Published article:

Khan, MAI, Noakes, CJ and Toropov, VV (2012) *Development of a numerical optimization approach to ventilation system design to control airborne contaminant dispersion and occupant comfort.* Building Simulation, 5 (1). 39 - 50. ISSN 1996-3599

http://dx.doi.org/10.1007/s12273-012-0058-7

Development of a numerical optimization approach to ventilation system design to control airborne contaminant dispersion and occupant comfort

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Abstract

Airflow, contaminant concentration and temperature distribution during heating and ventilation in a model room represented by a square cavity with inlet and outlet ports, has been studied. The aim of this work is concerned with the development and implementation of a practical and robust optimization scheme based on the combination of response surface methodology (RSM) and Genetic algorithm (GA) with the aim of assisting hospital ward designers and managers /operators to enhance infection control (i.e. reduce the risk of airborne transmission) without compromising patient comfort and environmental impact

Introduction

Ventilation of healthcare environments serves a dual purpose; to provide a thermally comfortable indoor environment for occupants and to control the distribution of contaminants, particularly the transmission of airborne infectious particles. Design of appropriate ventilation depends on the level of infection risk, heat loads in the space and clinical activity. Ventilation in all occupied environments must consider comfort, energy use and contaminant control, however healthcare environments present a particular challenge. Hospitals operate 24 hours per day, so cannot easily adopt practices such as night-venting that may be used to keep office environments thermally comfortable. The patients that occupy hospital wards may have less tolerance to poor comfort control than in other environments and are less able to adjust their surroundings to compensate during temperature extremes. Infection control is a key issue in all parts of a hospital, and the design of ventilation in some spaces such as isolation rooms and operating theatres is dominated by the need to control the risk of infection. Understanding how to balance the sometimes conflicting comfort and infection risk requirements is increasingly important, particularly as the energy demands of the ventilation system are also now a critical factor. The balance will vary throughout the building, with the clinical function and the particular patient cohort determining whether comfort or infection risk is the critical design factor in a certain space.

Development of design tools that allow architects and building services engineers to evaluate the performance of ventilation in different parts of a hospital are likely to be of considerable benefit. The application of computational approaches to study ventilation airflow patterns in enclosed spaces such as hospital wards, office rooms etc. has attracted considerable interest among engineers and scientists over the last few decades (see Yam et al. 2011; Chow and Fung 1996; Fan 2000; Jones and Waters 1993; Nielsen 1988). Much of the work to date uses Computational Fluid Dynamics (CFD) for parametric study of the influence of the airflow on the transport of heat and contaminants, including airborne pathogens (Noakes et al. 2006; Ho et al. 2009) in enclosed spaces. While such studies indicate that certain ventilation regimes or rates may be better than others for a particular scenario they do not formally seek an optimum design. In addition, running multiple CFD simulations at design stage can be time consuming and prohibitively expensive for many organisations.

Numerical optimization approaches offer the potential to both find the best design in a particular scenario and also create design tools that allow a more robust selection of parameters in a given case. Numerical optimization is widely used in fields such as structural engineering and the aerospace industry; however application of optimization techniques to airflows in building environment control is a more recent area of development. Genetic Algorithm (GA) approaches have been successfully used for building thermal design (Wright et al. 2002; Wright et al. 2007), HVAC system control (Wang and Jin 2000; Huang and Lam 1997) and also for green building design (Wang et al. 2005). However application of simulation based optimization in conjuction with CFD approaches to indoor air flows is limited. Gyulai et al. (2007) investigated optimizing the window opening angles in a smelting room to minimise temperature and showed that the numerical results concurred with expectations. Zhou et al. (2009), appear to be the only authors who have considered general indoor environments. They showed that it was possible to optimise thermal comfort and indoor air quality (IAQ) in an office environment using a GA approach with an integrated artificial neural network (ANN) based response surface methodology (RSM). However, to date there is no work which uses the formal tools of simulation based optimization in the context of infection control and patient and/or health care worker comfort in hospital wards.

In the present study it is shown for the first time that in the context of ventilation system design for hospital wards, that it is possible to use simulation based optimization techniques to find the best ventilation design incorporating the requirement of infection control and patient and healthcare worker comfort. The study uses a simplified 2D room model based on a driven cavity approach to develop and implement a practical and robust optimization scheme based on the combination of GA (Wright et al. 2002) and RSM (Myers and Montgomery 1995). The model is used to demonstrate that it is feasible to use such an approach to produce a tool that considers infection control and comfort in design, and explore how the optimum design depends on spatial location of monitoring regions and parameter weighting.

Problem formulation: fluid flow in a cavity

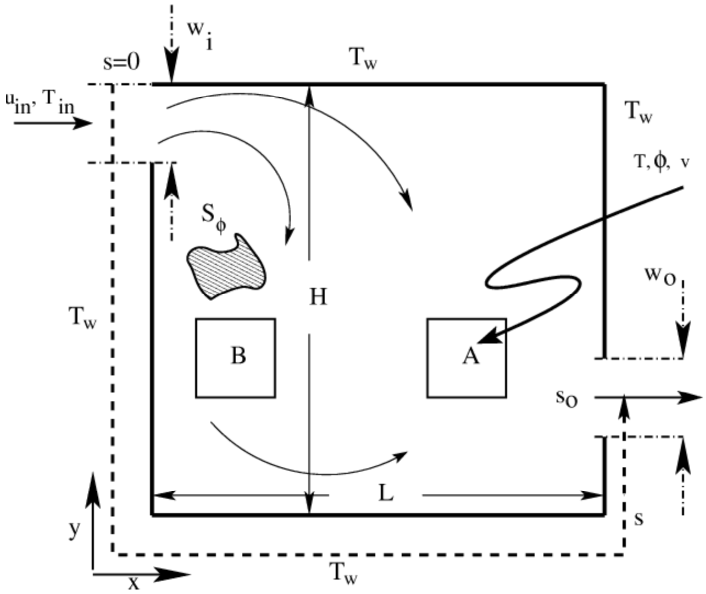


Figure 1 Schematic diagram of the 2D cavity with a scalar source S_ϕ and monitoring regions A and B centred at x=0.65H,y=0.45H *and* at x=0.25H,y=0.45H *respectively.* The width Δx *and height* Δy *of these regions are assumed to be* 0.1H .

Fluid flow in cavities with or without driven lids and/or with inlet and outlet ports have been studied extensively due to their usefulness as a test bed for benchmarking numerical tools for the solution of complex flows with recirculation (Saeidi and Khodadadi 2006). Cavity flow systems have relevance in a wide range of engineering applications including electronic components cooling and building ventilation and there has been a quite a lot of interest in the parametric study of such flow configurations (Saedi and Khodadadi 2006).

Forced convection in a cavity in particular has been used as an analogy for ventilation in buildings by several authors. Investigation of velocity and temperature distribution in a two dimensional room heated by warm air introduced via an inlet and extracted by an outlet at various locations on the wall was studied by Sinha et al. (2000). Singh et al. (2003), studied six different configurations of inlet and outlet positions in order to find the best configuration for maximum cooling efficiency of a cavity. Moureh and Flick (2005), combined numerical and experimental parametric study of inlet and outlet positions of a ventilated cavity and showed how to improve environmental parameters such as temperature and contaminant concentration inside the cavity. More recently Xaman et al. (2009) presented results of a numerical study to find the optimum ventilation configuration for overall ventilation effectiveness for temperature distribution inside a ventilated cavity. However, although these authors claim to have found an optimum design through their parametric studies, none of them considered the use of formal techniques of optimization to achieve their results.

In our case we represent a room as a two-dimensional cavity with a single supply air inlet located at high level on the left hand wall and a single outlet located on one of the other three walls (Figure 1). The flow inside the cavity is considered to be steady and the air is considered to be incompressible with constant physical properties. The flow is such that laminar flow exists in most of the regions of the room. While this is unlikely to be the case in a real room space, the assumption of laminar flow enables the model development without the complication of turbulence in the numerical solutions. Heat generation inside the room is not considered but the incoming air is considered to be at a higher temperature than the ambient room temperature (Sinha et al. 2000). We have a source S_ϕ of scalar concentration field ϕ that is representative of an airborne contaminant or pathogen concentration (Noakes et al. 2004). The schematic diagram Fig. 1 shows the cavity and the coordinate systems used. The height H and width L of the cavity are considered to be equal H=L. Fluid with constant density ρ enters the cavity through a supply inlet width w_i. An outlet port of width w_o can be located on any of the walls without the inlet port. In this work we have considered the inlet and the outlet ports to have the same width w. The distance along the walls have been parameterised using a special co-ordinate system (Saeidi and Khodadadi 2006) consisting of a quantity s such that the origin of the system is at x=0, y=H. In these co-ordinates the centreline of the inlet and outlet ports are 0.5w and s_o, respectively (Figure 1). The temperature of the air entering the cavity is T_{in} and the walls are maintained at a constant temperature of T_w such that $T_w<T_{in}$. The dimensionless form of the governing equations was obtained by using the cavity dimension H and the inlet velocity u_{in} as the scaling constants used to scale the length scales and the velocities respectively. The difference between the inlet temperature T_{in} and wall temperature T_w=295K was used to non-dimensionalise the temperature. The scalar source strength ϕ_0 was used to scale the pathogen concentration field ϕ. The dimensionless variables are then defined as:

$$x^* = \frac{x}{H},\quad y^* = \frac{y}{H},\quad u^* = \frac{u}{u_{in}},\quad v^* = \frac{v}{u_{in}},$$
$$p^* = \frac{p}{\rho u_{in}^2},\quad T^* = \frac{T - T_w}{T_{in} - T_w},\quad \phi^* = \frac{\phi}{\phi_0}. \tag{1}$$

Here the variables u, v, p, T and ϕ are the velocity components in the x-, y-directions, pressure temperature and pathogen concentration, respectively of the fluid inside the cavity. Based on the above dimensionless variables, the dimensionless equations for the conservation of mass, momentum, thermal energy and pathogen concentration are (the superscripts have been dropped for brevity in all the following discussions)

$$\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} = 0, \tag{2}$$

$$\frac{\partial}{\partial x}(uu) + \frac{\partial}{\partial y}(uv) = -\frac{\partial p}{\partial x} + \frac{w}{H}\frac{1}{\mathrm{Re}}\left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}\right), \tag{3}$$

$$\frac{\partial}{\partial x}(uv) + \frac{\partial}{\partial y}(vv) = -\frac{\partial p}{\partial y} + \frac{w}{H}\frac{1}{\mathrm{Re}}\left(\frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2}\right), \tag{4}$$

$$u\frac{\partial T}{\partial x} + v\frac{\partial T}{\partial y} = \frac{w}{H}\frac{1}{\mathrm{Pr}\,\mathrm{Re}}\left(\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2}\right), \tag{5}$$

$$u\frac{\partial \phi}{\partial x}+v\frac{\partial \phi}{\partial y}=\frac{w}{H}\frac{1}{Sc\,\mathrm{Re}}\left(\frac{\partial^2 \phi}{\partial x^2}+\frac{\partial^2 \phi}{\partial y^2}\right)+S_\phi\,. \qquad (6)$$

Here the Reynolds number is defined as $Re=u_{in}w/\nu$, the Prandtl number is $Pr=\nu/\alpha$ and the Schmidt number is $Sc=\nu/\sigma$, where ν is the kinematic viscosity, σ is the mass diffusivity of the pathogen concentration and κ is the thermal diffusivity of air respectively.

The dimensions of our cavity (length L and height H) are both taken to be 1.0m. The air enters the cavity with constant velocity u_{in}=0.02 m/sec (equivalent to 7 air changes per hour), temperature T_{in}=300K and Re=200, Pr=0.7 and the Sc=15. The dimensionless boundary conditions (with $w^*=w/H$ *and* $s^*=s/H$ we will again drop the sign * for brevity) are
At the inlet (x=0, y=(1-w) to 1):

$u=1$, $v=0$, $T=1$, $\phi=0$.

On the walls:

$u=v=0$, $T=0$ and $\frac{\partial \phi}{\partial n}=0$, where n is the wall normal direction.

At the outlet port ($s=s_0-0.5w$ to $s_0+0.5w$), the velocity and temperature were taken to be fully developed i.e. we adopted a Neumann boundary condition for flow variables ($\psi=u, v, T, \phi$) at outlet, $\frac{\partial \psi}{\partial n}=0$. Where n is the direction normal to the outflow boundary.

In all simulations the pathogen source was simulated as a dimensionless scalar source term with a non zero fixed value of S_ϕ=1 within a finite circular zone of radius 0.05H, inside the cavity located at $x=0.2H$, $y=0.4H$ and implemented in the model through a user defined function (FLUENT, ANSYS Inc 2009). In the context of a hospital ward this is considered to be representative of continuous release from a static patient source.

Numerical Optimization

The goal of optimization is to find a set of design variables X (such as temperature, velocity etc.) which optimizes (minimises or maximises) an objective or cost function $f(\mathbf{x})$ (Rao 2009) subject to certain, defined constraints.

$$f(\mathbf{x});\mathbf{x}\in\mathbf{R}^n \qquad (7)$$

Here $\mathbf{x}=[\,x_1, x_2 .... x_n\,]$ is an n-dimensional vector whose components x_i's represent the n design variables of the problem and $\mathbf{R}^n$ represents the n-dimensional design space. The above objective function could be subjected to the following inequality

$$g_j(\mathbf{x})\le 0;\ j=1,2,\ldots m\,, \qquad (8)$$

and equality constraints

$$h_k(\mathbf{x})=0;k=1,2,\ldots r\,, \qquad (9)$$

where, m and r are the number of constraints of each type respectively. In the context of room air, constraints could relate to physical location of ventilation system components or acceptable bounds for parameters such as velocity and temperature. Figure 2 (Rao 2009) illustrates a hypothetical two-dimensional design space with contours of objective function and the corresponding constraints.

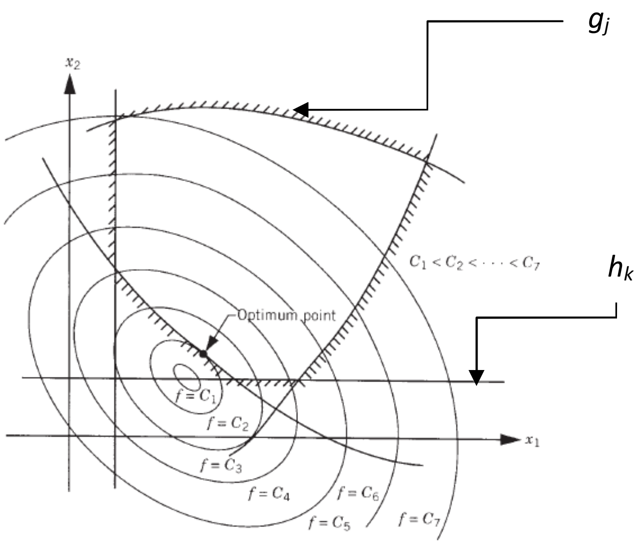


Figure 2 Contours of objective function *f*(x) in a hypothetical two-dimensional design space and few of the constraint functions (reproduced from Rao, 2009)

Numerical optimization techniques can be broadly classified as either deterministic (Deb 2001) or stochastic. The nonlinear nature of flow phenomena inside enclosed spaces, such as rooms, leads to discontinuous outputs being generated which in turn causes problems for deterministic methods (Wetter and Wright 2003). Since these methods are based on mathematical procedures, in most cases they are generally prone to find the local extrema and the convergence speed and the value of the final results are strongly dependent on the initial guess values (Wang and Jin 2000). In contrast, stochastic methods, also referred to as global methods are better suited to building or indoor environment applications. One of the most popular in this category and a widely accepted global optimization technique is the GA method (Holland 1975). Inspired from Darwin's theory of natural selection, this method has demonstrated its capability to handle discontinuous variables and also noisy objective functions (Wright et al. 2002). In addition it can find near-optimal solution using less computing time compared to other methods such as mixed-integer programming (Sakamoto et al. 1999), and can be used in conjunction with some non-differentiable RSM methods (Chow et al. 2002; Lu et al. 2005). Furthermore, GA being a stochastic method has a better chance to explore the entire design space and reach global optimum. Hence we chose GA as the optimization engine in all our study.

Multi-objective optimization methods that are based on evolutionary algorithms, especially multi-objective GAs, require hundreds or sometimes thousands of evaluations of the objective functions to search for the optimal solutions (Magnier and Haghighat 2010). In building or indoor applications, where evaluation of the objective function comes from computationally expensive and time consuming CFD simulations, the optimization process could therefore take a prohibitively long time to achieve its goal. Hence, in order to save computational time associated with GA, a RSM method is used to mimic the behavior of the system response with respect to the change in design variables. In our case, this is the indoor air flow field as the extract position is changed. The RSM models which are constructed from high-fidelity simulations provide fast approximations of the objective and constraint functions at new design points, thereby saving computational time and making optimization studies using GA feasible (Queipo et al. 2005).

Optimal Latin Hypercube (OLH) (Bates et al. 2004) Design of Experiments (DOE) and moving least squares methods (MLSM) (Toropov et al. 2005) were used to create the surrogate objective function from a minimal number of expensive CFD simulations. The surrogate model circumvented the need to run full CFD analysis to assess the performance of each and every design variable choice. Next, an optimization algorithm based on GA was implemented, to find the global minimum of the surrogate (approximated) function with respect to the design variables (position of outlet etc.). Figure 3 shows the methodology for obtaining the global optimum (minimum in our case).

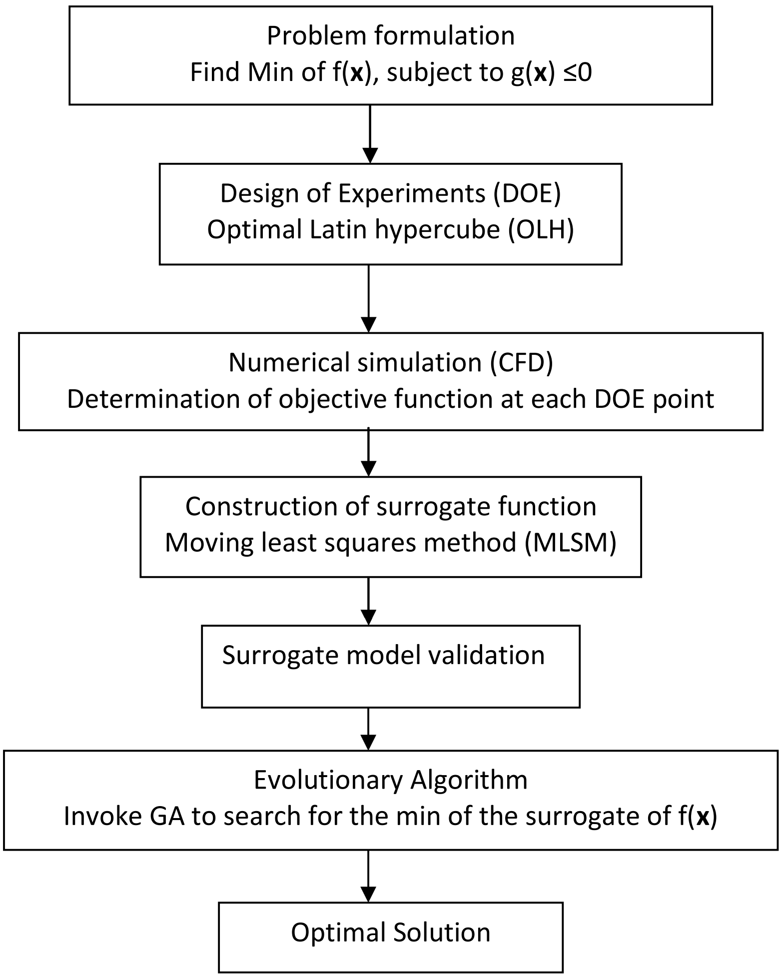


Figure 3 Optmization framework.

Results

The flow inside the 2D room was solved using the commercial CFD software FLUENT v12.1 (ANSYS Inc) and the optimization was carried out using HyperStudy v10 software (Altair Engineering). The two dimensional governing equations were discretised on a uniform grid, using the finite volume method (Versteeg and Malalasekera 2007) and solved iteratively using the SIMPLE algorithm (Patankar 1980) inside the cavity. The interpolation of the gradients of velocities, temperature and scalar concentration used the second order upwind scheme. The iterative procedure for the solution was considered to be converged when the residuals of all the equations were less than 10^{-05}. Grid independence tests were carried out using the well known method of Roache (Roache 1994) based on the grid convergence index (GCI) on the baseline CFD case (inlet s=0.5w and outlet s=2+0.5w) (Chen et al. 2010; ASME V&V 20-2009). Table 1 presents the results of this study. The grid densities studied were defined by the total number of cells N_1, N_2 and N_3 respectively. The volume averaged values of the non-dimensional velocity magnitude $|\boldsymbol{v}|$ in monitoring region A was used in the evaluation of uncertainties. Relative percentage errors of the CFD solutions based on GCI between coarse, and medium (GCI^{32}_{medium}) and between medium and fine (GCI^{21}_{fine}) are also shown in the table. On the basis of the magnitudes of the GCI error estimates (less than 5%) of the flow field we chose to use a grid of size N_3, consisting of 40000 cells, for all subsequent simulations.

Grid Type	Cell count	Volume average $\lvert\boldsymbol{v}\rvert / \lvert\boldsymbol{v}_{in}\rvert$
Fine (N_1)	640000	0.274
Medium (N_2)	160000	0.252
Coarse (N_3)	40000	0.224
Relative Errors		
GCI^{21}_{fine}(%)		3.35
GCI^{32}_{medium}(%)		4.61

Table 1: Variation of the flow solution with grid density and the corresponding relative errors.

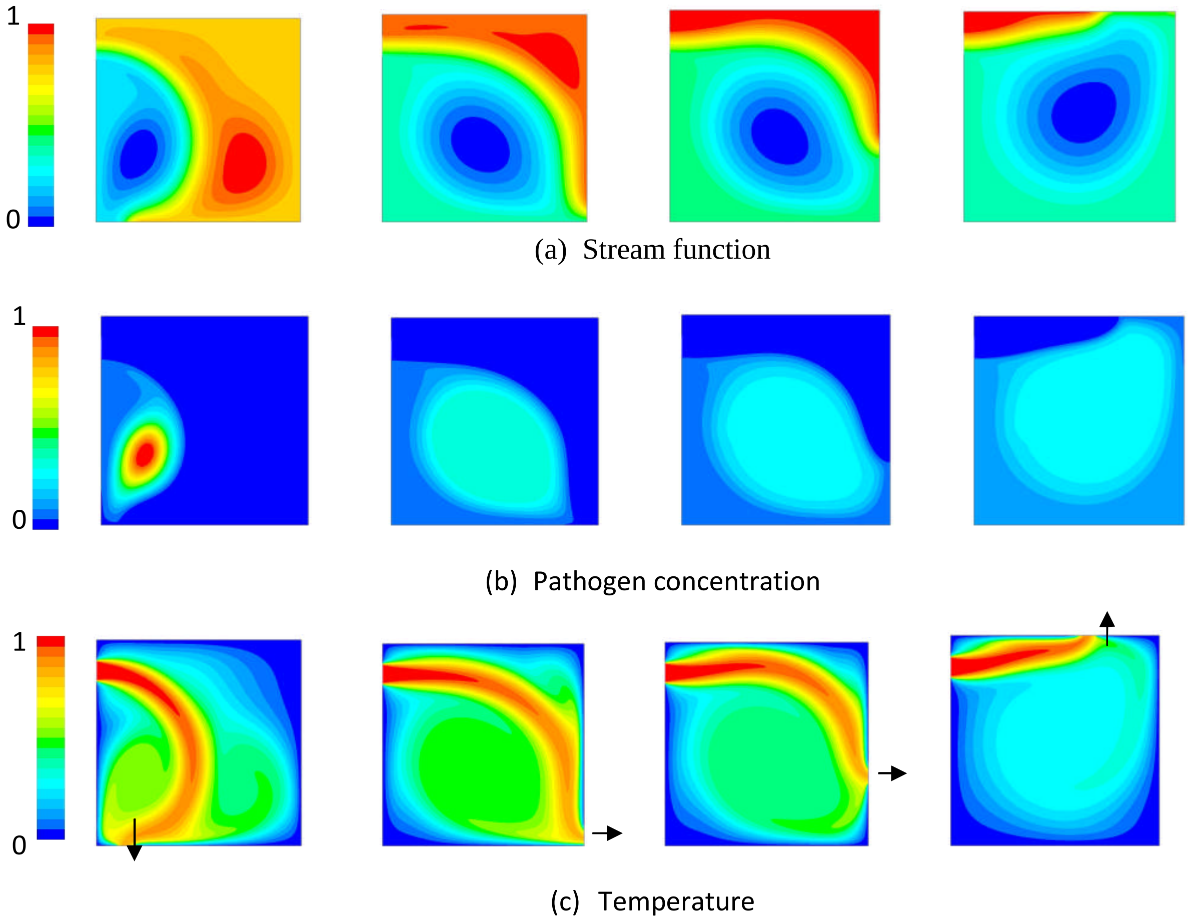


Figure 4 Normalised Contours inside the forced convection cavity for four outlet positions (left to right) left hand side of floor, low level right hand wall, mid level right hand wall, ceiling.

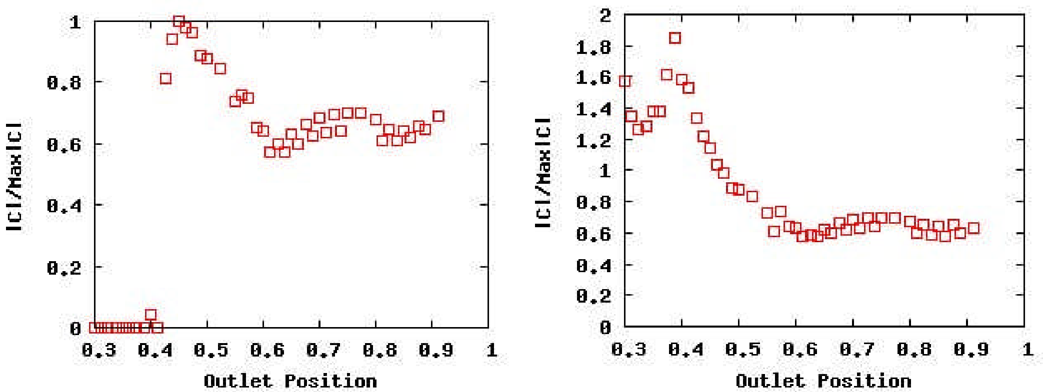
Figure 4 shows normalised contour plots of stream-function, pathogen (scalar) concentration and temperature for four different extract locations with the pathogen released from the location shown in Figure 1. The results demonstrate the clear presence of recirculation regions in all cases and it is quite evident from these plots that although the ventilation rate remains constant, the flow pattern is quite different inside the cavity for each choice of the ventilation design, in our case the position of the outlet. It is also evident from these results that the optimum ventilation design will depend on the required function of the ventilation. For example, in the case of pathogen concentration, the left hand simulation with the extract located on the floor is the most effective at preventing dispersion, which may be desirable in a multi-occupancy hospital ward (Noakes et al. 2006) or in a treatment room where clinical procedures that generate aerosols are carried out. However, the right hand result with a ceiling located extract provides the most uniform mixing which may be desirable in a single occupancy isolation room where it is important to ensure that healthcare workers have the same level of risk regardless of where in the space they are working.

While it is clear from Figure 4 that the outlet position influences both comfort and infection risk parameters, it is not obvious which design may be the most appropriate choice in a given situation where more than one variable has to be considered. To explore this, an objective function (Equation 7) was constructed which incorporated weighted system response parameters representing pathogen concentration and thermal and draught comfort (Fanger et al. 1988), as a function of the design variable (position of outlet vent)

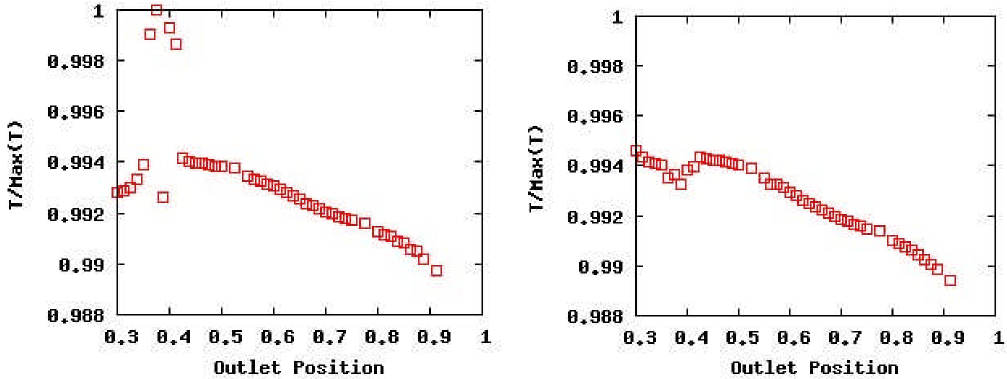
$$f(\mathbf{x}) = w_C\,\overline{|C|} + w_{T_{res}}\,\overline{|T_{res}|},$$
$$\text{where} \quad T_{res} = \frac{T_r + T_a\sqrt{10\,\overline{|\mathbf{v}|}}}{1+\sqrt{10\,\overline{|\mathbf{v}|}}} \quad \text{and} \quad w_C + w_{T_{res}} = 1. \tag{7}$$

Here C, T_{res} and $\mathbf{v}$ are the pathogen concentration (related to infection risk); dry resultant temperature (CIBSE 2006) and air velocity (related to thermal and draught comfort at the monitoring region) respectively. T_r is the radiant temperature (constant and equal to the wall temperatures) and T_a the air temperature at a point within the cavity. $\mathbf{x}$ represents the design variable i.e. the position of the outlet along the walls, w_c and w_{Tres} represent weights and |..| with over-bar represents volume averaged absolute value of the quantity inside. The constructed function $f(\mathbf{x})$ is a typical example of a multi-objective cost function (Rao 2009).

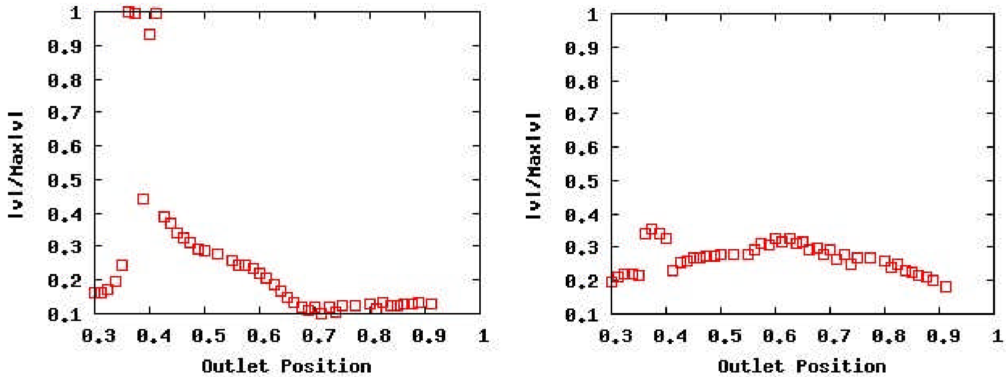
For every choice of pathogen source and monitoring region we ran 40 (Loeppky and Sacks 2009) CFD simulations to find the behaviour of each of the system response parameters at different outlet positions. Figure 5 shows two such choices of the monitoring regions *A* and *B* for a fixed source S_ϕ and the corresponding behaviour of the system response parameters. It can be seen from these results that the pathogen concentration (Figure 5(a)) shows the greatest variance in the space with exhaust position for both monitoring regions. Depending on the chosen monitoring region, the minima of the concentration appears at different positions of the outlet. For monitoring region A, at the right hand side of the room, the minimum concentration corresponds to floor located outlet which prevents dispersion to the monitoring region, as in Figure 4 (b). However for monitoring region B, which is much closer to the pathogen source, the minimum concentration is achieved with high wall or ceiling mounted extracts corresponding to the higher mixing apparent in Figure 4 (b).



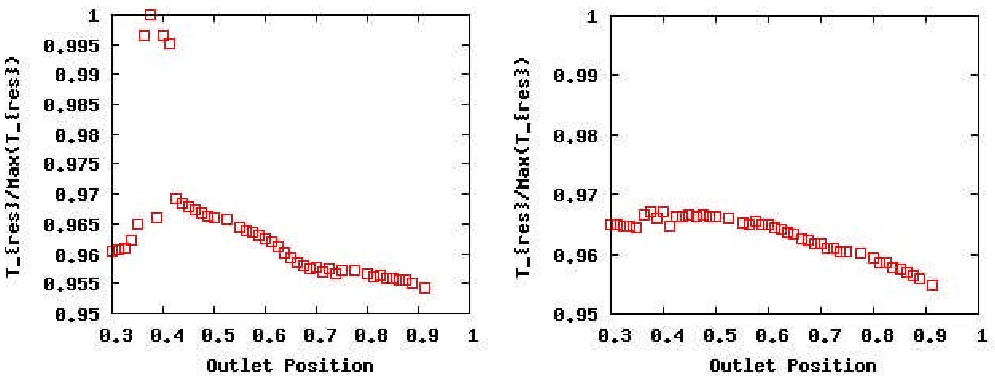
(a) Pathogen Concentration



(b) Temperature



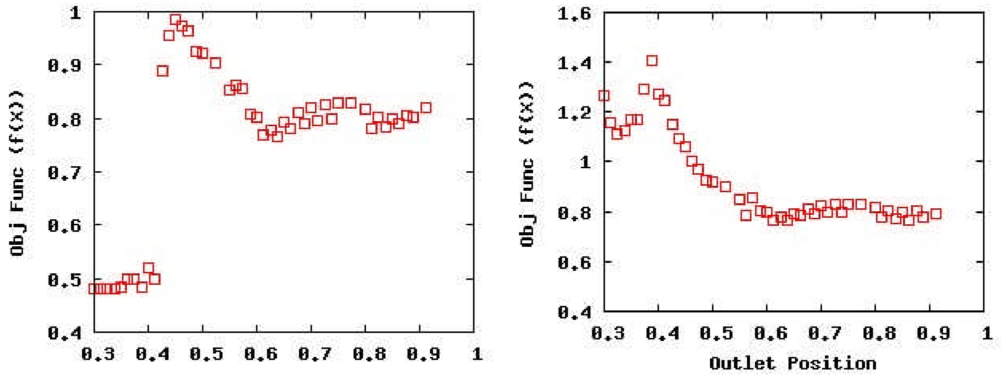
(c) Velocity magnitude



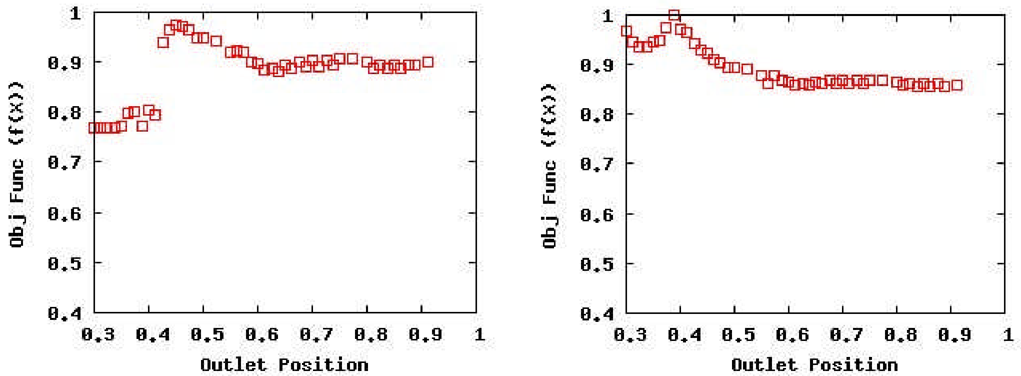
(d) Dry resultant temperature

Figure 5 Variation of non-dimensional system response parameters with design variable (outlet position). Left plots and right plots are for two different square monitoring regions A and B, centred at *x*=0.65*H*, *y*=0.45*H* and *x*=0.25*H*, *y*=0.45*H* respectively. ***The maximum values of the system response parameters in monitoring region A were used to rescale all the plots.***

The minima of the objective function constructed (Figure 6) from above responses will depend on the weights used in Equation 7. Furthermore, the minimum is also dependent on the position of the monitoring region inside the cavity or room (see Figure 6).



a) Chosen weights w_c=w_{Tres}=0.5



b) Chosen weights w_c=0.2 and w_{Tres}=0.8

Figure 6 Variation of the non-dimensional objective function with design variable (outlet position) for two different set of weights and monitoring regions A (Left plot) and B (Right plot).

Figure 7 shows the surrogate objective function constructed using MLSM for weights w_C =0.5 and w_{Tres} =0.5. This surrogate function was then used in conjunction with GA to find the minima. Figure 8 shows the convergence history of the objective function *f*(**x**) and the design variable **x** using GA for two different monitoring regions. Clearly we can see that the minima and the corresponding design variable (outlet position in our case) found by the optimization algorithm are completely different for the two monitoring regions under consideration. For monitoring region A the optimum position corresponds to the floor level extract at the left hand side of the room, while for monitoring region B the optimum is located on the ceiling extract at the left hand side of the room. However these optimums are for the case where the pathogen concentration and comfort both have equal weightings. Sensitivity analyses of the optimum design configuration, with respect to the variation of the weight of the indices, were also performed (see Figure 9). Figure 9 clearly shows that depending on the chosen monitoring region (A or B) the optimal design configuration i.e. the converged position of the outlet found by the GA algorithm was either insensitive (region A) or moderately sensitive (region B) to the weights used(see Figure 9). In particular, both cases shown in figure 9 indicate that when the weighting on the pathogen concentration dominates, the optimal ventilation solution is likely to be different than when comfort is the primary design factor. For monitoring region A, the optimum outlet position moves from 0.3 to 0.4 as w_C increases from 0.5 to 0.95. This equates to the outlet position moving from floor level extract at the left hand side to one located in the middle of the floor. Region B, which shows more sensitivity, indicates a shift in the optimum design when w_C exceeds 0.5.

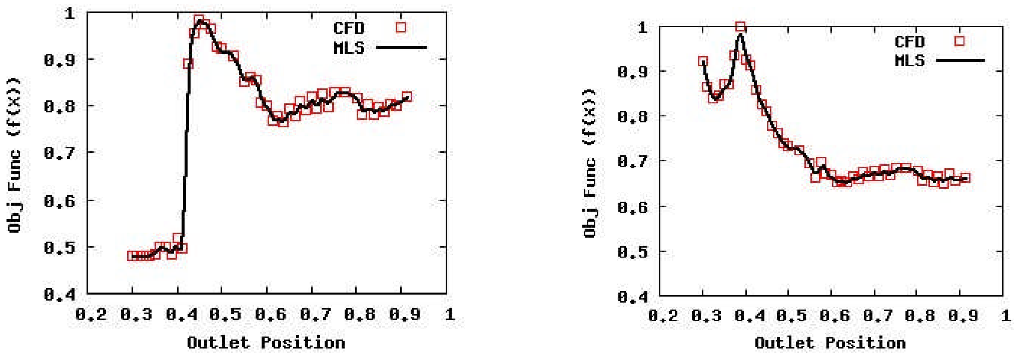


Figure 7 Variation of the surrogate objective function (using MLSM) with design variable (outlet position) for two different monitoring regions A and B. The CFD data points are also shown.

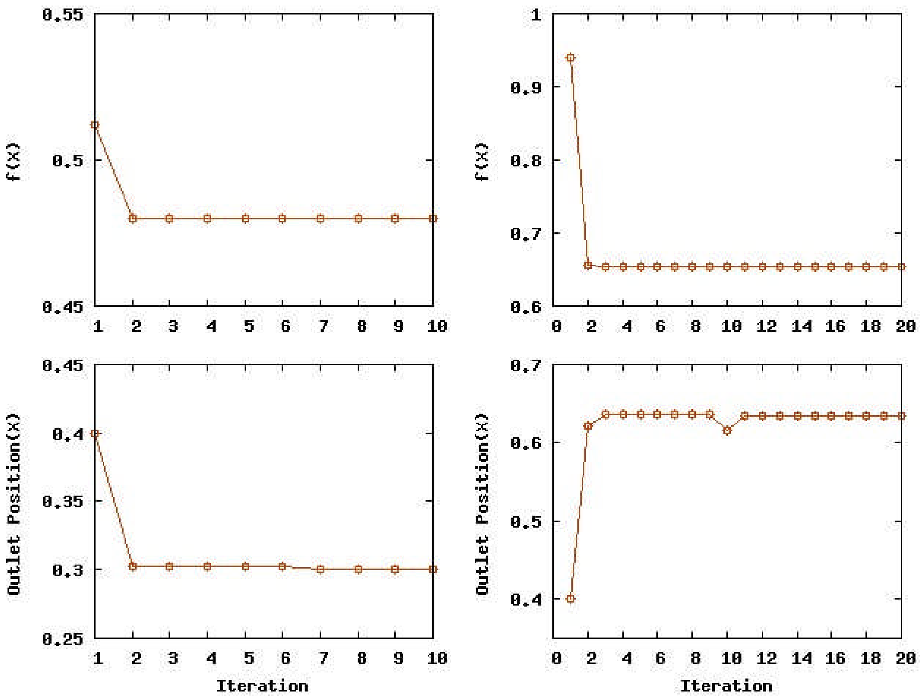


Figure 8 Convergence history of optimization GA search algorithm for the normalised objective function and the corresponding design variable (outlet position). Left and right plots are for two different monitoring regions A and B.

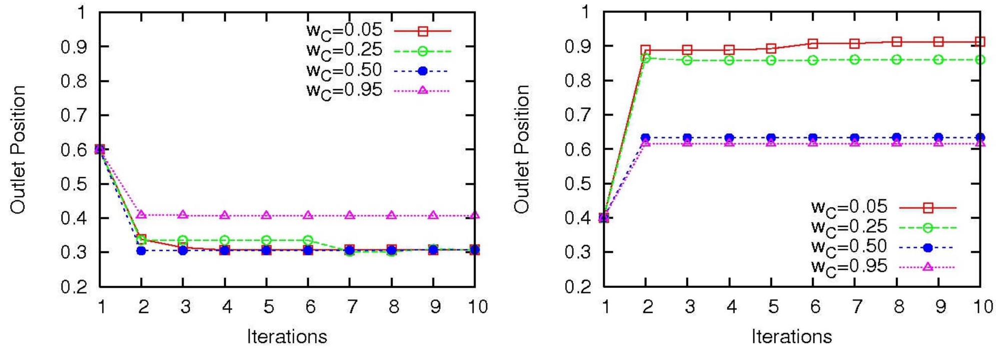


Figure 9 Variation of the convergence history of GA search algorithm for the optimal outlet position with respect to weights. Left and right plots are for two different monitoring regions A and B respectively. Here w_C, represents the weight of pathogen concentration used in Equation 7.

Discussion and Conclusions

We have used numerical optimization techniques to develop an approach for assessing ventilation design in terms of both infection control and comfort inside a hospital room/ward. Simulations on a simplified two-dimensional room, represented by a square cavity with a single supply and extract port, have shown that the method is feasible and that the formal optimization routine yields realistic results that concur with the expected behaviour from a parametric study. While our results show that the optimum design configuration of the ventilation system in a simple test room is attainable, it is important to consider the applicability and limitations of the model.

The results clearly show that the sensitivity of the weights chosen by the designer and the choice of monitoring regions have a substantial influence on the results. In order to apply such an approach to a design scenario it is clearly necessary to give a relative importance to the response parameters which will depend on the environment and level of perceived risk. In many hospital spaces it may be reasonable to assume that infection risk and thermal comfort take equal priority, and in some spaces such as admin and office zones or consulting rooms where the patients are very unlikely to have or be susceptible to infection, the thermal comfort may well be the dominant design driver. However in specialist environments such as operating theatres, isolation rooms, wards for immune compromised patients and even general wards where there are vulnerable patient groups, infection control is likely to merit a higher weighting. The results presented here indicate that where a higher weighting is placed on the infection control the optimum ventilation is likely to be different to that which would be chosen where thermal comfort is the primary concern. While environments such as operating theatres already have specialist ventilation for infection control, this result potentially gives insight into design for patient rooms where ventilation most commonly follows comfort principles. Similarly the choice of monitoring locations needs to be carefully considered. In the case of thermal comfort, optimizing comfort in patient areas and other occupied zones is clearly a priority. For infection risk, the occupied zones are also of greatest importance however the choice may depend on whether a particular occupant (patient, healthcare worker, visitor) is considered a source or susceptible. In many cases it may be most appropriate to consider the whole occupied zone, or even the whole room, particularly if it is difficult to say with confidence what distribution is suitable or where the source is located.

The main limitation with the process presented in this paper is that it only considers a simplified case of a 2-D room. While this demonstrates the potential for using numerical optimization to assist in healthcare design it does not consider the three-dimensional and turbulent airflows that are present in real spaces. The choice of a 2-D room for this study was deliberate as the most computationally challenging and intensive aspect is running the initial CFD simulations that are required to create an objective function. Conducting 2-D simulations enabled the study to focus on developing and testing the optimization approach without the need to deal with the inherent complexities and computational requirements of 3-D models. Work is ongoing to apply the approach in a 3-D room airflow. Initial indications from our work (Khan et al. 2011) and the results presented by Zhou and Haghighat (2009) suggest it is feasible to apply optimization techniques in 3-D flows. Including realistic room geometry and details such as ventilation diffusers will make the generation of the design points via CFD simulations in our DOE considerably more expensive. It is also possible that the number of simulations required to cover the design space is higher due to the increased variability in the flow due to turbulence. However, the optimization procedure will remain same; once the CFD data is available the construction of the surrogate function is straightforward and will not be affected by the 3-D nature of the flow. Application of numerical optimization approaches to the ventilation design in real spaces is therefore likely to be constrained by the computational requirements of carrying out the large number of CFD simulations required to build the surrogate function. Advances in computing power and new developments in CFD approaches may reduce this constraint. Recent work by Mora et al. (2003) on coarse grid CFD and Zuo and Chen (2010) on Fast Fluid Dynamics (FFD) programmed on Graphics processing units (GPU's) both offer the possibility to accelerate this computationally intensive aspect while still solving the flow field at an acceptable level of accuracy. Furthermore, the increasing access to massively parallel machines also offers a realistic method of speeding up the CFD simulations.

It is also appropriate to consider here how this optimization approach may develop to become a usable tool for real hospital environments. Clearly it is not sensible to conduct multiple CFD simulations and then apply an optimization approach for every new design of hospital room. However, many hospital rooms are based on standard footprints governed by the need to ensure good access around the bed or space for the clinical procedure, with some constraints already placed on the ventilation flow rates by guidance documents (Department of Health 2007). There is therefore the potential that this process could be conducted as part of developing future design guidance with simulations conducted for typical rooms and sensitivity to room size incorporated within the study. The response parameters from such simulations could then be used by designers with appropriate weightings and constraints for their environments to ensure that the ventilation is best suited to the specific requirements of the room.

References

Bates SJ, Sienz SJ, Toropov VV (2004). Formulation of the optimal Latin hypercube design of experiments using a permutation genetic algorithm. In: Proceedings of the 45th AIAA Structures, Structural Dynamics & Materials Conference.

Chow TT, Zhang GQ, Lin Z, Song CL (2002). Global optimization of absorption chiller system by genetic algorithm and neural network, *Energy and Buildings,* 34:103–109.

Chow WK, Fung WY (1996). Numerical studies on the indoor air flow in the occupied zone of ventilated and air-conditioned space. *Building and Environment,* 31 (4):319–344.

CIBSE (2006) Guide A: Environmental Design. The Chartered Institution of Building Services Engineers, London, 7th Edition.

Deb K (2001). Multi-Objective optimization using evolutionary algorithms, New York: John Wiley & Sons.

Department of Health. (2007). Health Technical Memorandum HTM 03-01: Specialised ventilation for healthcare premises, Part A: Design and Validation. The Stationary Office, London.

Fan Y (1995). CFD modelling of the air and contaminant distribution in rooms. *Energy and Buildings* 23: 33–39.

Fanger PO, Melikov AK, Hanzawa H, Ring J (1988). Air Turbulence and Sensation of Draught, *Energy and Building*, 12:21-39.

FLUENT documentation, version 12.1, ANSYS Inc 2009.

Gyulai L, Szabo S, De Kock DJ, Synman JA (2007). A study of the feasibility of using mathematical optimization to minimise the temperature in smelter pot room. *Building and Environment*, 42: 2268-2278.

Holland JH (1975). Adaptation in natural and artificial systems: an introductory analysis with application to biology, control and artificial intelligence, USA: University of Michigan Press.

Ho Son H, Rosario L, Rahman MM (2009). Three-dimensional analysis for hospital operating room thermal comfort and contaminant removal. *Applied Thermal Engineering*, 29: 2080-2092.

Huang W, Lam HN (1997). Using genetic algorithms to optimize controller parameters for HVAC systems. *Energy and Buildings*, 26:277–282.

HyperWorks v10, Altair Engineering Inc, USA, (2009).

Jones P, Waters R (1993). The practical application of indoor airflow modelling, in: N. Nagada (Ed.), *Proceedings of the Conference on Modelling of Indoor Air Quality and Exposure*, American Society for Testing and Materials, Philadelphia, pp.173–181.

Khan MAI, Noakes CJ, Toropov VV (2011). Multi-objective optimization of the ventilation design in hospital wards with an emphasis on infection control In: Proceedings of the ECCOMAS Thematic Conference on CFD & OPTIMIZATION Methods and Applications, Antalya, Turkey.

Li Y, Leung GM, Tang JW, Yang X, Chao CYH, Lin JZ, Lu JW, Nielsen PV, Niu J, Qian H, Sleigh AC, Su1 H-JJ, Sundell1 J, Wong TW, Yuen PL (2007). Role of ventilation in airborne transmission of infectious agents in the built environment – a multidisciplinary systematic review. *Indoor Air*, 17: 2–18.

Loeppky JL, Sacks J (2009). Choosing the sample size of a computer experiment: A practical guide. Technometrics, 51:366-376.

Lu L, Cai WJ, Xie LH, Li SJ, Soh YC (2005). HVAC system optimization-in building section, *Energy and Buildings,* 37:11–22.

Magnier L, Haghighat F (2010). Multiobjective optimization of building design using TRNSYS simulations, genetic algorithm, and Artificial Neural Network. *Building and Environment*, 45(3): 739-746.

Mora L, Gadgil AJ, Wurtz E (2003) Comparing zonal and CFD model predictions of isothermal indoor airflows to experimental data. *Indoor Air*, 13:77-85.

Moureh J, Flick D (2005). Airflow characteristics within a slot-ventilated enclosure. *Int. J. Heat Fluid Flow,* 26: 12-24.

Myers RH, Montgomery DC (1995). Response Surface Methodology: Process and Product Optimization using Designed Experiments: Wiley: New York, NY.

Noakes C J, Beggs, C B, Sleigh P A (2004). Modelling the Performance of Upper Room Ultraviolet Germicidal Irradiation Devices in Ventilated Rooms: Comparison of Analytical and CFD Methods. *Indoor and Built Environment*, 13:477-507.

Noakes CJ, Sleigh PA, Escombe AR, Beggs CB (2006). Control of Infections: Use of CFD Analysis in Modifying a TB Ward in Lima. *Indoor and Built Environment*, 15: 41-47.

Nielsen PV (1988). Numerical prediction of air distribution in rooms—status and potentials, In: *Proceedings of the Conference on Building Systems: Room Air and Air Contaminant Distribution, ASHRAE,* University of Illinois Press, Urbana-Champaign, IL, USA, pp. 31–38.

Patankar SV (1980). Numerical Heat Transfer and Fluid Flow, McGraw-Hill, New York.

Queipo NV, Haftka RT, Shyy W, Goel T, Vaidyanathan R, Kelvin P (2005). Surrogate-based analysis and optimization. *Progress in Aerospace Science*, 41: 1-28.

Riffat SB, Kohal JS, Shao L (1994). Measurement and CFD modelling of buoyancy-driven flows in horizontal openings, In: *Proceedings of the Conference on IAQ'94: Engineering Indoor Environments, ASHRAE*, St. Louis, pp. 159–166.

Rao SS (2009). Engineering Optimisation: Theory and Practice. Hoboken, New Jersey: John Wiley & Sons, Inc.

Roache PJ (1994). Perspective: a method for uniform reporting of grid refinement studies. *ASME J Fluids Eng*, 116: 405–413.

Sakamoto Y, Nagaiwa A, Kobayasi S, Shinozaki T (1999). An optimization method of district heating and cooling plant operation based on genetic algorithm, *ASHRAE Transactions*, 105 (2):104–115.

Saeidi SM, Khodadadi JM (2006). Forced convection in a square cavity with inlet and outlet ports, *Int. Journal of Heat and Mass Transfer*, 49: 1896-1906.

Singh S, Sharif M (2003). Mixed convective cooling of a rectangular cavity with inlet and exit openings on differentially heated side walls. *Numerical Heat Transfer, Part A* 44: 233-253.

Sinha SL, Arora RC, Roy Subhransu (2000). Numerical simulation of two-dimensional air flow with and without buoyancy. *Energy and Buildings*, 32:121-129.

Toropov VV, Schramm U, Sahai A, Jones R, Zeguer T (2005). Design optimization and stochastic analysis based on the Moving Least Squares Method. In: 6th World Congress of Structural and Multidisciplinary Optimization, Rio de Janeiro, Brazil. CD-ROM Proceedings, eds.: J. Herskovits, S. Mazorche and A. Canelas, ISBN 85–285–0070–5.

Versteeg HK, Malalasekera W (2007). An Introduction to Computational Fluid Dynamics: The finite volume method, 2nd Edition: Pearson Education Ltd.

Wang SW, Jin XQ (2000). Model-based optimal control of VAV air-conditioning system using genetic algorithm. *Building and Environment*, 35 :471–478.

Wang WM, Zmeureanu R, Rivard H (2005). Applying multi-objective genetic algorithms in green building design optimization. *Building and Environment*, 40:1512–25.

Wetter M, Wright J (2004). A comparison of deterministic and probabilistic optimization algorithms for nonsmooth simulation-based optimization Program. *Building and Environment*, 39: 989 - 999.

Wright JA, Loosemore HA, Farmani R (2002). Optimization of building thermal design and control by multi-criterion genetic algorithm. *Energy and Buildings*, 43: 959–72.

Wright JA, Zhang Y, Angelov P, Hanby V, Buswell R (2007). Evolutionary synthesis of HVAC system configurations: Algorithm development (RP-1049). *HVAC&R Research*, 14: 33-54.

Xaman J, Tun J, Alvarez G, Chavez Y, Noh F (2009). Optimum ventilation based on the overall ventilation effectiveness for temperature distribution in ventilated cavities. *International Journal of Thermal Science*, 48:1574-1585.

Yam R, Yuen PL, Yung R, Choy T (2011). Rethinking hospital general ward ventilation design using computational fluid dynamics. *Journal of Hospital Infection*, 77: 31-36.

Zhou L, Haghighat F (2009). Optimization of ventilation system design and operation in office environment, Part I: Methodology. *Building and Environment*, 44: 651–656.

Zuo W, Chen Q (2010). Simulations of air distributions in buildings by FFD on GPU. *HVAC&R Research*, 16: 785-798.