Optimal ventilation strategy for multi-bed hospital inpatient wards: CFD simulations using a genetic algorithm

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Abstract

Optimising ventilation strategy for an indoor environment necessitates systematically evaluating the influence of a diverse combination of physical and operational parameters in the design space. This study proposes a methodology that couples an evolutionary algorithm (genetic algorithm) with an evaluation mechanism (Computational Fluid Dynamics) to determine the optimal ventilation strategy for an inpatient ward. The traditional approach would exhaustively simulate numerous scenarios to identify the optimal combination of parameters meeting the design objective. The proposed methodology would iteratively evaluate diverse design solutions with fewer CFD simulations than the traditional approach. The results of design space exploration suggest that design parameters, namely, location of the infected patient; air change rate; flow rate through local exhaust grille; number, location, and size of supply air diffuser and local air exhaust grille are critical in minimising the risk of cross-infection caused through contact transmission in a ward.

Keywords: GA-CFD, optimisation, ventilation, healthcare facility, bioaerosol, infection control, coupled simulation

Introduction

Building ventilation systems is vital in maintaining indoor air quality (IAQ). Its primary function is to provide fresh outside air and extract the heat generated indoors. Although, in a healthcare facility, the system should also assist in preventing diseases and treating patients. It is only in buildings under healthcare segments where ventilation must consider infection control in its control strategies.[1] However, there needs to be more proper guidelines regarding ventilation design in inpatient environments, such as wards, outpatient facilities, etc., to mitigate nosocomial infections.[2, 3] The three major respiratory disease infection transmission modes are airborne, droplet and contact transmission.[4, 5] The exposure of susceptible patients to pathogens deposited on surfaces through contact and touching their eyes, nose or mouth can cause potential infection of respiratory disease.[6] This mode of infection transmission is termed indirect contact transmission. Most studies do not consider the indirect contact transmission route as the most

dominant mode of infection transmission. Still, it has a significant contribution in causing the transmission of respiratory diseases.[7-9] A study by Nicas and Jones[10] revealed that about 31% of infection transmission occurs through hand contact with facial membranes. Additionally, the exposure time through indirect contact transmission can be greater than the other two modes of transmission.[11] The lifetime of infectious pathogens in indoor air was estimated to last from a few seconds to hours,[12, 13] whereas the pathogens deposited on surfaces can survive for hours to weeks.[11, 14]

Elevated air change rates can efficiently eradicate infectious particles present in the air, thereby reducing the probability of exposure and subsequent transmission. Nonetheless, several studies challenged this perspective, which indicated that, in specific circumstances, elevating the air change rate amplified the likelihood of pathogen exposure risk.[15, 16] Augmenting the air supply rates may aid in the dispersion of indoor air pollutants; however, it may only sometimes prove efficacious in impeding the transmission of infectious diseases. According to Ren et al.,[17] the placement of exhaust systems may be critical in eliminating pollutants within a mechanically ventilated ward for patients with coronavirus disease 2019 (COVID-19). Compared to general hospital wards, COVID-19 inpatient wards have been observed to implement more rigorous and stringent ventilation protocols. Nielsen et al.'s[18] investigation of a two-bed hospital ward with downward ventilation highlighted the significance of return openings on contaminant distribution. Thus, it is imperative to consider additional factors such as air circulation, room layout and filtration.[19-21] Apart from air change per hour (ACH), the ventilation system configuration is a controlling element for pollutant flow pathways, as previous studies suggested.[19, 22, 23]

A highly accurate and robust numerical simulation model would greatly benefit the design of an effective ventilation strategy to mitigate infection transmission risk. Three methods, namely, multi-zone models,[24] zonal models[25] and computational fluid dynamics (CFD),[26] are commonly employed to predict the air distribution within a building. Multi-zone models are a low-cost computational modelling solution, but it has limited applicability due to low accuracy and the treatment of each room as a single node. Zonal methods are treated as an intermediary between multi-zone models and CFD. CFD divides the computational domain into numerous control volumes and numerically solves the Navier-Stokes equations to provide a detailed description of fluid parameters. The accuracy of results is also high compared to multi-zone or zonal methods. However, the reliability and accuracy of results are partly attributed to experienced users following best practices guidelines. CFD has been considered one of the most popular numerical simulation methods in diverse fields such as aerospace, manufacturing, buildings, and so on.[27] With rapid advancements in computing, CFD has become a vital tool for designing, analysing and evaluating physical and operational configurations attributed to an indoor environment.[28, 29] CFD simulations can provide a high spatial and temporal resolution of flow patterns, temperature and contaminant distribution within the computational domain of interest.[30, 31]

There can be several parameters that could influence the distribution of airflow and contaminants within an indoor environment. Generally, parametric assessments are performed to evaluate and optimise the effectiveness of ventilation strategies in indoor environments. In parametric studies, the problem is solved several times with various sets of parameter variables to identify solutions.

Wang et al.[32] showed that a virus carrier's sneezing could promote cross-infection. The study offered two evaluation parameters: Total Maximum Time (TMT) and Overall Particle Concentration (OPC), which can be utilised to reflect particle motion and cross-infection risk. In the study, ten air distribution systems were examined using CFD. Through numerical analysis, the authors recommended bottom-in and top-out ventilation as an optimal air distribution strategy that lowers cross-infection risk. In another study, Méndez et al.[33] assessed the ventilation effectiveness of a two-bed hospital room in terms of the age of air and velocity fields using a CFD simulation. The analysis of the initial layout found inadequate ventilation at the patient's location. Thus, three potential configurations were assessed, and the one that provided satisfactory patient comfort and execution cost was determined. In practice, the studies above indicate that beginning with an unacceptable design, they attempted two or three possibilities before settling on the optimal one. This pertains to optimisation, albeit in a limited way.

Parametric investigations employing CFD simulations have the considerable drawback of being tedious and time-consuming. Every change in a parameter's value requires the CFD user to rebuild, re-mesh and recalculate the airflow, which is laborious. Moreover, tracking the intricacy of interactions between a collection of design parameters and the resulting design purpose is frequently challenging. Furthermore, the trade-off of alternative design adjustments remains to be determined.[34] Therefore, it is challenging to explore the design space methodically and solutions may be overlooked.

Consequently, the resulting enclosing environment may not satisfy the goal of the design. Thus, implementing a robust ventilation design can be challenging since it can be difficult to systematically evaluate and estimate the influence of all parameter combinations on the specific design goals using CFD alone. Therefore, the conventional approach for optimising the physical and operational characteristics that lead to a healthy indoor environment is ineffective.

In designing heating, ventilation and air-conditioning (HVAC) systems for indoor environments, combining CFD with optimisation techniques like the adjoint approach and genetic algorithm (GA) has shown potential.[35] In the adjoint approach, the direction to minimise an objective function is determined by computing the derivative of an objective function over a design variable. Since its inception in 1971 by Lions,[36] it has been widely applied to heat transport problems, design optimisation and pollutant source identification. Liu and Chen[37] proposed a CFD-based adjoint approach. The thermo-fluid boundary conditions were employed in their study as design variables, while the flow and temperature fields were specified as design objectives. Various initial inlet air conditions resulted in different optimal air conditions, showing multiple solutions. In addition, Liu et al.[38] considered the location and size of the air supply as design variables. The adjoint approach based on CFD is accurate and can manage many design parameters without significantly increasing computing expenses. However, it may provide a locally optimal design that satisfies the design's constraints.[35]

Several studies have indicated that optimisation algorithms, namely GA, can aid in finding global sub-optimal or optimal solutions from minimal design iterations. Under the gradient-free optimisation techniques, the GA is a stochastic search method that simulates the natural evolution to obtain optimal solutions to a given problem.[39] GA has found application in diverse fields such

as engineering, economics, medical science and many more.[40] However, the coupling of GA with CFD in early studies was restricted to optimising external geometry, for instance, the optimisation of pressure distribution of a NACA0012 airfoil.[41] Malkawi et al.[42] were the first to combine CFD and GA in the design of an indoor environment. Malkawi et al.[34] suggested a decision-support design evolution model utilising the GA and CFD. Using CFD analysis, this method iteratively evaluates the design to maximise thermal and ventilation parameters. Adaptations to the design are made, re-meshed and shown in accordance with the evolutionary algorithms. The procedure continues until the designer can visualise the evolution of the final design choices, and the user can feel the alteration of the design based on its performance. Kato and Lee[43] utilised a similar strategy to optimise a hybrid air-conditioning system. Using CFD and a GA, Mousavi et al.[44] determined the ideal number of sensors and their placement for monitoring indoor air quality in a parking lot of a residential complex. After optimisation, the number and location of sensors that provide the most extensive coverage at the lowest cost would be established.

Nonetheless, it is quite baffling that this methodology has never been applied previously to enhance infection control strategies in healthcare facilities. Thus, by identifying this research gap, this study proposes a method that couples GA with CFD to determine the ventilation strategies that minimise the risk of exposure to infectious pathogens in a general inpatient ward cubicle. This study provides a guide that recommend a combination of physical and operational parameters to enhance the infection control measure within the ward cubicle to concerned stakeholders.

Inpatient ward design:

In hospitals, the total floor space occupied by inpatient wards is typically substantial.[45] The general ward layout with occupants greater than 30 often consists of ward cubicles connected to the ward corridor to a nurse station. The rectangular design of a six-bedded ward cubicle is usually found in the United States of America (USA) and the United Kingdom (UK). The UK pioneered this design by breaking the nightingale ward design into smaller ward cubicles.[46] The layout depicted in Figure 1 represents the general ward layout during the severe acute respiratory syndrome (SARS) outbreak in Hong Kong.[47] The ward had a nursing station, a storage room and four patient cubicles. Each of the four semi-enclosed cubicles was separated from the others by a corridor, and the ward was equipped with central air conditioning. The fan coil unit drew in fresh air from the exterior of the building and mixed it with the previously circulated air inside the building. The resulting mixture was then distributed to the ward via a false ceiling-mounted four-way air supply diffuser. In addition, the exhaust grille in the corridor rerouted air into the fan coil unit for reuse. It is a configuration typical of Hong Kong's general inpatient wards.

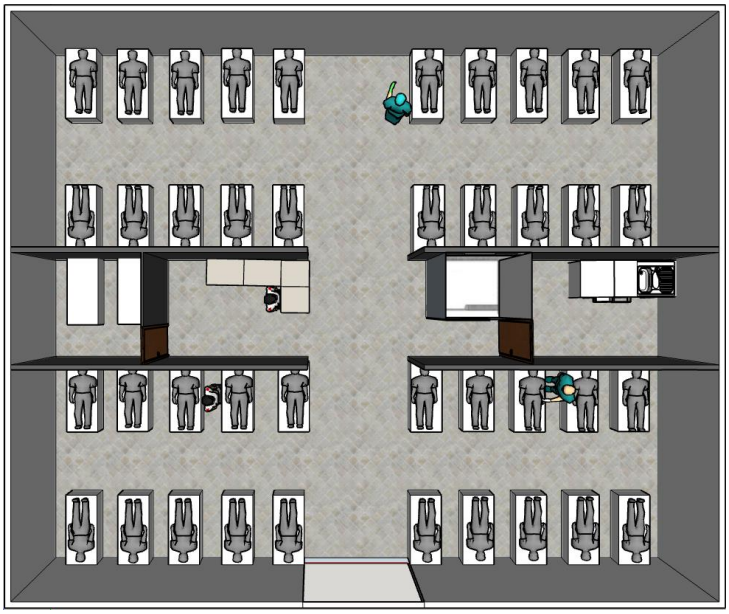
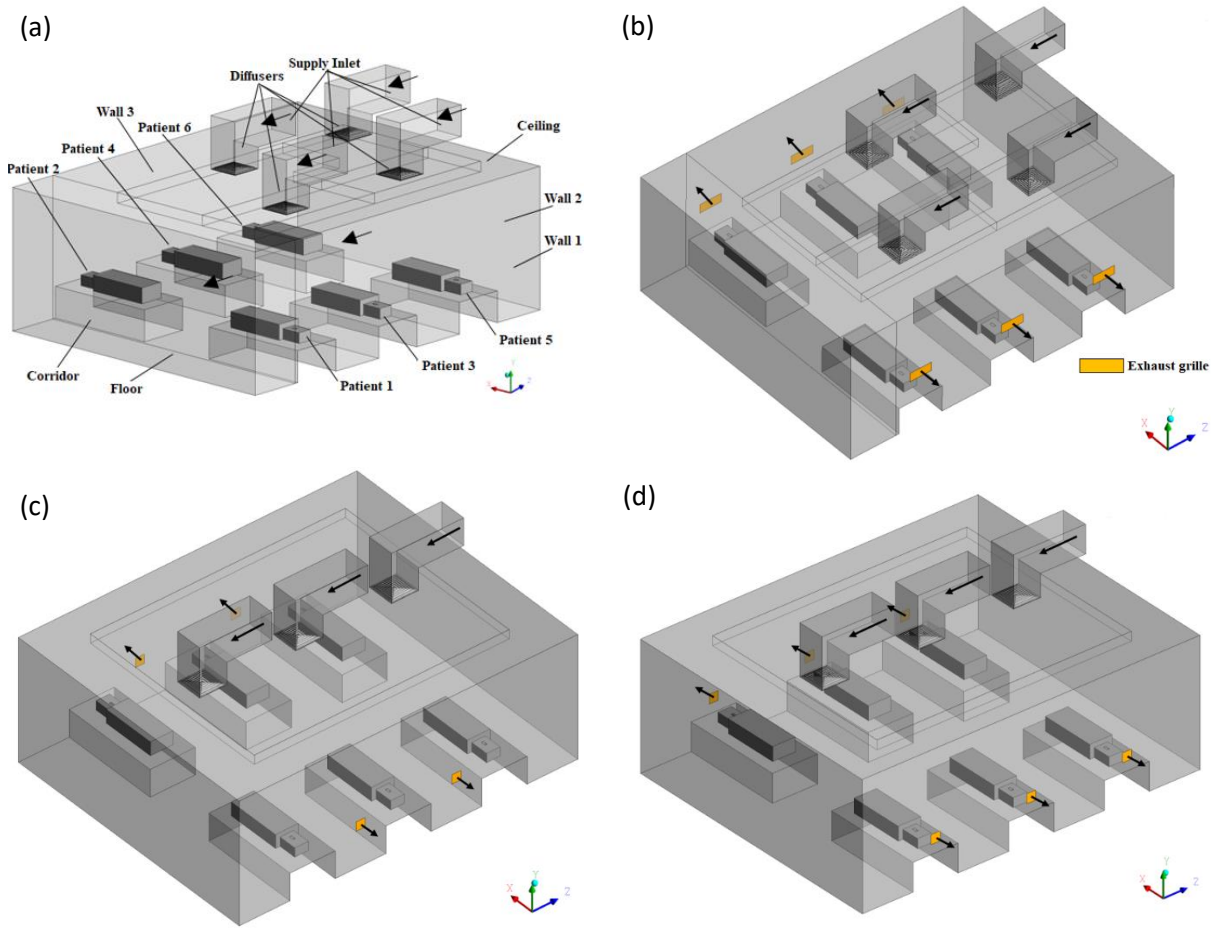


Figure 1. Representative image of general inpatient ward with four cubicles

In this study, a typical layout of an inpatient ward cubicle with dimensions 7.5 m (L) x 6 m (W) x 2.7 m (H) was adopted. The existing ward design (base case) was equipped with four supply diffusers of size 0.6 m x 0.6 m located on the ward ceiling, as shown in Figure 2 (a).[26] The six-bedded ward cubicle was mechanically ventilated, maintaining a positive pressure towards the corridor. Our prior research evaluated the transport, dispersion and deposition of Middle East Respiratory Syndrome Coronavirus (MERS-CoV) droplet nuclei in the same ward layout.[26] The significance of the air change rate and exhaust grille for infection mitigation in indoor settings is well-established. In addition, source control is a commonly employed method of infection control. However, the combined impact of air change rate, exhaust flow rate and the specific location of local exhaust grilles for infection control had not been investigated in inpatient ward settings before our study. Therefore, in our previous investigation, we analysed the influence of air change rate and the local exhaust grille positioned above the patient bed to mitigate the spread of infections by expelling 10% and 50% of the supplied air.[26] However, due to the computational time and expense associated with CFD simulations, only a limited number of simulation scenarios were considered in that study. Thus, the present study explored a cost-effective and time-efficient strategy to examine how alterations in combinations of parameters considered in our prior research and some additional characteristics affected airflow and contaminant dispersion in the ward cubicle.

This study adopted four air change rates (3 h^{-1}, 6 h^{-1}, 9 h^{-1}, 13 h^{-1}) and supplied air based on these air change rates to the cubicle through the ceiling-mounted diffusers. Local exhaust grilles were installed near the patient bed, and exhaust airflow of 10%, 30% and 50% of supply air was regulated through the exhaust grilles for each air change rate condition. The exhaust grilles' height varied within the breathing zone, ranging from 0.8 m to 1.7 m above the floor.[48] In the base case, the supply and ward air exhausted to the corridor were maintained equally. In cases with exhaust grilles, indoor air remaining in the ward after extraction through exhaust grilles was exhausted to

the corridor. The number and location of supply diffusers and exhaust grilles were varied to explore the influence of design changes in ward cubicles on airflow and contaminant distribution. Figures 2 and 3 depict a few configurations to illustrate the existing ward, its modifications and related terminologies. These are not exhaustive, but a few designs utilised in the optimisation process are discussed in this paper. At the same time, this study also considered the variation in the size of the supply diffusers and the exhaust grilles. Thus, this research study aimed to explore a more comprehensive design space to obtain an effective ventilation strategy for an inpatient ward cubicle by overcoming the limitations associated with our previous work.



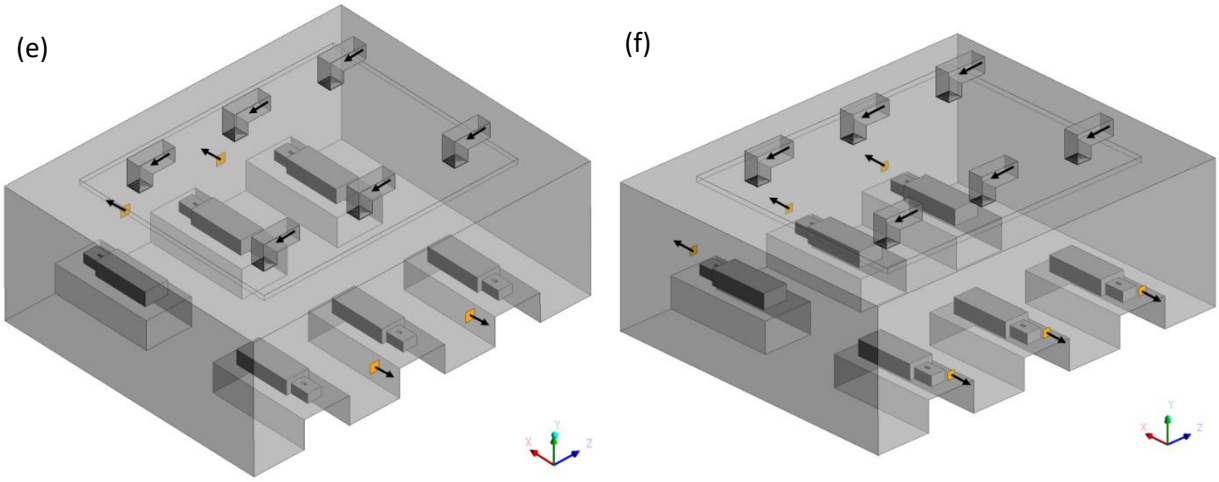


Figure 2. Inpatient ward cubicle designs with patients: (a) Existing cubicle with four supply diffusers and no local exhaust grilles (base case); (b) cubicle with four supply diffusers and six local exhaust grilles; (c) cubicle with three supply diffusers and four local exhaust grilles; (d) cubicle with three supply diffusers and six local exhaust grilles; (e) cubicle with six supply diffusers and four local exhaust grilles; (f) cubicle with six supply diffusers and six local exhaust grilles.

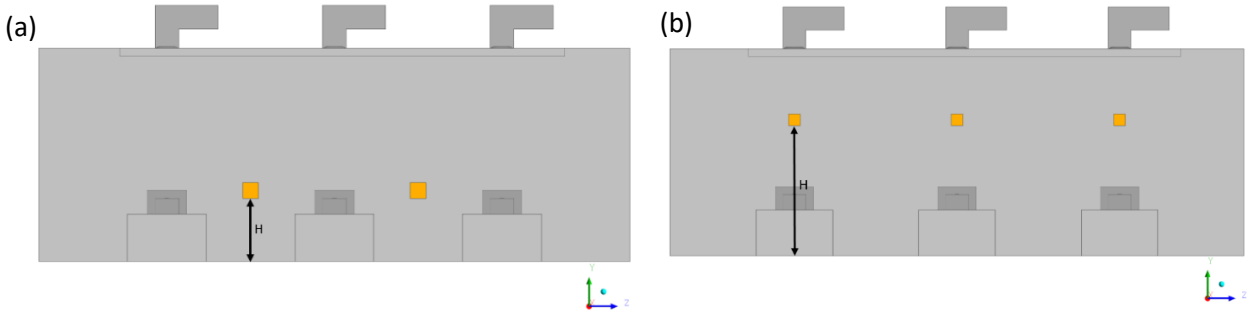


Figure 3. Height (H) of the exhaust grille from the floor

Exposure to infection in a ward cubicle

Exposure to pathogens could heighten the risk of infection to an individual. The exposure risk is considerably high in a healthcare setting such as an inpatient ward cubicle. Wards often have patients with pre-existing health issues and are more likely to have poor immune systems than the general population. Therefore, when a patient with an undiagnosed infectious disease is admitted, the risk of cross-infection would be high amongst the vulnerable patients in the ward. Moreover, there is a high likelihood for healthcare personnel also to become infected as they serve multiple patients.[46]

The location of the infected patient is one of the major determinants in determining the severity of cross-infection in the ward. The deposition of pathogens on susceptible patients due to the exhalation activity of an infected patient would lead to cross-infection within the ward cubicle. In

this study, the contribution of an infected patient i in causing cross-infection within the ward cubicle by depositing pathogens on susceptible patient j was estimated through Equation (1):

$$D_i = \sum_{j=1}^{n} d_j; j \neq i \quad (1)$$

where D_i accounts for the pathogens deposited on other patients due to the exhalation activity of infected patient i, d_j is the particle deposited on patient j and n is the total number of patients in the ward cubicle.

Methodology

Computational modelling and boundary conditions:

A multiphase numerical modelling technique similar to Satheesan et al.[26] was employed in this study to analyse the airflow distribution and transport mechanism of bioaerosols in a general inpatient ward. A detailed description of the modelling technique is presented in their study. Briefly, the air was treated as a continuum phase, whereas the bioaerosols were modelled as the discrete phase. The governing equations of continuity, momentum and energy were solved for the continuum phase in an Eulerian framework. In contrast, bioaerosols' dispersion and deposition mechanisms were modelled in a Lagrangian framework. The finite-volume-based CFD code (Ansys Fluent 13.0) was utilised to solve air and discrete phase governing equations with a second-order upwind solution scheme. At the same time, the semi-implicit method for the pressure-linked equations (SIMPLE) algorithm was used for the pressure-velocity coupling of the continuum phase. The airflow was modelled as a three-dimensional incompressible turbulent flow in a steady-state condition. The indoor airflow turbulence was modelled using the Reynolds-averaged Navier Stokes (RANS) equation.

Droplets expelled through exhalation activities such as sneezing would quickly evaporate within a short period (< 0.1s). Hence evaporation was not modelled, and in turn, their dried-out residuals, namely, droplet nuclei, were considered in this study. Furthermore, considering the droplet nuclei size and density in indoor environments, forces such as pressure gradient force, virtual mass force and Basset force are insignificant.[49] However, considering the droplet nuclei size, non-isothermal condition and drag force, other influential forces such as Brownian, thermophoretic and Saffman lift forces were modelled.[26] More details concerning the parameters adopted for CFD simulation of the ward cubicle in this study are shown in Table 1.

Table 1. CFD simulation parameters

Computational domain	7.5 m (L) × 6 m (W) × 2.7 m (H), RNG k-ε turbulence model with enhanced wall treatment
Total supply airflow rate	0.1240 kg·s^{-1} (for ach = 3), 0.2480 kg·s^{-1} (for ach = 6), 0.3720 kg·s^{-1} (for ach = 9), 0.5374 kg·s^{-1} (for ach = 13), 285K (air temperature)
Each diffuser	4-way spread pattern, air supplied at an angle of 15° from the ceiling, adiabatic
Corridor	Outflow with flow rate weighting, 295K (backflow temperature), adiabatic, escape boundary type

Exhaust grille	Outflow with flow rate weighting, 295K (backflow temperature), adiabatic, escape boundary type, Exhaust air 0%, 10%, 30%, 50% of total supply air
Walls, ceiling, floor, and beds	No-slip wall boundary, adiabatic, trap boundary type
Patients	Six patients, No-slip wall boundary, 23.3 Wm^{-2} for each patient, trap boundary
Mouth of patient (0.05m×0.05m)	Single shot release with an exhalation upward velocity of v_b = 50 ms^{-1},[50] n_s = 10,000 virus particles, density of bioaerosol particles ρ_b = 1,100 kgm^{-3}
Species and their aerodynamic diameters	MERS-*CoV* (0.167±0.012 μm)

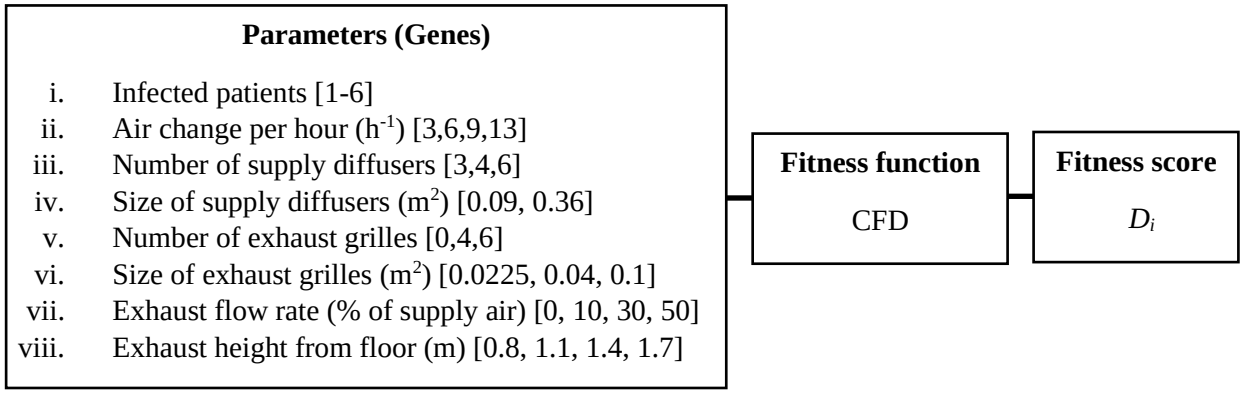
Genetic algorithm for optimisation:

The risk of infection in a general inpatient ward can be associated with various physical and operational characteristics of the indoor environment. A few characteristics, including but not limited to air change rate; number, location and size of air supply diffusers as well as exhaust grilles; location of the infected patient; type, direction and velocity of exhalation activity; etc., could all play a vital role in the transport, dispersion and deposition of infectious pathogens. Optimising ventilation strategies following specific design objectives requires systematic evaluation and prediction of the effects of these parameters on airflow and contaminant distribution. Numerical simulation techniques such as CFD could be employed to design, analyse and evaluate the influence of various indoor environment characteristics on the infection spread mechanism. The conventional method would exhaustively simulate all parameter combinations to determine the optimal ventilation strategy for an indoor environment. However, such an approach with solely CFD could be computationally expensive and time-consuming. Hence, this study combined CFD with an optimisation strategy like a GA to uncover essential parameter combinations that lower infection risk by iteratively evaluating various design options with fewer CFD simulations than the conventional approach.

There are two classes of optimisation algorithms: gradient-based and gradient-free. Gradient-based methods cannot effectively deal with nonlinear problems and are susceptible to becoming trapped in optimal local values.[51] The airflow and contaminant distribution issues in indoor environments are highly nonlinear, necessitating gradient-free methods. Under the gradient-free optimisation techniques, the GA is one of the most popular population-based stochastic search techniques based on natural selection and genetics. The GA can resolve nonlinear and multi-solution problems while requiring less computing time than other methods to find the global optimum.[52]

Unlike traditional search techniques, GA starts with a seed population of random solutions to a given problem. Each solution in this population is termed a *chromosome,* and these chromosomes evolve through successive iterations known as *generations*. Each chromosome is characterised by a set of parameters known as *genes,* which are combined to form a chromosome. The chromosomes were evaluated in this study during each generation using some form of *fitness*. The creation of a new generation is done through (i) selection based on fitness score and (ii) rejection of weak chromosomes to keep the size of the population constant. In each generation, a new chromosome called *offspring* would be formed either through (i) a combination of two chromosomes through *crossover* operation or (ii) spontaneous modification of chromosomes through *mutation*.

Generation after generation, the algorithm would converge to the best chromosome representing the optimal or suboptimal solution to the problem in the best-case scenario. The components and general outline of the GA process are illustrated in Figures 4 and 5, respectively.



Parameter input values for CFD are bracketed.

Figure 4. Components of the genetic algorithm process

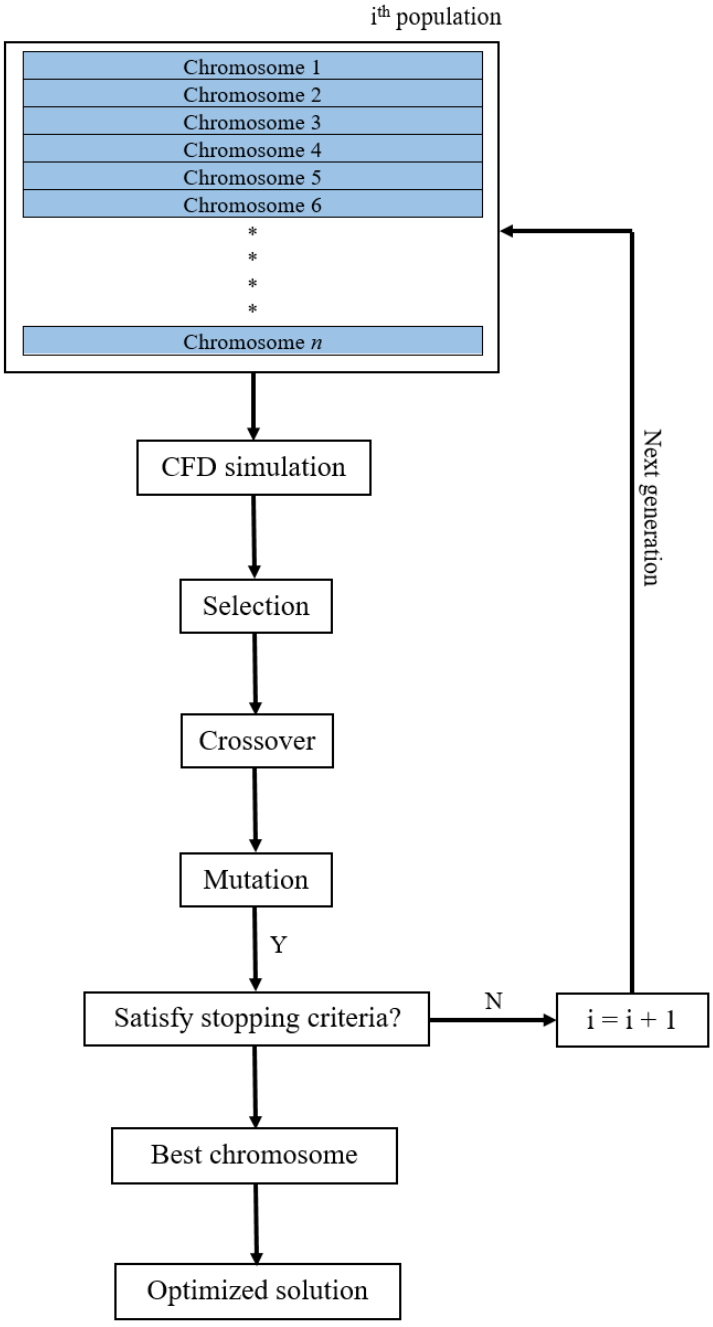


Figure 5. Flow chart of genetic algorithm process

This study chose 133 random input parameter combinations (chromosomes) to form the initial population, and CFD simulation was conducted for each chromosome. The CFD simulation would provide the deposition count in the ward cubicle, and based on Equation (1), particle deposition count was earmarked. This single-objective optimisation study utilised CFD simulations as the fitness function and deposition count as the fitness score to rank each input parameter combination. The GA process in this study used a crossover rate of 0.5 and a mutation rate of 0.1. The study adopted a maximum number of generations as the stopping criteria for the GA process. The GA

implementation was done using Python programming, and the steps involved in the GA process are listed below:

1. Generate *n* random chromosomes with the input parameters to form the initial population.
2. Determine the particle deposition count (fitness score) in the ward from CFD simulation (fitness function) for each chromosome in the population.
3. Evaluation and selection of chromosomes were based on fitness score.
4. Parents were subjected to crossover and mutation.
5. Based on the crossover and mutation rates, new chromosomes were generated, leading to a new population.
6. CFD simulation was run on the new chromosomes to determine the fitness score.
7. One iteration or generation of a GA was completed.

Steps 3-6 were repeated until a stopping criterion was met.

Numerical verification and validation

Flow field

Wang and Chen[53] developed three benchmark cases with high-quality experimental data under the ASHRAE RP-1271[54] project that can be utilised for validating the CFD simulation model within enclosed spaces. The studies encompassed intricate flow characteristics, such as separations and thermal plumes, frequently encountered in this category of phenomena. The measurements were performed within a testing enclosure with overall dimensions of 2.44 m × 2.44 m × 2.44 m and equipped with both an inlet and outlet for airflow. The supply flow rate of air was measured to be 0.1 m^3/s, and the supply-air temperature was 22.2°C. A slot diffuser was positioned on the room's left wall at an opening height of 0.03 m spanning the entire width of the room. An exhaust slot measuring 0.08 m in height and spanning the whole width was situated adjacent to the floor on the right-hand wall.

Benchmark's Case 1 pertained to an isothermal condition. In the second case, also conducted under isothermal conditions, an obstruction (box) was introduced at the centre of the chamber floor. The impediment mentioned above, with approximate measurements of 1.22 m × 1.22 m × 1.22 m, resembles typical furnishings that produce flow separations while simultaneously augmenting turbulence reduction. Case 3 involved the application of heat to the obstacle (box), generating a heat output of 700 W while maintaining a controlled supply temperature of 22.2°C. This scenario introduced an additional flow characteristic, namely convective thermal plumes. The objective of Case 3 was to investigate the impact of thermal buoyancy flow within a room subjected to forced convection. The validation task presented by Case 3 is notably intricate and bears the most significant resemblance to the indoor airflow of this study. Hence, Case 3 was selected for validation in the present study. The experimental configuration, including the measurement poles, is depicted in Figure 6. Further details with respect to the benchmark case can be found in the work done by Chen and Wang.[54]

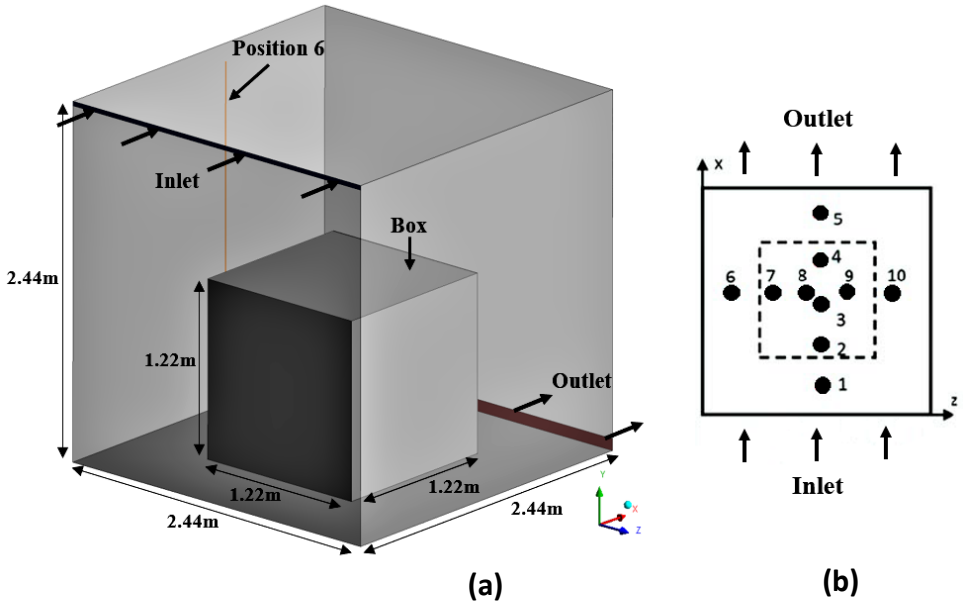


Figure 6. (a) Computational model of the ASHRAE RP-1271[54] experimental test room (b) Plan view of measurement poles adapted from Wang and Chen [53]

A hexahedral mesh generated using ICEM-CFD 13.0 maintained a grid spacing of 1.2 and a 0.001 m first cell height from the wall of the computational domain for three grid systems: coarse (1678 k), medium (1750 k) and fine (1823 k). The topology of the generated computational grid is shown in Figure 7. The mesh near the wall was refined well enough to maintain a y^+ value below 5. The near-wall modelling is done with the enhanced wall treatment approach.

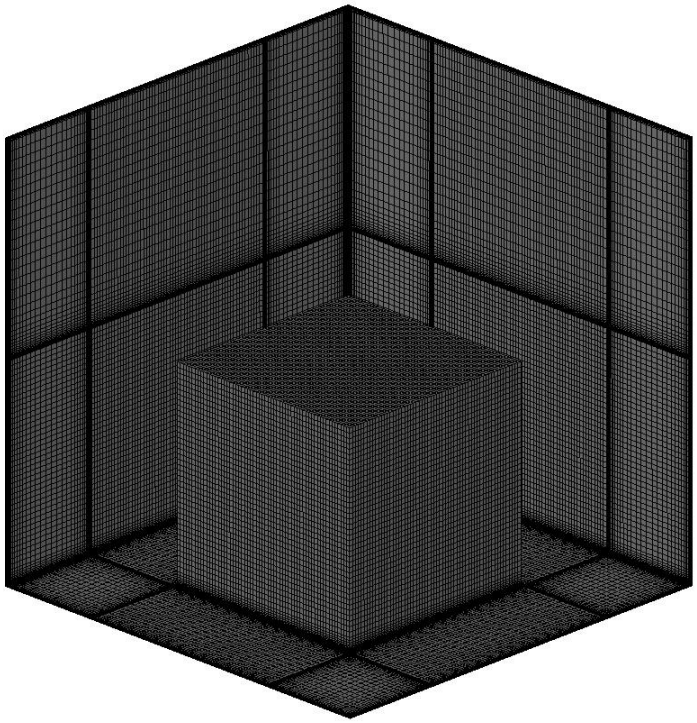


Figure 7. Computational grid of experimental test room

To assess the grid sensitivity of our simulations, we have employed a comparative analysis of the experimental data and simulation outcomes. The velocity data at pole six plotted across three gird systems are shown in Figure 8. The results, measured and simulated, were nondimensionalised.[53] The normalisation of length was based on the room size (L = 2.44 m). Similarly, the velocity was normalised by the maximum velocity observed in all three benchmark cases (U_{max} = 1.5 m per second). The simulation outcomes obtained by employing the fine grid and RNG K-ε turbulence model exhibit a high degree of conformity with the experimental data across most measured points, as illustrated in Figure 8. The RNG k-ε model can accurately simulate the velocity distribution in a mixed convection scenario, given the current grid resolution. The findings provide adequate validation for numerical simulations in a scenario that involves mixed convection, such as in a ward used in the present study.

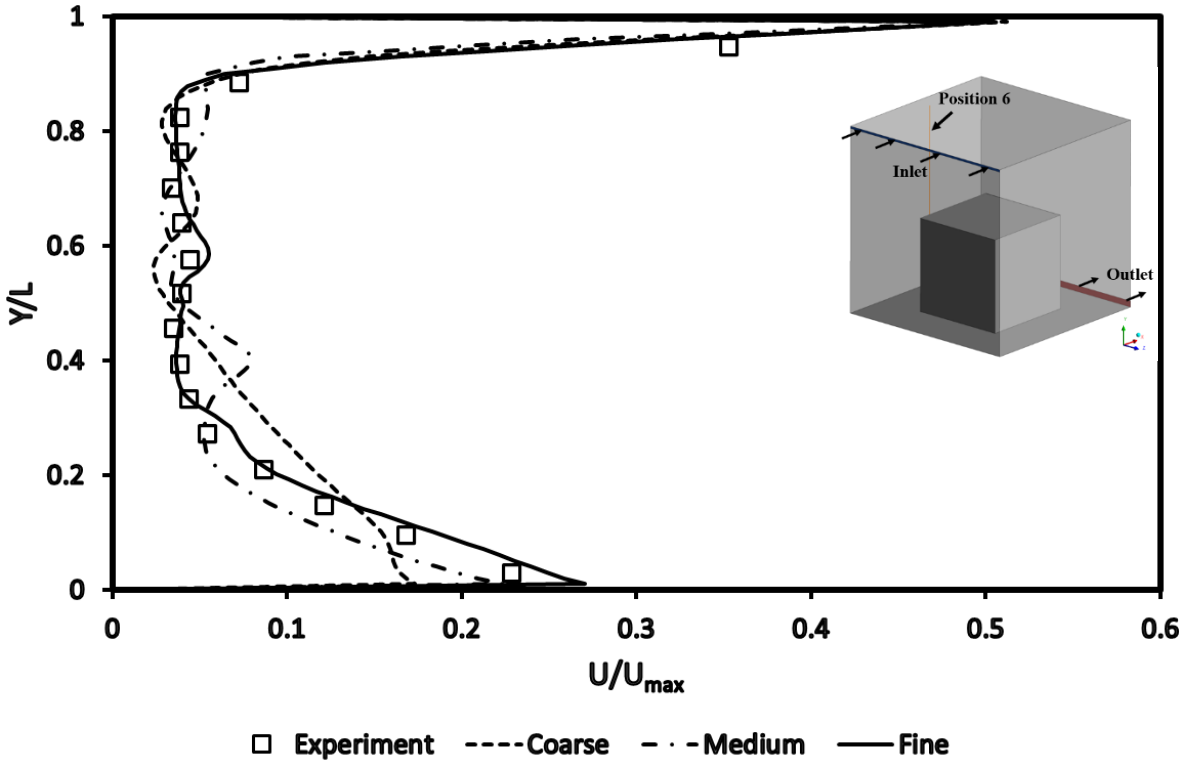


Figure 8. Velocity profiles for ASHRAE benchmark case 3 across three grid systems at position 6

Particle transport:

The validation of the particle modelling employed in this study was carried out through a study conducted by Yu et al.[55] The study conducted by Yu et al.[55] aimed to assess the impact of air change rates on the dispersion and deposition mechanisms of bioaerosols, with a specific focus on the MERS-CoV. The bioaerosols were emitted by a source patient in a mechanically ventilated inpatient ward cubicle, as depicted in Figure 2(a). The investigation examined the impact of patient source location on infection transmission across varying air change rates while considering different emission locations within the ward cubicle. The validation process utilizes the particle

exhausted ratio (r_e). This ratio was computed by dividing the number of particles that are exhausted into the corridor by the total number of particles that are expelled by the infected patient, as demonstrated in Equation (2).[55]

$$r_e = \frac{n_e}{n_s} \tag{2}$$

The exhausted ratio accounts for the possibility of infection transmission from a ward cubicle to the corridor due to the spread of expelled particles from an infected patient to the corridor. According to Chen et al.,[56] these particles could also move to neighbouring spaces connected to the corridor. The CFD simulation for validation was conducted for the base case scenario of the ward cubicle without any local exhaust grille, as shown in Figure 2 (a). The exhausted ratio of three source patients, namely, patient 1, patient 2 and patient 5, under an air change rate of 9 h^{-1} and 13 h^{-1} were taken for validation from the study conducted by Yu et al.[55] As depicted in Figure 9, the exhausted ratio documented for varying air change rates and source patients in this investigation aligns closely with the simulation findings of Yu et al.[55] This reflects the accuracy and reliability of the CFD simulation of this study to conduct further exploration.

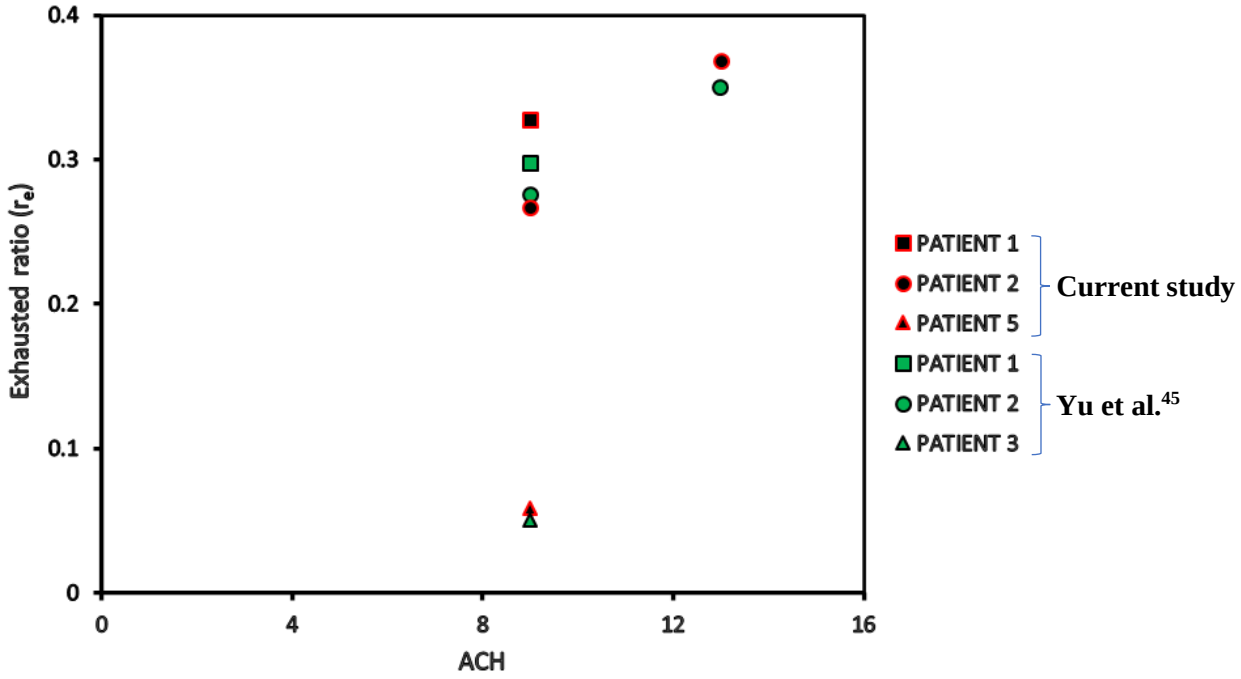


Figure 9. Comparison of exhausted ratio results under different air change rates and source locations

Grid independence study of ward cubicle:

The numerical simulation methodology was further utilised to predict the airflow and particle distribution within the general inpatient ward cubicle. For the grid convergence investigation, airflow simulations were run on three grid systems: 1002 k (System 1), 3202 k (System 2) and 5110 k (System 3). A few instances of the computational grid generated for the inpatient ward cubicle are illustrated in Figure 10.

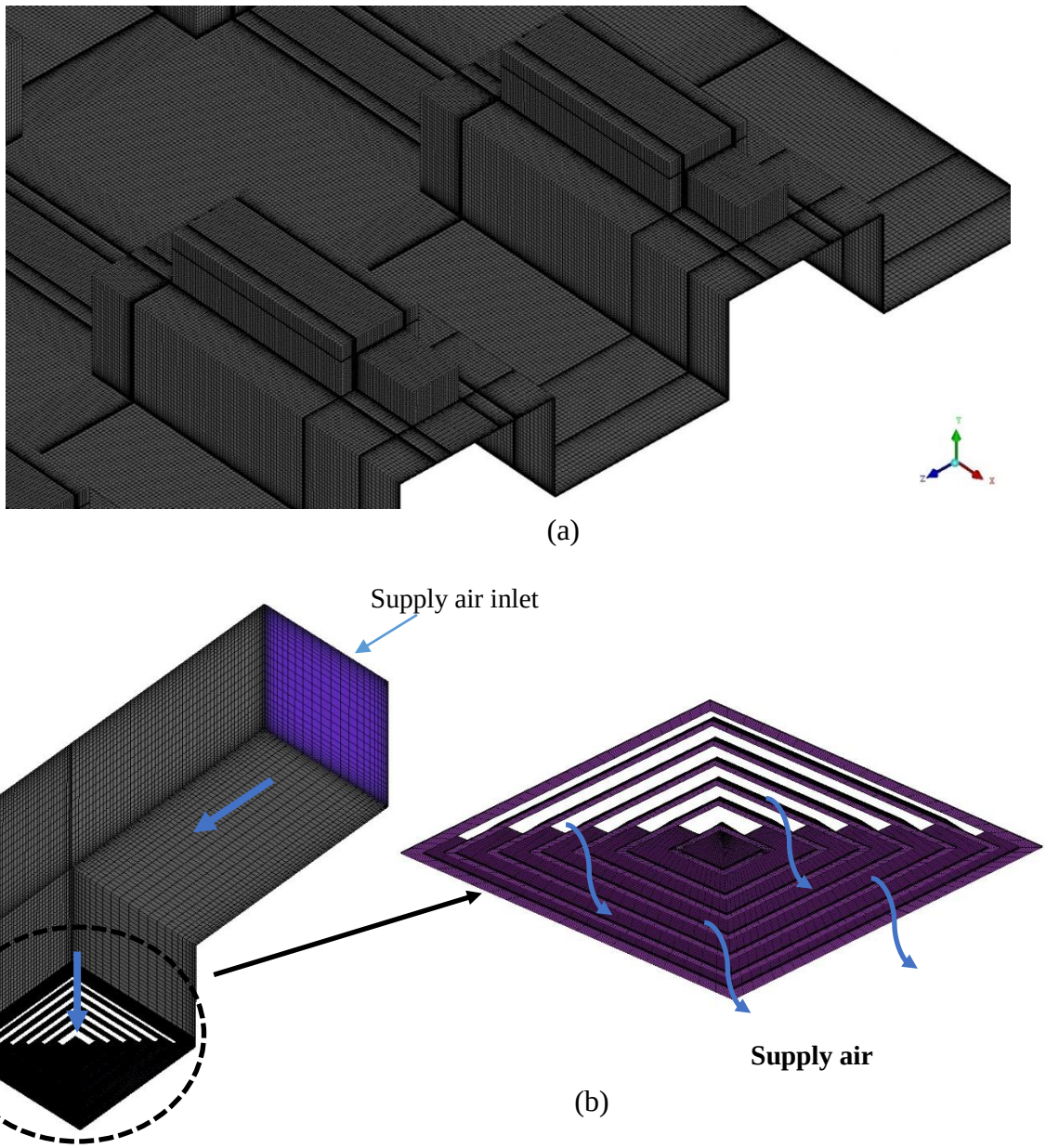


Figure 10. Grid generated within the computational domain (a) Thermal manikin on the bed (b) Supply air diffuser and flow deflector vanes (inset).

The values of fluid velocity along the vertical line located at the centre of the ward cubicle for different grid systems adopted in this study are depicted in Figure 11. The grid convergence index (GCI) was used to analyse the convergence of the grid systems.[57, 58] The grid system GCIs were calculated using the root-mean-square of the relative error for the fluid flow mean velocities (u) detected at 100 sites along a vertical line at the centre of the ward cubicle. Consequently, systems 2 and 3 had GCIs of 3.11% and 3.40% with reference to System 1. Considering computing time and solution correctness, System 2 was chosen to study fluid flow characteristics further.

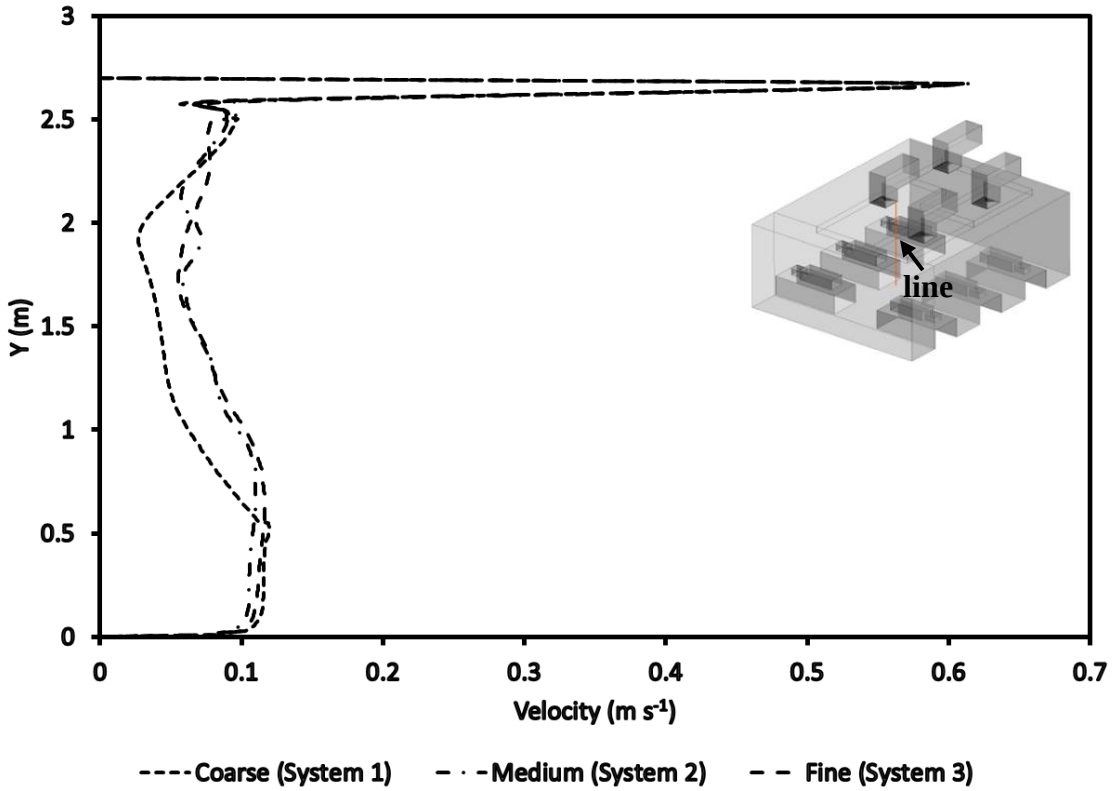


Figure 11. Velocity profile under different grid systems along a line

Results and discussion

Airflow pattern:

Airflow patterns and temperature distribution can play a vital role in the transport mechanism of infectious pathogens. Numerical simulations through CFD provide a quantitative visualisation of velocity and temperature distribution within the ward. Figure 12 showcases the velocity distribution and airflow pattern in the ward across the XZ plane at y = 1.35 m from the floor at two different ACHs (9 h^{-1}, 13 h^{-1}). From Figure 12(a), at 9 h^{-1}, the air velocity near patients 1 and 2 was comparatively less compared to the rest of the patients in the ward. Also, as observed in Figure 12(c), the general airflow pattern in the ward is towards the corridor. Hence, these two factors would let the patients near the corridor play a less critical role in causing cross-infection among other patients in the ward. Several eddy formations were noticed due to the presence of an obstruction in the form of the patient and bed. The recirculation zones can create an unsafe environment as it would trap infectious pathogens for a long time, increasing the risk of infection. The velocity distribution and air flow pattern were observed to improve with an increase in ACH, as shown in Figures 12 (b) and (d). Figures 13 (a) and (b) illustrate the XY plane's temperature distribution and airflow pattern located at a distance of z = 1.6 m in the ward cubicle with a local exhaust grille installed on the bed sidewall. The thermal manikins generate a thermal plume which would significantly affect the vertical airflow pattern of the ward cubicle. The mixing of cold supply air with thermal plume can be evidently seen in Figures 13 (a) and (b).

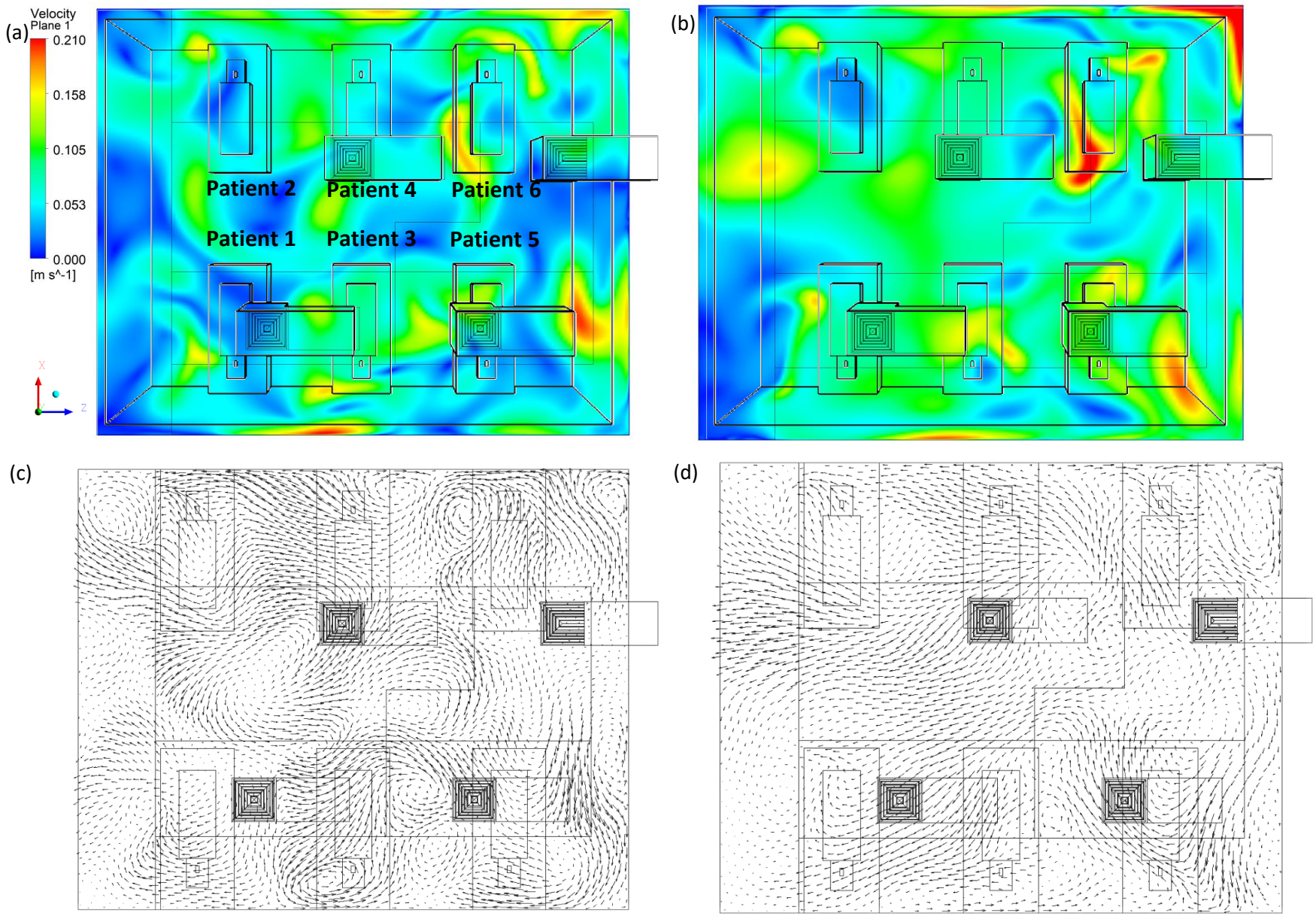


Figure 12. Air velocity distribution and airflow pattern across a horizontal plane at y = 1.35 m under (a) 9 ACH; and (b) 13 ACH.

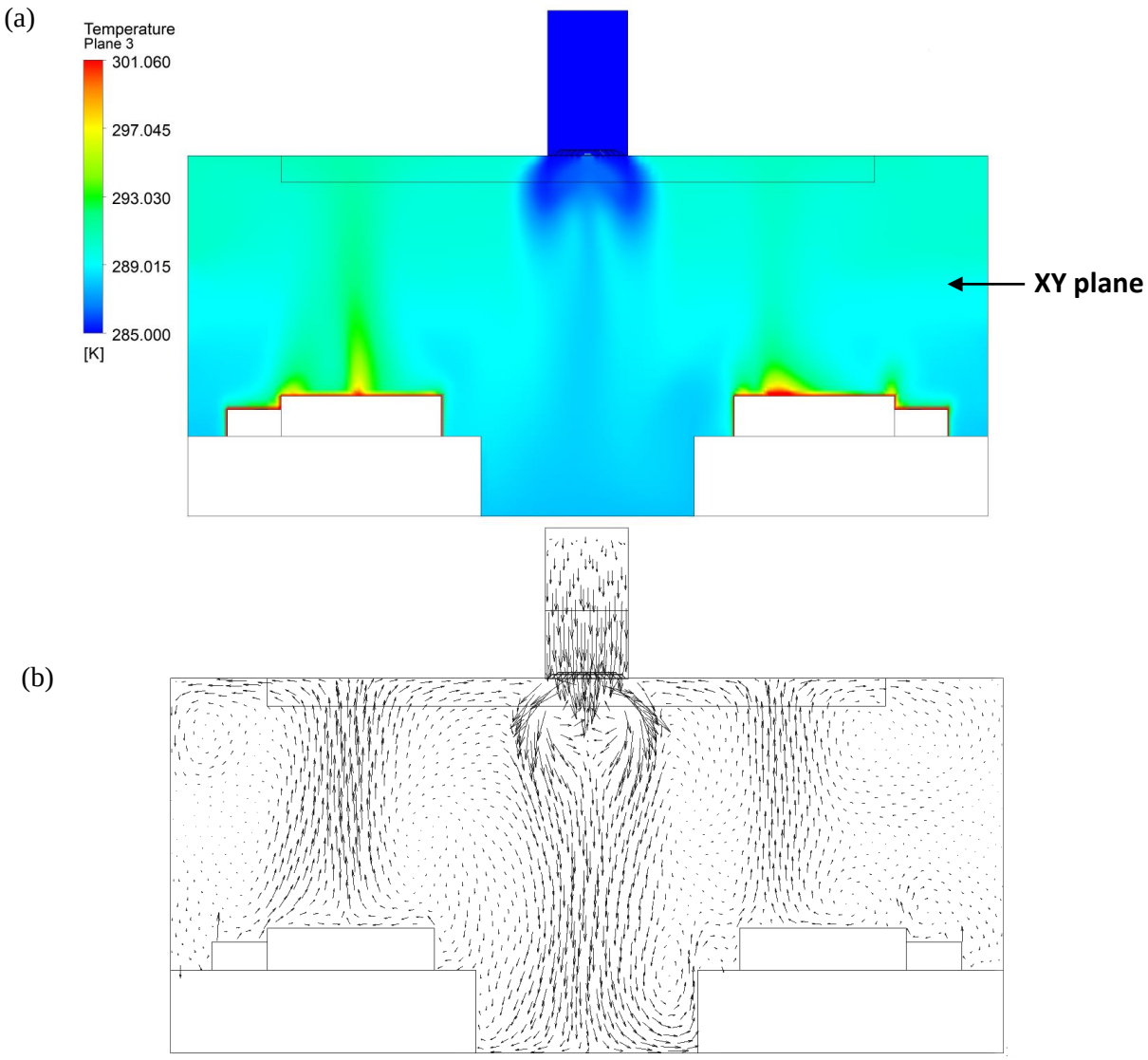


Figure 13. The plots of the ward cubicle with three supply diffusers on the ceiling and four local exhaust grilles on the sidewall at 6 ACH and exhaust air = 30%: (a) temperature distribution (b) airflow pattern.

Exposure risk for patients through cross-infection:

The evolution of generations in the GA process with the fitness value for the best chromosome is plotted in Figure 14. The best input parameter combinations resulting in the lowest exposure for cross-infection after 10 generations are listed in Table 2. The fitness score (D_i) indicates the number of particles deposited on other patients due to the exhalation activity of an infected individual in the ward cubicle. As shown in Table 2 that patient 2, located near the corridor, has a minor contribution towards causing cross-infection in the ward. Therefore, placing a new incoming patient near the corridor for the initial few days would be ideal to avoid super-spreading events in a ward cubicle. From Table 2, the ventilation system design could be crucial in reducing the risk of cross-infection in the ward. In a ward cubicle maintained at an air change rate of 6 h^{-1}, three supply diffusers of size 0.36 m^2 located on the ceiling and exhaust flow (30% of supply air) through

four exhaust grilles of size 0.04 m^2 located in nearby patient bed were shown to be the best scenario resulting in the least risk of cross-infection. Moreover, installing a local exhaust grille near the patient would provide a localised control to restrict the dispersion of infectious pathogens from an infected patient to other locations within the ward cubicle. Furthermore, healthcare workers attending to the patients should follow standard infection control guidelines, such as hand hygiene, eye protection and wearing a face mask with high filtration efficiency regardless of the ventilation strategy adopted.

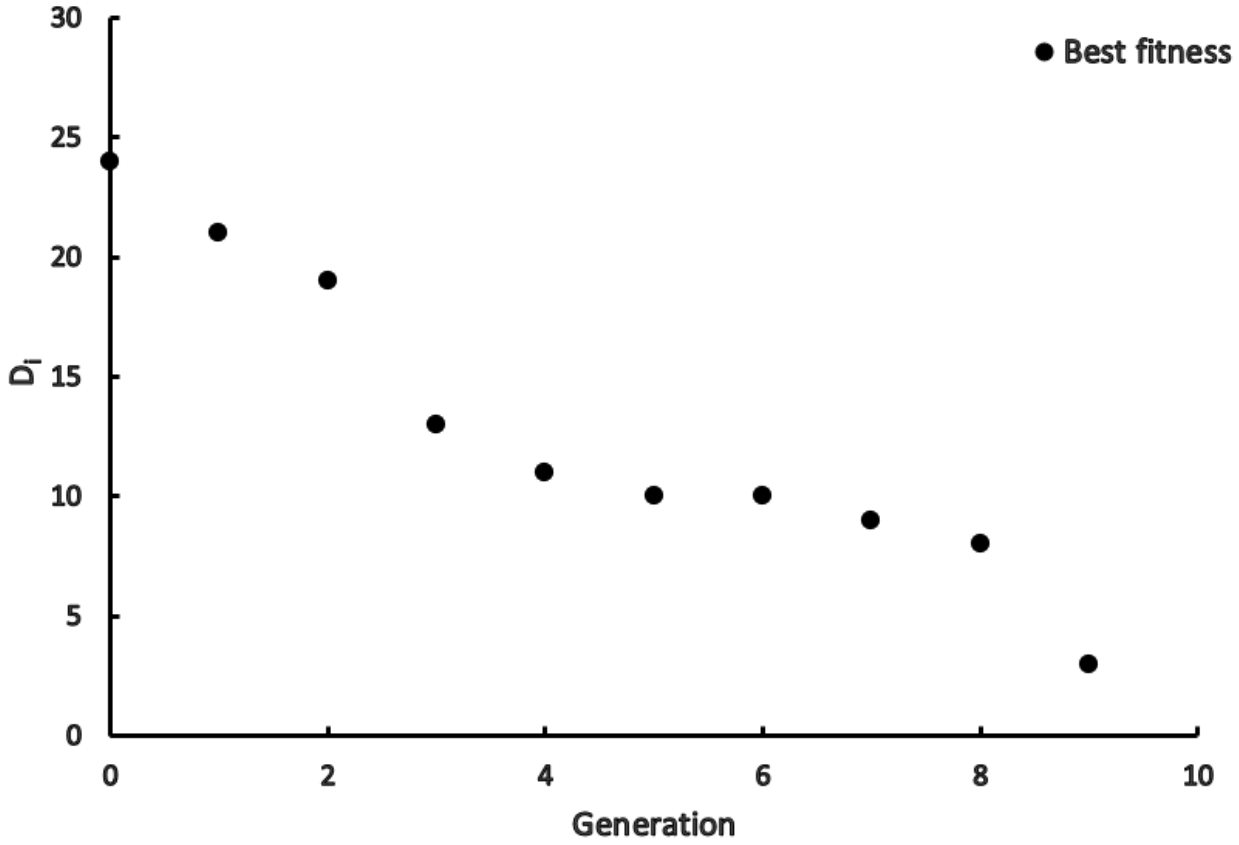


Figure 14. Evolution of generation in the GA process

Table 2. Input parameter combination with the lowest exposure for cross-infection

Parameters								Fitness Score
i	ii	iii	iv	v	vi	vii	viii	D_i
2	6	3	0.36	4	0.04	30	0.8	3

* Refer to Figure 4 for the denotation of Roman numbers

The GA-CFD process indicated that by adopting the ventilation configuration listed in Table 2, the source patient 2 would provide the least risk of infection transmission in the ward cubicle. However, the source location in a ward cubicle could be random. Therefore, an analysis was further done to determine the effectiveness of the ventilation solution recommended by the GA-CFD process considering other source locations. Furthermore, the efficacy of the aforementioned approach was evaluated in relation to the pre-existing ventilation strategy in the base case scenario having no local exhaust grilles. In this comparison, the air change rate only varied from 3-13 h^{-1}

for the base case scenario. According to Figure 15, the optimal ventilation solution suggested by GA-CFD is more effective than the base case scenario under different air change rates while considering patient 1, patient 2, patient 3 and patient 5 as the source. However, while considering patients 4 and 6 as sources, infection control can be better with a high air change rate (13 h^{-1}) compared to the optimal ventilation solution in the base case scenario. Although, adopting a high air change rate would also result in higher energy consumption. The results indicate that the optimal ventilation configuration listed in Table 2 is a superior solution for most of the analysed scenarios as shown in Figure 15. However, additional analysis is emphasized to identify the ventilation configuration that could potentially mitigate infection transmission within the ward cubicle, regardless of the source location. In this regard, deploying the proposed GA-CFD coupled methodology would be a cost-effective and time-efficient approach.

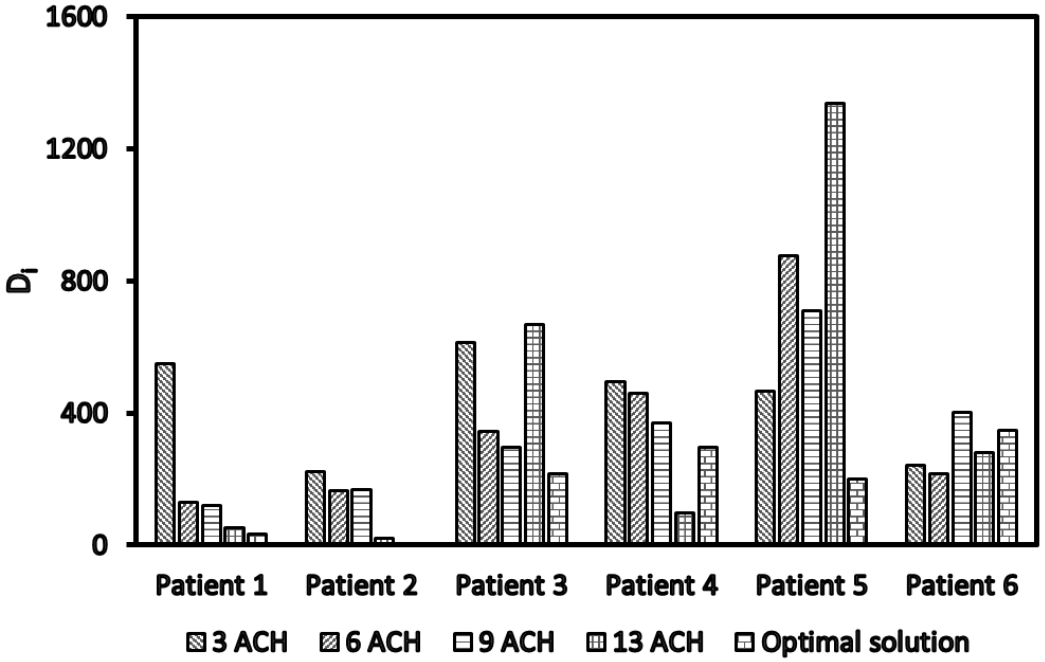


Figure 15. Pathogen deposition (D_i) for different source (Patient) locations under GA predicted optimal ventilation strategy and varying air change rates (3-13 h^{-1}) in the base case scenario.

Conclusion

Optimising ventilation strategy for an indoor environment through the conventional approach necessitates complete simulation of all combinations of design space parameters and systematically evaluating each scenario to propose the best solution. However, this approach could be more effective regarding time and expense. This study developed a coupled simulation approach by combining an evolutionary algorithm (GA) with an evaluation mechanism (CFD) to determine a ventilation strategy to mitigate the spread of infection in an inpatient ward cubicle. The proposed methodology would iteratively evaluate diverse design solutions with fewer CFD simulations than the traditional approach. The results of design exploration with GA-CFD suggest that the combination of design parameters, namely, location of the infected patient; air change rate; airflow rate through local exhaust grille; number, location and size of supply diffuser and local

exhaust grille, can be critical in minimising the risk of cross-infection in a ward. Further, the study highlights the need for healthcare workers to judiciously practice and implement standard infection control guidelines such as hand hygiene, eye protection and wearing face masks with high filtration efficiency, irrespective of the ventilation strategy adopted.

As a concluding remark for this study, a few crucial insights are highlighted that would be explored to improve the work further. The three major factors influencing the viral transmission mechanism are generation, transport and destination (inhalation or deposition). This study considers only contact transmission of infection through the deposition of infectious pathogens. However, airborne disease transmission through inhalation is also significant in indoor environments. In a follow-up study, the methodology proposed in this paper will be utilised to determine ventilation strategies to mitigate the risk of infection by inhaling particles suspended in indoor air. Moreover, this study only considered mixing ventilation, whereas displacement ventilation needs to be evaluated for infection control.[59, 60] Hence, future work will consider different ventilation configurations as additional design parameters.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Author contributions:

All authors contributed equally to the preparation of this manuscript.

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