Quantifying uncertainty in health impact assessment: A case-study example on indoor housing ventilation

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ABSTRACT

Quantitative health impact assessment (HIA) is increasingly being used to assess the health impacts attributable to an environmental policy or intervention. As a consequence, there is a need to assess uncertainties in the assessments because of the uncertainty in the HIA models. In this paper, a framework is developed to quantify the uncertainty in the health impacts of environmental interventions and is applied to evaluate the impacts of poor housing ventilation. The paper describes the development of the framework through three steps: (i) selecting the relevant exposure metric and quantifying the evidence of potential health effects of the exposure; (ii) estimating the size of the population affected by the exposure and selecting the associated outcome measure; (iii) quantifying the health impact and its uncertainty. The framework introduces a novel application for the propagation of uncertainty in HIA, based on fuzzy set theory. Fuzzy sets are used to propagate parametric uncertainty in a non-probabilistic space and are applied to calculate the uncertainty in the morbidity burdens associated with three indoor ventilation exposure scenarios: *poor*, *fair* and *adequate*. The case-study example demonstrates how the framework can be used in practice, to quantify the uncertainty in health impact assessment where there is insufficient information to carry out a probabilistic uncertainty analysis.

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1. Introduction

Health impact assessment (HIA) evaluates prospectively the health impacts attributable to an environmental policy or intervention. HIA requires sources of evidence and a number of analytical tools are available for the estimation of health impacts that range from qualitative to quantitative methods. To date, most HIA methods have been qualitative rather than quantitative. Although some quantitative HIAs have been conducted in the past (de Nazelle et al., 2011; Fehr et al., 2012; Schram-Bijkerk et al., 2009; Veerman et al., 2005), their take-up has been slow. The quantification of health impacts in a HIA has desirable features for decision support. It provides a measure of the magnitude of health consequences of an environmental policy or intervention. Also, it can help decision-makers evaluate the significance of the potential health impacts based on the assessment before a policy or an intervention is implemented.

Although quantifying the health impacts is considered necessary in HIA, such quantification can be met with limitations in practice (Bhatia and Seto, 2011). Quantifying the health impacts requires the knowledge of various measures such as exposure–response functions (or relative risks), location and size of the population affected, and the distribution of exposure over the affected population. Limitations on conducting a quantitative HIA can occur due to lack of information on the above measures or lack of evidence on the causal pathways linking changes in exposure with health outcomes. Such limitations, commonly characterised by "lack or imprecision in knowledge", can be an important source of uncertainty in the quantification of health impacts (Walker et al., 2003).

Uncertainty is inherent in most environmental HIA, partly due to lack of understanding of the associations between environmental exposures and health outcomes, or due to random variations in these associations (Briggs et al., 2009). Most approaches for quantifying uncertainty in environmental HIA models cannot deal with uncertainty due to lack of knowledge (Mesa-Frias et al., 2012). It is important to note that lack of knowledge yields to imprecision in defining parameters. Most probabilistic approaches assume that the uncertainty in model parameters is due to random variations and they characterise the uncertainty in model parameters using probability distributions. However, random variation in model parameters is only one type of uncertainty in environmental HIA. Uncertainty in model parameters might also arise from limitations in knowledge (or incomplete data), and it is important to incorporate methods that can deal with the uncertainty due to this limitation. As such, this paper provides an alternative non-probabilistic approach to incorporate parameter uncertainty due to imprecision in knowledge using an application of fuzzy set theory, which is novel in health impact assessment. Fuzzy

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set theory provides a non-probabilistic method for characterising uncertainty. Fuzzy set theory is a method that does not require knowledge of the statistical properties of parameters such as its mean, variance or correlations to propagate its uncertainty, which makes it ideally suited to handle uncertainty that might arise due to imprecision in knowledge or incomplete data (Smithson and Verkuilen, 2006).

We believe that a more thorough examination of HIA methods for handling the uncertainty in the quantification of health impacts is required. As methods for the quantification of health impacts are beginning to take-up (Lhachimi et al., 2010; Lhachimi et al., 2012; Liu et al., 2012), this paper adds to this literature by developing and applying a new HIA modelling framework to quantify the health impacts and its uncertainty. In this paper, we will focus on parametric uncertainty. Other issues associated with uncertainty such as the formulation of a model or its framing assumptions are addressed elsewhere (Mesa-Frias et al., 2013). Our approach involves the development of a case-study example and the application of the HIA framework in three sequential steps: (i) selecting the exposure metric and quantifying the evidence of potential health effects of the exposure, (ii) estimating the size of the population affected by the exposure and selecting the outcome measure, and (iii) quantifying the health impacts and associated uncertainty. The framework is demonstrated through a HIA case study which examines the health impact of housing ventilation in England.

2. Housing ventilation case-study

Housing energy efficiency measures, and changes in building designs are currently implemented as part of the UK government's effort to reduce carbon greenhouse emissions and energy cost from domestic sources. UK government initiatives require improvements in insulation retrofits to avoid heat loss and encourage energy savings (DCLG, 2003; DCLG, 2009). However, there are concerns regarding changes in building designs retrofits and energy efficiency measures because they can potentially reduce indoor ventilation rates due to an increase of air-tightness (Manuel, 2011; Stephens et al., 2011). It is worth noting that ventilation needs are not always considered when assessing the performance of energy-efficiency interventions, and some studies suggest that a majority of newer airtight energy efficiency homes are under-ventilated (Stymne et al., 1994). It is important therefore to ensure an adequate ventilation level in dwellings for better health and well-being. In the next section, we explore how indoor ventilation can affect health through the development of a quantitative framework.

3. Quantitative framework for HIA

In general, the key steps for quantifying health impacts in a HIA include: (1) selecting the exposure metric and quantifying the evidence of the potential health effects of the exposure; (2) estimating the size of the population affected by exposure and selecting an outcome measure; (3) quantifying the health impacts and associated uncertainty. The steps are applied to the case-study of housing ventilation as follows.

3.1. Selecting the exposure metric and quantifying the evidence of potential health effects of the exposure

Adequate ventilation is required to remove indoor pollutants, with several studies having associated poor indoor ventilation with negative health outcomes (Engvall et al., 2001; Engvall et al., 2003; Wright et al., 2009; Zuraimi et al., 2007). Common negative health outcomes reported due to poor ventilation exposure include allergies, rhinitis, asthma, wheezing, among others. Several qualitative reviews have concluded that a minimum ventilation rate of 0.5 air changes per hour (ACH) is required for health reasons (Dimitroulopoulou, 2012; Li et al., 2007; Seppanen and Fisk, 2004; Sundell et al., 2011; Wargocki et al., 2002). However, these reviews have not produced quantitative *summary* estimates associating poor indoor ventilation and health.

Currently most quantitative studies rely on different experimental intervention studies, to provide estimates of an association between ventilation rate and health. Some experimental intervention studies have provided inconclusive results due to limitations in the size of the population, measurement methods of ventilation, and the diversity of geographical locations and climate (Norbäck et al., 2000; Nordstrom et al., 1995; Skov et al., 1987; Sterling and Sterling, 1983). No previous study has provided quantitative *summary* estimates based on epidemiological study design. It is important to review the evidence based on epidemiological studies, with studies that have adjusted for key confounders, to assess limitations and provide a quantitative summary estimate. As such, we conducted a systematic review and a meta-analysis, as an initial step towards quantifying the evidence and determining the strength of the association between poor ventilation rates and health outcomes.

3.1.1. Systematic search and meta-analysis

A systematic search was conducted in the Ovid Medline academic database from inception (–1948) through to August 2012, using the following free-text search string: "Ventilation" OR "Ventilation Rate" OR "Air flow*" OR "Air exchange*" AND "Health" OR "Sick Building*" OR "Allergy*" OR "illness*" OR "Asthma" AND "Housing" OR "Home" OR "Apartment" OR "Dwelling" OR "Building" OR "Residence" in the title and the abstract. Details of the search strategy are shown in Appendix A. Papers were screened according to the following inclusion criteria: (i) studies published in peer-reviewed articles in English; (ii) original studies that used primary data (e.g. not reviews, commentaries, etc.); (iii) studies that provided a measure of effects (e.g. odd ratios or relative risks, hazard ratios); (iv) only studies of cohort, cross-sectional or case-control study design were included; (v) studies which defined health outcomes and measurement of ventilation. Studies meeting the inclusion criteria were carefully examined, and their main characteristics were recorded. The following information was extracted from the included studies: authors, year of publication, study design, geographical location, study population, building setting (offices, residences, schools), sample size, health outcomes assessed, ventilation exposure measurement, degree of adjustment and effect estimates for a given ventilation exposure category. Ventilation exposures were defined and classified into two categories: "low ventilation" for ventilation rates below 0.5 ACH, and "reference ventilation" for ventilation rates equal or above 0.5 ACH.

The studies presented different effect estimates (e.g. relative risks, odds ratio, and hazard ratio) alongside several types of risk comparison groups for measures of ventilation exposures. We standardised the effect estimates and the different types of risk comparison into a log scale assuming a log-linear relationship of health symptoms with ventilation category. Risk comparisons were defined into two categories: "reference group" for the population exposed to ventilation rates greater than 0.5 ACH and "exposure group" for those exposed to ventilation rates less than 0.5 ACH ("exposure group"). The natural logarithm of the effect estimates and standard errors were calculated from the published studies estimates and confidence intervals (CIs). Odds ratio (ORs), using random-effects models, and 95% CI were used to represent the final quantitative summary estimate and associated uncertainty. In addition, quality scoring or weighting of studies was not performed because quality scoring can introduce some bias (Greenland and O'Rourke, 2001). We instead assessed heterogeneity using subgroup analysis to examine the sensitivity of different aspects of the studies had on final study results (Appendix A).

3.2. Estimating the size of population affected by exposure and selecting outcome measure

For the population affected by the exposure, we identified the total population of England up to mid-2011 projections from the UK Office

of National Statistics (ONS) data. In terms of outcome measures, common symptoms in relation to poor ventilation exposures were identified through the systematic review and meta-analysis from Step 1. In this case-study, we defined the outcome measure as *respiratory-related morbidity* to describe the range of symptoms associated with poor ventilation exposure. Based on this outcome definition, we identified data from the Health Survey for England (HSE) 2010 report on respiratory health to obtain estimates of the total annual number of existing respiratory-related morbidity cases in England (Craig and Mindell, 2011).

3.3. Quantifying the health impacts and associated uncertainty

We calculated the health impacts of poor ventilation and associated uncertainty as part of the case-study. This step involved quantifying the percentage increase in morbidity risk (i.e. excess morbidity risk) due to poor ventilation exposure and estimating the excess annual number of cases by comparing the disease burden from three theoretical population exposure scenarios. The methods are briefly described below.

Firstly, the excess morbidity risk due to poor ventilation exposure per ACH below threshold (0.5 ACH) was quantified by calculating the natural logarithm of the odds ratio and its 95% CI, obtained from the meta-analysis in the previous step. Secondly, the health impacts of housing ventilation were estimated by comparing the disease burden (i.e. annual respiratory-related morbidity cases) attributable to the exposure under three ventilation exposure scenarios: (i) *poor* ventilation with ventilation rates less than 0.48 ACH, (ii) *fair* ventilation with ventilation rates between 0.48 ACH and 0.77 ACH, and (iii) *adequate* ventilation with ventilation rates of at least 0.48 ACH and above. These exposure scenarios were classified according to ventilation standards for indoor air quality (Taylor and Morgan, 2011).

3.3.1. Fuzzy set approach to uncertainty

In the absence of sufficient information to quantify probabilistically the uncertainty in a parameter (e.g. ventilation rate), fuzzy set theory can be used for this purpose. In general, fuzzy set theory is used to quantify parameter uncertainty in non-probabilistic space (Dubois and Prade, 2000; Smithson and Verkuilen, 2006; Zimmermann, 1995). Fuzzy sets are defined by a *membership function* that measures the *degree* (between zero and unity) to which a parameter value belongs to a set (Maravas et al., 2012; Zimmermann, 1995). In the case-study, fuzzy sets were used to characterise (i) the imprecise nature of each ventilation exposure scenario and (ii) the uncertainty in the logarithm of the odds ratio obtained from the meta-analysis in the previous step. In order to perform common arithmetic operations with fuzzy sets such as multiplication, division, subtractions and other operations, interval arithmetic was used. Interval arithmetic performs arithmetic operations with interval values using a lower and an upper α-cut bound to determine the values of the fuzzy set. We present below the mathematical definitions of a fuzzy set, the membership function and the lower/upper α-cut bounds, followed by their illustration.

Definitions. A fuzzy set is described mathematically as (Zimmermann, 1995):

$$A(x) = [x, \mu_A(x) | x \in X \text{ and} \mu_A[0, 1]] \tag{1}$$

where x is an element ($\in$) of the set X; $A(x)$ is a fuzzy set of X; $\mu_A(x)$ is the membership function. The membership function of fuzzy set $A(x)$ can be given by:

$$\mu_A(x) = \begin{cases} 0, & \\ \left| \dfrac{x-a_1}{a_2-a_1} \right| & \text{if } x < a_1 \\ \left| \dfrac{a_3-x}{a_3-\alpha_2} \right| & \text{if } a_1 \leq x \leq a_2 \\ & \text{if } a_2 \leq x \leq a_3 \\ 0, & \text{if } x > a_3 \end{cases} \tag{2}$$

where a_1, a_2, a_3 are real numbers. The values of $\mu_A(x)$ range from 0 to 1, where 1 denotes full membership of the set, and 0 denotes no membership. By membership we refer to the *degree* in which a value belongs to a set. For example, the closer $\mu_A(x)$ is to 1, the more likely is that x belongs to the set A, and the closer $\mu_A(x)$ is to 0, the less likely is that x belongs to A.

Additionally, a fuzzy set is defined by specifying its lower and upper α-cut bounds as follows. For $0 \leq a \leq 1$ and $a_1 \leq a_2 \leq a_3$, these are defined by

$$A_\alpha : [A_L(\alpha), A_U(\alpha)] \tag{3}$$

$$[(a_2 - a_1) \times a + a_1, -(a_3 - a_2) \times a + a_3] \tag{4}$$

where A_α is the α-cut bounds of A, which describes an interval of confidence at level α whose membership values are greater than the value at α. The lower bound of the interval is defined by $A_L(\alpha) = \inf \{x \in \mathbb{R} : A(x) \geq \alpha\}$; and the upper bound of the interval is defined as $A_U(\alpha = \sup\{x \in \mathbb{R} : A(x) \geq)$, where the terms *inf* and *sup* mean respectively the greatest lower bound and the lowest upper bound.

Interval arithmetic operations with fuzzy sets are approximated using the α-cut bounds for $0 \leq \alpha \leq 1 \in (0,1)$ each. Arithmetic operations are given in a general form as:

$$(A \otimes B)\alpha = A_\alpha \otimes B_\alpha \tag{5}$$

where $\otimes$ denotes a basic arithmetic operation ($+, -, \cdot$ or $/$) and A, B are arbitrary fuzzy sets.

For example, addition operations using fuzzy sets are given in a general form by

$$(A + B)_\alpha = A_\alpha + B_\alpha = [A_L(\alpha) = B_L(\alpha), \quad A_U(\alpha) + B_U(\alpha)]. \tag{6}$$

Details of other interval arithmetic operations using fuzzy sets are given in Appendix B.

For ease of understanding, we present Fig. 1 to explain the mathematical definitions and operations of the fuzzy set approach. Fig. 1(a) illustrates the concept of a fuzzy set, and its membership function. The x-axis displays the range of values of ventilation rates (ACH) and the y-axis displays the degree of membership. X is the set of all feasible ventilation rates, and x is a single ventilation rate (i.e. the uncertain parameter) which belongs to this set. Three subsets of X are shown in this figure: "*poor*" ventilation, "*fair*" ventilation and "*adequate*" ventilation. The dotted, dashed and continuous lines define respectively the membership functions of *poor*, *fair* and *adequate* ventilation sets. To explain the concept of a membership function, consider the *poor* ventilation fuzzy set. The poor ventilation set is defined by Eq. [2]. In this set, a ventilation rate of $x = 0.19$ ACH belongs unequivocally to this set. As the ventilation rate increases above 0.19 ACH, the degree of membership of the *poor* ventilation set decreases linearly until it reaches zero at $x = 0.48$ ACH. Conversely, as the ventilation rate decreases below 0.19 ACH, the degree of membership of the same set decreases linearly until it reaches zero at $x = 0.01$ ACH. Fig. 1(a) represents a triangular membership function of ventilation rate; other types of membership functions could also be used (Smithson and Verkuilen, 2006).

Fig. 1(b) illustrates the concept of a fuzzy set and its interval arithmetic operations using the α-cut bounds. The x-axis in the figure displays the combined range of *poor* and *fair* ventilation sets A and B and that of the set formed by summing them, $(A + B)$ The y-axis displays the α-cut of the fuzzy sets. To explain interval arithmetic using the α-cut bounds, consider the fuzzy set A. The lower and upper α-cut bounds of fuzzy set A are defined by Eq. [4] to preserve the triangular form of the fuzzy set during arithmetic operations. The lower bound $A_L(\alpha)$ describes the interval values or support of the fuzzy set when $\alpha = 0$ (e.g. $0.01 \leq x \leq 0.48$) and the upper bound $A_U(\alpha)$ describes the centre or core value of the fuzzy
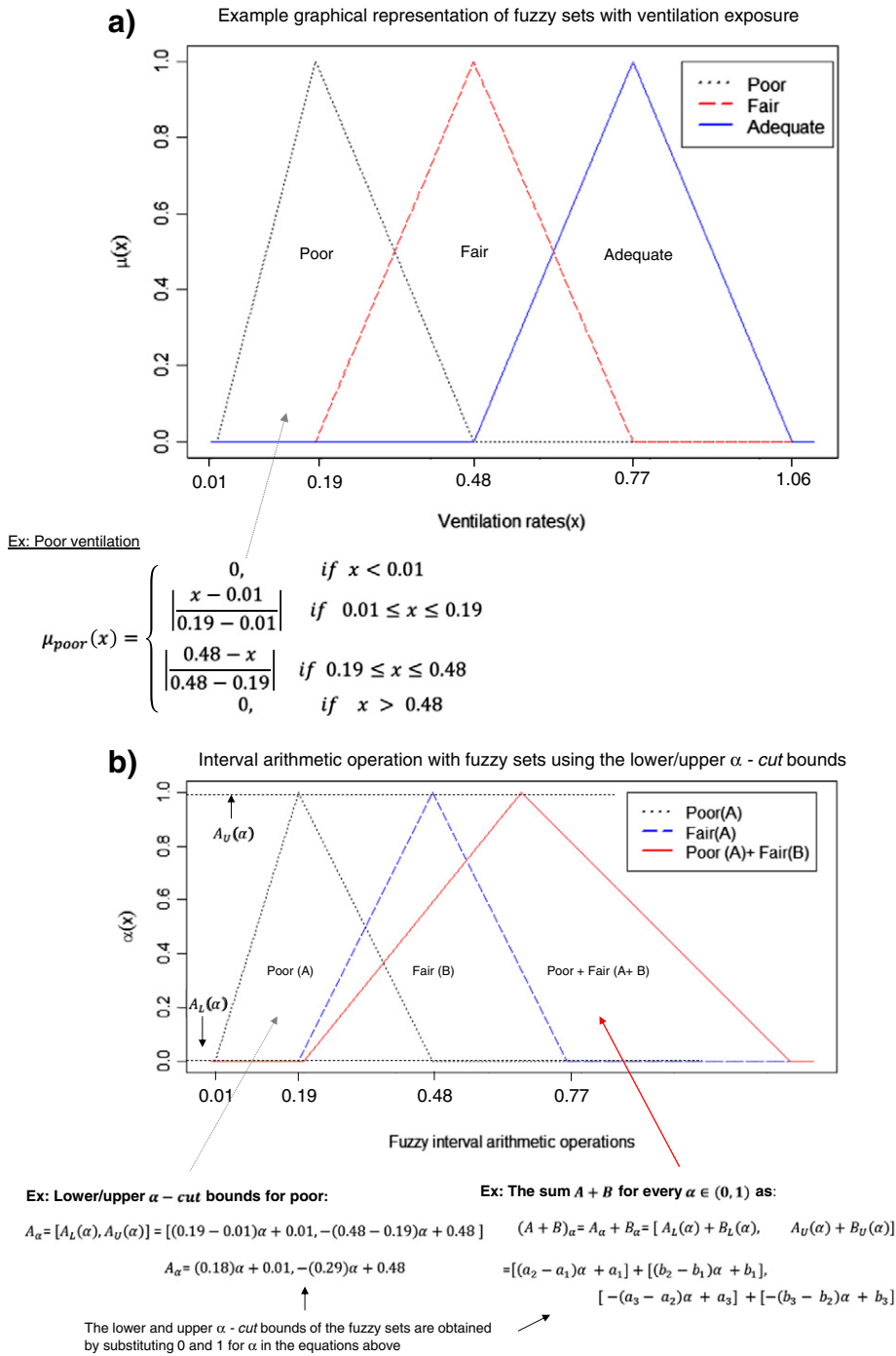
a) Example graphical representation of fuzzy sets with ventilation exposure

Ex: Poor ventilation

$$\mu_{poor}(x) = \begin{cases} 0, & if \ x < 0.01 \\ \left| \dfrac{x - 0.01}{0.19 - 0.01} \right| & if \ 0.01 \leq x \leq 0.19 \\ \left| \dfrac{0.48 - x}{0.48 - 0.19} \right| & if \ 0.19 \leq x \leq 0.48 \\ 0, & if \ x > 0.48 \end{cases}$$

b) Interval arithmetic operation with fuzzy sets using the lower/upper α - cut bounds

Ex: Lower/upper $\alpha - cut$ bounds for poor:

$A_\alpha = [A_L(\alpha), A_U(\alpha)] = [(0.19 - 0.01)\alpha + 0.01, -(0.48 - 0.19)\alpha + 0.48]$

$A_\alpha = (0.18)\alpha + 0.01, -(0.29)\alpha + 0.48$

The lower and upper α - cut bounds of the fuzzy sets are obtained by substituting 0 and 1 for α in the equations above

Ex: The sum $A + B$ for every $\alpha \in (0,1)$ as:

$(A + B)_\alpha = A_\alpha + B_\alpha = [A_L(\alpha) + B_L(\alpha), \quad A_U(\alpha) + B_U(\alpha)]$

$= [(a_2 - a_1)\alpha + a_1] + [(b_2 - b_1)\alpha + b_1],$

$[-(a_3 - a_2)\alpha + a_3] + [-(b_3 - b_2)\alpha + b_3]$

Fig. 1. (a): Example graphical representation of fuzzy sets with ventilation exposure. (b): Interval arithmetic operation with fuzzy sets using the lower/upper α-cut bounds.

set when $\alpha = 1$ (e.g. $x = 0.19$). The sum of fuzzy sets A and B is conducted using Eq. [6]. The α-cut bounds of the resulting fuzzy set $(A + B)$ are obtained by substituting the values "1" and "0" for α in the equation. In other words, the two values for α are needed to obtain: (i) the lower α-cut bound ($\alpha = 0$, and (ii) the upper α-cut bound ($\alpha = 1$ of the resulting fuzzy set. Further details of interval arithmetic operations using the α-cut bounds of a fuzzy set are shown in appendix B.

3.3.2. Calculating the burden of ventilation exposures using fuzzy sets

As part of this step, we estimated the annual morbidity burdens attributable to the three ventilation exposure scenarios. The process consisted of various sub-steps. We first calculated risk ratios associated with all ventilation exposure scenarios. The risk ratios were calculated assuming a log-linear function based on the level of ventilation exposure, the odds ratio and the unit threshold associated with the odds ratio (Scovronick and Armstrong, 2012). In the risk ratio, two input parameters were defined as fuzzy sets: the ventilation exposure scenario (i.e. *poor*, *fair* and *adequate*), and the excess risk in morbidity due to ventilation below 0.5 ACH threshold. The excess risk in morbidity was obtained by taking the natural logarithm of the odds ratio with its 95% CI, and mapping the bounds of the 95% CI to the bounds of the fuzzy set as shown in Appendix B. The risk ratio for each scenario is given by:

$$RR_i = exp[E \times (0.5 - X_i)] \qquad [7]$$

where RR_i is a fuzzy set which describes the risk ratio adjusted to the exposure in ventilation scenario i, E is a fuzzy set describing the excess risk in morbidity due to ventilation below the threshold unit in ACH, "0.5" is the ventilation threshold unit below which an adverse health effect is observed, and X_i is a fuzzy set describing the exposure parameter for each ventilation scenario i.

Changes in morbidity burdens attributable to the three ventilation exposure scenarios were calculated using the population attributable fraction (PAF). The PAF is an epidemiological method that calculates the health effect due to changes in exposure for the whole population (exposed and unexposed) (Hänninen and Knol, 2011; Rockhill et al., 1998; Rothman et al., 2008). The PAF is given by:

$$PAF_i = \frac{p(RR_i - 1)}{p(RR_i - 1) + 1} \qquad [8]$$

where p is the proportion of the population exposed (a value "1" for p represents that everyone in the population is exposed), and RR_i is the risk ratio associated with the exposure for each ventilation scenario.

In addition, we calculated the total number of annual respiratory-related morbidity cases attributable to changes in indoor ventilation as the final outcome of the assessment. The annual morbidity burden (AMB) attributable to each ventilation exposure scenario i is given by (Hänninen and Knol, 2011):

$$AMB_i = PAF_i \times B \qquad [9]$$

where B is the total annual number of existing respiratory-related morbidity cases in England and PAF_i is the population attributable fraction corresponding to ventilation exposure scenario i.

4. Results

4.1. Selecting the exposure metric and quantifying the evidence of potential health effects

As part of the systematic search, the literature yielded a total of 621 peer reviewed articles, of which 586 articles were deemed to be irrelevant or duplicates after reviewing titles and abstracts, leaving 35 articles to be retrieved for further evaluation. Of the 35 studies assessed, 8 articles met the inclusion criteria (Emenius et al., 2004; Hagerhed-Engman et al., 2009; Jaakkola and Miettinen, 1995; Milton et al., 2000; Oie et al., 1999; Stenberg et al., 1994; Sun et al., 2011; Walinder et al., 1998) and were included in the meta-analysis (9826 participants). Studies included in the meta-analysis controlled for a number of confounders, including age, sex, crowding, building age, history of eczema, asthma, allergic rhinitis and outdoor temperature. Table 1

shows the characteristics of included studies in the meta-analysis. The result of the meta-analysis yielded an overall odds ratio (OR) estimate of 1.34 (95% CI 1.15 to 1.57) as shown in Fig. 2, which gives a quantitative *summary* measure, with uncertainty presented as 95% CI, of the association between poor ventilation exposure (less than 0.5 ACH) and health. There was no evidence to suggest that the pooled estimate of OR and its 95% CI were affected significantly by heterogeneity (Appendix A).

4.2. Estimating population affected by exposure and selecting outcome measure

Based on the UK Office of National Statistics, the population in England is projected to be 53 million (53,107,000 people) up to mid-2011 projections (ONS, 2012). In terms of outcome measures, common symptoms in relation to poor ventilation exposures were identified as: allergies, rhinitis, asthma, wheezing and others (as shown previously in Table 1). Some authors have grouped these conditions under the terms "building-related symptoms" or "sick building syndrome" to describe a range of outcomes associated with indoor environmental exposures (Jaakkola et al., 2007; Tsai et al., 2012). According to the HSE report of annual respiratory-related cases in England, a total of approximately 8% including children and adults had reported in the last 12 months symptoms of wheezing, asthma and whistling in the chest (Craig and Mindell, 2011). In the HSE report, this was estimated to be a total of 4.2 million (4,178,720) of the current annual respiratory-related morbidity cases in England.
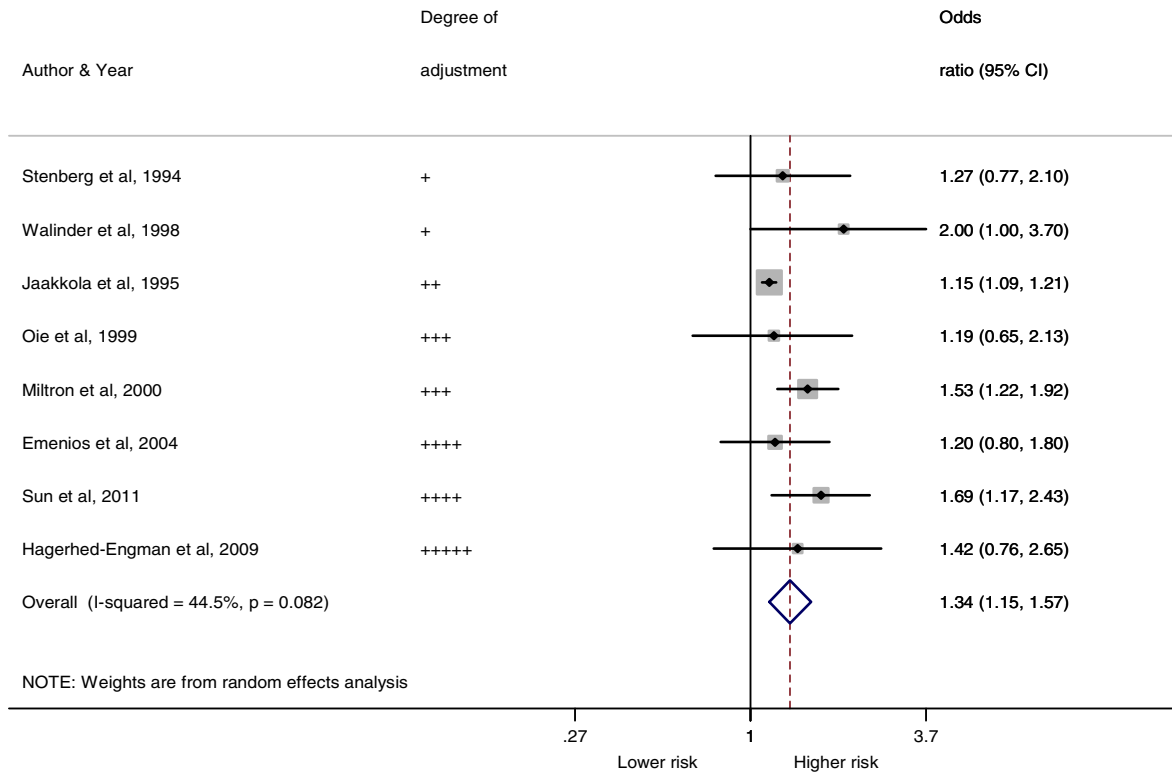
4.3. Quantifying the health impacts and uncertainty

The input parameters defined as fuzzy sets in the HIA model are shown in Table 2. Table 3 shows the morbidity burdens and corresponding uncertainty under the three ventilation scenarios. The negative values refer to health gains. In relation to annual respiratory-related morbidity cases, an excess of 371,097 cases were estimated under the *poor* ventilation exposure scenario; 24,997 excess annual respiratory-related morbidity cases were attributable to the *fair* ventilation exposure; and a reduction of approximately 352,562 cases in annual morbidity cases were attributed to the *adequate* ventilation exposure scenario. The uncertainty bounds of morbidity burdens under the *poor* ventilation scenario ranged between 99,398 to 1,028,008; under the *fair* ventilation scenario, they varied between a reduction of 539,846 cases and an increase of 706,364 cases; and finally, under the *adequate* ventilation scenario they varied between a reduction of between 1,197,605 and 48,605 cases. The fuzzy sets describing the adjusted risk ratios used in the calculation for each scenario is given in Fig. 3. The overall uncertainty (operating on fuzzy

Table 1
General characteristics of included studies.

Author, year	Design	Geographical location	Study population	Health outcomes assessed
Stenberg et al., 1994	Survey questionnaires, case–control study, 3 months, 1989	Sweden	464 office workers stratified for geographical areas with 83% of women in each group of the sample	Sick building symptoms (SBS)
Jaakkola and Miettinen, 1995	Questionnaires, cross sectional study, 12 months, 1991–1992	Finland	399 office workers selected randomly from 14 mechanical ventilated office buildings	Ocular, nasal symptoms and allergic reactions
Walinder et al., 1998	Self-administered questionnaires, cross sectional study, 24 months, 1993–1995	Sweden	234 school personnel working in the main buildings of 12 randomly selected primary schools	Nasal symptoms
Oie et al., 1999	Survey questionnaires, case–control study, 24 months, 1992–1993	Norway	172 children in residence homes	Bronchial obstruction
Milton et al, 2000	Questionnaires, cross sectional study, 12 months, 1994–1995	US	3720 employees of a large manufacturer in 40 buildings	Monthly short-term sick-leave
Emenius et al., 2004	Cohort study, 24 months, 1994–1996	Sweden	4089 children in residence homes	Wheezing
Hagerhed-Engman et al., 2009	Survey questionnaires, case–control study, 6 months, 2001–2002	Sweden	400 children in residence homes	Asthma, rhinitis, eczema
Sun et al., 2011	Survey questionnaires, case–control study, 12 months, 2006–2007	China	348 college students in college dorms at Tianjin University	Wheezing, rhinitis, dry cough

Result of meta-analysis: odds ratio (95% CI) for respiratory-related morbidity in high ventilation > 0.5 ACH (reference group) compared to low ventilation < 0.5 ACH (exposure group)

Author & Year	Degree of adjustment		Odds ratio (95% CI)
Stenberg et al, 1994	+		1.27 (0.77, 2.10)
Walinder et al, 1998	+		2.00 (1.00, 3.70)
Jaakkola et al, 1995	++		1.15 (1.09, 1.21)
Oie et al, 1999	+++		1.19 (0.65, 2.13)
Miltron et al, 2000	+++		1.53 (1.22, 1.92)
Emenios et al, 2004	++++		1.20 (0.80, 1.80)
Sun et al, 2011	++++		1.69 (1.17, 2.43)
Hagerhed-Engman et al, 2009	+++++		1.42 (0.76, 2.65)
Overall (I-squared = 44.5%, p = 0.082)			1.34 (1.15, 1.57)

NOTE: Weights are from random effects analysis

.27   1   3.7
Lower risk   Higher risk

+ adjustment for sex and age only; ++ for these plus history of atopy (e.g. history of eczema, asthma, allergic rhinitis and others); +++ for these plus crowding and building age ; ++++ for these plus smoking); +++++ for these plus outdoor temperature. Cochran Q= 12.61 (df= 7) P= 0.082, Tau squared = 0.0175

Fig. 2. Result of meta-analysis: odds ratio (95% CI) for respiratory-related morbidity in high ventilation > 0.5 ACH (reference group) compared to low ventilation < 0.5 ACH (exposure group).

sets of the ventilation exposure scenarios, and the risk ratios) was propagated using Eqs. [7] to [9] to give the uncertainty in the burdens shown in Fig. 4.

5. Discussion

In this study, we provided a framework that can be used as part of the assessment stage of a HIA. We applied the framework to a case-study example of indoor housing ventilation in England. In the case-study, we used meta-analysis to get an estimate of the odds ratio of the association between indoor ventilation and health, and a health impact model to calculate respiratory-related morbidity burdens attributable to changes in indoor ventilation exposures.

5.1. Findings from the case-study

The literature search in the case-study identified a total of 8 studies with 9826 participants that were included in the meta-analysis from which an exposure response relationship was derived: 1.34 OR (95% CI: 1.15 to 1.57), for ventilation rates below 0.5 ACH. We believe that the finding from the meta-analysis contributes to the body of the evidence linking poor ventilation rates and health. To the best of our knowledge, this is the first meta-analysis providing summary estimates of the associations between indoor ventilation rates and health using only epidemiological study designs. Results from the meta-analysis seem consistent with other research that summarised the evidence on ventilation rates and health using other experimental study designs, where the authors concluded that a decrease in ventilation rates

Table 2
Input parameters and corresponding fuzzy intervals.

Definition	Explanation	Intervals
Ventilation rate (X):		
Poor	Poor ventilation rates in air changes per hour (ACH) for "low" indoor air quality	$(0.01\ ACH \leq X < 0.48 ACH)$
Fair	Fair ventilation rates in air changes per hour (ACH) for "medium/fair" indoor air quality	$(0.48\ ACH \leq X < 0.77 ACH)$
Adequate	Adequate ventilation rates in air changes per hour (ACH) for "high" indoor air quality	$(0.48\ ACH \leq X < 1.06 ACH)$
Increase in risk (**E**):		
Excess risk in morbidity	Excess percentage (%) increase in respiratory-related morbidity risk	$(0.14 \leq E \leq 0.45)$

Table 3
Annual respiratory-related morbidity burdens attributable to each ventilation exposure scenario.

	Mid-year 2011 England population*	Excess respiratory-related morbidity cases (n) attributable to each exposure scenario
Ventilation scenarios	53,107,000	
Poor ventilation	–	(99,398 371,097 1,028,008)
Fair ventilation	–	(−539,846 24,997 706,364)
Adequate ventilation	–	(−1,197,605−352,562−48,605)

* Source: ONS, 2012

(from approximately 0.5 to 0.2 ACH) increases the prevalence of respiratory-related symptoms between 12%–32% (Fisk et al., 2009). In addition, based on the ventilation exposure scenarios from the case-study result, we found using a health impact model that respiratory-related morbidity due to "poor" ventilation scenario can potentially be a significant contributor to the total annual respiratory-related morbidity cases in England. Imprecision in the definition of each exposure scenario had a major implication on the uncertainty in the outcome of the model. The uncertainty ranged from (i) 99,393 to 1,028,008 excess morbidity cases under ventilation between 0.01 ACH to 0.48 ACH; (ii) a reduction of −539,846 cases and an excess of 706,364 cases under ventilation between 0.19 ACH to 0.77 ACH; and (iii) a reduction of morbidity cases from −1,197,605 to −48,605 under ventilation between 0.48 ACH to 1.06 ACH. In general, the lowest range of ventilation exposure (ACH) defined in the case-study resulted with the greater impact on health.

Our finding from the case-study emphasises the need to ensure adequate ventilation levels to minimise the potential health effects from poor ventilation exposure as buildings become more airtight in England. There is evidence in the wider literature to suggest that low ventilation rates increases air-borne pollutants concentration (Oie et al., 1999). For instance, one extensive review has suggested that ventilation rates lower than 0.5 ACH in cold climates can increase the risk of negative health outcomes (Sundell et al., 2011). Ventilation rates between 0.5 and 1.5 ACH in the UK are considered sufficient to stop condensation and to control indoor pollutants (Trust, 2006). This research finding adds to this evidence-based suggesting that 0.5 ACH can be considered an actual threshold from which a population health effect based on the exposure can be observed.

5.2. Strengths and limitations

As part of the framework, we applied a method based on fuzzy set theory to deal with the uncertainty in the parameters of a model. Given the lack of probabilistic information in some input parameters (e.g. statistical information regarding ventilation exposure for the English housing stock), the application of fuzzy set theory was considered appropriate for the quantification of uncertainty, as an alternative way of handling uncertainty to the probabilistic approach. The uncertainty in each exposure scenario was represented using fuzzy sets, and their spread was determined based on plausible information on ventilation rates' guidelines for indoor air quality. We also characterised the uncertainty in the 95% CI of the odds ratio as a fuzzy set, which was used as an input parameter for the health impact model. Fuzzy sets were defined in this study with a triangular membership function with an interval and a centre value, representing the lower and upper bounds of the fuzzy set respectively. It is important to note that there are many choices for membership functions of fuzzy sets such as trapezoids and Gaussian membership functions, which are described elsewhere (Smithson and Verkuilen, 2006).

This study was only able to quantify the health impacts of housing ventilation in England based on limited information found in the literature. The meta-analysis presents some limitations. The diversity of the study populations, geographical locations from individual studies in the analysis can make the overall estimate sub-optimal for the English context. Another limitation is that the smaller number of eligible studies (8 studies) might have influenced the power of the meta-analysis, although such bias and limitation regarding the small number of studies can be reduced as more studies become available in the literature. We also defined each exposure ventilation scenario with specific ventilation rate categories. Other ventilation rate categories were not considered in this analysis. For example, there are *very high* ventilation categories which exceed ventilation rates greater than 1.06 ACH, which were not considered. We also incorporated the uncertainty in the 95% CI of the odds ratio using fuzzy sets without probabilistic guarantees or distributional assumptions. A potential limitation of the fuzzy set approach is that the fuzzy set does not incorporate knowledge regarding correlation and other statistical information in parameters, and this can be a limitation in circumstances when there is sufficient information to incorporate statistical information such as mean, correlations and other.

5.3. A different point of view of uncertainty

When comparing the proposed method with other probabilistic approaches is important to note that both approaches deal with different aspects of uncertainty. Uncertainty can arise in the assessment from two underlying causes. Uncertainty can arise due to imprecision in knowledge because of limited information, or due to random variability found in the stochastic nature of most real-world variables. It could be argued that the fuzzy-set method provides a better measure for the characterisation of the uncertainty in circumstances characterised with limited information about statistical parameters or imprecision in knowledge. On the other hand, probabilistic approaches can provide a better characterisation of uncertainty if suitable assumptions can be made on the statistics of the variability in the input parameters. Monte Carlo (MC) methods rely on random sampling and simulations,
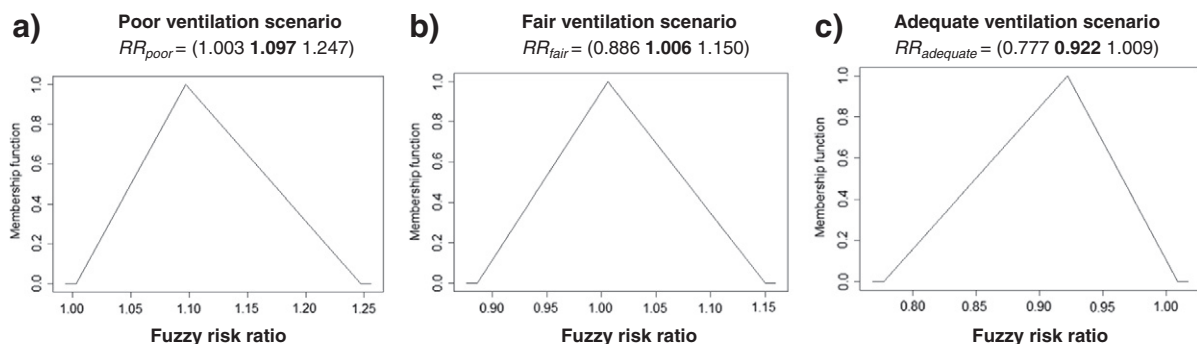
a) Poor ventilation scenario
$RR_{poor} = (1.003\ \mathbf{1.097}\ 1.247)$

b) Fair ventilation scenario
$RR_{fair} = (0.886\ \mathbf{1.006}\ 1.150)$

c) Adequate ventilation scenario
$RR_{adequate} = (0.777\ \mathbf{0.922}\ 1.009)$

Fig. 3. Fuzzy sets describing uncertainty propagation of adjusted risk ratios in model parameters.

a) Poor ventilation scenario

$AMB_{poor} = (99{,}398\ \mathbf{371{,}097}\ 1{,}028{,}008)$

b) Fair ventilation scenario

$AMB_{fair} = (-539{,}846\ \mathbf{24{,}997}\ 706{,}364)$

c) Adequate ventilation scenario

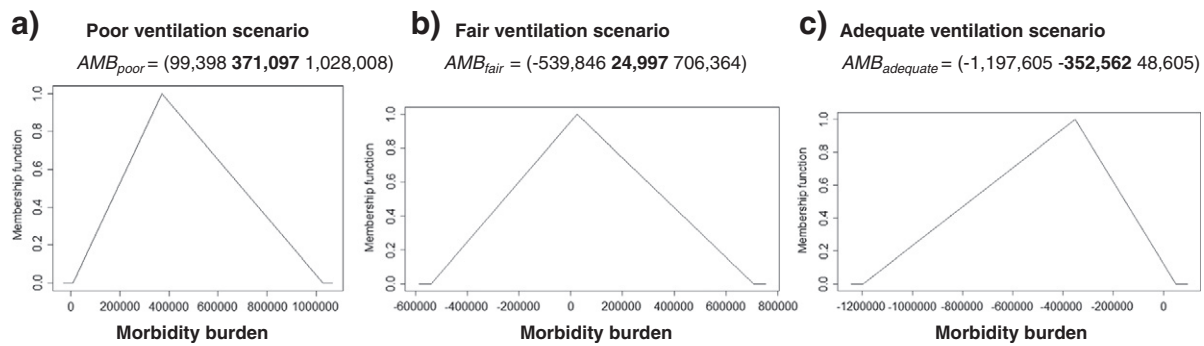$AMB_{adequate} = (-1{,}197{,}605\ \mathbf{-352{,}562}\ 48{,}605)$

Fig. 4. Annual respiratory-related morbidity burdens attributable to changes in indoor ventilation scenarios and corresponding uncertainty described in fuzzy sets.

to obtain probability distributions from which statistical parameters can be estimated to characterise the uncertainty. These methods assume model parameters to be random variables, using statistical inference with sampling techniques to obtain parameter distributions of the random variable. However, such probabilistic approaches to uncertainty analysis can be less suitable to deal with the uncertainty associated with lack or imprecision in knowledge than the fuzzy set approach. Assuming random variability in model parameters when there is limited statistical information can lead estimates in epidemiological models to very different conclusions if suitable assumptions on the statistics of the variability cannot be made (Fuentes, 2009). We instead propagated the uncertainty using interval arithmetic with the fuzzy set approach, and provided some interval estimates for the characterisation of uncertainty which assumed information in parameters to be imprecise by nature. Note however there are similarities between the probabilistic and fuzzy approaches. Both use expert judgments whether in selecting the probability density function (probabilistic approach) or the membership function (fuzzy approach). Furthermore, both can be computationally demanding.

6. Conclusion

We have proposed a non-probabilistic framework using fuzzy set theory to quantify the uncertainty in HIA and applied it to housing ventilation as an example. The framework could also enable the quantification of the health impacts by following three steps: (i) selecting the exposure metric and quantifying the evidence of potential health effects of the exposure, (ii) estimating the size of the population affected by the exposure and selecting the outcome measure, and (iii) quantifying the health impacts and associated uncertainty. The framework is demonstrated through a HIA case study which examines the health impact of housing ventilation in England. We have argued that this framework can be applicable to other examples of quantitative HIA where there is insufficient information for a probabilistic analysis. This includes situations where the uncertainty in model parameters cannot be described by probability density functions, because of either of lack of statistical information or the input parameters are not precisely defined.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.envint.2013.10.007.

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