

Modeled Infiltration Rate Distributions for U.S. Housing

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Abstract

A set of 209 dwellings that represent 80 % of U.S. housing stock is used to generate frequency distributions of residential infiltration rates. The set of homes is based on an analysis of the 1997 U.S. Department of Energy's Residential Energy Consumption Survey, which documents numerous housing characteristics including type, floor area, number of rooms, type of heating system, foundation type and year of construction. The infiltration rate distributions are developed using the multizone network airflow model, CONTAM (Walton and Dols 2005). In this work, nineteen cities are selected to represent U.S. climatic conditions, and CONTAM simulations are performed for each of the 209 houses in these cities to calculate building air change rates for each hour over a year. Frequency distributions are then developed and presented nationally as well as based on house type and region.

Key words: distributions, frequency, housing, infiltration, residential, ventilation,

Practical Implications

These distributions will support indoor air quality, exposure and energy analyses based on a truly representative collection of U.S. homes, which has previously not been possible. In addition, the methodology employed can be extended to other countries and other collections of buildings. For U.S.-specific analyses these homes, and their models, can be extended to include occupants, contaminant sources and other building features to allow a wide range of studies to address other ventilation and indoor air quality issues.

Introduction

Building ventilation rates are primary determinants of indoor contaminant levels and hence occupant exposure, as well as energy consumption for heating and cooling (ASHRAE 2009; Persily 2006). The ventilation or air change rate of a given building is a function of its layout and configuration, building envelope airtightness, weather conditions, the design and operation of its ventilation systems, and occupant activities (Concannon 2002). As a result of these dependencies, ventilation rates in a given residential building can vary over a range of 5 to 1 or more. The ventilation rate of a building under specific conditions can be measured; many measurement studies are listed in the references to the chapter on Ventilation and Infiltration in the ASHRAE Fundamentals Handbook (ASHRAE 2009). These measurement studies tend to involve only a small number of homes, which are not representative of the broader housing stock, and typically include a relatively small number of measurements in each home. However, because of the variability in ventilation rates, developing a complete characterization of a given building requires numerous measurements, which can be costly and time consuming. Modeling is an easier means of determining building ventilation rates under specific conditions but requires reliable input data (ASHRAE 2009). In either case, measurement or modeling, the ventilation data generated applies only to the specific building being considered. If typical or representative ventilation rates are needed, consideration of a single building or a small group of buildings will not provide such information.

Distributions of ventilation rates for a characteristic group of buildings are needed to perform an exposure assessment. The EPA Exposure Factors Handbook (EPA 1999) presents summary

statistics of residential ventilation rates. However, the analyses on which those statistics are based are derived using a dataset that is not representative of the U.S. housing stock (Pandian et al. 1998). In addition, there are methodological issues associated with the measurement technique employed to collect those data, as discussed later in this paper.

In order to enable more representative analyses of ventilation and indoor air quality issues in U.S. residences, a collection or “suite” of homes was defined to represent the housing stock of the United States (Persily et al. 2006). This collection of dwellings is based on two residential housing surveys, the U.S. Department of Energy Residential Energy Consumption Survey (RECS) and the U.S. Census Bureau American Housing Survey (AHS), both of which are conducted periodically to characterize the U.S. housing stock (DOE 1999; HUD 1999). The RECS dataset includes about 6000 U.S. residences and the AHS about 60,000. Based on these datasets, just over 200 dwellings were defined that together represent 80 % of the U.S. housing stock. These dwellings are grouped into four categories: detached, attached, manufactured homes and apartments. Among the key characteristics used to define these dwellings are age, floor area, number of floors, foundation type and presence of a garage. In addition, as part of the effort to define these dwellings, multizone representations of the dwellings were created in the airflow model CONTAM (Walton and Dols 2005) and are available for analyses of residential ventilation, indoor air quality and energy issues.

The study presented in this paper involves using this set of dwellings to generate annual distributions of building infiltration rates for use in exposure analysis and other applications. The manner in which climate and air handling system operation are considered in the analysis are

described, and the results are presented by region of the country, building type and building age. The resulting distributions are then compared with measured data from two previous studies (Pandian et al. 1998; Wilson et al. 1996). It is important to note that the results presented in this paper are infiltration rates, which account for uncontrolled air leakage through building envelope leakage that is caused by weather effects and building equipment operation. These infiltration rates do not include natural ventilation, airflow through intentional openings such as windows, or outdoor air intake through mechanical ventilation systems. While air change rates that consider these other effects would be desirable, that would require data on these building features and occupant usage patterns that is currently not available. Also this study is based on surveys from the late 1990s and therefore does not fully reflect the current housing stock. However, as new surveys are completed and analyzed, this collection of house models and the distributions can be updated.

Methods

The multizone airflow model CONTAM is used to perform hourly simulations over a year to generate infiltration rate distributions for the representative set of 209 dwellings. In order to produce nationwide frequency distributions, these annual simulations are conducted for a range of U.S. climates. These simulations also account for the impacts of ventilation system operation on infiltration rates, which also vary by climate as well as by dwelling and system configuration.

Building Models

As noted above, the analysis in this paper employs a previously described collection of residences that was developed to represent the housing stock of the United States (Persily et al.

2006). These dwellings are grouped into four categories: detached, attached, manufactured homes and apartments. The characteristics used to define these dwellings include floor area, year built, number of floors, foundation type, whether or not they have a forced air distribution system and presence of a garage. The apartments are also defined by the number of units in the building. The details of the dwellings are described in the referenced report.

One of the key characteristics affecting the analysis is the envelope airtightness. The year of construction is used to assign the exterior wall leakage based on data from two studies of airtightness on single-family homes (Sherman and Dickeroff 1998; Chan, et al. 2003 and 2005). The exterior wall leakage for each home is defined as a function of both year built and house floor area as described in Persily et al. (2006) and presented in Table 1. The exterior wall leakage values are expressed as a dimensionless normalized leakage area based on the effective leakage area at 4 Pa as determined from a whole building fan pressurization test normalized by the floor area of the house (ASHRAE 2009). In the simulations, the leakage is assumed to be uniformly distributed over the exterior envelope. While the leakage distribution can impact building air change rates, there is insufficient data available in the literature to justify other than a uniform distribution.

Climate Selection

Nineteen US cities were selected to represent the climates of the nine US census divisions and the US climate in general. According to the 2000 US Census (US Census, 2005), the total US population was 281,421,906. This population is broken into nine geographical divisions as shown in Table 2. The US Census Bureau also reports the populations of metropolitan statistical

areas (MSAs) (OMB, 2005). The purpose of the MSAs is to more accurately estimate the number of people living in an urban area rather than using only the city population. In the present study, the weather of each census division from Table 2 is represented by two or three MSAs in that division that are selected based on the climatic variability within the division. The specific cities are based on the MSAs with a population of 250,000 or greater.

For each division, the most populous city plus one or two additional cities were chosen to represent the entire census division. The cities were chosen to represent all cities in the division that have a similar climate, based on the number of heating and cooling degree days in each city according to the following process. First, the difference between the number of heating and cooling degree days between each city in the division and a candidate representative city is calculated and weighted by population. Next, the average of these weighted differences is calculated for the census division. The representative cities are then chosen among the candidates to produce the smallest values of this weighted average.

Table 3 shows the Census divisions, the cities chosen to represent them, and the relevant climate and population data. Heating degree days (HDD) and cooling degree days (CDD) are given in terms of a base temperature of 18.3 °C (NOAA 2002). Heating design temperature (HDT) is the temperature that is exceeded for 99.6 % of hours in a typical weather year (ASHRAE 2009). Cooling design temperature (CDT) is the temperature that is exceeded during 1 % of hours in a typical weather year (ASHRAE 2009). Population is shown as a percentage of the division and of the entire US. The “Division covered” value in the last column indicates the percentage of each division represented by each of the nineteen cities. These percentages are calculated as the

sum of all cities over 250,000 in the division that are represented by this city, divided by the total population of all cities over 250,000 in the division. Thus, for each division, the percent of the division covered by the two or three cities chosen to represent it is 100 %.

The nineteen cities in Table 3 contain 31.4 % of the total US population. Therefore, this analysis uses the correct city to account for nearly one third of the US population. Table 4 presents statistics describing how well these nineteen cities represent other cities in their respective divisions. For each division, the percent of the population that resides in cities larger than 250,000 varies from 51 % to 92 %. These values are also shown as a percentage of the total US population; overall approximately 77 % of the US population resides in cities larger than 250,000 people. The “weighted average degree day difference” is the population-weighted average of the number of degree days in each city subtracted from the number of degree days in the city used to represent it in this analysis. Thus, a positive value means that the representative cities have more degree days (in the case of heating the representative city is colder; for cooling the city is warmer) than the cities in the division that they represent. A negative value indicates that the representative city has fewer degree days (warmer for heating; cooler for cooling) than the cities it represents. On a weighted average basis, almost all of the divisions are represented by cities that are within 100 heating or cooling degree days of the actual weighted average of cities larger than 250,000. For the overall US, the weighted average heating degree days are only about 5 °C•days colder than the nineteen representative cities, and the weighted average cooling degree days are 25 °C•days cooler than the nineteen representative cities.

Air Handling System Modeling

Air handling systems for the 209 prototype residences are defined to provide $6.1 \text{ L/s}\cdot\text{m}^2$ of conditioned supply air (ASHRAE 2005), with no outdoor air intake. Because residential heating and cooling systems do not generally introduce outdoor air, they do not influence air change rates when the supply and return airflows to and from the conditioned volume are equal.

However, when there is significant air leakage in the air distribution system to or from unconditioned space (e.g. attics and garages), system operation will impact the building air change rate. The building models include the effects of duct leakage in a manner that depends on the house layout and system type. These models also account for the influence of fan operating time as it determines the impact of duct leakage, since this duct leakage only impacts the air change rate when the fan is running. Fan operation is simulated using the control capabilities within CONTAM as described below.

For the apartments, as well as the detached, attached and manufactured homes with finished basements, any supply and return duct leakage is assumed to exist inside the conditioned space. The supply and return airflows are therefore balanced for these houses, and do not impact the building air change rate. It is therefore not necessary to account for duct leakage in these cases. Detached and attached houses with unconditioned basements are modeled with balanced supply and return leakage in the basement (each as 10 % of the total system supply flow rate). The air change rates calculated by CONTAM include flow from the ambient to zones that are designated as “conditioned space”. Because these basements are considered unconditioned, flow between these spaces and the conditioned volume affects the air change rate calculation, and the calculation must account for both the supply and return leakage.

Detached, attached, and manufactured houses without basements all have supply duct leakage into the attic, again 10 % of the total system supply airflow. If these houses also have an attached garage in which the air handling system is located, an identical return leakage airflow is located in the garage; otherwise no return leakage is modeled. When there is duct leakage in the attic and garage (both of which are considered unconditioned space), the infiltration of the conditioned portion of the house increases because the garage is more closely coupled to the house than the attic. This situation slightly depressurizes the house relative to the outdoors, and increases infiltration. In this case, both the supply and return leakage flows are modulated using controls to account for part load operation, i.e., when the air handler is not operating 100 % of the time.

When there is supply leakage in the attic with no return leakage in the garage, it is assumed that the return ductwork is all contained within the conditioned volume of the house. This means that the total return airflow is equal to the supply to the conditioned spaces plus the supply duct leakage. Since the attic is considered unconditioned space, the supply duct leakage causes the conditioned portion of the house to be depressurized, increasing air infiltration from the outdoors. To account for part load operation, both the supply leakage path and the portion of the return located within the house are modulated. A CONTAM fan control is applied only to the portion of the return airflow that balances the supply duct leakage.

The dependence of air change rates on duct leakage is modeled using the control capabilities of CONTAM to modulate the airflows to the supply and return points that represent the duct leakage. Implementing controls in the CONTAM models to account for air handling system run

time employs a control strategy that depends on the climate. This climatic dependence is achieved by assigning each of the nineteen cities to one of four “Control modes.” The control modes are defined based on the cooling design temperature because cooling occurs over a smaller range of temperatures, and therefore the control strategies are more sensitive to cooling data than to heating. However, the decision of how to assign each city to the groups is based on the heating design temperature. Table 5 shows the heating and cooling design temperatures (ASHRAE 2009) and the control mode assigned to each of the nineteen cities, sorted by cooling design temperature. Control mode 1 represents mild, Pacific climates. Control mode 2 represents Northern climates with cold winter temperatures and relatively mild summer temperatures. Control mode 3 includes primarily Southern climates with milder winters and hotter summers. St. Louis is included with this group despite its cold winters because of its high summer cooling design temperature. The two cities in control mode 4 have very hot summer design conditions and mild winter weather.

A CONTAM control strategy was created for each of the four control groups. All of the control groups have an indoor set point of 23.5 °C and a thermostat dead band of ± 2.0 °C. Figure 1 shows an example of how control group 3 responds to changes in outdoor temperature. The control strategies are designed for heating and cooling design temperatures equal to the average design temperature of the cities included in each group, and it is assumed that air handling systems are sized to operate two thirds of the time when the system is at its heating or cooling design condition. This control strategy is applied using a linear controller that approximates system run time effects by operating the system at a fixed percent of design flow for each hour. For example, at the design condition, the fan would operate at full capacity for two thirds of the

hour. An upper limit is placed on the controller so that it cannot exceed 100 % fan on-time during an hour. This is required because some conditions exceed those that would cause the control strategy to produce greater than 100 % flow for a few hours of the year. Data used to specify the controllers are shown in Table 6.

Simulations

Annual simulations are performed using one-hour time steps and TMY2 weather data (NREL 1995). Washington, DC is modeled using data from Sterling, VA, a suburb of Washington; Cincinnati, OH is modeled using data from Covington, KY, a suburb of Cincinnati; and Dallas/Fort Worth is modeled using weather data from Fort Worth. All other weather data are for the cities listed in Table 5.

CONTAMW allows hourly air change rate data to be output to a spreadsheet file. A Visual Basic™ macro was written for Microsoft Excel™ to extract the hourly air change rate data for each of the 209 houses and consolidate it into a single file for each city. The data were then further analyzed using a second macro that counted the number of hours for each house that occurred in various air change rate ranges or “bins”. These bins are based on increments of 0.05 h^{-1} , covering the range from 0 h^{-1} to 2.5 h^{-1} .

Bin data for each house and city are combined using weighting factors to account for the incidence of each house in the larger group of houses. These weighting factors represent the number of each of the 209 house models in each census division and are available from the census data. Houses are then allocated to the two or three cities representing each census division

according to the percentages shown in the rightmost column of Table 3. The result is a weighting factor representing the number of each house model occurring in each city.

For each house model in each city, the number of hours in each air change rate bin is multiplied by the weighting factor for that house to obtain the number of house hours in that bin. These house hours are then summed by house type (detached, attached, and manufactured) to obtain the number of house hours in each bin combined by city and house type. This total number of house hours is then divided by the sum of the house weighting factors for that city and house type to obtain bin data for the weighted average, or “typical” house of that type in each city.

The analysis method described above allows data to be grouped together in any desired combination, for example by census division. Infiltration rate frequency distributions are also generated for: single family housing (combining detached, attached and manufactured) in each city; detached, attached, manufactured, and combined single family housing in each census division; and detached, attached, manufactured, and combined single family housing for the entire US. These distributions can be analyzed to determine various summary statistics and plotted as frequency distributions.

Results

Single Family Homes

Figure 2 shows distributions of air change rates for the national average detached house, both as percentages of hours in air change rate bins and as a cumulative distribution. The lognormal nature of the distribution is evident from the first figure and is seen for other subsets of houses

defined by type, location and age. Figure 3 shows cumulative frequency distributions by house type, census division and age. Table 7 shows the air change rates as percentiles for the same categories shown in Figure 3, as well as for the apartment buildings by age. Table 8 summarizes the percent of hours below various benchmark air change rates for single-family houses in the nine census divisions and the 19 cities that were simulated.

The results in Tables 7 and 8, as well as the third plot in Figure 3, show a tightening of homes built after 1970, as evidenced by their lower air change rates. For example, the newest houses are below 0.25 air changes per hour for approximately 50 % of the year, but houses built before 1970 are below this threshold for only about 10 % of the year. Thus, one would expect these groups of houses to have corresponding differences in energy and indoor air quality performance.

The results described previously are based on average air change rates weighted by the number of houses in each city or region, or for each housing type. This averaging process tends to reflect mean performance and obscure more extreme (high and low) air change rates, which can be more relevant in some situations. It is important to examine these “extreme” cases and to know what percentage of values fall within some measure of “tight” or “leaky” infiltration conditions. These extremes can be examined using the percentiles described below.

Figure 4 shows the distribution of hours below several threshold air change rates for US single-family houses by percentile. Each line in this figure was generated by sorting in order each of the 140 single family house models in each of the 19 cities by the number of hours below some

threshold (for example, 0.25 air changes per hour). In other words, these 2660 combinations of house and city were sorted from lowest number of hours below the threshold to highest number of hours. After sorting the house/city combination, the weights representing each combination were added to obtain the number of houses under each threshold. These cumulative weights were then divided by the total number of single family houses in the US to determine the percentile ranking for each house model. For example, considering a threshold air change rate of 0.25 h^{-1} (the uppermost line in Figure 6), the house/city combination that corresponds to the 80th percentile of leakiness is below 0.25 h^{-1} about 3000 h during the year and the 20th percentile house/city combination is below this air change rate less than 500 h each year.

Figure 4 shows how individual house models (accounting for the climate in which they reside) vary from the average house weighted by climate and frequency of occurrence of that house. In the figure, the “leakier” homes (leakier in terms of physical leakiness combined with climate) have lower percentile values (fewer hours below each threshold) and tighter homes have higher percentile numbers (more hours below each threshold). For example, the weighted average single family home (from Table 8) experiences 23 % of its hours (about 2000 h during the year) below an air change rate of 0.25 h^{-1} . Figure 4 shows that the leakiest 20 % of homes spend only about 460 h (5 % of the hours during the year) below 0.25 h^{-1} , while the tightest 20 % of homes spend 3140 h (36 % of hours during the year) below 0.25 h^{-1} . When the higher threshold of 1.0 h^{-1} is considered, we see from Table 7 that the weighted average home exceeds this threshold for 10 % of its annual hours. However, Figure 4 shows that the tightest 40 % of homes exceed this threshold rarely or never, and that the leakiest 10 % of homes exceed it for 5820 h (66 % of the year) or more.

Single Family Homes – Comparison With Measured Data

Several published studies have reported on measured air change rates in large numbers of houses. In this section, two such studies are compared to the simulation results from this work.

Pandian et. al (1998) published statistical summaries of air change rates measured using long-term average, constant injection tracer techniques. The data in the study are sorted by geographic region, in addition to other measures. It should be noted that the Pandian data are presented in percentiles (5 %, 25 %, 50 %, 75 %, and 95 %). It is also important to note that the houses in the measured dataset were not selected to be statistically representative of the entire US, or even a given area, but simply include all measurements that were available. For example, the Pandian dataset includes very few measurements in some regions, particularly the Southeast.

Figure 5 shows five figures that compare the results of the current study to the measured values in the Pandian dataset. The first figure shows that comparison for single-family houses in the entire US. The measured data correspond to the simulation results reasonably well, with houses in the experimental dataset generally having slightly higher air change rates.

The Pandian data are also presented for four geographic regions, which unfortunately do not correspond to standard US census regions. Thus, the experimental data are compared to the predictions for these regions using the modeled air change rate data for cities located in the states from which the experimental data were obtained. The "Northeast" region (second graph in Figure 5) covers the states of CT, MD, MN, NJ, NY, and WI, and is shown with modeled data from the

cities of New York, Buffalo, Boston, and Minneapolis. This experimental dataset includes 842 houses. The experimental and modeled air change rates are similar, with the experimental data indicating slightly lower air change rates than the modeled data. This is consistent with the low bias inherent to the long-term constant injection tracer method, which has been noted by Sherman (2005, 1990, and 1989).

The "Northwest" region, shown in the third graph in Figure 5, covers the states of CO, ID, MT, OR, and WA and is shown with modeled data from Seattle and Denver. This dataset includes 585 houses. Here, there is more variation between the two modeled cities, with houses in Denver having lower air change rates than Seattle and matching the experimental data more closely. Again, the differences between the measurements and predictions are consistent with a low bias in the measurement data.

The "Southeast" region, shown in the third graph includes houses from FL and TX, and is shown with modeled data from Miami, Dallas/Fort Worth, and Corpus Christi. This dataset is smaller than the others, containing only 62 houses. Among the modeled cities, Miami houses have lower air change rates than those in the Texas cities. The experimental dataset indicates higher air change rates than obtained by modeling in any of these cities. This may be due to the effects of open windows, which impact the experiments but are not included in the models, and are more likely to impact results in mild climates.

The "Southwest" region, shown in the last graph in Figure 5, includes houses from AZ and CA, and is shown with modeled data from Phoenix and Los Angeles. The experimental data includes

1482 houses. Air change rates from the experimental dataset are much higher than those obtained by modeling. Again, this may be due to window opening in these milder climates.

Overall, the data presented by Pandian et al. appear to agree well with the predictions in this study, particularly for the average US and the northern climates. For southern climates, particularly those including Southern California, the experimental data indicate higher air change rates. This finding would be consistent with occupants opening windows to increase air change rates during periods of mild weather. This behavior was not accounted for in the simulation study, but presumably would have occurred during the air change rate measurements. This effect would likely be more pronounced for milder climates where there are more times during which windows would be open.

In another publication, Wilson, et. al (1996) summarized air change rate data from two studies conducted in the Southern California. Air change rates were again determined using constant injection tracer gas techniques over periods of one week or two days. Participating homes were selected using a quasi-random design that considered some housing characteristics, including appliance type (gas, electric, etc.). However, the houses were not selected according to the same parameters of age, size, etc. that were used for the present study. Also, since most of the tests (600 houses) were conducted in 1984-85 and the remainder (75 houses) in 1991-92, very few of the houses would have been constructed after 1990.

Data for the Los Angeles area were summarized by the month or season in which they were collected, specifically January, March, July, and "Winter" (between December and April).

Average air change rates measured during these time periods are identified in Figure 6 in a plot of simulated air change rates for the typical Los Angeles single family house. The comparison shows that these investigators measured higher air change rates in the Los Angeles area than would have been expected based on the simulations. The average measured air change rate in January is 0.58 h^{-1} , a value that the simulations indicate would be exceeded only 19 % of the time. The March and winter averages are 0.78 h^{-1} and 0.79 h^{-1} respectively; the simulated air change rates would exceed this value only about 5 % of the time. The average July measurement is 1.51 h^{-1} , which the model predicts would be exceeded only 0.2 % of the time. These averages are obtained using sample sizes ranging from 75 measurements for the “winter” data to 571 measurements for the “March” data.

A primary consideration in the difference between these measurements and our analysis is again the existence of open windows. The simulations did not account for window opening during periods of mild temperature. In contrast, the measurements were made under normal occupancy in which windows were opened when the temperature was mild. Wilson, et al. discuss this effect in their report, showing that the measured air changes rate nearly double when the outdoor temperature increases from a range of $16.1 \text{ }^{\circ}\text{C}$ to $18.3 \text{ }^{\circ}\text{C}$ to a range of $18.9 \text{ }^{\circ}\text{C}$ to $21.1 \text{ }^{\circ}\text{C}$. Both the March and July sampling periods include such periods of mild temperature during which the measured air change rates are much higher. The "winter" sampling period include a smaller number of measurements than the other groups, and temperatures for this period ranged from $13.3 \text{ }^{\circ}\text{C}$ to $18.3 \text{ }^{\circ}\text{C}$. The January measurements were taken when the outside temperature was less than $15.6 \text{ }^{\circ}\text{C}$; thus this group of measurements is likely to include the fewest instances of open windows. Thus, one might conclude that the January measurements show more reasonable

agreement with the model's predictions and that differences between the model and the other data are likely primarily due to the effects of window opening.

A recent study of residential air change rates (Yamamoto et al. 2010) presents summary data for three U.S. metropolitan areas based on about 500 measurements made between 1999 and 2001. This study includes a range of housing types, i.e., site-built, manufactured homes and apartments. The median air change rates in each geographical area were 0.87 h^{-1} , 0.88 h^{-1} and 0.47 h^{-1} in Elizabeth NJ, Houston TX and Los Angeles County CA respectively. For comparison, the current study found median air change rates (see Table 7) of 0.41 h^{-1} , 0.42 h^{-1} and 0.40 h^{-1} in the Middle Atlantic, West South Central and Pacific census regions respectively, corresponding to these three cities. The median measured values were about twice as high as the simulation medians for the first two locations, which is presumably due to a combination of factors – window openings, different housing types and weather conditions. It is not clear why the agreement is so much better for the Los Angeles data.

Results - Apartment Buildings

Apartment buildings were analyzed to obtain national average, census division, and city plots using the same method used for single family houses. It should be noted that the specification of the apartment models involved a number of assumptions related to building layout, leakage between units, and HVAC systems for which little published data is available. Also, the leakage values used are based on measurement data from single family homes, due to a lack of published data specific to apartment buildings. This lack of data also prevents the results of this section of

the study from being compared to experimental data. Persily et al (2006) documents the various assumptions and other parameters used to develop the apartment building models.

The data analysis also requires an extra step because the weighting factors for apartment buildings refer to the number of units, rather than the number of buildings. Thus, the RECS weighting factor for each of the 69 modeled apartment buildings was divided by the number of units in each building to obtain a building weighting factor. This building weighting factor was then used with the building air change rate data to determine air change rates in the weighted average apartment building.

This method requires that the building air change rate is equal to the average air change rate of the apartments in the building, which is only true if the building is made up of apartments of identical volume. Assuming each apartment in a building has the same volume, the building air change rate can be used for the individual apartments in the weighting calculation. This allows the building weighting factor, obtained by dividing the unit weighting factors by the number of units in each building, to be used to generate the national average data. Figure 7 shows air change rate frequency distributions for the national average apartment buildings.

Figure 7 presents cumulative frequency distributions for the apartments in two plots. The first divides apartments between those with and without corridors and those with fewer than or more than three stories. This distinction illustrates the difference between apartments with and without outdoor air ventilation supplied to the corridor. In the CONTAM models, apartments with corridors have a 100 % outdoor air system that supplies 21 L/s per unit opening into each

corridor. This airflow serves to maintain pressurization of the building and supply makeup air to each unit's exhaust fans. Air change rates for buildings without corridors are based on infiltration, and their profile is similar to those for single family housing. Apartments in buildings with corridors have a non-zero baseline air change rate, and generally higher air change rates due to the effect of the corridor ventilation. Because buildings with more than three stories usually have corridors, and buildings with fewer than three stories usually do not, this trend is also apparent when the curves are differentiated according to building height. However, there are some large two story building plans in the study that do have corridors and ventilation systems, while some four or six story buildings with small total numbers of units do not.

The second graph in Figure 7 shows the air change rate distribution for apartments divided into four age categories. Newer apartment buildings, while having tighter construction, are also more likely to have corridors with ventilation systems. Thus, the weighted average newer building has a larger number of hours below each air change rate, but the distribution also has a discontinuity near 0.4 air changes per hour, where apartments with corridors operate for a large percentage of hours each year.

Conclusions

The analysis presented in this paper has generated a series of frequency distributions of residential infiltration rates for potential use in exposure analyses as well as studies of residential energy use and indoor air quality. Previous to this work, no database of residential air change rates was available that was based on a representative collection of homes. While a number of assumptions were necessary to generate these distributions, they constitute the first statistically representative datasets that account for building features of size, age and layout. Since the buildings used in this analysis are based on existing

housing surveys, they can be supplemented with other important data on the number and age of occupants, appliances and other factors that relate to occupant exposure for additional indoor air quality and exposure analyses. Additional research could improve the quality of the calculated distributions, primarily in the apartment buildings where there is little data on airtightness and ventilation system performance. Another key area where additional research is needed regarding intentional and natural ventilation, where information on window opening patterns as a function of weather conditions and other factors, plus improved airflow models of naturally ventilation buildings, would allow these distributions to cover more than just conditions in which infiltration dominates.

It is worth noting that the data used to generate the house models used in the simulations, as well as the measured data examined in the comparisons with the predictions, is all at least 10 years old. As construction practice continues to evolve and new energy efficient design and construction techniques are pursued, it is important to collect data and to simulate newer homes to reflect the impact of these newer approaches and to examine the impact that they are having on energy and indoor air quality.

References

ASHRAE. *Pocket Guide for Air Conditioning, Heating, Ventilation, and Refrigeration*. Atlanta: American Society of Heating, Refrigerating, and Air Conditioning Engineers. 2005.

ASHRAE. *Handbook of Fundamentals*. Atlanta: American Society of Heating Refrigerating and Air-Conditioning Engineers; 2009.

Chan W, Price P, Sohn M, Gadgil A. *Analysis of U.S. Residential Air Leakage Database*, LBNL 53367. Lawrence Berkeley National Laboratory; 2003.

Chan WR, Nazaroff WW, Price PN, Sohn MD, Gadgil AJ. Analyzing a Database of Residential Air Leakage in the United States. *Atmospheric Environment*. 2005; 39: 3445-3455.

Concannon P. *Residential Ventilation, Technical Note 57*. Brussels: Air Infiltration and Ventilation Centre; 2002.

DOE. *A Look at Residential Energy Consumption in 1997*, DOE/EIA-0632(97). U.S. Department of Energy; 1999.

EPA. *Exposure Factors Handbook*, EPA/600/C-99/001. U.S. Environmental Protection Agency; 1999.

HUD. *American Housing Survey for the United States*, H150/99. U.S. Department of Housing and Urban Development, U.S. Department of Commerce; 1999.

NOAA. United States climate normals 1971-2000. Annual degree days to selected bases. In: *Climatology of the United States No. 81. Supplement No. 2*. National Oceanic and Atmospheric Administration, National Climatic Data Center; 2002.

NREL. *User's Manual for TMY2s (Typical Meteorological Years)*, NREL/SP-463-7668. National Renewable Energy Laboratory; 1995.

OMB. *Combined statistical areas and component core based statistical areas. Nov. 2004, with codes*. Population Division, U.S. Census Bureau; 2005. Available at:
<http://www.census.gov/population/estimates/metro-city/List6.txt>.

Pandian M, Behar J, Ott W, Wallace L, Wilson A, Colome S, Koontz M. Correcting errors in the nationwide database of residential air exchange rates. *Journal of Exposure Analysis and Environmental Epidemiology*. 1998; 8: 577-586.

Persily A. What we think we know about ventilation. *International Journal of Ventilation* 2006; 5: 275-290

Persily A, Musser A, Leber D. *A Collection of Homes to Represent the U.S. Housing Stock*, NISTIR 7330. National Institute of Standards and Technology; 2006.

Sherman M. Analysis of errors associated with passive ventilation measurement techniques. *Building and Environment*, 1989; 24: 131-139.

Sherman M. Tracer-gas techniques for measuring ventilation in a single zone. *Building and Environment*, 1990; **25**: 365-374.

Sherman M, Dickeroff D. Air-tightness of U.S. Dwellings. *ASHRAE Transactions*, 1998; 104(2): 1359-1367.

Sherman M. *Efficacy of intermittent ventilation for providing acceptable indoor air quality*, *Technical Note AIVC 60*. Brussels: Air Infiltration and Ventilation Centre; 2006.

US Census. *Annual estimates of the population for the United States, regions, and divisions: April 1, 2000 to July 1, 2005*, NST-EST2005-08. Population Division, U.S. Census Bureau; 2005.

Walton GN, Dols WS. *CONTAMW 2.4 User Guide and Program Documentation*, NISTIR 7251. National Institute of Standards and Technology; 2005.

Wilson A, Colome S, Tian Y, Becker E, Baker P, Behrens D, Billick I, Garrison C. California residential air exchange rates and residence volumes. *Journal of Exposure Analysis and Environmental Epidemiology*, 1996; 6: 311-326.

Yamamoto N, Shendell. DG, Winer AM, Zhang J. Residential air exchange rates in three major US metropolitan areas: results from the Relationship Among Indoor, Outdoor, and Personal Air Study 1999–2001. *Indoor Air*, 2010; 20: 85-90.