Appraising healthcare ventilation design from combined infection control and energy perspectives

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ABSTRACT

This paper considers an approach for assessing the balance between energy use and infection control in hospital ward ventilation by combining a stochastic disease outbreak model with a cost evaluation. Disease dynamics are simulated using a Susceptible-Exposed-Infector-Removed (SEIR) infection modelling approach, with the contact rate due to airborne transmission incorporated through coupling with the Wells-Riley model. Results presented for a hypothetical ward scenario demonstrate that stochastic effects in a small population, such as a hospital, are a controlling factor in the risk of an outbreak and that conventional deterministic models may give misleading results. Cost appraisals clearly show the trade-off between ventilation provision and infection risk depends on many factors including the disease characteristics, people concerned, ventilation system design and rate and the costs of both providing ventilation and treating infections. Although limitations in the input data currently reduce the robustness of the outputs, the approach is shown to be a useful framework for a tool that can quantitatively assess ventilation design from different perspectives for healthcare environments. The paper also highlights some of the knowledge required from further research to enable better quantification of the behaviour of pathogens and the transmission processes for hospital infections.

INTRODUCTION

The choice of ventilation system for hospital environments is influenced by many factors. High risk environments, such as isolation rooms, operating theatres and pharmaceutical areas, are generally dominated by infection concerns with this driving the ventilation agenda. For example in the case of airborne infection isolation rooms, and the provision of a high airflow rate to ensure dilution of pathogens within the room and an appropriate pressure regime to limit transfer of pathogens between the room and neighbouring spaces, delivered by a mechanical means, tends to be the ventilation system of choice (Booth et al. 2009). Depending on the application and level of risk, fine particle filtration or other air disinfection techniques may be employed on the supply and/or extract air (Department of Health 2007, Jensen et al. 2005). Ventilation is also driven by the infection control agenda in operating theatre environments with the complexity of the system increasing with risk. At the highest end, Ultra Clean Ventilation theatres for high risk surgery such as orthopaedics have downflow air movement of up to 0.6 m/s (1.97 ft/s) in the central zone (Friberg et al. 2002) with room airflow circulated through ceiling mounted High Efficiency Particulate (HEPA) filters to provide a constant velocity downflow region over the operating area (Chow and Yang 2004). While factors such as energy use and plant size will be considered during design, they are generally not the primary drivers in the specification of these specialised ventilation systems. In both these cases air flow rates, pressure differentials and levels of air cleaning generally increase with the likely risk in the environment. Clearly this will substantially increase costs but on the whole is easily justified by the better clinical outcomes for the patients. For example the ventilation costs for an immune-compromised transplant patient who requires positive pressure isolation with a HEPA filtered supply after surgery are likely to be minor compared to the clinical costs of carrying out a transplant.

However in most patient environments such as wards, waiting areas, outpatient clinics and treatment rooms the most appropriate ventilation design is not so clear cut. In this case the thermal comfort of patients and the energy performance of the system are seen as equal, if not more important concerns than the transmission of infection. Balancing these demands is typically tackled by a broad guidance approach, using generic ventilation rates and comfort temperatures set out in national documents (Department of Health 2007) and the choice of mechanical or natural ventilation determined by local conditions, other elements of the building design and the expertise of those designing the system. The resulting ventilation, while probably adequate will generally have no formal evaluation that considers the balance between infection control, comfort and energy. As ventilation for infection control is associated with airborne transmission, this on the whole takes a back seat as most infections in general patient environments are regarded as being contact borne. However there is increasing evidence that the transport of pathogens through the air is linked to many common healthcare acquired infections (HCAI's) that are not regarded as airborne infections.

In recent years several studies have linked Methicillin-resistant *Staphylococcus aureus* (MRSA) with airborne transmission, both through the analysis of outbreaks (Farrington et al.

1990, Kumari et al. 1998) and through the sampling of air and surfaces in the environment (Noble 1962, Hathway et al. 2008). Many such studies indicate the role of general nursing activities such as bed-making (Roberts et al. 2006, Hathway et al. 2008) on the dispersion of the bacteria in the environment leading to environmental contamination and a increased risk of subsequent infection through indirect contact transmission. *Clostridium difficile* has also been associated with environmental dissemination and anecdotal suggestions of an airborne route have recently been supported by the sampling and culturing of *Clostridiumdifficile* spores from the air and high surfaces in a ward (Roberts et al. 2008). Of particular concern for hospitals, and of relevance to this paper, are those pathogens that are highly contagious and have a relatively short incubation period such that infected individuals are likely to spread the infection during the timescale that they are hospitalized. Several infections fall into this category including norovirus and influenza, which have the potential to rapidly infect whole wards, including the healthcare staff, resulting in ward closures, cancelled operations and pressure on the hospital operation (Chadwick et al. 2000). The incubation period for influenza is typically 1-3 days and patients may then be infectious for a period of 4-6 days (Hawker et al. 2001). Norovirus has a similar incubation period (1-2 days), but the patient is usually only highly infectious for around 2 days (Farr et al. 2004).

With mounting pressure on those who design and manage healthcare estates to meet both stringent infection and CO_2 reduction targets, there is a need for a better understanding of the interrelationships between airflow, infection, energy and comfort that can be applied to generic patient areas. This paper considers an approach to formally evaluating the trade-off between infection risk and energy performance through linking epidemic models with cost data. A stochastic formulation of a Susceptible-Exposed-Infector-Removed (SEIR) model coupled with the Wells-Riley equation is applied to a hypothetical hospital ward to explore the influence of environmental and disease parameters on the progression of an outbreak. A cost comparison is then made by evaluating the cost of treating infections against the costs of ventilating an environment. The study examines the level of uncertainty in the model and the data required to attain a reliable output.

AIRBORNE INFECTION OUTBREAK MODEL

Disease Dynamics

Models describing the dynamics of infectious diseases have been developed since the 1900's when scientists started to recognise patterns in the transmission of diseases that could be described mathematically. Today, general models for disease transmission are widely used and are well documented (Bailey 1957). A disease outbreak in a general population is commonly described by the process illustrated in Figure 1.

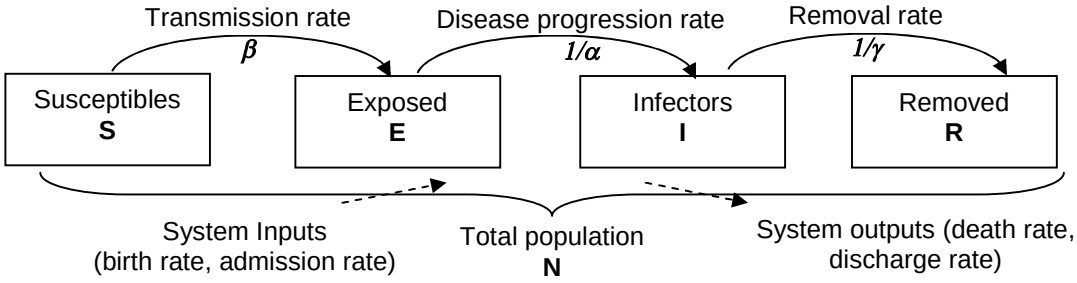


Figure 1: SEIR approach to evaluating a disease outbreak

Susceptible individuals (S) are exposed to infection at a particular rate (β) depending on the disease, transmission characteristics and prevalence within the population. Once exposed (E), individuals incubate the disease for a period of time (α) before becoming infectious themselves. As infectors (I) they potentially transmit the disease to others for a period of time (γ) before they are removed (R) from the process. The term removed is commonly used as a "catch-all" state that could include those who recover, those who may be physically removed by say isolation and those who die from the disease. If appropriate the process can be amended to separate out these different states. The total population involved in the process (N) comprises the sum of the Susceptible, Exposed, Infectors and Removed states at any point in the outbreak.

The basic process outlined in Figure 1 is known as an SEIR model and forms the underlying approach in this analysis. In its simplest deterministic form it is a series of differential equations that describe the rate of transition of people between the four states (Noakes et al. 2006). This can be appropriate for evaluating overarching behaviour and the role of different parameters as well as modelling disease transmission in large populations. However as the focus on this study is on a hospital ward, where the population is small and potentially transient it is essential to consider further the dynamics of transmission and the application of the SEIR model.

It is straightforward in an SEIR model to include the rates at which people enter or leave a population. In a population as a whole, this is most commonly the birth and death rates while in the context of a hospital outbreak this could be admission and discharge rates (Cooper et al. 1999). The model can also be extended to incorporate a range of other effects including the impact of vaccination and immunity (Chen and Liao 2008) and interaction between different diseases such as the impact of HIV/AIDS on tuberculosis dynamics (Massad et al. 1993). Dealing with different groups within a population is also possible although is more complex. Populations in hospital wards will comprise a range of people including patients, visitors, nursing staff, clinicians and ancillary staff, and the type of ward and management of the hospital will determine the time that each group spend on a ward and the frequency of visits. Cooper et al (1999) considered the dynamics of MRSA transmission on a ward and separated the population into separate staff and patient cohorts to incorporate the different interaction between them.

Several researchers including Fraser (2007) have developed models to simulate transmission within and between households to address the non homogeneous mixing seen in real populations; such an approach could also be applicable to mixing between groups in hospital wards.

In this case here we simplify the approach by considering that the population remains constant and not differentiating between groups of people. However we consider a stochastic formulation to include "chance" effects that are inherent in small populations. In this case we follow the approach used in Noakes and Sleigh (2009) and consider the outbreak as a series of events over time. In a small time interval, *dt*, such that the probability of more than one event is negligible, one of four outcomes is possible:

1. A new susceptible becomes exposed with probability Pr(SE) (S-1, E+1, I, R remain the same)
2. An exposed person becomes infectious with probability Pr(EI) (E-1, I+1, S,R remain the same)
3. An infector is removed with probability Pr(IR) (I-1, R+1, S, E remain the same)
4. Nothing happens (S,E,I,R remain the same)

In each case the probability of the event happening is governed by the rate parameters in Figure 1 and the current values of S,E,I and R to give

$$\Pr(SE) = \beta SI, \qquad \Pr(EI) = \frac{E}{\alpha}, \qquad \Pr(IR) = \frac{I}{\gamma} \tag{1}$$

Following Renshaw's (1991) approach as described in Noakes and Sleigh (2009) the model uses a computationally efficient method to consider the time to the next event. This is done by first calculating the total probability that an event (outcomes 1-3 above) may occur which is given by

$$\Sigma \Pr = \Pr(SE) + \Pr(EI) + \Pr(IR) \tag{2}$$

Each event probability can then be normalized to give

$$\Pr(se) = \frac{\Pr(SE)}{\Sigma \Pr}, \qquad \Pr(ei) = \frac{\Pr(EI)}{\Sigma \Pr}, \qquad \Pr(ir) = \frac{\Pr(IR)}{\Sigma \Pr} \tag{3}$$

The inter-event time, t can then be determined using

$$t = -\ln(Y) / \Sigma \Pr \tag{4}$$

Where Y is a uniformly distributed random number $0 \le Y \le 1$

The numerical simulation of the outbreak then follows the process:

- calculation of Pr(se), Pr(ei) and Pr(ir) at the current time-step
- generation of a first random number, $0 \le Y \le 1$ to find the inter-event time
- generation of a second random number $0 \le X \le 1$ to select the infection event with:
  Event 1 if $0 \le X \le \Pr(SE)$,
  Event 2 if $\Pr(SE) < X \le \left(\Pr(SE) + \Pr(EI)\right)$,
  Event 3 if $\Pr(SE) + \Pr(EI) < X \le \left(\Pr(SE) + \Pr(EI) + \Pr(IR)\right)$
  Event 4 if $\Pr(SE) + \Pr(EI) + \Pr(IR) < X \le 1$.
- Change in the values of S,E,I and R according to the infection event

The infection simulations were conducted using Excel and VBA (Microsoft) with a Monte-Carlo approach to enable each model to be run up to 500 times to establish the mean and variance in behaviour. As the inter-event times are different in every simulation due to the random number in the event time definition, the results were mapped onto a regular time scale at the end of each run to be able to compare data across more than one simulation.

Airborne transmission model

The risk of airborne transmission is incorporated through the widely used Wells-Riley model (Riley et al. 1978) which relates infection risk to the pulmonary ventilation rate of susceptible individuals, p (l/min or ft^3/min), the ventilation rate of a space, Q (l/min or ft^3/min) and the rate of infectious material produced by each infector known as the quanta generation rate, q (quanta/h). As shown in Noakes et al. (2006) the Wells-Riley model can be incorporated into the SEIR model through defining the transmission rate parameter β as

$$\beta = \frac{pq}{Q} \tag{5}$$

It is important to note that this model is not without its limitations and while more detailed discussion is given elsewhere (Noakes and Sleigh 2009, Sze To and Chao 2010) there are two points that should be acknowledged here. Firstly the risk model assumes a completely mixed airflow which is unlikely in the best ventilated rooms and even more unlikely across a whole hospital ward. Although not included here, this limitation can be relatively easily addressed by combining the model with multizone ventilation tools such as CONTAM or Computational Fluid Dynamics (CFD) models to assess the role of airflow patterns on the spatial distribution of infectious quanta (Noakes and Sleigh 2009, Qian et al. 2009). The model results also depend upon the value of quanta generation which is a difficult parameter to define as it essentially encompasses the concentration of infectious material, the virulence of the pathogen, the host susceptibility and the ability of the infector to produce an aerosolised pathogen. Values of quanta are generally derived from past outbreaks and rely on often incomplete knowledge of airflows and averaged infection rates to determine typical values. Values reported in the

literature for a number of infections are given in Table 1 and indicate the variability even within a particular disease.

Table 1: Quanta production rate for a range of infectious diseases (*LN = Log normal)

Disease	Case	Quanta/h	Reported by
Tuberculosis	Average patient	1.25	Nardell *et al* (1991)
Tuberculosis	Outbreak in office building	12.7	Nardell *et al* (1991)
Tuberculosis	Human to guinea pig transmission	0.3-44	Escombe et al (2007)
Multi-drug resistant Tuberculosis	Human to guinea pig transmission (highest infectors)	40,52,226	Escombe et al (2008)
Measles	Outbreak in a school	570	Rudnick and Milton(2003)
Influenza	School cases in Taiwan	66.91 (LN*)	Liao et al (2005)
Influenza	Aircraft outbreak	79-128	Rudnick and Milton(2003)
SARs	Taipei Hospital outbreak	28.77 (LN*)	Liao et al (2005)
Rhinovirus 16	Experimental data of Dick et al 1987	1-10	Rudnick and Milton(2003)

OUTBREAK MODEL BEHAVIOUR

The behaviour of the infection model was examined using a hypothetical case that is intended to be representative of a ward environment. The parameter ranges used in the model are given in Table 2. As the focus of the modelling here is on the level of control offered by ventilation, it is assumed that there is no physical isolation of infected cases and therefore people move from state I to state R in the SEIR model at a rate determined by the infectious period of the disease.

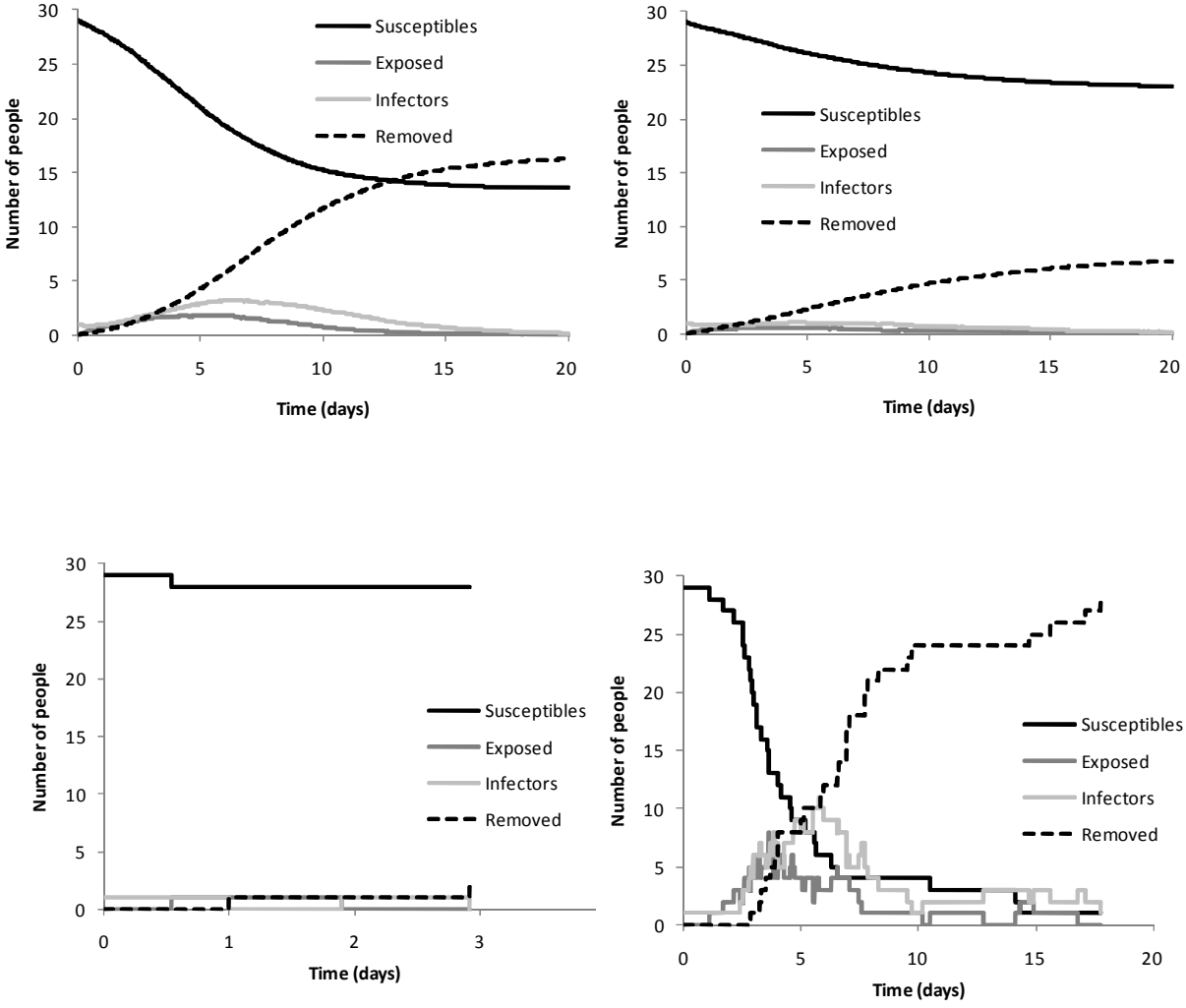
Table 2: Parameters used in the simulations.

Ward volume, V	1000 m^3 (35315 ft^3)	Pulmonary ventilation rate, p	10 l/min (0.35 ft^3/min)
Ventilation rate	3-12 AC/h	Quanta generation rate, q	5-20 quanta/h
Initial number of susceptibles, S	30	Disease incubation period, $1/\alpha$	1 day
Initial number of infectors, I	1	Disease infectious period, $1/\gamma$	1-2 days
Initial number of exposed, E	0	Duration of simulation	20 days
Initial number of removed, R	0		

Outbreak Dynamics

Figures 2 and 3 show typical simulation results, presenting average behaviour over 500 simulations and outbreak dynamics from a single run respectively. As expected, the mean results in Figure 2 show classic epidemic model behaviour that concur with previous deterministic approaches (Noakes and Sleigh 2006, Chen and Liao 2008) and suggest that an increase in ventilation rate may reduce both the total number of cases of an infection and the peak number of infectors. However the stochastic model enables the variability of the transmission process to be modelled, and as can be seen in Figure 3 the same set of conditions can lead to very different results. In Figure 3(a), the first infector (index case) only manages to

infect one other before both are removed. The infection therefore fails to spread and as such there is no outbreak. However in Figure 3(b) the infection has started to spread before cases are removed and a full blown outbreak occurs. As both scenarios have the same set of physical and disease parameters the difference between the two cases is due to the random nature of the stochastic model and the particular combination of parameters.



(a) Index case removed before infection spreads

(b) Infection spreads before removal leading to full outbreak.

Figure 3: Results from two single runs of the simulation with data as Table 2, q = 10 quanta/h, γ = 2 days and ventilation rate = 3 AC/h (a) Index case removed before infection spreads (b) Infection spreads before removal leading to full outbreak.

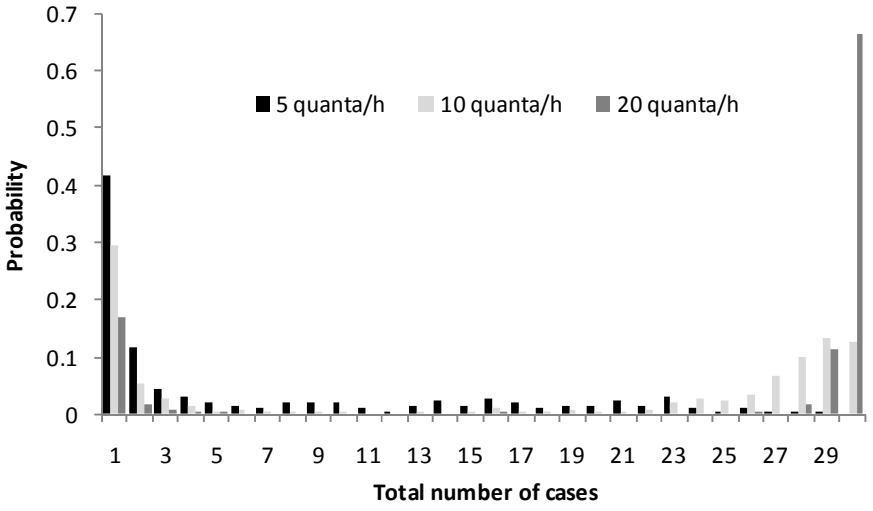
To further examine the variability in the model and the influence of disease and environmental parameters Figure 4 presents the probability distributions for the total number of cases over 500 simulation runs for both air change rates. A probability of only one case indicates that the infection has not spread beyond the index case, while 30 cases indicates that every person has succumbed to the infection. The results clearly show that as the transmission rate (β) increases, the distribution of the total size of the epidemic changes. As may be expected a lower value of β (lower quanta rate or higher ventilation rate) results in a distribution that is skewed to the left with the epidemic tending to die out before significant numbers are infected. However as β increases the results show a bimodal distribution with the likely outbreak size clustered at either end of the graph. Although the average behaviour of the model for such scenarios indicates that the number of cases will be in the middle of the range (Figure 2), the results in Figure 4 suggest that in most cases the behaviour is at the extremes; either the outbreak fails to get going with only a small number of cases or it progresses to a critical point whereby the majority of people are likely to be infected. This behaviour has been identified in mathematical texts examining the total size of stochastic epidemics and is related to the reproductive rate of the infection. In classic epidemic modelling theory the Reproduction Rate, Ro, of an outbreak is a measure of the average number of infections produced by a typical case and defined as

$$Ro = \frac{\beta}{\gamma} N \qquad (6)$$

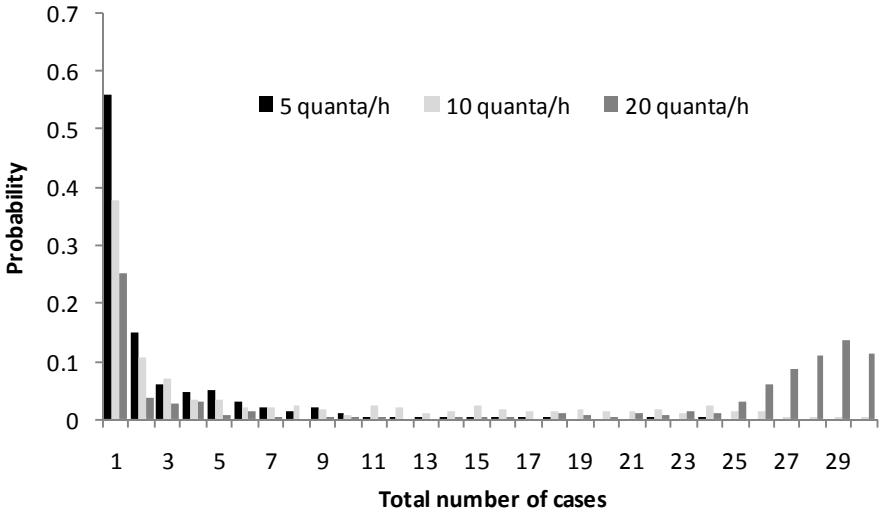
The parameter gives an indication of the likelyhood of an epidemic, and in a deterministic model Ro<1 indicates that the disease will die out, while Ro>1 is indicative of a full outbreak. Similar behaviour is seen in the probability distributions produced by stochastic models. Allen (2008) indicates that an outbreak with Ro less than or close to one will tend to die out early on, and the distribution for the number of cases will be skewed to the left. When Ro>1 the distribution becomes bimodal and increasingly skewed to the right as Ro increases. The values of Ro for the cases modelled in Figure 4 are given in Table 3 and can be seen to concur with the behaviour indicated in Allen (2008).

Table 3: Reproduction Rate (Ro) for conditions in Figure 4.

Ventilation rate (AC/h)	Quanta/h	β	Ro
3	5	1×10^{-3}	1.49
	10	2×10^{-3}	2.98
	20	4×10^{-3}	5.96
6	5	5×10^{-4}	0.74
	10	1×10^{-3}	1.49
	20	2×10^{-3}	2.98



(a) ventilation rate = 3 AC/h



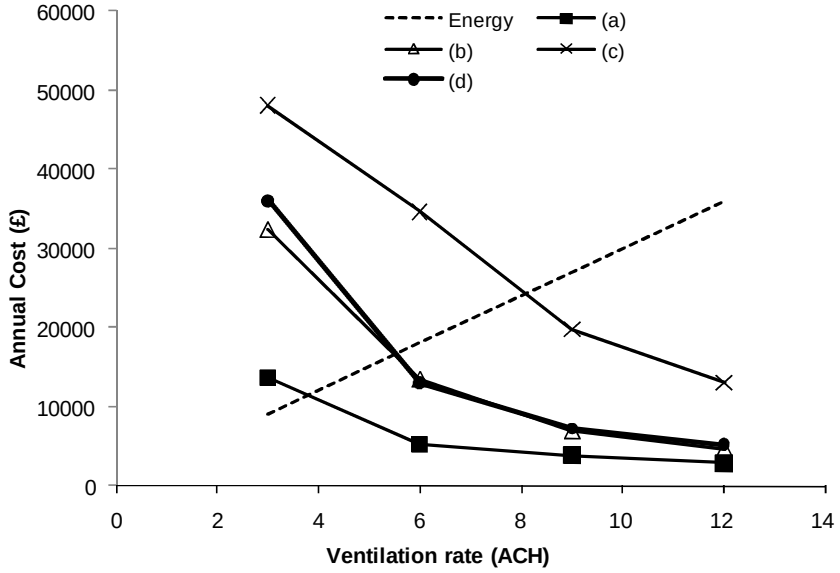
(b) ventilation rate = 6 AC/h

Figure 4: Probability of total number of cases for conditions in table 2, γ = 2 days and quanta production between 5 and 20 quanta/h

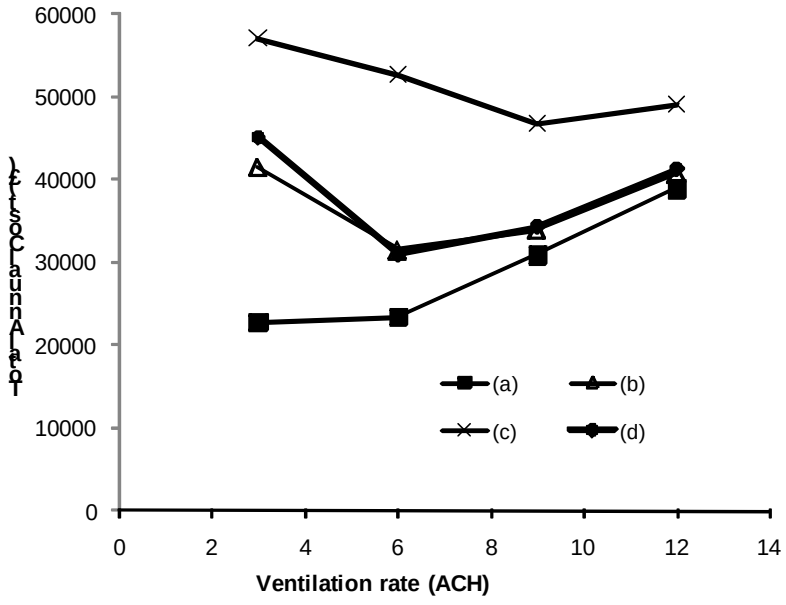
COST-BENEFIT ANALYSIS

While the results suggest that for some infections improved ventilation leading to greater dilution of airborne pathogens could potentially reduce the size and severity of an outbreak, it is not immediately clear whether investing to improve ventilation is really a viable approach for a hospital to take. To provide a means for formally assessing this, a simple financial appraisal method is explored by considering a cost for each air change provided and a cost to treat each case of an infection. By running the infection risk model for a range of disease and environmental parameters to determine the average total number of cases, it is straightforward

for a particular scenario to create a plot typical of Figure 5(a), showing the costs versus air change rate for both treatment of infections and energy consumption. For a particular disease scenario it is then possible to determine the optimum ventilation from the minimum total cost, as shown in Figure 5(b).



(a) Energy and treatment costs



(b) Total cost curves

Figure 5 Potential trade-off between energy and treatment costs for a hypothetical case considering costs associated with air movement only (a) q= 5 quanta/h, γ = 2 days (b) q= 10 quanta/h, γ = 2 days (c) q= 20 quanta/h, γ = 2 days (d) q= 20 quanta/h, γ = 1 day

In the case of Figure 5 it was assumed that in a hospital with 8 wards of 1000 m^3 (35315 ft^3) that there was one outbreak of an infection in a year that followed the average behaviour predicted by the infection risk model. The infection had an incubation period of 1 day, an infectious period of 1 or 2 days and a quanta generation rate per infector of 5 or 10 quanta /h. Each infection was assumed to cost the hospital £2000; this could be in treatment, lost bed days or staffing issues. The energy cost per air change rate for all 8 wards was assumed to be £3000 based on continuous operation of a mechanical system with a fan power of 2 W/l/s (56.6 $W/ft^3/s$) and a cost of electricity of 7.7p/kWh. The results clearly show that the trade-off between energy costs and infection will depend very strongly on the disease characteristics, with the optimum ventilation ranging from 3 AC/h for the lowest infectivity disease (case (a)), to 6AC/h for cases (b) and (d) and 9AC/h for case (c). As may be expected a higher quanta generation rate or a longer infectious period both increase the likely severity of an outbreak and hence the treatment cost for a hospital. In such cases the case for improved ventilation provision becomes stronger even to prevent only one outbreak per year.

Although in theory this approach is straightforward, there is a considerable challenge in practice in being able to incorporate both the variability in the risk of infection and to put realistic costs to both the treatment of the infection and the ventilation provision. The case considered in Figure 5 serves to demonstrate potential outcomes, but will be very dependent on the specifics of the disease and the various costs. Here the most appropriate level of ventilation appears to be between 3 and 9 air changes per hour, but this will change significantly depending on the cost of the infection. In addition the ventilation costs presented here only consider those that are associated with moving the air. While this would be reduced in a naturally ventilated hospital, regardless of the ventilation approach there is almost certainly a cost associated with heating and/or cooling and conditioning the air which will be very dependent on local climate, design of system and regulations. For example in the UK, heating is a certainty for at least six months of the year, cooling/conditioning will depend on application and location and recirculation of mechanically ventilated air is not permitted (Department of Health 2007) restricting energy saving to heat recovery devices which are again system dependant. In other climates, cooling and conditioning will be the primary concern with heating a negligible aspect. However, regardless of system design or location the need to modify the condition of the air will add to the cost, in many cases substantially and will rise with air change rate.

To evaluate this further, if it is assumed that that the hospital is in a region requiring heating but no cooling/conditioning and has a full fresh air system with 50% heat recovery the ventilation heat loss can be estimated through combining the ventilation conductance (CIBSE 2006) with the degree day approach using the equation.

$$\text{Annual heat loss (Wh)} = 0.5\frac{1}{3}NV24D_dE \qquad (6)$$

Here N is the ventilation rate (AC/h), V is the volume of the space (m^3), Dd are the number of degree days and E is the intermittancy factor. For the case in Figure 5 with 2100 degree days (typical for London region in the UK), E = 1 and an energy cost for heating of 4p/kWh (assumed to be gas and therefore lower than the electricity costs), this would increase the cost per air change rate from £3000 to £11064. As a consequence this would put the optimal ventilation rate at 3 air changes per hour or less and any increases will only be cost effective for the highest risk infections. While this is a simple theoretical example it is clear that the heating and/or cooling costs will almost certainly dominate in a real case, will vary substantially with system design and climate, and unless there is effective heat recovery in place will substaintially change the result. However despite this variation, putting a cost to the ventilation in a real case, while specific to a particular building and climate, is likely to be the easiest of the values to determine with modern Dynamic Thermal Modelling software tools and/or Building Energy Management system data. Other than fluctuations in weather conditions and energy costs the ventilation costs will remain broadly constant in a particular space regardless of infection, clinical process or operational procedures.

However putting costs to an infection presents a much greater challenge. In this case the costs will encompass both direct treatment costs, such as antibiotics, and the impact of the infection on the operation of the hospital. The later may include the costs of additional patient stay, the costs associated with staff shortages, the costs associated with cancellation of operations and procedures, the costs of additional cleaning and disinfection and even the need to accommodate patients in another ward or even another hospital. The actual costs here will depend on the actual infection concerned and the other pressures that the hospital is under at the time, and in reality may even change over time depending on the severity of an outbreak. For some infections the social and economic costs that result from the spread of an infection may also be a significant factor, as seen particularly in the SARs outbreak and to a lesser extent with the 2009 H1N1 influenza pandemic. In both cases the high mortality rate and/or high level of transmissibility make reducing the risk of transmission to the wider community a priority that should also be considered in cost calculations. Indeed in the UK it has been estimated that the preparation and response to the influenza pandemic totalled £1.2 billion (Hine 2010) for the vaccine and antiviral drug manufacture, extra face-masks and respirators and public health campaigns alone, without even including the cost of work absenteeism and other societal impacts. While in this case there is no evidence that higher levels of control in hospitals could have reduced the costs, it serves to emphasise the very high economic cost of major infectious disease outbreaks and the savings that can be made where containment is a viable option.

Even considering just the hospital aspects of an infectious disease outbreak, establishing costs will also depend on the method of calculation. In many cases this dominated by how a marginal bed-day is valued which is in part linked to a countries healthcare system (Graves et al 2010). Published data on costs is both limited and variable, however a number of authors give evaluations that are useful for establishing very rough appropriate costs. Plowman et al. (2001) considered 4000 patients admitted to a district general hospital in 1994-5 and estimated the

additional cost across all infections to be of the order of £3000 per patient. In a disease specific assessment, Ghantoji et al. (2010) reviewed published studies on C diff infections and from the limited data available indicated costs of $2871-$4846 (approx. £2000-£3300) per primary case within the USA and $5243-$8570 (approx. £3500-£5800) outside. Zingg et al. (2005) estimated the cost of a norovirus outbreak among 16 patients and 29 healthcare workers to be $40675 (approx. £27500) which equates to a per patient cost of approx. £1700. Based on these very approximate estimates Figure 6 indicates the effect that changing both the cost of infection and the cost of energy may have on the total cost and hence the optimum ventilation for case (b) in Figure 5. The results indicate that changing either cost has a dramatic effect on the overall outbreak cost and supports the need for good economic data if such a model is used for assessment.

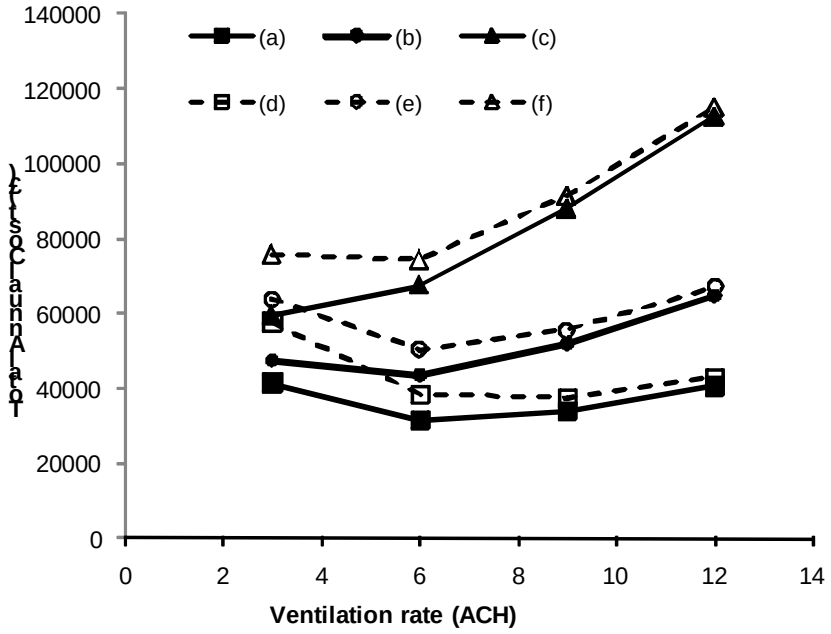


Figure 6: Influence of infection and energy costs on the outcome of the model for case (b) in Figure 5, q = 10 quanta/h, γ = 2 days. (a) energy £3000 per AC/h, infection £2000 per case (b) energy £5000 per AC/h, infection £2000 per case (c) energy £9000 per AC/h, infection £2000 per case (d) energy £3000 per AC/h, infection £3000 per case (e) energy £5000 per AC/h, infection £3000 per case (f) energy £9000 per AC/h, infection £3000 per case

A further consideration is the stochastic variance in the likely dynamics of an infection as demonstrated in Figure 4. Figure 7 takes this into account by plotting the total cost (energy + treatment cost) against probability for four different air change rates. Here the disease parameters are again q = 10 quanta/h and γ = 2 days and the energy and treatment costs are assumed to be £9000 per AC/h and £3000 per case respectively. At the lowest air change rate, the base cost associated with energy only is minimised, however such low dilution is ineffective

against airborne transmission and results indicate that there is around a70% chance that the cost will be approximately five times greater. Increasing the ventilation rate to 3 AC/h increases the base energy cost, but substantially reduces the risk of a high cost outbreak to approximately 13%. A further increase to 6AC/h shows that the ventilation is now effective at reducing the epidemic however increasing the air change rate to 12 AC/h is clearly not cost effective for this particular infection scenario although it is the only case where the value of Ro is reduced below one.

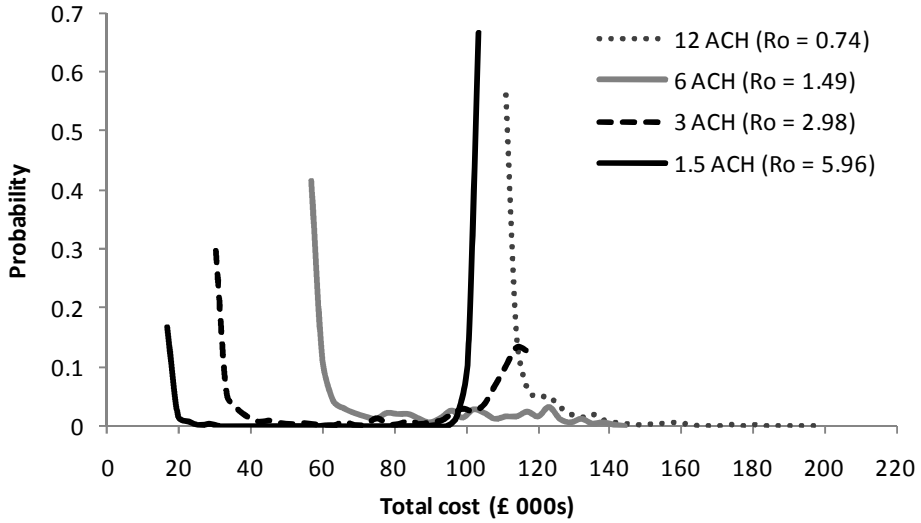


Figure 7 Probability of annual cost of an infectious disease outbreak assuming q = 10 quanta/h, γ = 2 days, energy cost £9000 per AC/h, treatment cost £3000 per case

Comparing Figures 6 and 7 suggests that using the optimum ventilation rate derived from a mean infection rate is a reasonable approach for design. While it doesn't capture the variance that will be present in reality, a hospital could regard the mean as the trend that they are likely to see over a period of a number of years. Although increasing the ventilation rate will not guarantee a reduction in infections it will reduce the probability of an outbreak occurring. However it is likely that in some cases when an outbreak does occur the severity will be the same regardless of the ventilation rate. As a result the cost and operational impact of a single large outbreak may remain the same despite changes to the ventilation, but the frequency with which a hospital is likely to experience a large outbreak could well be reduced.

DISCUSSION

The models presented here offer some insights into the risk of airborne related outbreaks in hospital environments. While the models as they stand could not be considered as robust or validated, they do provide a greater understanding as to the factors that influence the transmission of infection and therefore the criteria for designing ventilation in hospital wards. Perhaps the most valuable insights are around the level of uncertainty that is involved in predicting disease outbreaks in small populations and the need for case specific data to be able

to validate and subsequently use such models. The cases presented here, although based on appropriate parameters for infectious diseases in hospitals, deliberately do not attempt to simulate an actual infection as the level of uncertainty in the model parameters are such that there is a danger of the results being misinterpreted. Although limitations in the ventilation parameters are starting to be addressed (Noakes and Sleigh 2009, Qian et al. 2009), disease parameters present a greater difficulty. The infectious and incubation periods for most diseases are variable and although the range can be estimated with reasonable certainty fixed rate constants cannot deal with the change in infectiousness as a disease progresses or the increasing likelihood that a person will leave the state with time (Wearing et al. 2005). The value of quanta is perhaps the greatest unknown and as discussed with Table 1, is both variable and difficult to establish for the majority of diseases. As infections relevant to hospital outbreaks are likely to be transmitted by a combination of airborne, droplet and contact routes, determining the value of quanta is even more of a challenge. Researchers are looking to address some of these issues through developing disease transmission models based on a dose-response approach (Chen et al. 2009), and it is clear that further research in this area is essential to improve the robustness of risk models for hospital environments.

Dealing with the complexities of the population and the management of the hospital should also be considered for a real case. While the static population of 30 patients simulated here using a stochastic approach may be representative for certain hospital environments, in others it is too simplistic and it will be necessary to consider the interaction between different groups and the impact that this may have on the risk of transmission (Fraser 2007, Cooper et al 1999). This is particularly of concern where transmission of infection may occur prior to symptoms appearing, which is shown by Fraser et al (2004) to make control of an outbreak much more difficult. While using ventilation as a control strategy may offer greater protection in such cases compared to reliance on identification and isolation of infected cases alone, environments where there is movement of patients or staff between wards may still allow undetected transmission between spaces. The models presented here only consider the role of ventilation and in some senses are therefore a worst case scenario. In reality combining ventilation or other airborne controls with good surveillance and prompt treatment or isolation may enable an outbreak to be brought under control more easily than the models presented here suggest.

It is also worth commenting on the challenge of validating such models by comparing to real outbreak data. In many cases this is particularly difficult, as data records dates of cases rather than when individuals were actually infected and there are often several cases in an outbreak before it is identified as such and therefore the early cases are often missing (Fraser 2007). The issue is further compounded as changes in infection control procedure in response to the outbreak will probably change the dynamics of transmission and therefore alter modelling assumptions. Fraser (2007) describes an approach for developing reproduction numbers at an individual level which take account of the fact that the contact rate parameter □ may change during the course of an outbreak and indicates that this offers a potential solution to dealing with incomplete infection data during a real outbreak.

Despite these difficulties, the models presented here set out an approach for evaluating the ventilation design parameters from a cost-benefit perspective and as such offer a potential framework for assessment. While there are challenges in appropriately simplifying the transmission scenario and determining suitable costs for both ventilation provision and the consequences of infection, the ability to consider the ventilation from a quantitative risk perspective at the design stage offers a rational for selecting appropriate ventilation that is beyond the comfort and energy requirements of a space. For example, the results presented here for short incubation period infections with a quanta generation rate under 20 quanta/h, support the case for good ventilation in the region of 3-8 AC/h depending on the actual infection, local climate and ventilation system, but do not show significant further benefit beyond this range for any of the costs considered. Even this level of knowledge at the design stage, combined with a view on patient cohort and the likelihood of a ward to experience outbreaks could help ensure that ventilation is not over or under specified. In addition, the models have the potential to help understand the likely extent and financial impact of an outbreak in an existing ward benefiting those planning mitigation strategies.

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