A Review of Air Exchange Rate Models for Air Pollution Exposure Assessments

Michael S. Breen,[a*] Bradley Schultz,[a] Michael D. Sohn,[b] Thomas Long,[c] John Langstaff,[d] Ronald Williams,[a] Kristin Isaacs,[a] Qing Yu Meng,[e] Casson Stallings,[f] Luther Smith[f]

[a] National Exposure Research Laboratory, U.S. Environmental Protection Agency, Research Triangle Park, NC 27711, USA
[b] Energy Analysis and Environment Impacts Department, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA, mdsohn@lbl.gov
[c] National Center for Environmental Assessments, U.S. Environmental Protection Agency, Research Triangle Park, NC 27711, USA
[d] Office of Air Quality and Planning Standards, U.S. Environmental Protection Agency, Research Triangle Park, NC 27711, USA
[e] Department of Environmental and Occupational Health, UMDNJ-School of Public Health, Piscataway, NJ 08854, USA, mengqi@umdnj.edu
[f] Alion Science and Technology Inc., Research Triangle Park, NC 27709, USA, lasmith@alionscience.com, cstallings@alionscience.com

* Corresponding author: Michael S. Breen, Ph.D.
U.S. Environmental Protection Agency
Office of Research and Development
National Exposure Research Laboratory
Human Exposure and Atmospheric Sciences Division
Exposure Modeling Research Branch
109 T.W. Alexander Drive, Mail E205-02
Research Triangle Park, NC 27711
tel: 919-541-9409
fax: 919-541-9444
email: breen.michael@epa.gov

Running title: Review of Air Exchange Rate Models

Abstract

A critical aspect of air pollution exposure assessments is estimation of the air exchange rate (AER) for various buildings where people spend their time. The AER, which is the rate of exchange of indoor air with outdoor air, is an important determinant for entry of outdoor air pollutants and for removal of indoor-emitted air pollutants. This paper presents an overview and critical analysis of the scientific literature on empirical and physical AER models for residential and commercial buildings, which are feasible for exposure assessments. Models are included for the three types of airflows that can occur across building envelopes: leakage, natural ventilation, and mechanical ventilation. Guidance is provided to select the preferable AER model based on available data, desired temporal resolution, types of airflows, and types of buildings included in the exposure assessment. For exposure assessments with some limited building leakage or AER measurements, strategies are described to reduce AER model uncertainty. This review will facilitate the selection of AER models in support of air pollution exposure assessments.

Keywords

Air exchange rate models, air pollution, exposure assessment, leakage, natural ventilation, mechanical ventilation

INTRODUCTION

Assessing the health effects of air pollutants requires estimates of human exposures. On average, people living in the United States (US) spend 87% of their time within enclosed buildings.[1] Therefore, an important aspect of air pollution exposure assessments is the air exchange rate (AER) for the various types of buildings where people spend their time (Figure 1). The AER, defined by

$$\mathrm{AER}=Q/V \qquad (1)$$

where Q is the rate of airflow into and out of a building and V is the building volume, is a determinant of entry of outdoor-generated air pollutants and removal of indoor-generated air pollutants. The exchange of outdoor air with air inside occupied spaces of buildings can be separated into three categories: leakage, natural ventilation, and mechanical ventilation (Figure 2). Leakage is the airflow through unintentional openings in the building envelope (e.g., cracks around windows and doors). Natural ventilation is the intentional airflow through controlled openings in the building envelope (e.g. open windows and doors). The airflows for leakage and natural ventilation are driven by pressure differences across the building envelope due to indoor-outdoor temperature differences (stack effect) and wind (wind effect).[2] Mechanical ventilation is the airflow from outdoor-vented fans. A primary goal of this paper is to describe models that consider each of these airflows, and to provide guidance on the various models and their appropriate use for exposure assessments.

The fraction of the outdoor pollutant concentration that enters and remain airborne indoors (infiltration factor, F_{inf}) is defined at steady-state conditions as

$$F_{\mathrm{inf}}= P*\mathrm{AER}/(\mathrm{AER}+k) \qquad (2)$$

where P is the fraction of outdoor pollutant passing indoors (penetration coefficient) and k is the indoor loss rate.[3] For some gaseous pollutants (e.g., carbon monoxide) with negligible k compared to AER (F_{inf} ~P), F_{inf} can be considered relatively independent of the AER.[4] For air pollutants with k>0 (e.g., particulate matter and ozone), F_{inf} depends on the AER, which can vary from building to building and across time.[5] Studies with particulate matter show that the AER can explain a substantial amount of the variability of the F_{inf} .[6-9]

The AER affects the magnitude of indoor air pollutant concentrations. For outdoor-generated pollutants, indoor concentrations C_{in} at steady-state conditions can be described by

$$C_{in}=F_{inf}*C_{out} \tag{3}$$

where C_{out} is the outdoor concentration.[10] In Equation 2, setting P=0.9 and k=1.0 h^{-1} based on average reported values for airborne particles (diameter = 2.5μm),[3,11] C_{in} for a tight (k_a =0.1 h^{-1}) and leaky (k_a=2.0 h^{-1}) building[2] is 0.08 and 0.60 times C_{out}, respectively. For indoor-generated pollutants, C_{in} at steady-state conditions can be described by

$$C_{in}=S/(V(k_a+k_d)) \tag{4}$$

where S is the source emission rate and V is the building volume.[10] Assuming k=1.0 h^{-1}, C_{in} for a tight (k_a =0.1 h^{-1}) and leaky (k_a=2.0 h^{-1}) building is 0.91 and 0.33 times S/V, respectively. Therefore, the AER can substantially affect the level of C_{in} under steady-state conditions.

The AER also affects the time-course behavior (e.g., peak level and delay time to peak level) of indoor air pollutant concentrations. For time-varying outdoor concentrations (e.g., morning and evening traffic rush hours), indoor concentrations can be described by the dynamic mass balance equation[10]

$$dC_{in}/dt=k_a P C_{out}-(k_a+k_d)C_{in} \quad (5).$$

Computer simulations for different scenarios of time-varying outdoor concentrations showed that indoor concentrations increase slower and reach lower peak levels for tighter buildings.[12] Predicting this dynamic indoor concentration behavior can be used for exposure assessments of chemicals with toxicity influenced by peak concentrations and short-term exposures.

AER models have several possible applications. First, AER models can reduce the uncertainty of exposure models by accounting for the various factors that affect the AER (Figure 2). These factors include the physical driving forces of the airflows (e.g., pressure differences across building envelope from wind, indoor-outdoor temperature differences, and mechanical ventilation), building characteristics (e.g., local wind sheltering, tightness of the building envelope), and occupant behavior (e.g., opening windows, operating outdoor-vented fans, thermostat temperature setting during heating and cooling seasons). Therefore, substantial AER variations can occur from temporal and geographical differences in weather conditions, building characteristics, and occupant behavior. The resulting temporal and geographical variations in exposure may help explain the differences observed in epidemiologic associations between ambient concentrations and health effects in different US communities.[13] The AER variations may also help to better understand the impact of AER for individuals with exceptionally high and low exposures. Second, AER measurements are often limited due to the costs of collecting site-specific field data, participant burden, and building access restrictions. Therefore, AER models integrated within individual and population exposure models can be a feasible method to determine exposure metrics for epidemiological analysis and regulatory risk assessments.[14-18] Finally, AER models can be used to evaluate the impact of alternative future scenarios, such as sheltering-in-place due to local toxic release, and changes in weather, building characteristics or operation due to climate change, energy conservation, and air pollution risk management decisions.

There are a few reports of using physical AER models within exposure models to examine possible future scenarios, such as sheltering-in-place.[19-20] Other exposure models estimate AER using empirical methods.[16-18] Descriptions of the physical AER models are scattered in the literature and often provided in national laboratory reports and building engineering handbooks.[2] Also, certain types of physical models cannot be applied for exposure assessments due to extensive input requirements.

This paper provides an overview and critical analysis of the scientific literature on the various AER models that are feasible for exposure assessments, and provides guidance to select the appropriate AER model for a particular situation. Below, we first describe the various types of AER models for residential and non-residential buildings. Then, we describe the strengths and limitations of each model, considerations for selecting models for exposure assessments, and gaps in current knowledge with recommendations for future research.

MEASUREMENTS FOR ESTIMATION OF AER AND LEAKAGE

The primary measurement methods to determine the AER and leakage of building envelopes are tracer gas methods and whole-building fan pressurization (blower door) tests, respectively. Tracer gas methods determine AER for the current weather conditions, and account for airflows due to leakage, natural ventilation, and mechanical ventilation.[2] Alternatively, fan pressurization measures critical inputs (i.e., building properties that typically vary little with time and weather) for leakage models.[2] Below, we briefly describe these measurement methods.

Tracer Gas Measurements

To determine the AER, a non-reactive tracer gas is released into the building, and allowed to mix with the indoor air.[2] The tracer concentration is then monitored to determine the AER. The various tracer gas methods are based on a mass balance of the tracer gas in the building. Assuming the outdoor concentration is zero and the tracer gas is well-mixed within the building that is considered a single compartment, the mass balance is

$$V\left(\frac{dC(t)}{dt}\right)=I(t)-Q(t)C(t) \tag{6}$$

where V is building volume, $C(t)$ is the tracer gas concentration at time t, $I(t)$ is the tracer gas injection rate at time t, $Q(t)$ is the airflow across building envelope at time t due to leakage, natural ventilation, and mechanical ventilation. The different tracer gas methods, and their benefits and limitations are described elsewhere.[2]

Pressurization Measurements

To model the AER due to leakage, fan pressurization determines the leakage of a building envelope.[2,21] A large fan is mounted to an exterior doorway using a specialized frame to seal the opening. The fan airflow ($Q_{\Delta P}$) is adjusted to generate various indoor-outdoor pressure differences (ΔP, typically increased incrementally from 10 to 75 Pa) with natural ventilation openings closed and mechanical ventilation turned off.

The pressurization measurements ($Q_{\Delta P}$, ΔP) are used to calculate inputs for some of the AER models described below. First, the constant rate (CR) leakage model requires the AER at ΔP=50 Pa (AER_{50}). Second, the Alberta Air Infiltration Model (AIM-2) requires the power law coefficients (n, c), which are estimated by fitting the set of measured $Q_{\Delta P}$ and ΔP to the empirical power law equation

$$Q_{\Delta P}=c(\Delta P)^{n} \tag{7}$$

where c is the flow coefficient and n is the pressure coefficient.[22] The power law, which can be derived theoretically based on laminar flow in short pipes, approximates the relationship between

$Q_{\Delta P}$ and ΔP for small openings in a building envelope.[2] To reduce measurement errors, buildings are pressurized at higher ΔP than the desired reference ΔP (typically 4 Pa). The power law relationship is used to extrapolate $Q_{\Delta P}$ at the reference ΔP.[22] Third, the Lawrence Berkeley Laboratory (LBL) and the Extended LBL (LBLX) models require the effective leakage area (A_{inf}) defined by

$$A_{\text{inf}} = c \cdot \Delta P^{n-0.5} \cdot \sqrt{\frac{\rho}{2}} \tag{8}$$

where ρ is the air density, and ΔP is set to the reference ΔP (4 Pa). Equation 8 is derived from fluid mechanics using the Bernoulli equation, which reduces to the orifice equation

$$Q_{\Delta P} = A_{\text{inf}} \sqrt{\frac{2\Delta P}{\rho}} \tag{9}$$

since the airflow resistance from drag can be considered negligible for small openings in the building envelope at the reference ΔP.[22] Combining Equations 7 and 9 yields Equation 8.

OVERVIEW OF AER MODELS

Three broad categories of AER models can be distinguished: empirical models, single-zone physical models, and multizone physical models (Figure 3). This review focuses on empirical and simplified single-zone models. Multizone models are typically not feasible at this time for air pollution exposure assessments due to intensive data needs and high level of expertise required for implementation.[23]

Empirical AER models are data-driven approaches, whereas physical models are based on fundamental physical theory. We will first describe empirical approaches that include sampling methods based on AER measurements from other buildings, constant rate models based on pressurization tests, scale factor models based on building characteristics, and regression-based models based on AER driving factors. We will then describe physical models that separate the airflows from leakage, natural ventilation, and mechanical ventilation. After the summary descriptions, we provide guidance on selecting AER models for exposure assessments.\

A comprehensive literature search was performed on September 13, 2012 with Web of Science and Pubmed to retrieve articles related to AER modeling. To identify a subset of articles describing specific AER models, we screened the search results for relevance based on the model type (i.e., empirical and simplified single-zone AER models). We also identified relevant AER models cited by key publications.

EMPIRICAL MODELS

Sampling AER Distributions from Residences and Large Buildings

Sampling distributions of literature-reported AER measurements from various field studies can be used to estimate AER. Exposure assessors can select AER measurements based on various factors (e.g., building characteristics, season, geographical region) most similar to the exposure assessment,[16-18] and several studies of AER measurements have been published. For US residences, measured AER distributions have been reported by region and season.[24,25] For small to medium size commercial buildings, studies reported AER distributions[26,27] and individual[28] AER measurements with and without mechanical ventilation. The mechanical ventilation for commercial buildings can vary by season for energy efficiency with higher rates during mild seasons (spring and fall) and lower rates in summer and winter. For office buildings, one study reported AER from seven large multi-story buildings ranging from 0.45 to 1.45 h^{-1}.[29] Another study reported ventilation rates measured in 100 US office buildings.[30]

For exposure assessments, sampling AER distributions based on particular characteristics (e.g., season, region) requires few inputs. The main limitation is the uncertainty of using AER measurements from other buildings and from sampling periods with different weather conditions, natural ventilation, and mechanical ventilation.

Constant Rate (CR) Leakage Model based on Pressurization Measurements

The CR (rule-of-thumb) models are typically used to estimate the annual average leakage by dividing AER_{50} by a scale factor of 20 or a scale factor based on climate and building characteristics (e.g., height, local wind shielding, leakiness correction factor).[31] Limitations of the CR models include uncertainty and low temporal resolution from not considering the leakage driving forces (indoor-outdoor temperature differences, wind) and airflows due to natural ventilation and mechanical ventilation. For exposure assessments, the CR models provide a long-term average AER that may be sufficient for air pollution studies examining long-term health effects.

Scale Factor (SF) Model based on Building Characteristics

The SF model relates the AER at 50 Pa (AER_{50}) to the AER under typical conditions (4 Pa) using a scaling factor (F) defined as

$$AER_{\mathrm{SF}} = \frac{AER_{50}}{F} = \frac{Q_{50}/V}{F} \tag{10}$$

where V is set to the floor area (A_{floor}) multiplied by the ceiling height (H_{c}).[22] To describe AER_{50} in terms of the normalized leakage area NL defined as

$$NL = 1000 \frac{A_{\mathrm{inf}}}{A_{\mathrm{floor}}} \left(\frac{H}{2.5} \right)^{0.3} \tag{11}$$

where H is the building height, Equations 7, 9, and 11 are combined to yield

$$AER_{50} = 48\left(\frac{2.5}{H}\right)^{0.3} \frac{NL}{H_C} \tag{12}$$

Using residential AER measurements, the values for *F* were empirically derived based on house height, local sheltering, and climatic region, without using meteorological data (i.e., wind and temperature).[14,22]

The *NL* can be determined from pressurization measurements[22] or estimated from leakage area models.[22,32] One reported leakage area model was developed based on year of construction Y_{built} and floor area A_{floor} as described by

$$NL = \exp(\beta_0 + \beta_1 Y_{\text{built}} + \beta_2 A_{\text{floor}}) \tag{13}$$

where $\beta_0, \beta_1, \beta_2$ are the regression parameters, which were estimated for three housing types: low-income, conventional, and energy-efficient.[22] Using a goodness of fit, the measured and modeled geometric means categorized by year built, floor area, and housing type showed R^2 ranges from 0.86 to 0.92. Any collinearity that may occur between the variables can increase the model uncertainty. Another similar regression-based leakage area model was reported, which requires three additional variables: building height, foundation type, and climate zone.[32] These two leakage area models were shown to perform equally well with a 0.3% difference between the root mean square of the residuals. [32]

For the purposes of exposure assessments, the benefit of the SF model is the consideration of building characteristics, which can be obtained from various sources (e.g., questionnaires, public databases). The main limitation of the model is the uncertainty and low temporal resolution from not including the weather conditions. Therefore, the SF model can provide long-term average AER for exposure assessors. An evaluation of the model using a building leakage database showed the modeled AER distribution was in good agreement with measured AER distributions from other studies.[22]

Regression-based Models based on AER Factors

Regression models can be used to examine the empirical relationship between AER and the various driving factors. The main driving force of leakage is the indoor-outdoor temperature difference. Several studies found a linear relationship between the AER and temperature difference.[33-39] Reported correlation ranges were Spearman r=0.74-0.75 and Pearson r=0.77-0.83.[37-39]

The wind (speed and direction) is the other driving force for leakage. The reported relationship between wind and leakage is variable. One study found no effect from wind speed.[38] Other studies showed a linear or quadratic relationship between the AER and wind speed[33-37,39] and wind direction.[36]

For exposure assessments, regression models can typically predict daily or long-term average AER with relatively few or no input data requirements for building characteristics. The main limitation of regression-based models is the limited ability to extrapolate to other buildings and weather conditions. Also, the building leakage area is often not included as a separate independent (predictive) variable since the AER driving forces are often being investigated. Therefore, a regression model may not perform well for buildings with different leakage characteristics.

Hybrid Leakage Model

A reported hybrid leakage model includes a balance between theoretical and empirical approaches.[40] This model was developed based on physical factors shown to be correlated with measured air leakage rates. These factors include building leakage, indoor-outdoor temperature difference, wind speed that can be modified by local sheltering from surrounding structures (e.g., buildings, trees). Based on measured residential leakage rates, the AER was defined as

$$\mathrm{AER}_{\mathrm{hybrid}} = L(0.006(|T_{\mathrm{in}} - T_{\mathrm{out}}|) + \left(\frac{0.03}{C}\right)U^{1.5} \tag{14}$$

where L is the generalized building leakiness factor ($1<L<5$) and C is the generalized terrain sheltering factor ($1<C<10$). The model has two parameters (L, C) and three input variables (T_{in}, T_{out}, U). The empirical leakiness factor has values for tight (L<1.5) and leaky (L>2.5) homes. The empirical sheltering factor has values for low (C=1), moderate (C=3), and high (C=10) wind sheltering based on the local terrain.

The benefit of the hybrid model is the few inputs required. The main limitation is the uncertainty of determining building-specific values for L and C. Based on a goodness of fit, evaluations of the hybrid model showed a mean absolute error of 13% in predicted AER across 11 homes.[40] For exposure assessors, the hybrid model could provide a screening-level or qualitative assessment of the AER.

PHYSICAL MODELS

Physical models can separately estimate the AER for the three types of airflows (leakage, natural ventilation, mechanical ventilation), which can be combined to predict the overall AER. Even though interactions can occur between these three airflows, we did not identify any simplified single-zone models that considered these dependencies. Physical models can be classified into two primary categories: single-zone and multi-zone models (Figure 3).[23] Single-zone models are appropriate for small buildings and residences that can be represented as a single, well-mixed compartment with no internal resistance to airflow. The more complex multizone models are required for large buildings that need to be represented by a series of interconnected compartments with distinct pressures and temperatures. Since the input data for multizone models (e.g., spatial configuration of internal walls) is typically unavailable for air pollution exposure assessments, this paper considers only single-zone models. There are two types of single-zone models: simplified and network models (Figure 3).[41] Network models account for each flow path across the building envelope, whereas simplified single-zone models require only the whole house leakage. Since the data requirements for network models (e.g., flow path distribution and characteristics) are typically not available for exposure assessments, this paper focuses on simplified single-zone models. We first describe leakage models, then models for natural and mechanical ventilation.

Lawrence Berkeley Laboratory (LBL) Leakage Model

The LBL model is widely used to predict residential leakage rates.[2,42] The model assumes leakage is described by the orifice equation derived from fluid mechanics (Equation 9). The driving force for the two physical processes (stack and wind effects) are calculated separately, and then combined using superposition. The stack-induced airflow is described by

$$Q_{\mathrm{s}} = k_{\mathrm{s}} A_{\mathrm{inf}} \sqrt{\left| T_{\mathrm{in}} - T_{\mathrm{out}} \right|} \tag{15}$$

and the wind-induced airflow is defined as

$$Q_{\mathrm{w}} = k_{\mathrm{w}} A_{\mathrm{inf}} U \tag{16}$$

where k_{s} is the stack coefficient that depends on building height, k_{w} is the wind coefficient that depends on building height and local sheltering from nearby buildings and natural structures, T_{in} and T_{out} are the indoor and outdoor temperatures, and U is the wind speed. Since the physical details of each leakage opening of the building are unknown, a superposition method is required to simplify the complex interactions that can occur between the stack and wind effects. A robust superposition equation was empirically-derived from measurements[43,44] as defined by

$$Q_{\mathrm{LBL}} = \sqrt{Q_s^2 + Q_w^2} \tag{17}$$

The AER is calculated as Q_{LBL} divided by V.

The LBL model has two parameters (k_s and k_w) and five input variables (A_{inf}, T_{in}, T_{out}, U, and V). The variable A_{inf} can be measured (Equation 8) or modeled (Equations 11 and 13), T_{out} and U are measurements from local weather stations, and T_{in} can be measured, set to a constant, or estimated from outdoor temperatures using thermal comfort models.[45,46] Parameters k_s and k_w are set to literature values based on building height and local sheltering.[2,42]

For exposure assessments, the benefit of the LBL model is the consideration of building characteristics and weather conditions. The LBL model can predict hourly or daily AER as well as long-term averages, based on the temporal resolution of the metrological data. Therefore, the LBL model can be applied for a variety of exposure studies. The main limitation of the LBL model is the detailed building information needed for the inputs. This information can be obtained from questionnaires for individual exposure assessments, and obtained from public databases such as censuses, property assessments, and residential surveys for population-based exposure assessments. Evaluations of the LBL model using leakage area measurements showed mean absolute errors of 26-46% [47] and 25% [48] for detached homes. Using a leakage area model, the LBL model had a mean absolute error of 43% for 31 detached homes across four seasons.[14]

Extended LBL Leakage Model (LBLX) for Natural Ventilation

The LBL model predicts the AER due to leakage, but does not account for natural ventilation. To address this limitation, the LBL model was extended (LBLX) to predict the natural ventilation airflow through large intentional openings (e.g., windows, doors).[14] Briefly, the natural ventilation airflow Q_{nat} was calculated as

$$Q_{\text{nat}} = \sqrt{Q_{\text{nat,wind}}^2 + Q_{\text{nat,stack}}^2} \tag{18}$$

where $Q_{\text{nat,wind}}$ and $Q_{\text{nat,stack}}$ are the natural ventilation airflows from the wind and stack effects, respectively. The combined airflow Q_{LBLX} from both leakage and natural ventilation was calculated as

$$Q_{\text{LBLX}} = \sqrt{Q_{\text{LBL}}^2 + Q_{\text{nat}}^2} \tag{19}$$

The AER for the LBLX model is the Q_{LBLX} divided by V. Input data include the area of the natural ventilation openings, indoor and outdoor temperatures, and wind speed.

For exposure assessments, the benefit of the LBLX model is the consideration of occupant behavior related to natural ventilation. In homes without air conditioning, the AER due to natural ventilation could be substantial in the warmer seasons. The LBLX model could be applied for exposure studies when window opening data are available from questionnaires for individual exposure assessments or from public databases for city or county-level exposure assessments. The main limitation of the LBLX model is the detailed information needed for natural ventilation (e.g., size of opened windows, doors). Using literature-reported parameter values, AER predictions from the LBLX model were compared to data from 642 daily AER measurements across 31 detached homes in central North Carolina, with corresponding window opening and meteorological data.[14] For individual model-predicted and measured AER, the median absolute difference was 40% (0.17 h^{-1}).

Alberta Air Infiltration (AIM-2) Model

The AIM-2 infiltration model is an enhancement of the LBL leakage model.[2,49] Unlike the LBL model, the AIM-2 model assumes leakage is described by the empirical power law relationship (Equation 7), considers the stack and wind effects from chimney flues, and considers the wind effect from slab and crawlspace foundations.[2] Similar to the LBL model, the driving force for the stack and wind effects are calculated separately, then combined using the superposition. The stack-induced airflow Q_s and wind-induced airflow Q_w are defined as

$$Q_S = cC_S \left|T_{\text{in}} - T_{\text{out}}\right|^n \tag{20}$$

$$Q_W = cC_W \left(sU\right)^{2n} \tag{21}$$

where C_s is the stack coefficient that depends on chimney flue and house height; C_w is the wind coefficient that depends on chimney flue, house height, and foundation type; and s is the shelter factor that depends on local wind sheltering from surrounding buildings, house height, and chimney flue. Using superposition (Equation 17), the total airflow Q_{AIM} is defined as

$$Q_{\text{AIM}} = \sqrt{Q_s^2 + Q_w^2} \tag{22}$$

The AER is calculated as Q_{AIM} divided by V.

The AIM-2 model has three parameters (C_s, C_w, s) and six input variables (c, n, T_{in}, T_{out}, U, and V). Inputs c and n can be estimated from measurements (Equation 7) or set to literature values.[20] Parameters C_s, C_w, and s can be set to literature values based on building height, foundation type, and presence of flue.[2]

For exposure assessments, the accuracy of the AIM-2 model (19% mean error) can be better than the LBL model (25% mean error) when the parameters are well known for the building.[48] The limitations of the AIM-2 model are the additional input requirements as compared to the LBL model, and no model available for the leakage-related inputs c and n, unlike the leakage area models available for the LBL model.

Shaw-Tamura Leakage Model for Tall Buildings

Modeling leakage for large multi-story buildings is more complicated than small buildings. Large buildings tend to have more internal partitions, which inhibit stack-effect airflows, and airflow connectivity structures (e.g., ventilation ducts, elevator shafts, stairwells), which enhance stack-effect airflows.[20] For tall buildings, the indoor-outdoor pressure difference can vary substantially with height. A model was developed to predict leakage rates of tall buildings.[50] Simple adjustment factors account for the effects of internal partitions and airflow connectivity structures in large buildings. The model inputs include building characteristics, indoor-outdoor temperatures, and wind speed. The model has been used for a community-scale analysis.[20] For exposure assessments, the Shaw-Tamura model provides a critical need for exposure assessors, the ability to estimate the leakage of multi-story buildings (e.g., offices, schools, apartments) where people can spend a substantial percentage of their day. A limitation for applying this leakage model for exposure assessments is that mechanical ventilation used in many tall buildings will likely be the dominate airflow for the total AER.

Combining Leakage and Mechanical Ventilation

Mechanical ventilation systems can be divided into two categories: balanced and unbalanced. Balanced-flow systems (e.g., air-to-air heat exchangers) have two fans, one pumping air into the building (intake fan) and one pumping the same amount of air out (exhaust fan). Therefore, there is no change in the internal pressure and no subsequent interaction between the mechanical system and leakage. Unbalanced-flow systems have either an intake or exhaust fan that changes the internal pressure and alters the leakage. Unbalanced airflows can occur from bathroom exhaust fans, outdoor-vented kitchen range hoods, vented clothes dryers, window fans, whole-house fans, and window/wall air conditioners operated with open outdoor vents. Since mechanical ventilation and leakage occur simultaneously, a model was developed for the combined airflow Q_{comb} as defined by

$$Q_{\text{comb}} = Q_{\text{bal}} + \sqrt{Q_{\text{unbal}}^2 + Q_{\text{leak}}^2} \tag{23}$$

where Q_{bal} and Q_{unbal} are the balanced and unbalanced mechanical ventilation airflows, respectively, and Q_{leak} is the leakage airflow.[2,51]

The benefits of using this model for exposure assessments is the ability to reduce the modeled AER uncertainty in buildings with substantial mechanical ventilation, such as commercial buildings (e.g., offices) where many people work and spend much time. The main challenge with applying this model for exposure assessments is the need for input data on the operation and type of intake or exhaust fans in homes (e.g., window fan, bathroom fan) and offices (e.g. mechanically ventilation systems).

MODELING STRATEGIES WITH LEAKAGE OR AER MEASUREMENTS

As previously noted above, physical models can be used to support exposure assessments without measurements of leakage (based on pressurization tests) or AER (based on tracer gas) (Figure 4A). Limited leakage or AER measurements can be used to reduce the uncertainty of the physical models when predicting AER under different weather and ventilation conditions (Figures 4B and 4C). Using leakage measurements has several benefits. First, the uncertainty of leakage measurements is expected to be less than the uncertainty of leakage models. Second, for many exposure studies, a reasonable simplifying assumption can be that the effective leakage remains relatively constant for the duration of the study. Then, a single leakage measurement for a home can be sufficient to predict the AER for other days with different weather conditions (Figure 4B). Additionally, by using a physical model that considers available data on natural ventilation (e.g., opening windows) and mechanical ventilation (e.g., operating window fans), one could expand the approach to predict the AER for other days with different ventilation conditions. Finally, this method may be useful to reduce the cost of studies since pressurization-derived leakage measurements are typically less expensive[52] and performed only one time, as compared to tracer gas-derived AER measurements.

Limited AER measurements can be used to calibrate physical AER models to reduce model uncertainty when predicting AER on days without measurements (Figure 4C). AER measurements obtained on certain days are not necessarily predictive for other days with different weather conditions. However, the measured AER and weather conditions can be used to estimate the leakage parameter of a physical model. The estimated leakage can then be used to predict the AER for other days (Figure 4B). Using a physical model that considers natural ventilation and mechanical ventilation, this approach could be expanded to predict the AER for other days with different ventilation conditions. This method can be useful for studies that require long-term exposure assessments and have limited AER measurements. This approach can estimate individual hourly or daily AER as well as long-term averages, based on the temporal resolution of the meteorology data.

SELECTION OF AER MODELS

There are various factors that influence AER and thus contribute to the selection of an appropriate AER model for specific exposure assessments. For residences, temporal AER variations are due to changes in meteorology (temperature and wind speed) and occupant behavior (opening windows, operating window fans, indoor temperature from thermostat setting during heating and cooling seasons).[14] The AER variations across residences in the same geographical region are due to differences in occupant behavior (opening windows, operating window fans, indoor temperature), and building characteristics (leakage of building envelope). For residences in different geographical regions, the AER variations can also include differences in wind speed (near coast versus inland) and outdoor temperature. For commercial buildings, temporal AER variations can occur from occupancy level and seasonal energy-saving settings on HVAC systems (intake air flows increased during periods of higher occupancy and during seasons with comfortable temperatures).[20]

Selecting the preferable AER model for a particular application depends on the available data, desired temporal resolution, airflows (e.g., leakage, ventilation), and building type. A summary of the input requirements, benefits, and limitations (Table 1) can be used as a model selection guide. The AER models not incorporating weather data have lower temporal resolution, and their uncertainty may be greater since they do not explicitly consider the AER driving forces. The empirical models often require fewer inputs than physical models, but can have greater uncertainty from extrapolation to other buildings and different weather conditions. All of the models are appropriate for houses and small buildings without internal partitions, except the Shaw-Tamura leakage model and the sampling of AER distributions that support large tall buildings. The physical models estimate airflows from leakage, except the LBLX model that accounts for natural ventilation.[14]

Various factors need to be considered for including models that support natural ventilation. Intentional openings may not substantially increase the AER because there is a dependence on the natural (wind and stack) driving forces.[14] The stack effect can be small for natural ventilation since windows and doors are generally opened more often on days when the indoor-outdoor temperature differences are small, and indoor-outdoor thermal equilibriums can be reached soon after opening windows or doors. Therefore, wind effect may dominate the AER due to natural ventilation and may be small for days with low winds.[14] Due to these non-intuitive effects of natural ventilation, models can be used to help quantify the total AER and the individual contributions from leakage and natural ventilation.

Input data for the AER models (e.g., building characteristics) can be obtained from various sources. For cohort health studies with individual health outcomes, individual-level AER can be estimated from questionnaires and public property assessment databases. For city or county-level exposure assessments, population-level AER can be estimated from public databases such as censuses and residential surveys,[53] and occupant window opening surveys.[54]

GAPS IN CURRENT KNOWLEDGE

Further development and evaluation of AER models appropriate for exposure assessments are needed for (1) estimating AER for different types of buildings, (2) predicting AER due to natural ventilation, and (3) mechanical ventilation. First, the AER models described above have primarily been evaluated for single-family detached homes. Since many people live in multi-family residences (e.g., apartments, townhomes) and work in commercial buildings, AER estimates are needed for these building types to support exposure assessments for health studies and regulatory risk assessments. New or modifications to existing AER models together with field study measurements for model evaluation, will be needed to address this knowledge gap.

Second, there is a need to further develop and evaluate AER models for natural ventilation.[14] By combining information from window opening studies, modeled distributions of natural ventilation airflows (Equation 18) could be estimated. This research would address a critical need for exposure assessments since people in US and Canada spend approximately 66% of their time indoors at home,[1,55] and their exposures can vary from differences in AER from opening windows as compared to operating air conditioners.

Third, models are needed to predict the AER due to mechanical ventilation. This is a critical aspect for commercial buildings with outdoor-vented forced-air systems, which can provide the bulk of the total AER. For residences, forced-air distribution systems can have leaks with the outdoors (e.g., attics, unfinished basements, crawlspaces). On hot and cold days when these systems are operated for long durations, the AER due to mechanical ventilation would tend to be highest. However, the AER due to leakage from the stack effect would also tend to be highest on hot and cold days. Thus, a better quantitative understanding of the contribution of mechanical ventilation could help develop more predictive AER models for exposure assessments.

SUMMARY

This paper presented an overview and critical analysis of the various literature-reported AER models feasible for air pollution exposure assessments. Strategies to reduce AER model uncertainty were described to support exposure assessments with limited leakage or AER measurements. Guidance was provided for selecting the appropriate AER models based on the available data, desired temporal resolution, and type of buildings. The knowledge gaps identified can help guide future research to support improved exposure assessments.

ACKNOWLEDGEMENTS

We thank Jennifer Richmond-Bryant and Vito Ilacqua for review comments and helpful suggestions. Although the manuscript was reviewed by the U.S. Environmental Protection Agency and approved for publication, it may not necessarily reflect official Agency policy. Mention of trade names or commercial products does not constitute endorsement or recommendation for use.

REFERENCES

1. Klepeis NE, Nelson WC, Ott WR, Robinson JP, Tsang AM, Switzer P, Behar JV, Hern SC, Engelmann WH. The national human activity pattern survey (NHAPS): a resource for assessing exposure to environmental pollutants. J Expo Anal Environ Epidemiol 2001; 11: 231-252.

2. The 2009 ASHRAE Handbook-Fundamentals. American Society of Heating, Refrigerating, and Air Conditioning Engineers: Atlanta, GA, 2009.

3. Liu DL, Nazaroff WW. Modeling pollutant penetration across building envelopes. Atmos Environ 2001; 35: 4451-4462.

4. U.S. EPA. Integrated Science Assessment for Carbon Monoxide (Final Report). U.S. Environmental Protection Agency, Washington, DC, EPA/600/R-09/019F, 2010.

5. U.S. EPA. Integrated Science Assessment of Ozone and Related Photochemical Oxidants - Third External Review Draft. U.S. Environmental Protection Agency, Washington, DC, EPA/600/R-10/076C, 2012.; U.S. EPA. Integrated Science Assessment for Particulate Matter (Final Report). U.S. Environmental Protection Agency, Washington, DC, EPA/600/R-08/139F, 2009.

6. Meng QY, Spector D, Colome S, Turpin B. Determinants of indoor and personal exposure to PM2.5 of indoor and outdoor origin during the RIOPA study. Atmos Environ 2009; 43: 5750-5758.

7. Williams R, Suggs J, Rea A, Sheldon L, Rodes C, Thornburg J. The Research Triangle Park particulate matter panel study: modeling ambient source contribution to personal and residential PM mass concentrations. Atmos Environ 2003; 37: 5365-5378.

8. Wallace L, Williams R, Suggs J, Jones P. Estimating contributions of outdoor fine particles to indoor concentrations and personal exposures: effects of household characteristics and personal activities. EPA/600/R-06/023; United States Environmental Protection Agency: Washington, DC, 2006.

9. Allen RW, Adar SD, Avol E, Cohen M, Curl CL, Larson T, Liu LJ, Sheppard L, Kaufman JD. Modeling the residential infiltration of outdoor PM2.5 in the multi-ethnic study of atherosclerosis and air pollution (MESA Air). Environ Health Perspect 2012; 120: 824-830.

10. Wallace L, Williams R. Use of personal-indoor-outdoor sulfur concentrations to estimate the infiltration factor and outdoor exposure factor for individual homes and persons. Environ Sci Technol 2005; 39: 1707-1714.

11. Riley WJ, McKone TM, Lai AC, Nazaroff WW. Indoor particulate matter of outdoor origin: importance of size-dependent removal mechanisms. Environ Sci Technol 2002; 36: 200-207.

12. Chan WR, Nazaroff WW, Price PN, Gadgil AJ. Effectiveness of urban shelter-in-place-I: idealized conditions. Atmos Environ 2007; 41: 4962-4976.

13. Bell ML, McDermott A, Zeger SL, Samet JM, Dominici F. Ozone and short-term mortality in 95 US urban communities, 1987-2000. JAMA 2004; 292: 2372-2378.

14. Breen MS, Breen M, Williams RW, Schultz BD. Predicting residential air exchange rates from questionnaires and meteorology: model evaluation in central North Carolina. Environ Sci Technol 2010; 44: 9349-9356.

15. United States Environmental Protection Agency. Exposure Model for Individuals (EMI). Available at: http://www.epa.gov/heasd/emi.

16. Burke JM, Zufall MJ, Ozkaynak H. A population exposure model for particulate matter: case study results for PM2.5 in Philadelphia, PA. J Expo Anal Environ Epidemiol 2001; 11: 470-489.

17. United States Environmental Protection Agency. Total Risk Integrated Methodology (TRIM) - Air Pollutants Exposure Model Documentation (TRIM.Expo / APEX, Version 4.4) Volume I: User's Guide, EPA-452/B-12-001a; Office of Air Quality Planning and Standards, US EPA: Research Triangle Park, NC. Available at: http://www.epa.gov/ttn/fera/human_apex.html

18. United States Environmental Protection Agency. Total Risk Integrated Methodology (TRIM) - Air Pollutants Exposure Model Documentation (TRIM.Expo / APEX, Version 4.4) Volume II: Technical Support Document, EPA-452/B-12-001b; Office of Air Quality Planning and Standards, US EPA, Research Triangle Park, NC. Available at: http://www.epa.gov/ttn/fera/human_apex.html

19. Chan WR, Nazaroff WW, Price PN, Gadgil AJ. Effectiveness of urban shelter-in-place-II: residential districts. Atmos Environ 2007; 41: 7082-7095.

20. Chan WR, Nazaroff WW, Price PN, Gadgil AJ. Effectiveness of urban shelter-in-place III: commercial districts. Build Simul 2008; 1: 144-157.

21. ASTM 2003. Test method for determining air leakage rate by fan pressurization. Standard E779-03. American Society for Testing and Materials, West Conshohocken, PA.

22. Chan WR, Nazaroff WW, Price PN, Sohn MD, Gadgil AJ. Analyzing a database of residential air leakage in the United States. Atmos. Environ. 2005; 39: 3445-3455.

23. Orme M. Applicable Models for Air Infiltration and Ventilation Calculations, Technical Note 51; International Energy Agency Air Infiltration and Ventilation Centre, Sint-Stevens-Woluwe: Belgium, 1999.

24. Murray DM, Burmaster DE. Residential air exchange rates in the United States: empirical and estimated parametric distributions by season and climatic region. Risk Anal 1995; 15: 459-465.

25. Koontz MD, Rector HE. Estimation of distributions for residential air exchange rates (Final Report). United States Environmental Protection Agency: Washington DC, 1995.

26. Lagus PL, Grot RA. Consultant report: air change rates in non-residential buildings in California. Lagus Applied Technology, Inc., P400-91-034BCN. Sacramento, CA: California Energy Commission, 1995.

27. Cummings JB, Withers CR, Moyer N, Fairey P, McKendry B. Final report: uncontrolled air flow in non-residential buildings. FSEC-CR-878-96. Cocoa, FL: Florida Solar Energy Center, 1996.

28. Bennett DH, Fisk W, Apte MG, Wu X, Trout A, Faulkner D, Sullivan D. Ventilation, temperature, and HVAC characteristics in small and medium commercial buildings in California. Indoor Air 2012; 22: 309-320.

29. Persily AK, Grot RA. Pressurization testing of federal buildings. Measured air leakage of buildings, In: ASTM STP 904, Trechsel HR, Lagus PL (eds). American Society for Testing and Materials, Philadelphia 1986; pp 184-200.

30. Persily AK, Gorfain J, Brunner G. Survey of ventilation rates in office buildings. Building Research and Information 2006; 34: 459-466.

31. Sherman M. Estimation of infiltration for leakage and climate indicators. Energy and Buildings 1987; 10: 81-86.

32. McWilliams J, Jung, M. Development of a mathematical air-leakage model from measured data, Report LBNL-59041; Lawrence Berkeley National Laboratory: Berkeley, CA, 2006.

33. Laschober RR, Healy JH. Statistical analyses of air leakage in split - level residences. ASHRAE Trans 1964; 70: 364–374.

34. Wang FS, Sepsy CF. Field studies of the air tightness of residential buildings. In: Hunt CM, King JC, Trechsel HR (eds). Building Air Change Rate and Infiltration Measurements, STP 719. American Society for Testing and Materials, Philadelphia, PA, 1980; 24– 35.

35. Goldschmidt VW, Leonard GR, Ball JE, Wilhelm DR. Wintertime infiltration rates in mobile homes. In: Hunt CM, King JC, Trechsel HR (eds). Building Air Change Rate and Infiltration Measurements, STP 719. American Society for Testing and Materials, Philadelphia, PA, 1980; pp 107– 124.

36. Malik N. Field studies of dependence of air infiltration on outside temperature and wind. Energy and Buildings 1978; 1: 281–292.

37. Nazaroff WE, Feustel H, Nero AV, Rexvan KL, Grimsrud DT, Essling MA, Toomey RE. Radon transport into a detached one-story house with a basement. Atmos Environ 1985; 19: 31-46.

38. Wallace LA, Emmerich SJ, Howard-Reed C. Continuous measurements of air change rates in an occupied house for 1 year: the effect of temperature, wind, fans, and windows. J Expo Anal Environ Epidemiol 2002, 12: 296-306.

39. Persily A.K. Measurements of air infiltration and airtightness in passive solar homes. In: Trechsel HR and Lagus PL (eds), Measured Air Leakage of Buildings, STP 904. American Society for Testing and Materials, Philadelphia, PA, 1986, pp 46– 60.

40. Dietz RN, Goodrich RW, Cote EA, Wieser RF. Detailed description and performance of a passive perfluorocarbon tracer system for building ventilation and air exchange measurement. In: Trechsel HR, Lagus PL (eds). Measured Air Leakage of Buildings. ASTM STP904. American Society for Testing and Materials: Philadelphia, 1986, pp 203-264.

41. Feustel HE. Mathematical modeling of infiltration and ventilation. Air Infiltration and Ventilation Centre (AIVC) Conference, Dipoli, Finland, 1989; Paper 8. Available at: http://www.aivc.org.

42. Sherman MH, Grimsrud DT. Infiltration-pressurization correlation: simplified physical model. ASHRAE Transactions 1980; 86: 778-807.

43. Walker IS, Wilson DJ 1993. Evaluating models for superposition of wind and stack effects in air infiltration. Building and Environment 28:201-210 .

44. Sherman MH 1992. Superposition in infiltration modeling. Indoor Air 2:101-114.

45. Humphreys M, Nicol JF. Understanding the adaptive approach to thermal comfort. ASHRAE Technical Data Bulletin 14, 1998, pp 1-14.

46. De Dear R, Brager GS. The adaptive model of thermal comfort and energy conservation in the built environment. Int J Biometeorol 2001; 45: 100-108.

47. Palmiter L, Francisco PW. Modeled and measured infiltration phase III: a detailed case study of three homes. (Technical Report); Ecotope Inc, Seattle, WA, 1996.

48. Wang W, Beausoleil-Morrison I, Reardon J. Evaluation of the Alberta air infiltration model using measurements and inter-model comparisons. Build Environ 2009; 44: 309-318.

49. Walker IS, Wilson DJ. Field validation of algebraic equations for stack and wind driven air infiltration calculations. HVAC&R Research 1998; 4: 119-140.

50. Shaw CY, Tamura GT. The calculation of air infiltration rates caused by wind and stack action for tall buildings. ASHRAE Transactions 1977; 83: 145-158.

51. Sherman MH. Superposition in infiltration modeling. Indoor Air 1992; 2: 101-114.

52. Keefe D. Blower door testing. J Light Construction 2010; January, pp 1-7.

53. United States Department of Energy. Housing characteristics: residential energy consumption survey. Energy Information Administration: Washington, DC, 2001.

54. Price PP, Sherman M, Lee RH, Piazza T. Study of ventilation practices and household characteristics in new California homes, CEC-500-2007-033, Final Report, ARB Contract 03-326; California Energy Commission, PIER Program: Sacramento, 2007.

55. Leech, JA, Nelson WC, Burnett RT, Aaron S, Raizenne ME. It's about time: a comparison of Canadian and American time-activity patterns. J Exposure Anal Environ Epidemiol 2002; 12: 427-432.

Figure Legends

Figure 1. Role of AER models for air pollution exposure and risk assessments.

Figure 2. Factors contributing to AER due to airflows from leakage, natural ventilation, and mechanical ventilation.

Figure 3. Classification of AER models due to airflows from leakage. The highlighted categories (empirical models and simplified single-zone models) are considered in this review.

Figure 4. Modeling methods to estimate AER due to leakage with different input data (A: building characteristics, B: leakage measurements, C: AER measurements. Each method requires meteorological data (temperature and wind speed) from local weather station and building characteristics related to AER driving forces (e.g., sheltering, building height). With input data on building operations, these methods could estimate AER due to natural ventilation (opening of windows and doors) and mechanical ventilation (operation of outdoor-vented fans).

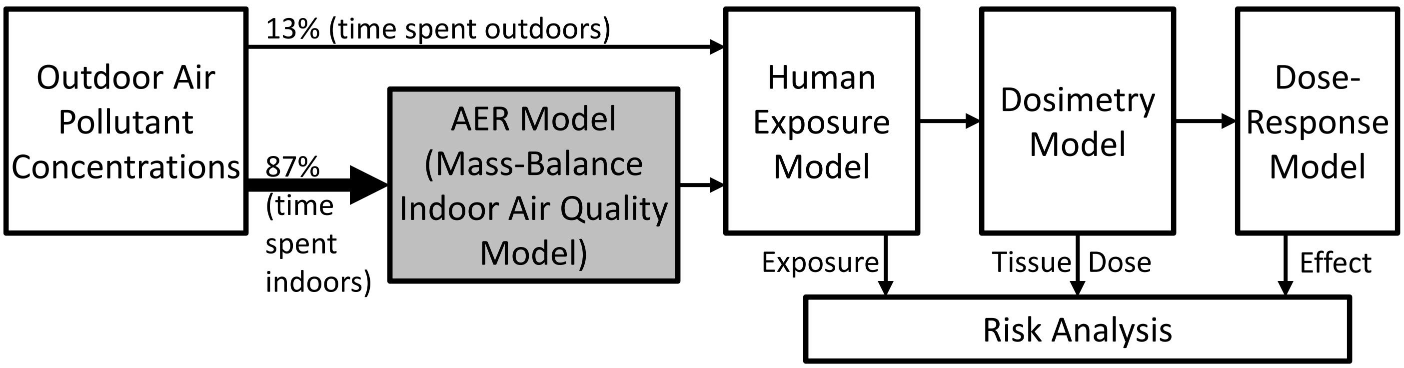
Outdoor Air Pollutant Concentrations
13% (time spent outdoors)
87% (time spent indoors)
AER Model (Mass-Balance Indoor Air Quality Model)
Human Exposure Model
Dosimetry Model
Dose-Response Model
Exposure
Tissue Dose
Effect
Risk Analysis

Figure 1

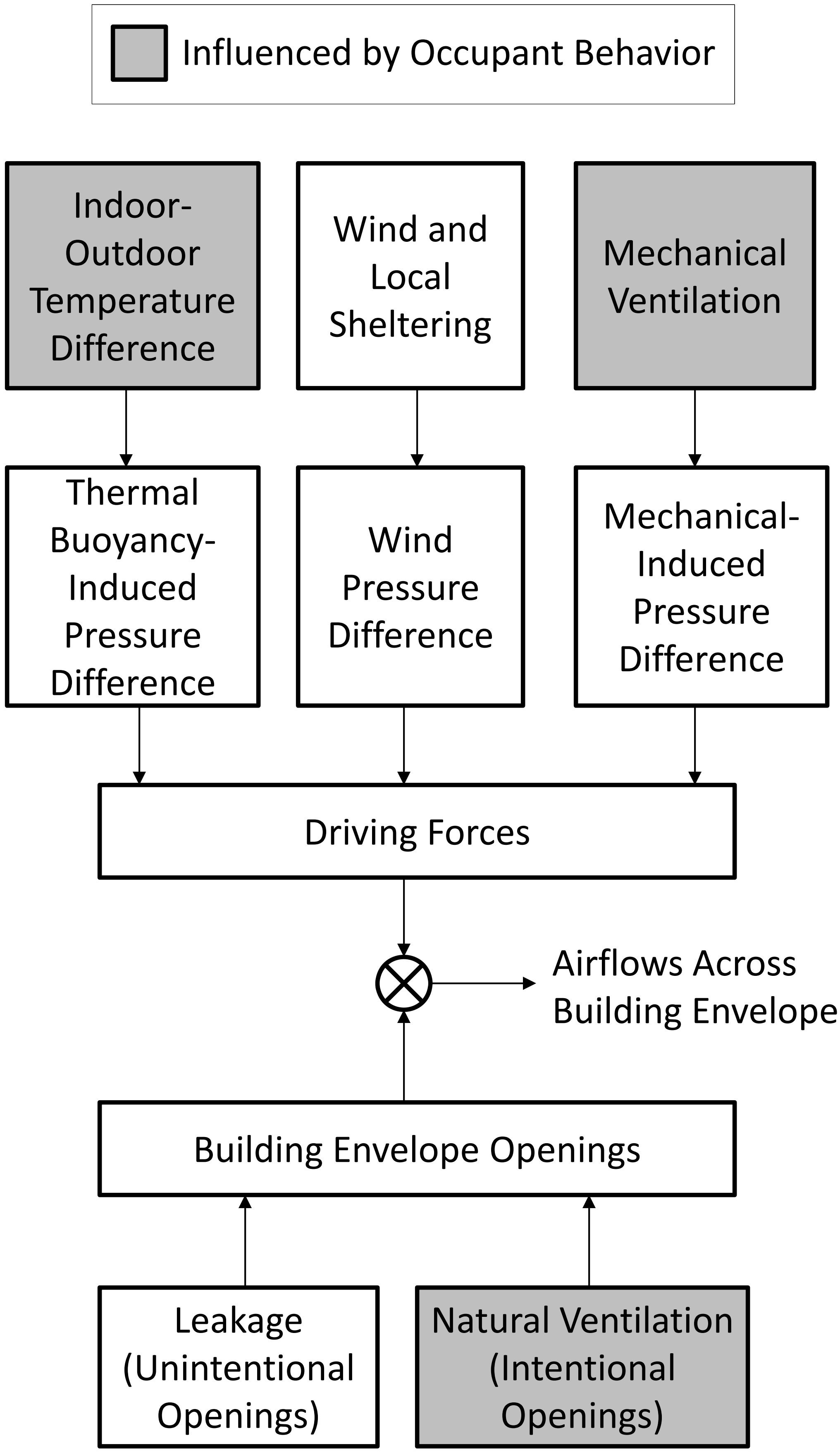
Influenced by Occupant Behavior
Indoor-Outdoor Temperature Difference
Wind and Local Sheltering
Mechanical Ventilation
Thermal Buoyancy-Induced Pressure Difference
Wind Pressure Difference
Mechanical-Induced Pressure Difference
Driving Forces
Airflows Across Building Envelope
Building Envelope Openings
Leakage (Unintentional Openings)
Natural Ventilation (Intentional Openings)

Figure 2

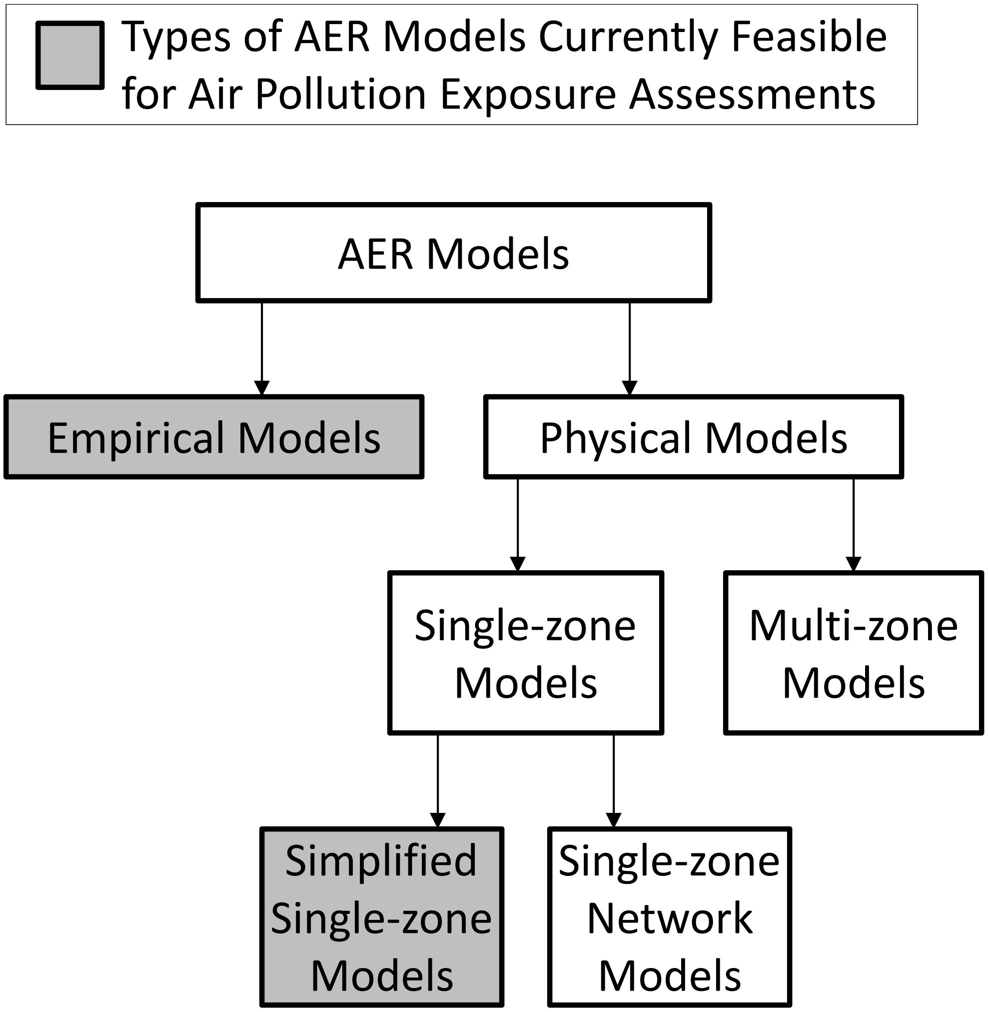
Types of AER Models Currently Feasible for Air Pollution Exposure Assessments
AER Models
Empirical Models
Physical Models
Single-zone Models
Multi-zone Models
Simplified Single-zone Models
Single-zone Network Models

Figure 3

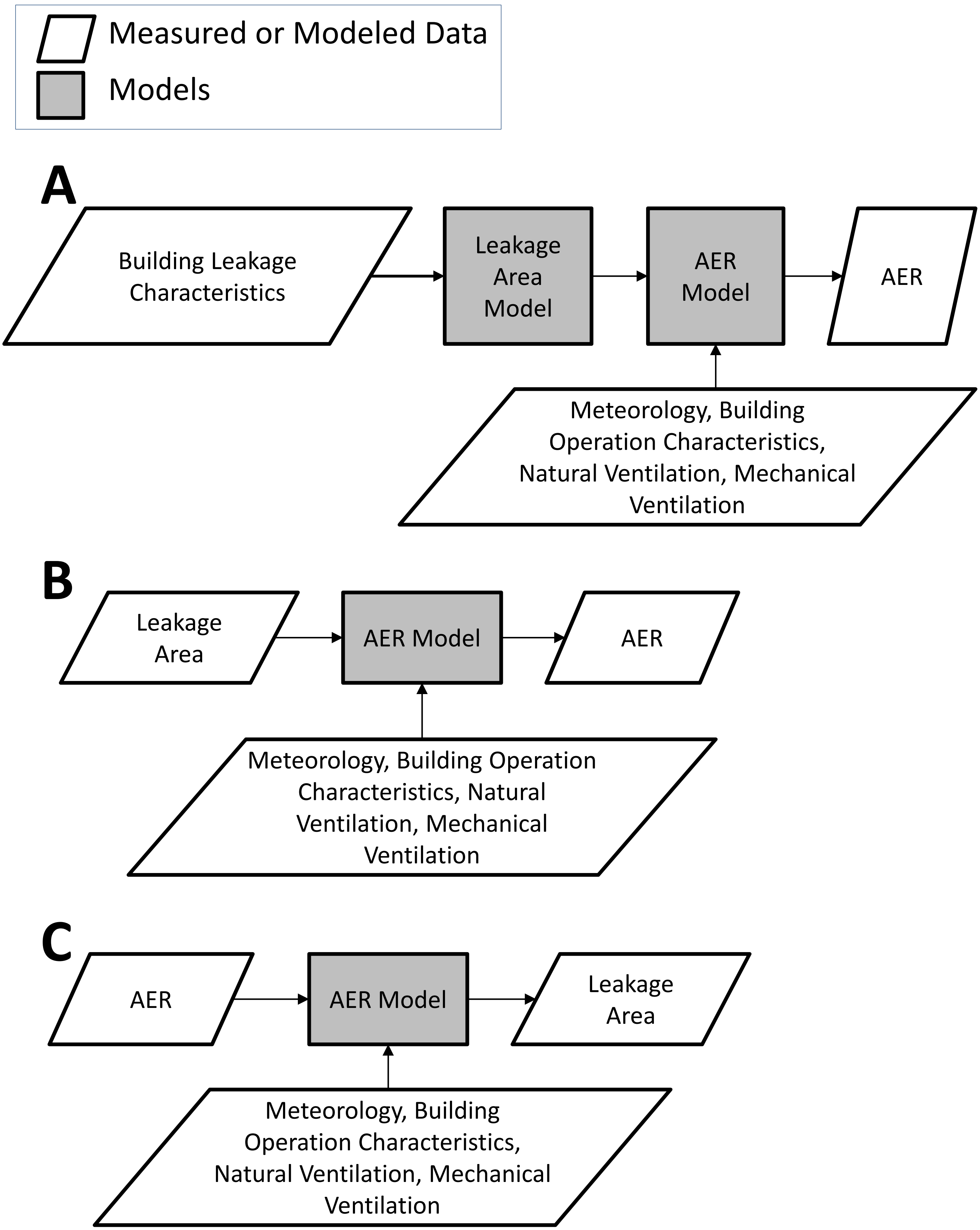
Measured or Modeled Data
Models
A
Building Leakage Characteristics
Leakage Area Model
AER Model
AER
Meteorology, Building Operation Characteristics, Natural Ventilation, Mechanical Ventilation
B
Leakage Area
AER Model
AER
Meteorology, Building Operation Characteristics, Natural Ventilation, Mechanical Ventilation
C
AER
AER Model
Leakage Area
Meteorology, Building Operation Characteristics, Natural Ventilation, Mechanical Ventilation

Figure 4

Table 1. Comparison of Models

Model	Empirical or Physical Model	Input Data Requirements	Limitations	Benefits
Sampling AER Distributions	Empirical	Summary statistics and distributions of measured AER	Uncertainty for extrapolation to other buildings and different weather conditions	Few input data required
Constant rate models	Empirical	Pressurization test data	Cost to measure building-specific leakage, low temporal resolution, uncertainty for extrapolation to other buildings	Includes building-specific leakage measurements
Scale factor model	Empirical	Building characteristics, climate	Uncertainty for extrapolation to different weather conditions	Includes building-specific characteristics for leakage
Regression models	Empirical	Indoor-outdoor temperature, wind speed	Uncertainty for extrapolation to other buildings	Few input data required, High temporal resolution from weather
Hybrid model	Empirical	Building leakage, terrain sheltering, indoor-outdoor temperature, wind speed	Uncertainty from subjective determination of building leakage	High temporal resolution from weather
LBL model				
- measured leakage	Physical	Pressurization test data, indoor-outdoor temperature, wind speed	Cost for pressurization test	High temporal resolution from weather, includes building-specific leakage measurements
- modeled leakage	Physical	Building characteristics, indoor-outdoor temperature, wind speed	Uncertainty from modeled leakage	No leakage data needed, high temporal resolution from weather, includes building-specific characteristics for leakage
LBLX model	Physical	Building characteristics, indoor-outdoor temperature, wind speed, natural ventilation openings	Availability of natural ventilation data	Same benefits as LBL model + includes natural ventilation
AIM-2 model	Physical	Pressurization test data, indoor-outdoor temperature, wind speed, chimney flue, foundation type	Cost for pressurization test	Same benefits as LBL model + includes leakage from chimney flue and foundation type
Shaw-Tamura model	Physical	Building characteristics, indoor-outdoor temperature, wind speed	Availability of input data for building characteristics, uncertainty of total AER from not including mechanical ventilation used in many tall buildings	Provides leakage for large tall buildings, high temporal resolution from weather, includes building-specific characteristics for leakage