IMPROVING THE DESIGN PROCESS USING SIMULATIONS AND MULTI-CRITERIA DECISION MAKING

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ABSTRACT

This paper introduces a newly developed multi-criteria decision making tool called RR-PARETO and its application to HVAC design. As an illustration, five criteria have been selected, namely, power consumption, thermal comfort, risk of infection of influenza and tuberculosis and effective differential temperature (Δt_{eq}) of body parts, with the objective of selecting the optimal air exchange rate that makes reasonable trade-offs among the criteria. Two scenarios have been studied:(i) an influenza outbreak with the objective to prevent the spread of infection, and (ii) energy prices are high and the primary objective is to reduce mean load.

INTRODUCTION

Simulation of building performance is getting increasingly reliable through the development of software such as EnergyPlus (2005) for thermal load simulation and Radiance (Ward and Shakespeare, 1998) for lighting simulation. However, the practical application of simulations is restricted by the paucity of methodologies that integrate multiple simulations into the design process. In particular, the decision making process involving multiple criteria is not well established. For example, lighting simulation might indicate that a solution performs well in terms of reducing lighting energy. But it may not perform that well with respect to the total energy consumption. Decision making in such situations is not straightforward because trade-offs have to be made between user's preference for natural day lighting and the goal of reducing energy consumption. This paper discusses the issue of evaluating simulation results according to multiple criteria and selecting the best solution in a design process. A recently developed algorithm called RR-PARETO is applied to HVAC design in order to illustrate the concept of multi-criteria decision making in design.

MULTI-CRITERIA OPTIMIZATION

Simulation can be used to improve designs when it is used in conjunction with optimization techniques. Black box optimization programs permit better design of building systems since large number of alternatives can be evaluated automatically to select good solutions. Each solution is evaluated by running simulations as external programs which are treated as black-boxes by the optimization algorithm. Unlike traditional mathematical optimization, mathematical characteristics of the evaluation function such as convexity, expression for the gradient, etc. are not needed. Such techniques are called direct search methods and are increasingly used in design optimization. Examples of direct search methods include Genetic Algorithms (Holland 1970), Simulated Annealing (Kirkpatrick et al. 1983) and PGSL (Raphael and Smith, 2003).

In most design applications, single objective optimization is used (Kampf and Robinson, 2010). However, complex engineering artefacts such as building systems have to be necessarily evaluated according to multiple criteria. The task of selecting the best design is complex since it involves making trade-offs among conflicting objectives. Rarely, we find solutions that perform equally well with respect to all the criteria. An approach to managing multiple criteria is Pareto optimization in which a population of solutions that are non-dominated is generated. Such techniques have already been used in the design of building systems. For example, Jelle and Arnold (2010) used genetic algorithms to find and select Pareto optimal solutions for the trade-off between energy and the risk of exposure to pollutants. However, they do not present a well-defined algorithm for selecting a single solution from the Pareto front. Instead, it is recommended that the practical selection of system configuration should be limited to the midrange spectrum of the Pareto front, where the curvature is the maximum. In fact, researchers have not paid much attention to the problem of selecting the best solution from the Pareto set.

RELAXED-RESTRICTED PARETO SELECTION (RR-PARETO)

A recently developed algorithm called RR-PARETO (Raphael 2010, Raphael 2011) aims to select a single solution with the best trade-offs within a multi-objective framework. In this algorithm, the solution with the best trade-offs among all the objectives is chosen using two pieces of information, ranking of

the objectives according to their importance; and the sensitivity of each objective

The sensitivity of an objective refers to the threshold which determines whether the differences in the objective function values are significant. All the points lying within the specified sensitivity band are considered to be equivalent with respect to that objective.

In order to illustrate the concept of sensitivity, consider the objective of minimizing the power consumption. The user might specify that reduction in power below 10% is not significant, and therefore, the sensitivity of this objective is defined as 10%. All the solutions lying within the sensitivity band are considered to be equivalent. These solutions are further filtered using other objectives.

The algorithm starts off with a set of solutions that are generated by any optimization process. Each solution point contains the values for all the objectives as well as decision variables (optimization variables). The set of solutions are sequentially filtered according to the order of importance of objectives. At each stage of filtering, the solution point with the best value for the current objective from among all the points in the current set is chosen. All the points that lie outside the sensitivity band of the chosen point are eliminated from the set. At the end of the process, one or more points might remain in the solution set. The user is asked to choose the preferred solution from this set or in the automatic mode, the best solution according to the most important criterion is selected.

A graphical user interface (GUI) was developed to help users explore the solution space and perform the selection of the most attractive solution. Users can evaluate various possibilities by setting constraints on the values of variables through selecting continuous regions along each axis. In addition, conventional Pareto filtering or the newly developed RR-Pareto filtering can be applied for the automatic selection of solution points.

SIMULATION AND EXPERIMENTS

The design of an air distribution system is taken as an example to illustrate the concept of multi-criteria decision making. The decision variable is the air exchange rate (ACH). Five criteria have been selected, namely, power consumption, thermal comfort, risk of infection of influenza and tuberculosis and effective differential temperature (Δteq) of body parts. The goal is to select the optimal ACH that makes reasonable trade-offs among all the objectives.

Measurement instruments

A Field Environmental Chamber (FEC) with the dimensions 11.1 m x 8 m x 2.6 m was used as the

experimental facility in this study. The air in the FEC was supplied from a dedicated Air Handling Unit (AHU) using ceiling mounted mixing ventilation (MV) air delivery system. The second (alternative) air delivery system used is a hybrid system consisting of personalized ventilation (PV) coupled with MV. Independent outdoor air AHU was used to supply a desktop personalized ventilation air terminal device (DPV ATD). Coupled PV and MV utilized two DPV ATDs together with ceiling mounted MV elements.

A cough machine was used to simulate multiphase flow consisting of expiratory droplets suspended in the air released by human cough. Human saliva was simulated with a mixture of water (94% of the total volume) and glycerin (6% of the total volume). This method of human saliva simulation has been used in several studies (Chao and Wan 2006; Pantelic et al., 2009).

Simulation of a susceptible person in an office environment was achieved using a seated breathing thermal manikin (BTM). The BTM was dressed to approximately 0.7 clo, typical office attire in the tropics. The 26 body segments of the BTM were heated and individually controlled under the 'comfort mode'. To simulate breathing under light office work, the pulmonary ventilation volume was set at 6 l/min, with a 10 times per minute breathing cycle comprising 2.5 s inhalation, 1.0 s break, 2.5 s exhalation and 1.0 s break again, similar to that adopted by Zhu et al. (2005). The equivalent inhalation–exhalation flow rate was set at 0.24 l/s. The exhaled air temperature was 34°C.

In order to obtain the concentration time profile of the simulated expiratory aerosols, aerosol counting is required. A Grimm 1.108 aerosol spectrometer with 16 size channels (measurable size range, 0.3–20 μm) was used to measure the real-time aerosol concentration in the inhalation zone of the breathing thermal manikin.

An INNOVA 1312 photoacoustic spectrometer multi-gas analyzer wasused to determine air exchange rate (ACH) in the FEC using tracer decay method by measuring the concentrations of sulphur hexafloride (SF6) over time.

Experimental Design

Experiments were designed to simulate susceptible occupant in the office environment supplied with ceiling mounted MV and DPV. The BTM was positioned at the centre of FEC sitting at the office table with hand placed at the table top together with DPV ATD's. Air was supplied at flow rates of 3, 6, 9 and 12 ACH to simulate various operating conditions. Airborne infection risk was also estimated, including when air was not supplied to the FEC to simulate condition of possible system failure. Changes of the supply flow rate cause different mean load of the HVAC system, thermal comfort of the

occupants and airborne infection risk levels. Droplet concentration in the breathing zone of the BTM was measured with Grimm 1.108 aerosol spectrometer with isokinetic sampling probe positioned 15 mm vertically below the manikin's nose and 15 mm horizontally from the BTM's upper lip. Cough was injected at several distances and for each point in 8 directions relative to the breathing zone of the susceptible person. Further details of the experimental design can be found in Pantelic et al., (2010).

The air temperature in the FEC was maintained at 23°C in all experimental runs. Two different supply flow rates were examined for the total volume ventilation systems producing 6 and 12 total ACH in the FEC. PV consisted of 100 % OA (outdoor air) with a total flow rate of 5 l/s (2.5 l/s for each ATD) at a temperature of 23°C. The relative humidity in the room was maintained below 70%.

Thermal comfort at various conditions for MV has been evaluated using the method proposed by Tanabe et al. (1994). BTM was used to measure the mean skin temperature under thermal neutrality for 26 body segments. Mean skin temperature (t_s) was used to calculate manikin based equivalent temperature for every BTM body segment. Manikin based equivalent temperature (t_{eq}) is defined as: "the temperature of a uniform enclosure in which a thermal manikin with realistic skin surface temperatures would lose heat at the same rate as it would in the actual environment". Value of manikin based equivalent temperature was used as air and radiant temperature for calculation of predicted mean vote (PMV) and percentage of people dissatisfied (PPD) (Fanger P. O., 1970). Other ambient parameters used for this calculation were air velocity of 0 m/s, relative humidity 60 % while metabolic rate used was 1.1 met and 0.7 clo for clothing level.

When PV was used local air movement on the facial region caused forced convection heat transfer while the rest of the body was exposed to natural convective heat transfer. This can cause thermal asymmetry since facial cooling is significantly higher than the rest of the body. This cooling asymmetry can be evaluated using manikin based equivalent temperature difference (Δteq). This criterion was added to the overall thermal body sensation to evaluate thermal performance of personalized ventilation. This additional criterion is very important parameter because PV temperature and flow rate are more critical than ambient temperature for occupant's thermal comfort (Gog Nan., 2006).

Mean load Evaluation

Total load was divided into two parts: (i) transportation and (ii) cooling load. Transportation load consumption was calculated using Bernoulli's equation taking into account frictional and losses due to changes of the ductwork geometry in the supply

and return system. Geometry of the FEC was modeled in EnergyPlus and thermal properties of walls, floor, ceiling and windows, lighting features, occupancy, additional internal heat sources were set in the software for the cooling load calculation.

Airborne Infection Risk Evaluation

Cough droplets concentration in the breathing zone of the BTM was measured at supply flow rate of 0, 3, 6, 9 and 12 ACH. Results were then averaged using methodology described in Pantelic et al., (2010). taking into account distance between infected and susceptible occupant, orientation of cough release relative to the breathing zone of the susceptible occupant, posture from which cough was released and contribution of different air patterns generated in the indoor environment. Dose–response model (Sze To et al., 2008) was used with averaged exposure results to calculate overall airborne infection risk.

DISCUSSION AND RESULT ANALYSIS

Mean load of the FEC for various supply flow rates is shown in Figure 1. For 0 ACH, load of 6000 W represent only cooling load of the FEC. Results show that PV consume more power than MV for every flow rate.
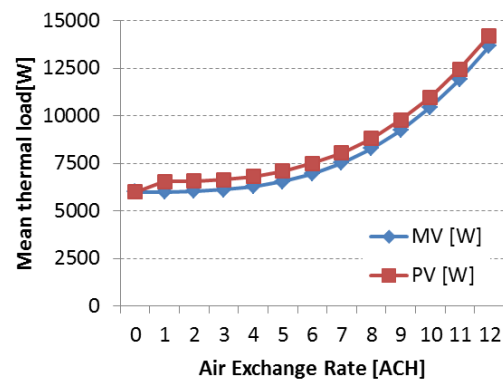

Figure 1 Mean load for MV and DPV

Changes of PPD (percentage people dissatisfied) with the increase of supply flow rate are shown in Figure 2. Up to 6 ACH, MV and DPV have very similar trend, but further increase of supply flow rate cause increase of PPD for DPV while decrease for MV.

The Pareto Front for the objectives Power Consumption and PPD is shown in Figure 3. PPD increases when Power is minimized through reduction in the air exchange rate (ACH).

The Pareto Front represents the trade-off between the two objectives. One objective cannot be improved without sacrificing the other objective. The area below the curve represents infeasible region (where no solutions are possible). The area above the curve represents inefficient region where improvements in

both objectives are possible. Points corresponding to ACH above 8 are not on the Pareto Front since they result in higher power and higher PPD. Thus the Pareto front helps to narrow down the selection to a smaller set of solutions. However, it offers no support for selecting the best solution.
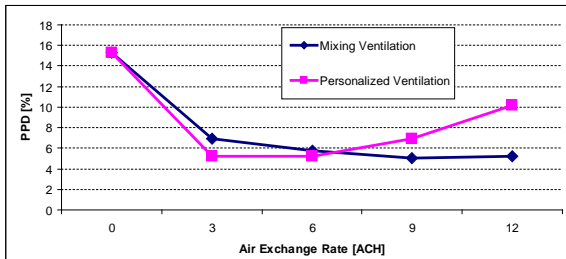

Figure 2 PPD for various air exchange rates for MV and DPV

The concept of optimal trade-off can be clearly seen in Figure 3. The increase in PPD below 3ACH is very sharp. The improvement in Power appears to be insignificant compared to the cost of increased PPD when the ACH is reduced below 3. However, the optimal trade-off point depends on the relative importance of these two objectives. Therefore, the best solution cannot be selected without a knowledge of how much increase in the mean load is acceptable to the user relative to the gain in PPD. RR-PARETO algorithm captures this information through the sensitivity parameter.

The Pareto front for Personalized Ventilation is shown in Figure 4. In this case, there are only three points on the Pareto front. All other points are filtered out because they cause simultaneous increase in power and PPD values. It should be noted that all the points plotted on the curves in Figures 3 and 4 are feasible, meaning that they do not violate any technical constraints. The ACH value of 1 is able to satisfy the cooling load requirements for the HVAC system used in the laboratory. However, in a large commercial unit this might not be feasible. In that case, this point will not appear on the Pareto front and will not be considered for the selection of the optimal solution.

The trade-off between infection risk and power consumption is shown in Figures 5 and 6. Increasing ACH reduces the infection risk of Influenza and the reduction in infection risk is marginal, while the tuberculosis (TB), but at the cost of increasing power consumption. It can be seen that after a certain level, increase in mean load is significant. Therefore, the choice of optimal air exchange rate should take into consideration the marginal improvements in the values of these conflicting objectives.

Results from RR-Pareto Algorithm

The RR-Pareto algorithm requires the sensitivity of objectives and the order (priority) of objectives as input. This section demonstrates that this information
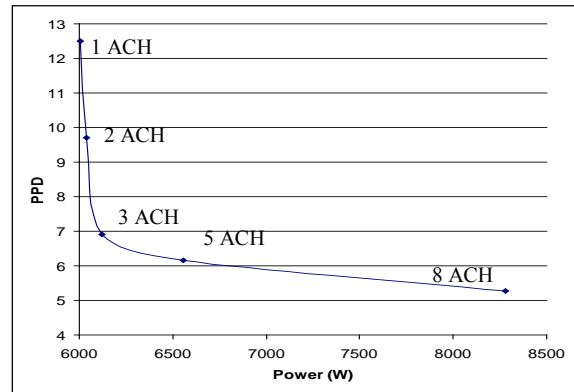

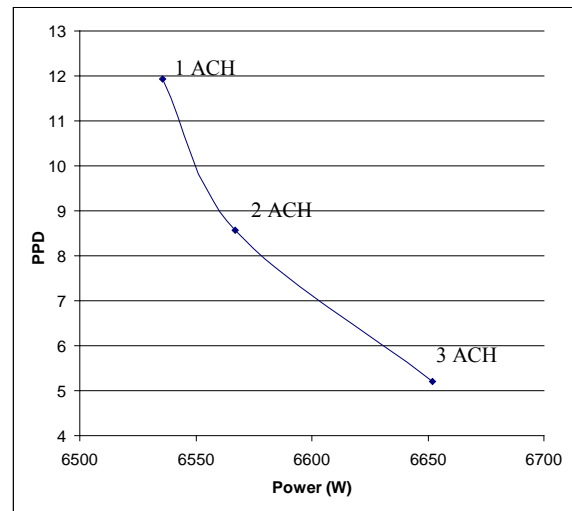*Figure 3 Pareto front for the objectives Power and PPD for Mixing Ventilation*

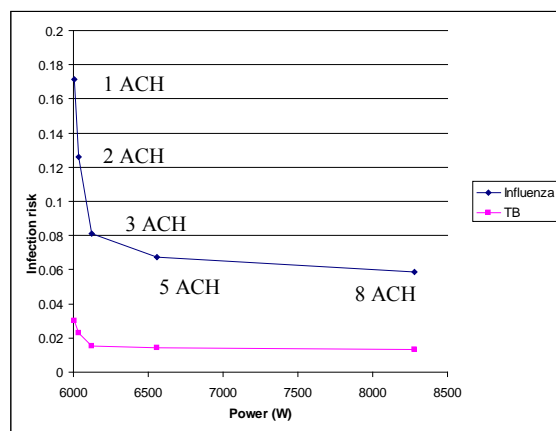*Figure 4 Pareto front for the objectives Power and PPD for Personalized Ventilation*

Figure 5. Pareto front for the objectives infection risk of Influenza and tuberculosis versus Power consumption for Mixing Ventilation

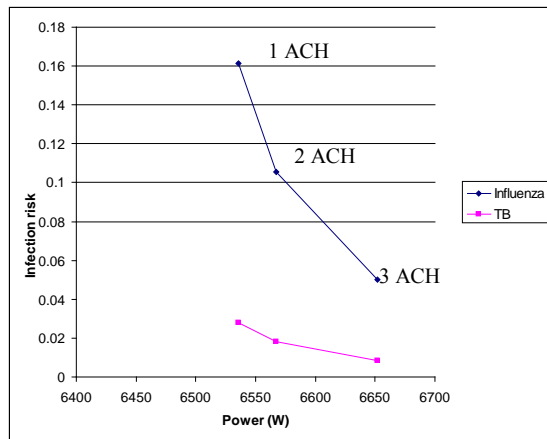can be generated through a rational and scientific procedure.

Figure 6. Pareto front for the objectives infection risk of Influenza and TB versus Power consumption for Personalized Ventilation

First of all, the order of objectives depends on the scenario. Two scenarios are considered here.

- Scenario S1: Influenza outbreak
- Scenario S2: High Energy Prices

In the first scenario, the reduction in infection risk becomes the primary objective. Other objectives become secondary. In second scenario, energy prices are high while there is no local disease outbreak or pandemic spread of airborne transmissible disease, and therefore, the power consumption becomes the primary objective.

The sensitivity of objectives can be obtained by examining what might be a significant deviation. For the infection risk, a value of 2% represents probability of less than one person getting the infection. This reasoning is based on well established epidemiological concept of basic reproductive number which imply that infection outbreak will die off in the long run if this number is kept below 1 (less than one new infected case). Therefore, this is used as the threshold. For power consumption, a 5% increase is insignificant compared to the normal operating costs of a building. Of course, it depends on the priorities and policies of the target organization and might be modified depending on the situation. A 5% difference in PPD is considered to be insignificant because it corresponds to less than one person in a population of 16 that the laboratory can accommodate. This criterion can be considered to be very strict since in the normal operation it is expected that about 20% of the people might express dissatisfaction with indoor conditions. Finally, the sensitivity of Δt_{eq} is taken as $1^{o}C$ since it is not known to cause significant discomfort and findings from tropical region indicate that subjects perceive air movement being the most acceptable when facial

thermal sensation is about "slightly cool" (Gong, 2006).

The priority order of objectives for the two scenarios are as follows:

Scenario S1:
1. Influenza
2. Power consumption[W]
3. PPD
4. TB
5. Δteq

Scenario S2:
1. Power consumption[W]
2. PPD
3. Influenza
4. TB
5. Δteq

The optimal solution for scenario S1 using mixing ventilation involves an ACH of 6 with a power consumption of 6.96 kW. For scenario S2, RR-PARETO filtering resulted in two solutions which lie within the specified sensitivity bands. From these, the one with the lowest value for the primary objective was chosen. This involves an ACH of 3 and a power consumption of 6.1 kW.

The optimal solutions for personalised personalized ventilation for Scenario S1 involves 5 ACH, where as that for scenario S2 involves 3 ACH. These correspond to power consumption of 7.1 and 6.6 kW respectively.

For scenario S1, the optimal solution identified for PV has higher power consumption than that for MV. This is because the infection risk for PV has a lower value than that for MV. If the infection risk for PV is kept at the same level as that of MV, the optimal solution is 3 ACH with a power consumption of 6.6 kW. Comparing this with the power consumption of the optimal solution for MV, there is a savings of 5.5%. That is, for the same level of infection risk, PV has a lower power consumption compared to MV. However, in the second scenario, PV has a higher mean load that MV. This is because, the reduction in load of PV below 3 ACH is not significant and all the values below this level lie within the sensitivity band of the energy objective. Table 1 summarises these results.

Table 1
Results of RR-PARETO filtering

SCENARIO	MODE	ACH	POWER (kW)
S1	MV	6	6.96
S2	MV	3	6.1
S1	PV	5	7.1
S2	PV	3	6.6

CONCLUSION

The interactions between the five objectives for the design of a ventilation system have been analysed using the multicriteria decision making tool RR-PARETO. It is shown that the objective of minimizing power consumption conflicts with other objectives such as thermal comfort and infection risk. The conclusions from this study are the following:

- A multi-objective optimization framework is necessary for selecting the air exchange rate for an HVAC system when criteria such as user comfort, infection risk and mean load need to be integrated

- RR-Pareto algorithm shows much potential for identifying solutions that achieve reasonable trade-off among conflicting objectives

- The optimal solution depends on the scenario under consideration. In the scenario of influenza outbreak, a solution with higher ACH is identified. In the scenario of high energy price, a lower ACH solution is identified

- For the same level of infection risk, the optimal solution for personalized ventilation has lower power consumption compared to that for mixing ventilation.

In both scenarios, in the solutions identified by the RR-PARETO algorithm there is a reasonable balance between the values of primary and secondary objectives. The example demonstrates that the multi-objective framework is valuable for designers in the decision making process.

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