of PMV contour between baseline case (upper) and case 2 (lower).

Variables	Baseline case	Case 1	Case 2
Weights	-----	[0.5,1]	[1,1]
T_{in} [C]	17.0	20.7	20.6
V_{in} [m/s]	0.10	0.14	0.17
PMV	0.27	0.18(33%)	0.05(81%)
Energy [W]	624.5	480.2(23%)	624.7(0%)

Table 3: Optimization results with different weighting factors.

From the Case 1 in Table 3, it can be observed that both the thermal comfort and energy consumption are improved in comparison to the baseline case (i.e. 33% and 23%, respectively). By comparing the Case 1 and Case 2, by reducing the weighing factor for energy, a higher (i.e. 81%) thermal comfort improvement could be achieved. Therefore, we can conclude that the results are sensitive to weighting factors and this method can only output one solution in each run. Moreover, because different designers would have different preferences, it is difficult to fix the weighting factors in advance and only giving one solution per run provides no flexibility of choosing alternative trade-off solutions.

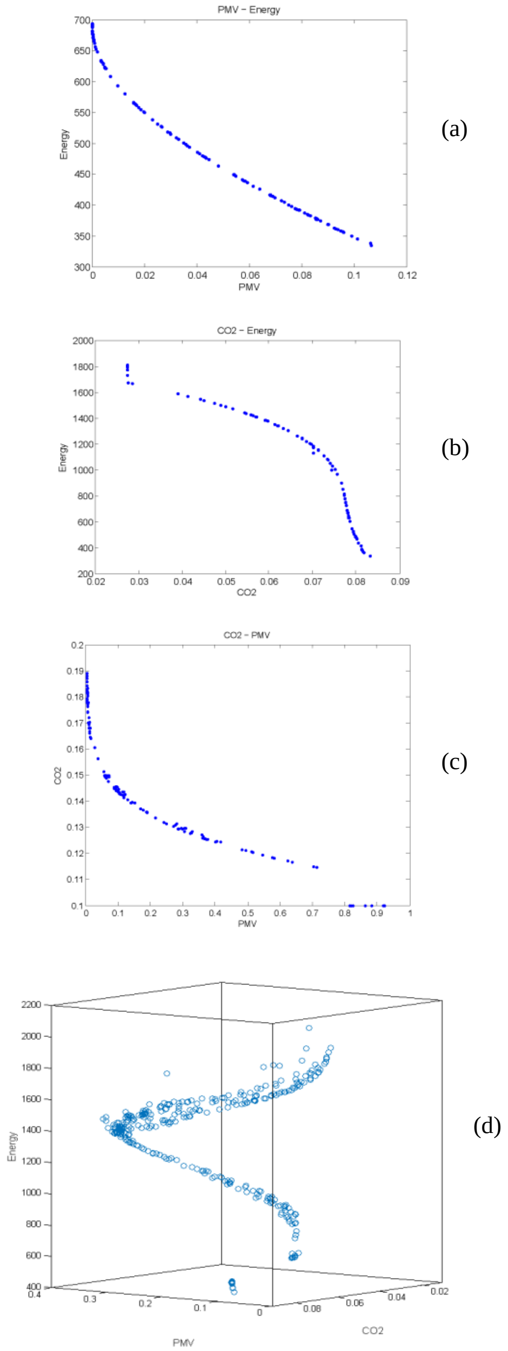

Figure 10: Nondominated solutions given by the NSM-PSO.

(b) Nondominated sorting method

To remedy the drawback of Method one, the NSM-PSO is a weighting factor free optimization procedure, and multiple trade-off solutions can be provided in one run. In this paper, the iteration number is set to be 100 and the nondominated solutions by NSM-PSO method are shown in Figure 10, where each of the blue dot represents a solution in the objective space. Figures 10(a~c) indicate the nondominated solutions of 2-objective provided by the NSM-PSO (PMV-Energy, CO2-Energy and CO2-PMV, respectively), and Figure 10(d) shows the nondominated solutions of a 3-objective problem considering all the three objectives (PMV-Energy-CO2). Obviously, the NSM-PSO could provide multiple nondominated solutions (i.e. improvement in terms of one objective comes from a sacrifice on at least one of other objectives), providing designers with flexibility of choosing alternative solutions which are equally good. After getting the optimal Pareto front, engineers can select one set of design parameter from the front according to their professional judgments or end-user preferences.

CONCLUSION

This paper presents some preliminary research work on the development of a multi-objective optimization algorithm which is tailored to be integrated with generic CFD packages. Different other previous studies in the literature, we proposed a weighting factor free algorithm – NSM-PSO to handle the multi-objective optimization problem. The advantage of the method is able to provide multiple trade-off solutions (i.e. Pareto Front) in one simulation run. With the visualization of solutions in objective space, designers could easily pick up the most appropriate one according to their professional judgments or end-user preferences, rather than being struggled to decide the value of weighting factor in advance using the traditional method. Furthermore, the CFD-NSMPSO coupling method also provides engineers more flexibility of choosing alternative solutions in only one simulation run. In this paper, a commercial software – ANSYS CFX was adopted as a CFD tool to predict the air flow and heat transfer in a typical occupied office room and MATLAB was used as an interpolation tool to generate the objective response surface. NSM-PSO algorithm was coded in MATLAB to search optimal design parameters. The results show that the combination of CFD and NSM-PSO is a feasible and promising method for multi-objective engineering optimization design.

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