



Assessing the effects of transient weather conditions on airborne transmission risk in naturally ventilated hospitals

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ARTICLE INFO

Article history:

Received 22 January 2024

Accepted 22 February 2024

Available online 4 March 2024

Keywords:

CONTAM

Transient

Weather conditions

Airborne transmission

Hospital

Natural ventilation



SUMMARY

Background: Many UK hospitals rely heavily on natural ventilation as their main source of airflow in patient wards. This method of ventilation can have cost and energy benefits, but it may lead to unpredictable flow patterns between indoor spaces, potentially leading to the unexpected transport of infectious material to other connecting zones. However, the effects of weather conditions on airborne transmission are often overlooked.

Methods: A multi-zone CONTAM model of a naturally ventilated hospital respiratory ward, incorporating time-varying weather, was proposed. Coupling this with an airborne infection model, this study assessed the variable risk in interconnected spaces, focusing particularly on occupancy, disease and ventilation scenarios based on a UK respiratory ward.

Results: The results suggest that natural ventilation with varying weather conditions can cause irregularities in the ventilation rates and interzonal flow rates of connected zones, leading to infrequent but high peaks in the concentration of airborne pathogens in particular rooms. This transient behaviour increases the risk of airborne infection, particularly through movement of pathogens between rooms, and highlights that large outbreaks may be more likely under certain conditions. This study demonstrated how ventilation rates achieved by natural ventilation are likely to fall below the recommended guidance, and that the implementation of supplemental mechanical ventilation can increase ventilation rates and reduce the variability in infection risks.

Conclusion: This model emphasises the need for consideration of transient external conditions when assessing the risk of transmission of airborne infection in indoor environments.

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<https://doi.org/10.1016/j.jhin.2024.02.017>

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Introduction

Airborne transmission is an infection route for many pathogens, including severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2), influenza viruses, measles virus

and *Mycobacterium tuberculosis* [1]. Transmission is strongly influenced by ventilation and indoor airflow [2,3], and this includes air movement to connected spaces, possibly causing infections in spaces where the infectious person is not present. Reducing the risk of airborne transmission is especially important on respiratory wards as patients are particularly vulnerable, there is high prevalence of lung infections caused by potential airborne pathogens, and respiratory disease is a major contributor to pressure on hospital systems [4].

UK guidance states that most hospital wards should have fresh air ventilation rates of 6 air changes per hour (ACH) [5]. However, a large proportion of wards rely on natural ventilation, usually by opening windows, making the ventilation rate highly dependent on weather conditions and the opening sizes of windows, doors or leakage [6]. Natural ventilation is wind driven, governed by wind speed and direction, or stack driven, governed by temperature differences [7]. These modes can work together or sometimes counteract one another, making natural ventilation an ambiguous method of ventilation [8]. Experimental studies in healthcare settings have reported a large variation in natural ventilation rates, ranging from 3.4 to 6.5 ACH with windows open in a UK Nightingale ward [9] to extremely high levels of ventilation up to 28 ACH in Peru [10] or 69 ACH in Hong Kong [11]. However, these studies were for single spaces with good openings, and all discussed how natural ventilation is uncertain and difficult to control, suggesting that mechanical ventilation may be more reliable [9,11]. Natural ventilation is highly dependent on occupant behaviour [6,11], and is reduced substantially if the occupant responds to external conditions by closing windows or doors [12–14]. Additional factors which reduce efficiency include safety features that restrict window opening, and reducing wall vents and leakage to improve energy efficiency [9].

Mathematical models are useful to understand the risk of infection in indoor spaces, but the majority of the current models consider single-zone spaces and overlook the importance of transient weather and occupancy effects [15]. Studies have begun to consider multi-zone approaches [15–17], and express the importance of connected spaces when considering airborne contaminant transport [18,19], with more recent work providing evidence of transmission to neighbouring zones [20,21]. CONTAM software [22,23] is commonly used to simulate contaminant transport directly within multi-zone indoor environments [14,24–26], or as a tool for airflow simulation alone, which can then be used in other models, such as a state-space model [27], to assess mitigation strategies [28,29] or to evaluate the risk of infection [30]. Previous studies have considered the impact of seasonality and weather conditions on disease transmission [13,25,31–38], and suggest the need to use varying weather effects within models. The majority of zonal models use steady-state weather conditions, including for contaminant transport in hospitals [39], offices [29] and dwellings [19,40]. More recent studies have begun to analyse the effects of using transient weather conditions to assess contaminant transport, such as using CONTAM software in dwellings [26,41,42]. Zhu *et al.* [43] used CONTAM software to conduct a whole-building simulation of two college halls of residence with transient weather conditions to model respiratory infections, with the use of measured Carbon Dioxide (CO₂) to validate the model; CO₂ has been used as a proxy for ventilation efficacy in calculating the risk of infection [44].

This study used a modelling approach to explore the likely variation in airborne infection risks due to external weather conditions in a multi-zone naturally ventilated respiratory ward. CONTAM software was used to simulate airflow, coupled with a previously developed susceptible-exposed-based transmission model [15]. Through this coupling, the effects of transient weather conditions on indoor airflow and risk of infection were assessed, applying the methodology to a specific fixed-occupancy scenario over longer time scales, and the variability in exposure to infection under different ventilation conditions was explored.

Methods

Airflow simulations

CONTAM 3.4.0.3 [22,23] was used to simulate the ventilation in a multi-zone hospital ward, based on a UK NHS hospital trust respiratory ward, which relies on natural ventilation through windows, doors and leakage as its main source of airflow. A 12-zone subset was selected to be representative of the space; this can be seen in Figure 1, showing room labels, volumes, building orientation and window location. The ward was representative of a typical layout of many UK hospitals, with a combination of multi-occupancy bays and single cubicles.

The CONTAM model set-up is described in detail in Supplementary Material A. Windows were assumed to remain open and doors closed for the full duration of the simulation. Corresponding leakage for the windows and doors in each zone represents small gaps present around these elements. Window open dimensions and model flow parameters considered the restricted openings present in NHS hospitals (Supplementary Table A1). Internal zones without windows (Zones 5–8) had an internal temperature of 25 °C. External zones with windows (Zones 1–4 and 9–12) had an internal temperature of 22 °C. For cases with additional mechanical ventilation, an air handling system is defined in CONTAM with a balanced supply and extract ventilation, so as not to create any new pressure differences in the ward.

The governing equations for the CONTAM simulation followed the methodology used in previous work [15] (Supplementary Material B.1). The airflow simulations were solved transiently over a 6-month period (1st April–30th September 2021), and the calculation time step was 30 min. A transient weather file for the Leeds area in 2021 [45] was used to represent the external environmental conditions throughout the simulation, such as ambient temperature, barometric pressure, wind speed and wind direction. The mean values in the weather data were air temperature of 10.18 °C, barometric pressure of 100,785.61 Pa, wind speed of 4.40 m/s and wind direction of 226.68° (south-westerly). A wind rose plot of the weather data is provided as Supplementary Figure C1. The only factors that varied within the simulations were weather conditions; all other conditions remained constant.

Transmission model

The airborne infection transmission model was adapted from the authors' previous work [15] (Supplementary Material B.2). The approach was based on the Wells–Riley equation, and assumes that an infectious individual emits a pathogen into

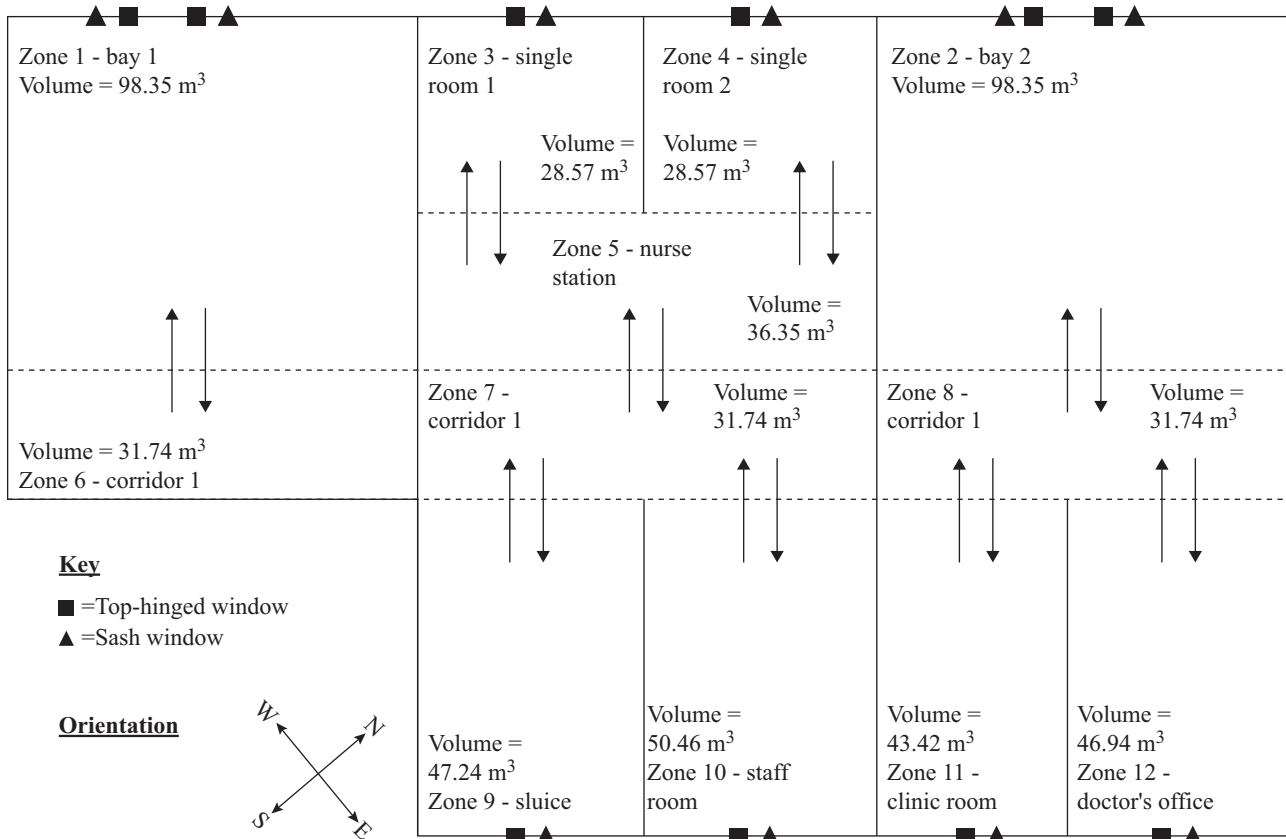


Figure 1. Twelve-zone subset of a UK respiratory ward showing the zone number, type and volume for each zone, orientation of the geometry, and location of windows. Modelled occupancy included four individuals in Zones 1 & 2, three individuals in Zone 10, two individuals in Zone 11, one individual in Zones 3, 4, 5 and 12, and zero individuals in Zones 6, 7, 8 and 9.

the air at a constant rate, defined as infectious doses or quanta per hour. The ventilation from the CONTAM model was used to determine the concentration of pathogen in air, which was linked to a pulmonary breathing rate to calculate exposure for susceptible individuals. To model transient variation in risk of infection, ventilation rates and interzonal airflow were exported from the CONTAM solution and used in the transmission model.

To assess the total number of predicted infection exposures, the simulation was split into weekly periods as the 6-month airflow simulation is an unrealistically long period to have a single infectious person present with no treatment or secondary infections emerging. The total predicted exposures from the model were recorded at the end of each week, considering whole-person exposures only, and then the initial conditions reset. This used the transient quanta concentration, calculated from the emission rate, airflow and corresponding weather conditions for that given week. This was repeated across the 26 weeks within the 6-month period of the simulation. These values were used to form a distribution, showing the probability of a particular number of exposures on a given week across the ward, assuming that one infected person was present for the duration of the week.

In addition to the probability distribution for predicted exposures, a risk index (RI) was calculated. The RI represents the average fraction of individuals exposed across the whole ward, and can be calculated using Equation (1).

$$RI = E \left[\frac{E(t)}{n} \right] \quad (1)$$

where $E(t)$ is a random variable which represents the predicted number of exposures, and n represents the total number of susceptible people. To calculate RI, $P\{E(t) = x\}$ is used as the probability, as a proportion out of all 26 weeks, that $E(t) = x$ predicted whole-person exposures. This probability is then multiplied by x and divided by the total number of susceptible individuals present, n . This is done for all possible values of x , and then the sum is used, as indicated in Equation (2).

$$E \left[\frac{E(t)}{n} \right] = \sum_{x=0}^n \frac{x}{n} P\{E(t) = x\} \quad (2)$$

Results

Comparison with measured data

To ensure the modelled airflow was realistic, CO₂ values were simulated using CONTAM and compared against experimental data measured for a single internal zone (Zone 5) using an Airvisual pro sensor (IQAir) at 10-s intervals in October 2019. The sensor was located on the nursing station and recorded temperature, humidity, particulates and CO₂ continuously, although only the CO₂ data were used in this study. The sensor

range for CO₂ measurement is 400–10,000 parts per million (ppm) with accuracy of 70 ppm ±3% at temperatures up to 50 °C and relative humidity up to 95%. In the model, individuals present are sources of CO₂, with a generation rate of 0.005 L/s [46] and are assumed to be in a fixed location for the full duration of the simulation. Although this is unrealistic in terms of specific individuals being present at the same location for the full duration, it is representative of the average ward occupancy over that period e.g., if a patient is discharged or moved, it was assumed they were replaced. The outdoor ambient concentration of CO₂ was taken to be 400 ppm. Simulations were carried out for the October weather data for two cases: (i) with all doors closed; and (ii) with the patient zone doors closed (Zones 1, 2, 3 and 4) and other doors open. The CO₂ concentrations for simulated and measured data are plotted as a histogram, separated into three bins; 400–800 ppm, 800–1200 ppm and >1200 ppm (Figure 2).

Despite the fact that the authors were unable to model the exact transient occupancy, window opening behaviour or weather conditions that the real ward experienced, the simulated and measured data show very good agreement. In the case where only the patient zone doors were closed, a difference <±5.5% was seen, which was considered to be sufficiently close to conclude that the CONTAM model can represent the airflow realistically within this multi-zone space. Although this was not a full validation, due to the difficulty in replicating the exact conditions of the measured data, this offers reassurance that the airflow simulation captures the features of this hospital ward.

Transmission model analysis

The simulations assume one infectious individual in Zone 5, and 16 initially susceptible individuals across the ward. The quanta emission rate of the infector is $q_5 = 0.5$ quanta/min, and the pulmonary rate of all individuals is $p_k = 0.01$ m³/min for all zones k [15,16]. The initial quanta concentration is $C_k(0) = 0$ in each zone.

Variability of natural ventilation

The first scenario considered the case where ventilation is provided solely by natural ventilation via the windows, and all doors are closed. Figure 3a shows the modelled transient concentration of airborne pathogen over the whole 6-month

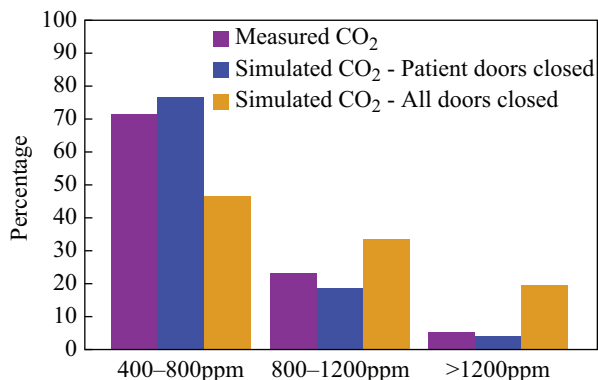


Figure 2. Comparison between simulated and measured CO₂ values for the month of October for Zone 5.

period (1st April–30th September 2021). Sharp peaks are a prominent feature, which suggests that particular hours or days may pose a higher risk of infection than others. As the transmission model imports the airflow from CONTAM, these peaks happen as a direct result of the airflow within the space, driven only by the transient weather conditions. To illustrate the frequency of peaks, a probability density histogram for the quanta concentration is shown in Figure 3b. The majority of values are <0.5 quanta/m³, with only 4.57% of values above this threshold; the zoomed portion of this plot only represents 0.35% of all concentration values. This is useful in showing that, although these spikes may appear to be the dominant feature in Figure 3a, the highest concentration values are highly infrequent in comparison with the majority of concentration values over time.

Figure 4a shows the predicted exposure distribution for a typical week, with the RI value [Equation (1)] superimposed. There is a relatively high risk of exposure across the ward, with the possibility of up to 12 of the susceptible population becoming exposed to infection. As the doors to each zone are closed, with the infector remaining fixed in one zone, the risk is driven solely by the interzonal airflow as a response to external conditions, leading to pathogen transport through the leakage around doors. This illustrates the importance of multi-zone models with connected airflow, as there may be a non-zero risk of transmission despite the absence of an infector. The large spread of the distribution, ranging from four to 12 individuals, suggests a significant variability in exposures, highlighting the uncertainty that is occurring due to the weather conditions. These results also suggest the possibility of elevated risk on particular days or weeks over the 6-month period, meaning that part of the risk experienced when visiting or being admitted to a hospital ward may be pre-determined by the weather.

In this scenario, RI = 0.5288, translating to 52.88% of individuals becoming exposed across the whole ward on a typical week. This appears to be a high value; however, it is a worst-case scenario, as it was assumed that the infector was present in the ward for the whole time period. In Figure 4b, the RI for each zone is illustrated as a heat map, giving an insight into the risk in each zone, rather than a ward as a whole. The RI for each zone is calculated using the zonal population as n in Equation (1), instead of the ward population, to give risk as a proportion of the number of people typically in the space. The variation in risk could be suggestive of a particular airflow pattern, where infectious material is more likely to be transported to particular zones. For example, Zone 10 has a considerably higher risk than the other zones, and also has a larger typical occupancy of three individuals compared with the other rooms. Similarly, Zone 2 experiences almost zero risk from the infector in Zone 5, but adjacent rooms have an elevated risk. The results here illustrate the uncertainty caused by natural ventilation, and the dominance of the weather conditions on determining the airflow and risk of airborne transmission in indoor environments.

Addition of mechanical ventilation

The effects of adding 3 ACH or 6 ACH mechanical ventilation alongside open windows, with all doors closed as before, were explored. The probability distribution for the predicted exposures, the overall ward RI, and the zonal RI heat map are shown in Figure 5. The results show a substantial reduction in risk,

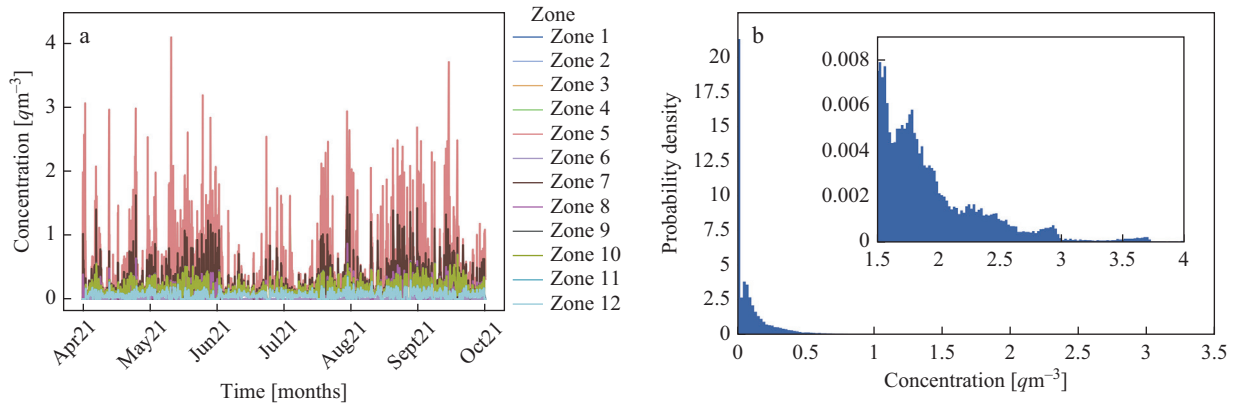


Figure 3. Simulated concentration of pathogen in the air for ‘natural ventilation only’. (a) Concentration in each zone for a 6-month period; (b) probability density histogram of the quanta concentration values, with a zoomed portion showing the infrequent higher values.

with predicted exposures now ranging from zero to two individuals, illustrating a much smaller spread to the distribution and, thus, less uncertainty. With 3 ACH additional mechanical ventilation, the ward RI = 0.0769, which is >85% reduction compared with the original case. This can also be illustrated in the heat map (Figure 5b), suggesting that the virus would be better contained with less-affected zones and only one zone with risk >40% (compared with five zones in the original case). In the case with 6 ACH mechanical ventilation (Figure 5c), the recommended rate for NHS patient wards [5], RI is reduced to 0.0168, which is >96% lower than the original case, and an additional 11% reduction from the 3 ACH scenario. The zonal RI heat map (Figure 5d) indicates low risk across all zones, with only one zone having a non-zero risk (<9%).

The addition of mechanical ventilation contained the infectious quanta concentration and reduced pathogen transport more effectively than weather-driven natural ventilation alone, eliminating the uncertainty that was originally present. It is possible that, under some weather conditions, natural ventilation and the consequent airflow make a greater contribution to the transport of pathogen into connected spaces, rather than being efficient at the removal of the infectious

quanta concentration. This further demonstrates that the effects seen in the original scenario were a direct consequence of the transient weather conditions. It is important to note that this is an idealised scenario, and, in reality, imperfect balancing of mechanical ventilation systems and the behaviour of people will likely mean that the difference between natural ventilation and mechanical ventilation is not as stark.

Ventilation rates

Figure 6a presents a probability density plot illustrating the ventilation rates predicted by the CONTAM model for a period of 6 months for the ‘natural ventilation only’ case and the ‘natural ventilation + 3 ACH mechanical ventilation’ case.

With natural ventilation alone, 82% of predicted ventilation rates fell below 1 ACH and 99.5% fell below 2 ACH, with the highest not surpassing 2.6 ACH, which is less than half of the recommended rate. The mean ventilation rate achieved across the ward is 0.61 ACH. The addition of 3 ACH mechanical ventilation resulted in the same shaped distribution as in the original case, but shifted to a higher value. However, ventilation rates still fell below the recommended rate of 6 ACH [5].

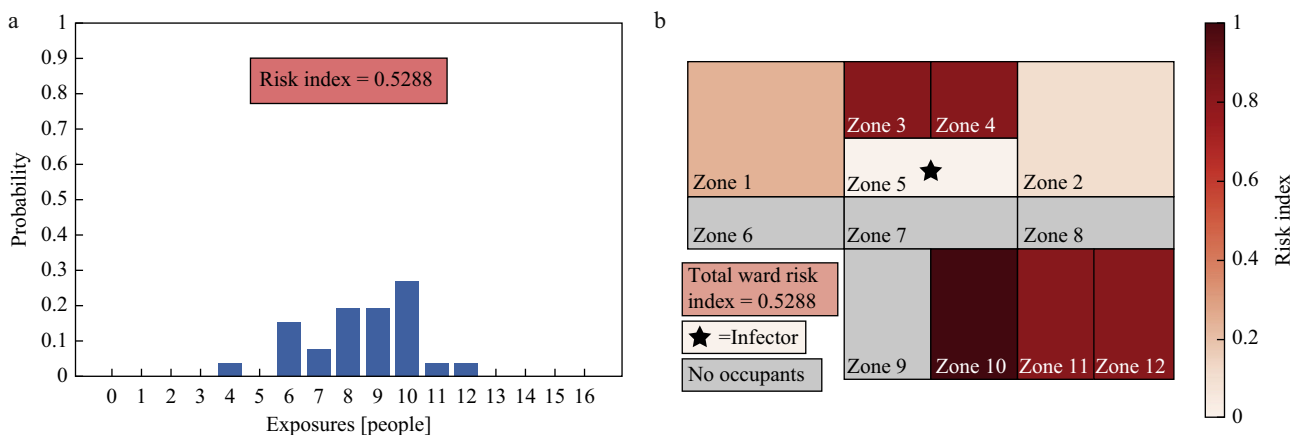


Figure 4. Predicted exposures for ‘natural ventilation only’. (a) Probability distribution showing predicted weekly exposures and risk index across the whole ward; (b) heat map showing the zonal risk index value based on predicted exposure.

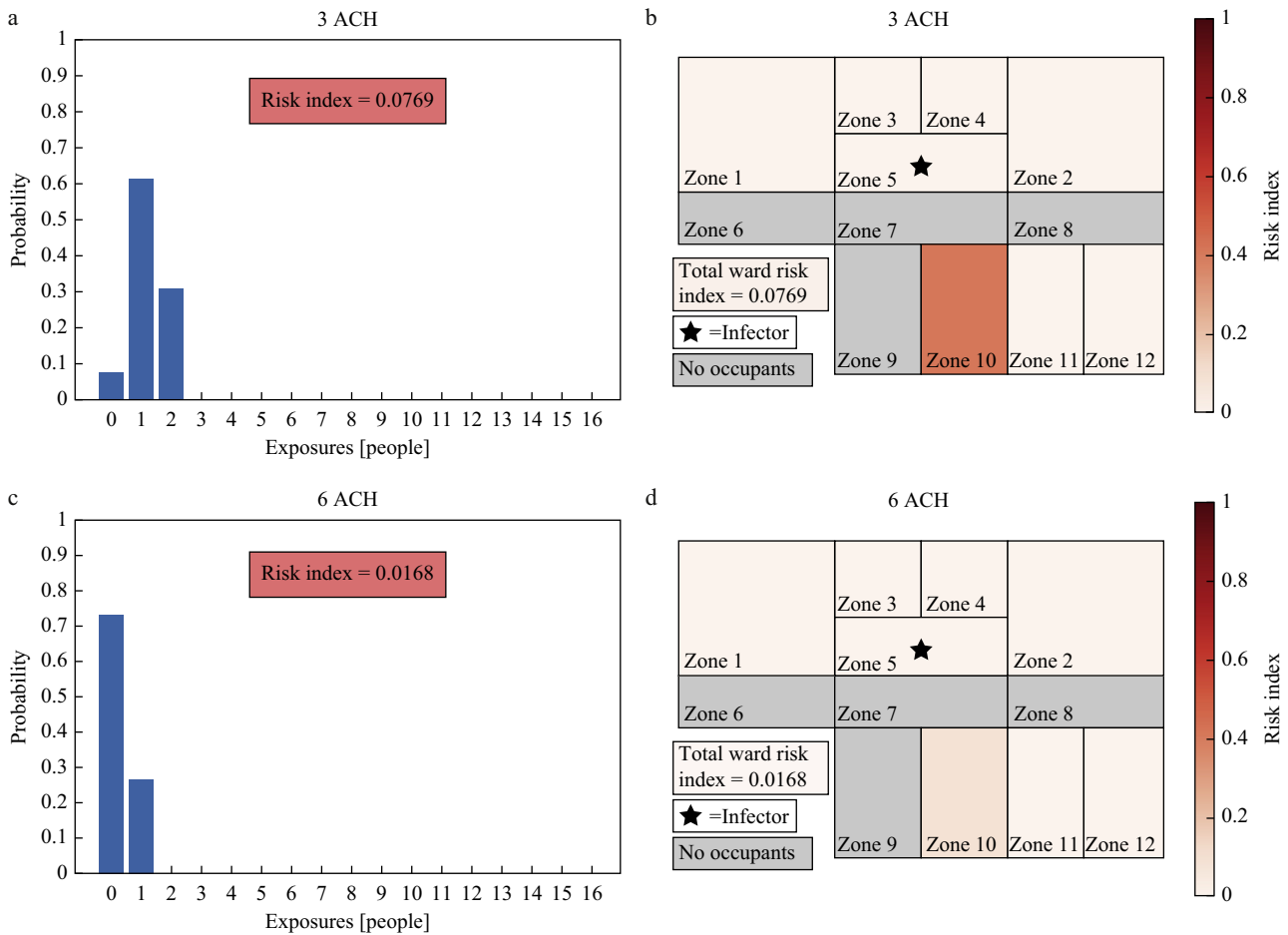


Figure 5. Predicted exposures with the addition of mechanical ventilation. (a,c) A weekly probability distribution across the whole ward together with the risk index value; (b,d) heat map showing the zonal risk index value based on predicted exposures. ACH, air changes per hour.

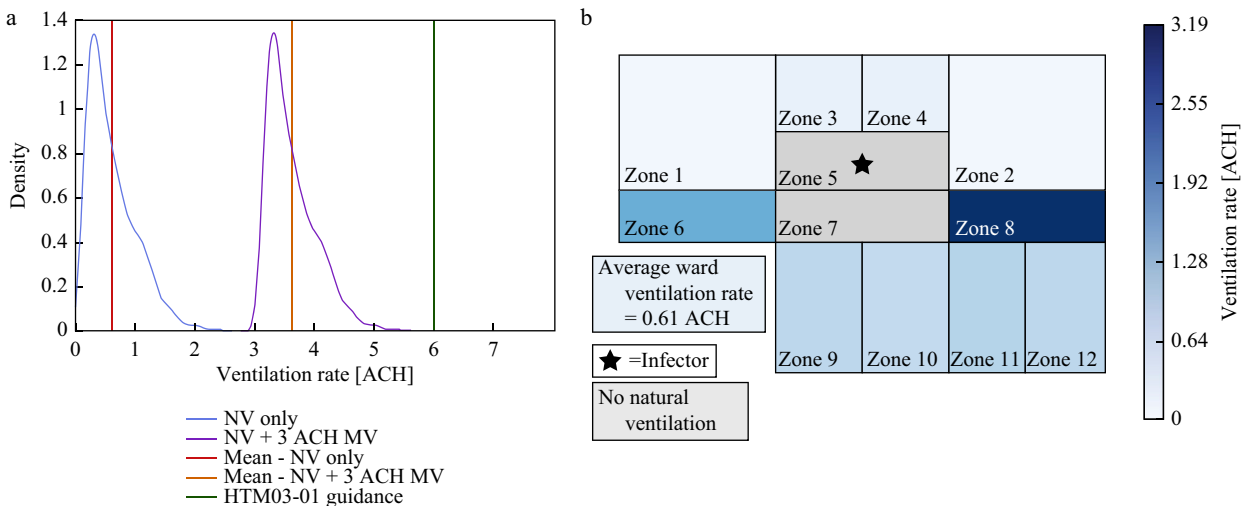


Figure 6. (a) Probability density plot showing the overall and mean ventilation achieved across the ward for both 'natural ventilation (NV) only' and 'natural ventilation + 3 air changes per hour (ACH) mechanical ventilation (MV)'; (b) heat map illustrating the average ventilation rates achieved for 'natural ventilation only' for each zone.

The heat map in Figure 6b indicates that the south-easterly side of the building was much better ventilated, giving an insight into the airflow pattern across this subset of zones. This could be useful in informing healthcare professionals of the best zones in which to place an infectious individual, or which zones may be in greatest need of additional intervention.

Open bay scenario

To fully assess the capabilities of natural ventilation alone, a final scenario was considered where all windows and doors were fully open for the duration of the simulation. This aimed to mimic a 'Nightingale-style' hospital ward, which is fully open.

The exposure probability distribution (Figure 7a) shows RI = 0.0505, which is one of the lowest values across any of the scenarios. The heat map (Figure 7b) is almost identical to the scenarios with open windows and mechanical ventilation. When natural ventilation is used on a ward with open bays, allowing for crossflow across the whole building, it can be an effective tool. The simulations predicted up to 48 ACH average ventilation rates in particular zones in the ward, which is comparable to measurements in Peru [10] and Hong Kong [11]. However, in practical terms, when window openings are restricted for safety and thermal comfort, and doors are installed and closed for privacy or infection prevention and control, natural ventilation rates are reduced significantly.

Discussion

These simulation results illustrate the effects of weather conditions, building design and behavioural factors on airborne transmission when relying on natural ventilation. The initial scenario with natural ventilation alone illustrates how weather conditions can vary the risk of infection. The highest quanta concentrations happen infrequently (Figure 3), but may be important for the transmission of infection. Other key factors will include the presence, type and transmissibility of infection. However, the models represent a worst-case scenario, which show that when a set of conditions come together, such

as the sustained presence of a more infectious individual combined with particular weather conditions, the chances of an outbreak become more likely.

The positive benefits of mechanical ventilation are well established and illustrated in the model when 3 ACH and 6 ACH are added to the natural ventilation. Despite 3 ACH of mechanical ventilation being half that of the UK recommended rate, it still dominated over natural ventilation, and dampened the effects of external weather conditions, reducing risk and uncertainty in both scenarios (>85% reduction in RI value). The addition of 6 ACH led to a further 11% reduction in the RI value. Thus, 3 ACH delivers the majority of the reduction, suggesting that even an underspecified mechanical ventilation system will provide better dilution and consistency as opposed to not acting at all. Whilst the application of air cleaners was not explicitly modelled, a similar result would likely be obtained.

This study demonstrated that poor ventilation rates are likely to be achieved when relying on natural ventilation alone, due, in part, to the internal design of hospitals and limited access to the ambient environment. Buildings contain many internal zones which do not have windows, leakage or vents to outside air; unless other mitigations are put in place, these locations may have no ventilation at all. Many hospitals designed with open bays have had doors added for patient privacy, and in older buildings, existing windows or outlets have more recently been reduced in size due to safety measures, or removed completely in an effort to improve energy efficiency [9]. Despite the original hospital design being able to provide sufficient ventilation, it is now likely that over time, many of these conditions are no longer met. It is critical that internal airflow is considered as part of a retrofit, and where modifications restrict window openings or reduce flow paths, additional ventilation should be considered to compensate.

This model has potential to identify dominant airflow patterns, and locations around the hospital which may alter ventilation and susceptibility to airborne infection. For example, in Figure 6b, zones on the south-easterly side of the building displayed higher ventilation rates than those on the north-westerly side, suggesting that air flows in a south-easterly

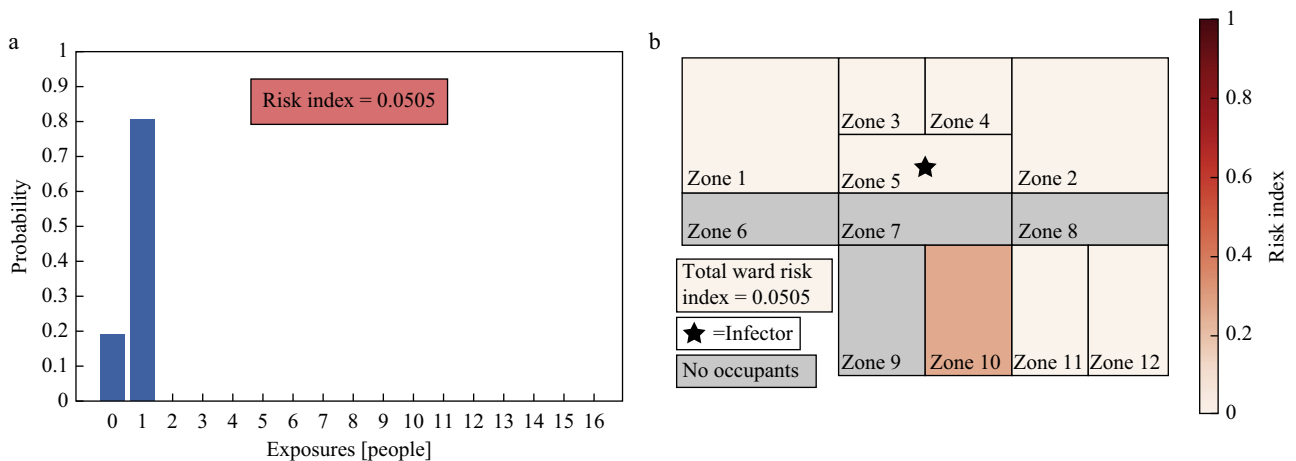


Figure 7. Predicted exposures for the 'open bay' scenario. (a) Probability distribution showing the weekly predicted exposures across the whole ward; (b) heat map showing the zonal risk index value based on predicted exposure.

direction. Additionally, in every scenario, the RI in Zone 10 was consistently higher, suggesting that this zone was susceptible to a dominant flow path carrying pathogens from the infector in Zone 5. It is possible that internal airflow rates governed by natural ventilation have a large impact on pathogen transport to these zones, but the zone ventilation rate is not efficient, nor fast enough for the removal of infectious material. This further supports the use of mechanical ventilation, or alternative approaches such as air cleaners, contrary to relying solely on natural methods.

As this study is based on a model, it has a number of limitations. The model is based on the floor plan, occupancy, windows and representative weather conditions for a single UK respiratory ward. However, the model does not aim to quantify risks explicitly on that ward. The scenarios were designed to be realistic, but only considered the influence of ventilation and not the complexities that exist in a real ward. The model is idealised and does not fully capture all the factors that create internal flows, including turbulent mixing, which is not present in the CONTAM airflow model, and variations in internal temperatures. However, the comparison of the airflow with CO₂ data suggests that the mixing achieved is realistic.

The use of a local transient weather file [45], using real historical data, enabled the modelling of possible scenarios. As with any transmission model, validation against infection cases is almost impossible, as identifying where the source of an outbreak originated, and replicating the exact transient behaviours, occupancy and external conditions at the time is difficult. The limitations of transmission models are discussed in Edwards *et al.* [15]. The choice of the infectiousness of an individual will adjust the RI values in these scenarios. For example, in the first scenario with natural ventilation alone, simulations with a pathogen emission rate of $q = 1$ quanta/h and $q = 10$ quanta/h result in RI values of 0.0337 and 0.2644, respectively. However, this does not alter the relative risk in each space, nor the overall spatial behaviour of pathogen transport to interconnected zones. In this study, the same infectiousness of $q = 0.5$ quanta/min ($q = 30$ quanta/h) was used as in previous work [15,16]. This is a realistic choice given that Mikszewski *et al.* [47] presented ranges of 15–4213 quanta/h for SARS-CoV-2, 18–8640 quanta/h for measles virus and 0.11–79 quanta/h for influenza virus. It was not the intention of the present study to predict exact outbreak patterns; rather, by using the modelling approach, the authors were able to develop a much better understanding of the long-term effects of natural ventilation and weather conditions on airflow and the potential for an outbreak.

The heat map illustrating the zonal RI could be used to help healthcare professionals identify areas of high risk, and to translate the complex modelling and mathematical assessment more easily into usable features for healthcare systems. This could be particularly useful in distinguishing between the ward or zone which requires intervention. In the scenario of a pandemic where the hospital is under elevated pressure with a scarcity of resources such as personal protective equipment (PPE), the heat map could help to assess whether the ward as a whole is high risk or whether it is only particular zones. For example, in Figure 4b, there are numerous zones with elevated risk and so it may be easier to apply a blanket mitigation of PPE to the whole ward. Whereas in Figure 5b, only Zone 10 has increased risk so here it could be more appropriate to only apply PPE to the visitors to this particular zone. Although this

study did not investigate the implementation of outputs (e.g. heat maps) into healthcare systems directly, this accessibility and comprehensible illustration of the results is a priority.

In conclusion, through the use of transient weather conditions within an airflow and transmission model, this study highlighted how weather conditions have a significant influence on internal airflow, and can lead to uncertainty and periods of higher pathogen concentrations within ward environments. When these conditions are combined with the presence of a more infectious person on the ward, the probability of a large outbreak increases. This uncertainty also extends to ventilation rates, with many naturally ventilated spaces falling far below the recommended standard. Reliance on closed internal doors and restricted window openings is not likely to provide sufficient ventilation for wards based on the recommendation of 6 ACH provided in the guidance [5].

Mechanical ventilation or other similar approaches, such as the use of air cleaners, can help to reduce the effects of transient weather on natural ventilation. This includes ensuring a more consistent in-room ventilation rate, and reducing the unwanted transfer of air between spaces, and can, in turn, decrease the risk to patients. Through illustrative outputs such as heat maps, the authors hope to be able to advise engineering and healthcare professionals of the risk distribution of their multi-room hospital wards, and help make informed choices of mitigation strategies; this will be explored in future work.

Acknowledgements

The authors wish to acknowledge the support of Dr Ian Clifton and Leeds Teaching Hospitals NHS Trust.

Author contributions

AJE: writing – review and editing, writing – original draft, visualization, validation, software, resources, project administration, methodology, investigation, funding acquisition, formal analysis, data curation, conceptualization. M-FK: writing – review and editing, conceptualization, funding acquisition, supervision. ML-G: writing – review and editing, conceptualization, funding acquisition, supervision. DP: writing – review and editing, conceptualization, funding acquisition, supervision. CJN: project administration, writing – review and editing, conceptualization, funding acquisition, supervision. Compliance with ethical standards.

Conflict of interest statement

During the COVID-19 pandemic, CJN was a participant in the UK Scientific Advisory Group for Emergencies (SAGE), and co-chaired the SAGE Environment and Modelling Sub-Group. The other authors have no competing interests to declare that are relevant to the content of this article.

Funding sources

AJE is funded by the Engineering and Physical Sciences Research Council Centre for Doctoral Training in Fluid Dynamics (Grant No. EP/S022732/1).

Data accessibility

The code and data are available at https://github.com/scaje/Contam_study_AJE.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jhin.2024.02.017>.

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