MULTI-OBJECTIVE OPTIMIZATION OF THE VENTILATION SYSTEM DESIGN IN A TWO-BED HOSPITAL WARD WITH AN EMPHASIS ON INFECTION CONTROL

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ABSTRACT

Airflow, contaminant concentration and temperature distribution in a two-bed hospital ward represented by simple model room with inlet and outlet vents, have been studied. Our work is concerned with the development and implementation of a practical and robust response surface based multi-objective optimization (MOP) scheme, 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

There is strong and sufficient evidence in the existing literature to demonstrate the association between indoor air movement and distribution due to ventilation (inside buildings or hospital wards) and the transmission and spread of infectious diseases such as TB, influenza etc (Li et al., 2007). Ventilation in hospitals may have a profound effect on the well-being of patients and employees in healthcare facilities, hence it is important to understand the role of ventilation airflow pattern on the spread and control of airborne pathogens in hospitals. Infection control is a concern in all parts of a hospital, but is particularly relevant in the design of ventilation in spaces such as isolation room and operating theatres where minimising the risk of infection is the the dominant factor. Besides controlling spread of infection, it is also essential to consider occupant comfort. However in the context of hospital environment which operates 24 hours a day this may be more constrained than many environmnents. Practices such as night venting that are applied in office environments may be inappropriate. Furthermore the patients who occupy the hospital wards maybe less tolerant to poor thermally comfortable environments compared to occupants in an office environment. Hence understanding how to balance the sometimes conflicting requirement of thermal comfort and infection risk is increasingly important, particulaly as energy consumption in ventilation systems is also now a critical factor.

Development of design tools that allow architects and building services engineers to evaluate the performance of ventilation in differenct parts of a healtcare facility 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 (Nielsen 1998, Jones et al., 1993, Fan 1995, Chow et al., 1996, Yam et al., 2011). Most 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 (Yam et al., 2011, Noakes et al., 2006) 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. While numerical optimisation is widely used in fields such as structural analysis and the aerospace industry, application of optimisation 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 (Son et al., 2009), HVAC system control (Wang et al., 2000; Huang et al., 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., investigated optimizing the window opening angles in a smelting room to minimise temperature and showed that the numerical results concurred with expectations (Gyulai et al., 2007). Zhou et al., considered an office environment and showed that it was possible to simultaneosly optimise thermal comfort and indoor air quality (IAQ) using a GA approach with an integrated artificial neural network (ANN) based response surface methodology (RSM) (Zhou et al.,2009).

The authors (Khan et al., 2012) previously demonstrated the potential for simulation based optimisation in the context of infection control and occupant comfort through the development of a simplified 2-D room model. The present study extends this work to a 3-D space to find the best ventilation design incorporating the requirement of infection control and patient and healthcare worker comfort. The study uses a simplified 3D test room based model that is interpreted in the context of two-bed hospital ward to develop and implement a practical and robust optimization scheme based on the combination of GA (Wright et al., 2002) and RSM (Myers et al., 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 explores how the optimum design depends on spatial location of monitoring regions and parameter weighting.

PROBLEM FORMULATION

In this investigation, CFD methodology was used to simulate the airflow, temperature and pathogen concentration distribution inside the model room (see figure 1.). The dimensions of the room were based on a experimental bioaerosol test chamber with the height *H*, width *W*, and length *L* set at 2.26m, 3.36m and 4.2m respectively. The room had multiple inlet and outlet vents on diametrically opposite walls. The walls, ceiling and the floor were modelled as constant temperature surfaces with a temperature of 22^{o}C. The inlet and outlet vents were represented with surfaces with constant velocity and zero pressure respectively. The three-dimensional flow inside the room was solved by steady incompressible Reynolds-averaged Navier-Stokes equations (RANS) with the control volume method (Versteeg et al., 2007).

No heat sources were defined in the space instead; we introduced warm air through the inlet and assumed a forced convective flow where buoyancy effects due to temperature variation was negligible. Turbulence was simulated using the standard k-ε (Launder et al., 1972) turbulence model with standard wall function approach. Transport equations for the temperature and passive scalar (representing airborne pathogen concentration) were also solved simultaneously with the flow field. Scalar sources (S1-S2) representing the potential locations of an infectious source were inserted inside the simulated room (see Figure. 1) and the corresponding monitoring regions (A1-A2) (representative of healthcare workers) were used as the basis for the optimization study. A constant airflow rate was employed in all the simulated cases, which is equivalent to six air changes per hour (ACH), the UK recommended ventilation rate for hospital wards (Dept Health, 2007). The outlet position was moved vertically on one side of the chamber to study the influence of the ventilation system design on the airflow, temperature and the pathogen concentration field.

Optimization was conducted using a combination of GA and RSM (Khan et al., 2012). Optimal Latin hypercube (OLH) (Bates et al., 2004), design of experiments (DoE) and moving least squares (MLS) (Toropov et al., 2005) were used to create the surrogate indicator function/model from a minimal number (20) of expensive CFD simulations (Zhou et al., 2009). The DoE consisted of 15-point model building DoE and 5-point model validation DoE. Due to our design space being one dimensional all our DoE points were distributed uniformly between the limits of our design parameter i.e. the position of the outlet $0 \leq X \leq H$. The MLS method used was based on quadratic base function and the weighting of points in the regression coefficients calculation were determined using a Gaussian decay function:

$$w_i = \exp(-\theta r_i^2). \qquad (3)$$

Where, w is the weighting of the i-th DoE build point, r_i is the normalized distance from the current point to model building point i, and θ is a closeness-of-fit parameter. $\theta=0$, reduces the above to the traditional least squares regression. The parameter θ was optimized to minimize the R^2 (a statistical measure of fitting quality) value for the obtained surrogate model, as calculated on the validation DoE. The surrogate is then rebuilt using the combined building and validation DoEs. Table 1 shows the values of all the setup parameters used for surrogate modelling.

The surrogate model circumvented the need to run full CFD analysis to assess the performance of each and every design variable choice. Next, a simulation based optimization algorithm based on GA was implemented (Hyperworks 2009), to find the global minimum of the surrogate (approximated) function with respect to the design variables (position of outlet). Figure 2 shows the methodology for obtaining the global optimum (minimum in our case) and table 2 shows all the corresponding parameters used to setup the GA optimization procedure.

RESULTS

The flow inside the test room/chamber was solved using the commercial software ANSYS FLUENT v12.1 (FLUENT 2009) and the optimization was done using Altair HyperStudy v10 (HyperWorks 2009). The three dimensional governing equations were discretised on a uniform grid, using the finite volume method (Versteeg et al., 2007) and solved iteratively using the SIMPLE algorithm (Patankar 1980) inside the room. 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}. In order to apply

our optimization approach to understand the influence of ventilation design on the flow pattern, temperature and pathogen concentration we fixed the supply inlet location at a height of 0.85W, temperature at 27 °C and velocity u = 0.49 m/s normal to the inlet, representing 6 ACH. We then varied the position of the air outlet along the vertical direction between 0.0H to 1.0H of the wall height, opposite the inlet wall.

For every choice of pathogen source (S1-S2) and monitoring regions (A1-A2) we ran 20 (Loeppky et al., 2009) CFD simulations to find the behaviour of the system response parameters. Figure 3 shows one such choice (source at S1 and monitor at A1) and the corresponding behaviour of the parameters. Figure 3 also shows contour plots of the normalised pathogen concentration C (on a plane normal to monitoring region A1 near the inlet) for two different outlet positions. It is clear from the figure that in spite of the ventilation rate being fixed, there is a considerable change in the flow field structure and the corresponding distribution of the transported quantities such as pathogen concentration C and the temperature T of the air. While it is clear from Figure 3 that the outlet position influences both comfort and infection risk parameters but it is not obvious which design may be the most appropriate choice in a given situation. To explore this, an indicator/cost function (Equation 1) was constructed which incorporated weighted system response parameters, pathogen concentration, thermal and draught comfort (Fanger et al., 1988), as a function of the design variable (position of outlet vent)

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

Here C, T_{res} and $\mathbf{v}$ are the pathogen concentration (related to infection risk), dry resultant temperature (CIBSE Guide 2006) and air velocity magnitude (related to thermal and draught comfort at the monitoring region) respectively. The quantity, T_r is the mean radiant temperature (CIBSE Guide 2006) representative of the room surface temperatures, which was assumed in our case to be same (22 °C) for all the surfaces. T_a is the ambient air temperature inside the room. X represents the design variable i.e. the position of the outlet along the vertical direction of the wall, w_C and w_{Tres} represent the weights and $\overline{|....|}$ represents volume averaged absolute value of the quantity inside. The constructed function $f(X)$ is a typical example of a one-dimensional multi-objective cost function (Rao 2009). Figure 4 shows two choices of the monitoring regions A1 and A2 for a fixed source S1 and the corresponding behaviour of the parameters. The plot (a) in Figure 4 shows the variation of the non-dimensional pathogen concentration as a function of the outlet position. Depending on the chosen monitoring region the minima of the concentration appears at different positions of the outlet. Similarly, plot (b) in Figure 4 shows the corresponding behaviour of the comfort parameter dry resultant temperature for the monitoring regions A1 and A2 respectively. The minima of the cost function constructed (Figure 5) from the above responses shows clear dependence on the chosen monitoring region. Furthermore, the minimum is dependent on the chosen source S1 or S2 and also to an extent on the weights (see Figure 6) used. Figure 5 also shows the surrogate objective function constructed using MLS method. This surrogate function was then used in conjunction with GA to find the global minima.

Figure 7 shows the convergence history of the objective function and the design variable using GA for two different monitoring regions (A1, A2) and sources (S1, S2). Clearly, we can see that when source S1 is chosen the minima and the corresponding design variable (outlet position in our case) found by the optimization algorithm are completely different for the two different monitoring regions under consideration. However, this difference in the minima for different monitoring regions is less obvious for source S2. Sensitivity analyses of the optimum design configuration, with respect to the variation of the weight of the indices, were also performed. Our results show that, depending on the chosen monitoring region and source position the objective function was either insensitive or moderately sensitive (see Figure 8). Similar behaviour of the objective function with respect to chosen position of the monitoring regions and weights were also observed in the two-dimensional simulation of Khan et al., (Khan et al., 2012).

DISCUSSIONS AND CONCLUSION

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 hospital ward, represented by a 3D test room with a single supply and extract port, have shown that the method is feasible and that the formal optimization routine yields realistic results that agree with the expected behaviour from a parametric study using CFD. 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. However, the sensitivity to the variation of weights does not appear to be as strong as in the

2D case studied previously (Khan et al., 2012). The reason behind this could be due to the increased mixing that is apparent in the three dimensional turbulent flow compared to the 2D case which was laminar. 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. It is also notable that there is little variation in the air temperatures experienced in the two monitoring regions considered and that the comfort is dominated by draft effects.

Application to a real design scenario will require weights to be chosen which will depend on the environment and level of perceived risk. In the case considered here, the emphasis is placed on the risk and comfort of healthcare workers; hence, the weighting will be influenced by the likely risk posed by patients. In a general ward environment, it may well be appropriate to place an equal weighting on infection risk and comfort, while in an infectious diseases unit the emphasis may be placed on the transmission risk. The model developed here could also be used to explore patient comfort and patient-to-patient risk by defining monitoring regions that represent each patient.

Finally, we have presented in this work the classical weighted aggregation based a priori approach to MOP, instead of Pareto set of designs based a posteriori technique (Konak et al., 2006). Our motivation towards using the aggregation approach stems from its ease of implementation, computational efficiency (Konak et al., 2006) and the assumption of prior knowledge of the designer of the relative importance of different objectives. Nevertheless, the major drawback lies in the choice of the weighting function prior to optimization and how to vary it so as to be able to explore all parts of the potential design space (Forrester et al., 2008). Furthermore, the classical optimization procedure results in a single Pareto optimal solution but designers often require equally optimal different alternatives to make an informed decision. Hence working with a set of optimal solutions with varying tradeoffs among different objectives is highly desirable. However, more work and effort is required to generate the Pareto set compared to the classical approach. Work is currently ongoing in this area.

ACKNOWLEDGEMENT

The authors would like to acknowledge the support of the Engineering and Physical Sciences Research Council (EPSRC) for funding this work.

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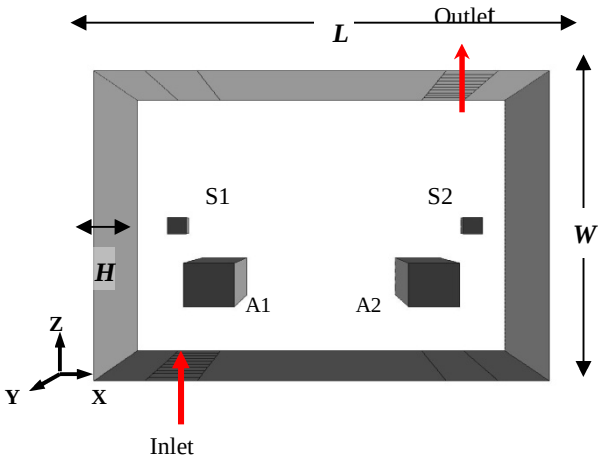


Figure 1 Schematic diagram (plan view) of the test chamber with multiple pathogen sources (S1-S2) and monitoring regions (A1-A2)

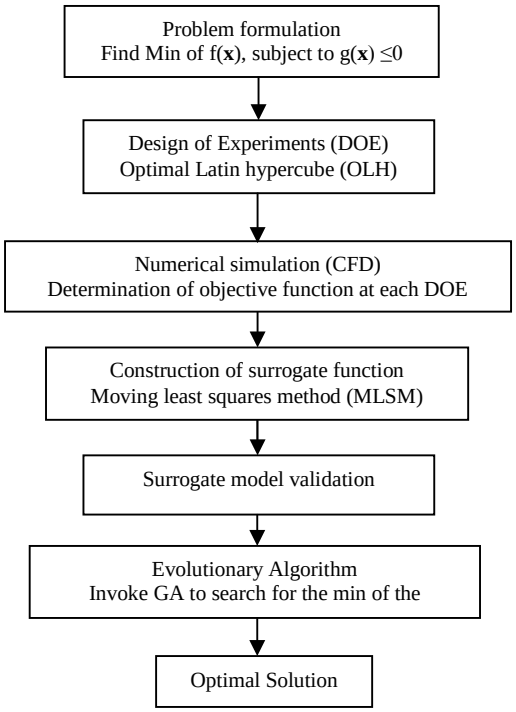


Figure 2 Flow diagram of the optimization procedure

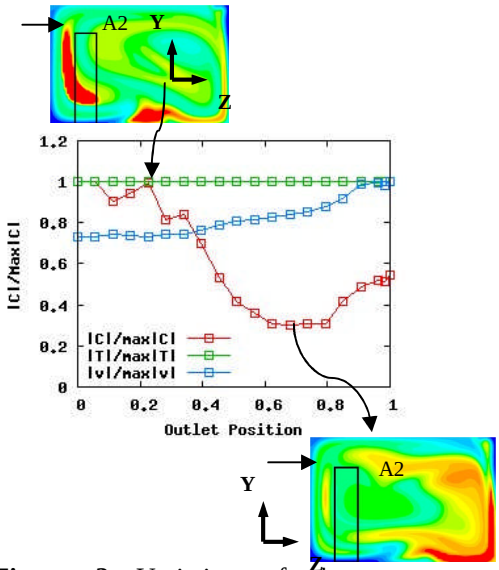
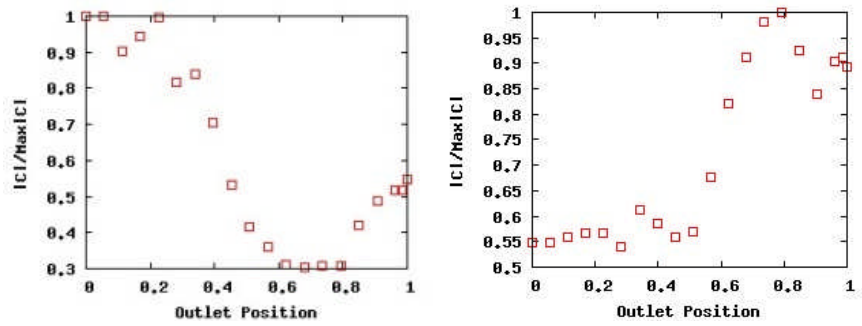
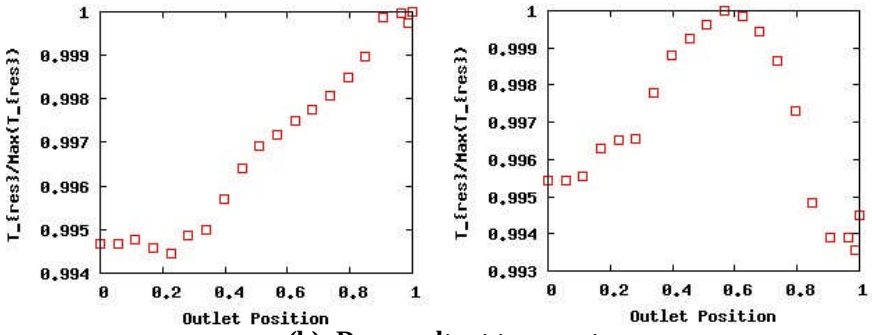


Figure 3 Variation of the system response parameters (volume average of concentration *C*, temperature *T* and velocity |**v**| magnitude) inside monitoring region A2 with source S1 as a function of the design variable (outlet position). The corresponding normalized CFD results for two different outlet positions are also shown.



(a) Pathogen Concentration



(b) Dry resultant temperature

Figure 4 Variation of non-dimensional system response parameters with design variable (outlet position). Left plots and right plots are for two different monitoring regions A1 and A2 and the same source S1. The maximum values of the system response parameters in the respective monitoring regions were used to the non-dimensionalise the plots.

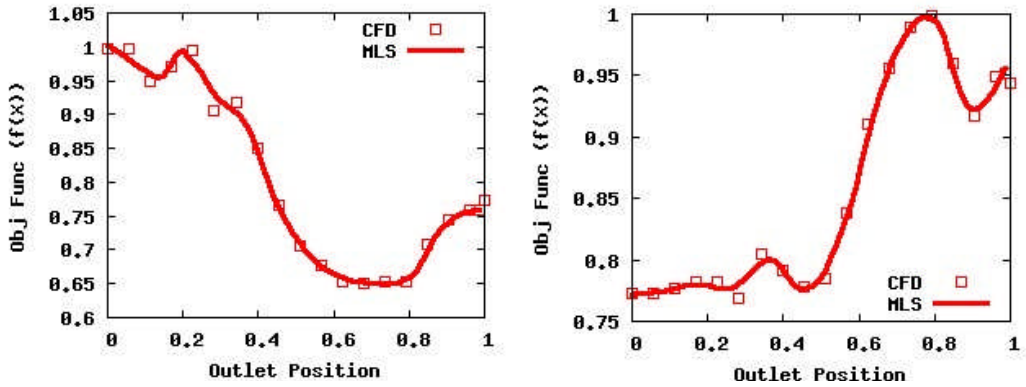


Figure 5 Variation of the surrogate objective function (using MLSM) with design variable (outlet position) for two different monitoring regions A1 and A2. The CFD data points are also shown. Here equal weights were used to construct *f(x)*.

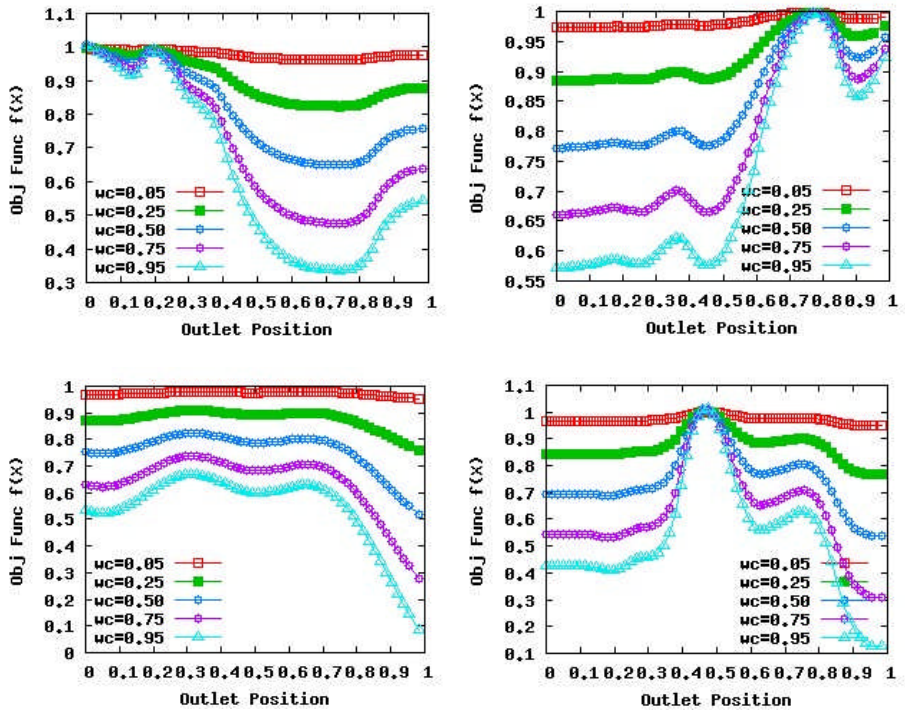


Figure 6 Variation of the surrogate objective function with respect to weights for monitoring region A1(left plot) and A2(right plot) for two different sources S1(top plot) and S2 (bottom plot)

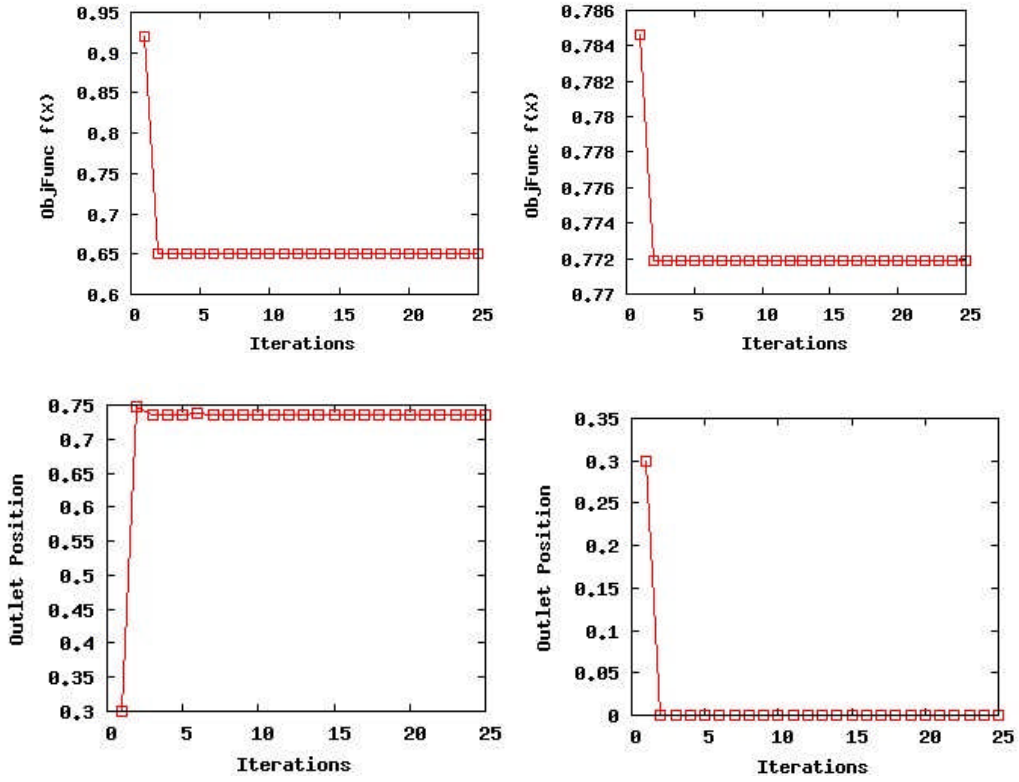
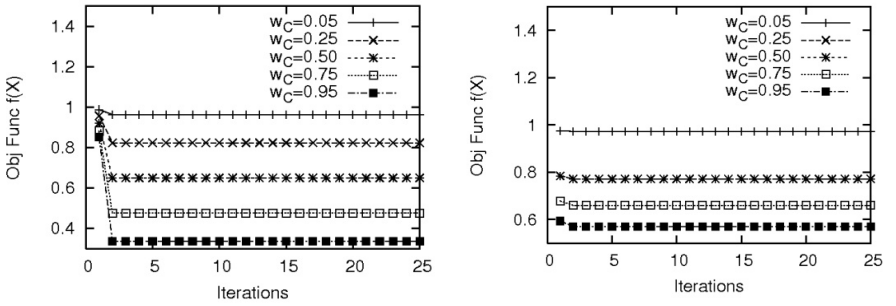
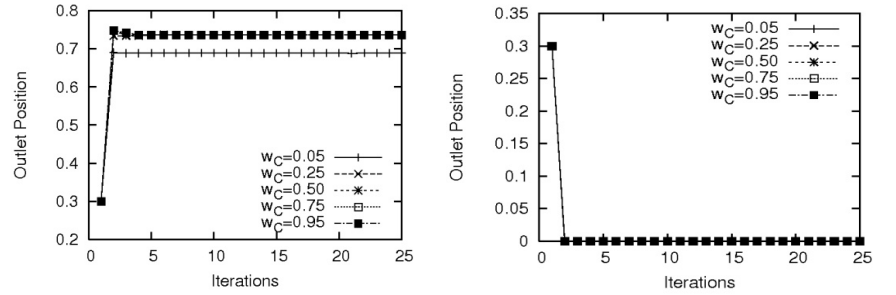


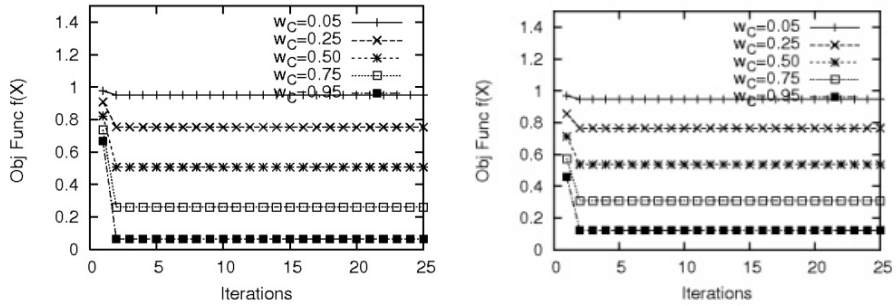
Figure 7 Convergence history of optimization GA search algorithm for the normalised objective function and the corresponding design variable (outlet position). Left and right plots are for two different monitoring regions A1 and A2 with the same source S1.



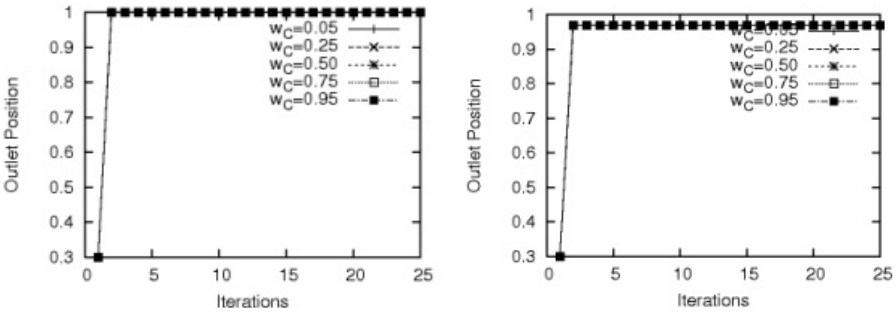
(a) Source S1



(b) Source S1



(c) Source S2



(c) Source S2

Figure 8 Variation of the convergence history of GA search algorithm for the optimal outlet position and the corresponding objective functions with respect to weights and two different sources S1 and S2. Left and right plots are for two different monitoring regions A1 and A2 respectively. Here w_C, represents the weight of pathogen concentration used in Equation (1).

Table 1

Setup parameters for the construction of the surrogate model (HyperWorks 2009)

PARAMETER	VALUE
Number of CFD responses used as building points	15
Number of CFD responses used as Validation points	5
R^2 Building points	0.9932
R^2 validation Points	0.9931
R^2 Merged	0.9947
RMS Error Build	0.0108
RMS Error Validation	0.0091
RMS Error Merged	0.0092

Table 2

Setup parameters of the Genetic Algorithm Optimization (HyperWorks 2009)

PARAMETER	VALUE
Maximum Iteration	200
Minimum Iteration	25
Coding Type	Real
Population size	20
Discrete States	1024
Mutation Rate	0.01
Global search	2
Elite Population %	10%
Random Seed	1
Number of Contenders	2
Penalty Multiplier	2.0
Penalty Power	1.0