

MODELING HUMAN EXPOSURE TO AIR POLLUTION*

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SYNOPSIS

This chapter is an introduction to the simulation of human exposure to air pollution by inhalation. It includes a review of basic inhalation exposure models, in which air concentrations are matched with individual human activity patterns. Since people spend most of their time inside buildings, and the modeling of indoor pollutant concentrations is simpler than for outdoor pollutants, the emphasis is on indoor exposures. Separate sections are devoted to residential exposure to secondhand tobacco smoke and a recent representative survey of US time-location patterns. Material is included on the advantages associated with the modeling of exposure as part of exposure assessment studies with respect to public health objectives. The final section discusses possible future directions in exposure modeling, including general approaches to model evaluation.

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1 INTRODUCTION

Exposure to *air pollution* occurs whenever a human being breathes air in a location where there are trace amounts of one or more airborne toxins. To model exposure to airborne elements, one uses the conceptually simple approach of matching the locations that each exposed person visits with the time-averaged or dynamic air pollutant concentrations that are thought to exist in each visited location. Exposure models simulate exposures for either real or hypothetical individuals and populations.¹ Inhalation exposure models do not strictly take into account the inhaled dose of toxic airborne species, but only the presence of air pollutants near the breathing zone of a person.²

The modeling ideas introduced in this chapter apply equally well to indoor and outdoor sources of air pollution. However, people spend most of their time indoors, and it is generally easier to model indoor pollutant behavior from simple first principles. Therefore, the focus of this chapter is on exposure occurring inside buildings.

2 BASIC FORMULAS USED TO MODEL INHALATION EXPOSURE

An important concept to understand in this chapter is the canonical mathematical formalism used to describe human exposure. How do exposure modelers go about calculating exposure?

Two fundamental pieces of information are necessary to calculate exposure: (1) the whereabouts of the human beings who are being exposed; and (2) the concentration of pollutants in different locations. These two inputs are typically obtained simultaneously in the course of a single exposure study, or they may be drawn from two or more independent studies. In more sophisticated exposure mod-

¹*Simulation* in general involves the artificial depiction of events with the intention of closely mimicking reality.

²You can find a general definition for exposure to all kinds of pollution in Zartarian et al. [1997].

els, they may be simulated using either deterministic or stochastic algorithms. Regardless of the complexity associated with specifying inputs for a given model, the same basic equation underlies all exposure models.

The mathematical formulation of exposure to air pollutants was first established by Fugas [1975], Duan [1982], and Ott [1982, 1984], and was dubbed the *indirect exposure assessment approach* in contrast to direct approaches in which exposure is measured using personal monitoring equipment. These early researchers introduced the concept of calculating exposure as the sum of the product of time spent by a person in different locations and the time-averaged air pollutant concentrations occurring in those locations. In this formulation, locations are termed *microenvironments* and they are assumed to have homogeneous pollutant concentrations. The standard mathematical formula for exposure is written as follows:

$$E_i = \sum_{j=1}^m T_{ij} C_{ij} \quad (1)$$

where T_{ij} is the time spent in microenvironment j by person i with typical units of minutes, C_{ij} is the air pollutant concentration person i experiences in microenvironment j with typical units of micrograms per cubic meter [$\mu\text{g m}^{-3}$], E_i is the integrated exposure for person i [$\mu\text{g m}^{-3} \text{ min}$], and m is the number of different microenvironments. The calculation amounts to a weighted sum of concentrations with the weights being equal to the time spent experiencing a given concentration. Each discrete time segment and its associated discrete concentration need not be sequential in time, i.e. there may be discontinuities in time and space, although Equation 1 is usually applied to contiguous time segments adding up to some convenient duration, such as a single day. Average *personal exposure* in concentration units of $\mu\text{g m}^{-3}$ is calculated by dividing E_i by the total time spent in all microenvironments.

The basis for the temporally and spatially discrete Equation 1, in which C_{ij} are supplied as average concentrations or concentrations that are constant during each corresponding time period T_{ij} , can be considered to arise theoretically from a fully continuous formulation:

$$E_i = \int_{t_1}^{t_2} C_i(t, x, y, z) dt \quad (2)$$

where $C_i(t, x, y, z)$ is the concentration occurring at a particular point occupied by the receptor i at time t and spatial coordinate $[x, y, z]$, and t_1 and t_2 are the starting and ending times of the exposure episode. This time-dependent personal exposure profile can be measured using a real-time personal monitoring device, which is affixed to a person as they move within and between all the locations that are a part of their daily routine. If discrete

microenvironments are considered rather than fully continuous space, then the following semi-continuous formulation applies:

$$E_i = \sum_{j=1}^m \left(\int_{t_{j1}}^{t_{j2}} C_{ij}(t) dt \right) \quad (3)$$

where $C_{ij}(t)$ is the concentration experienced by the receptor in the discrete microenvironment j at a particular point in time t over the time interval defined by $[t_{j1}, t_{j2}]$, where t_{j1} and t_{j2} are the starting and ending times of microenvironment j . Whereas in Equation 2 the exposure trajectory of the receptor is followed explicitly with no discontinuities, in Equation 3 there are no time discontinuities within any given microenvironment, but microenvironments need not correspond to contiguous time periods. With this formulation it is easy to see how arbitrary exposure profiles can be constructed by combining a variety of distinct microenvironment episodes – each with their own distinct concentration profile. The sum of integrals in Equation 3 can be written as a fully discrete sum of {average-concentration \times elapsed-time} products, i.e., the form of Equation 1.

If the same microenvironment concentrations are used for every person, a simple population version of Equation 1 can be derived in terms of the total time spent by all receptors in each microenvironment:

$$\tilde{E} = \sum_{j=1}^m C_j \tilde{T}_j \quad (4)$$

where m is the number of microenvironments visited, C_j is the average pollutant concentration in microenvironment j assigned to every person i , \tilde{E} is the integrated exposure over all members of the population, $\tilde{T}_j = \sum_{i=1}^n T_{ij}$, i.e., the total time spent by all persons in microenvironment j , and n is the total number of people in the population being modeled. If each person spends the same total amount of time across all microenvironments, $T = T_i = \sum_{j=1}^m T_{ij}$, or even if the time spent by some individuals in particular microenvironments is zero, then the average personal exposure (concentration) for the population is:

$$\overline{E}_c = \frac{1}{nT} \sum_{j=1}^m C_j \tilde{T}_j \quad (5)$$

3 AN ILLUSTRATIVE EXPOSURE SIMULATION

To provide a concrete focal point for later discussions of exposure models, this section presents the application of a real simulation model to the case of residential secondhand tobacco smoke (SHS) exposure. This example should help to address what may be the most basic question for a newcomer to exposure modeling: What does the output of an actual exposure model look like?

The SHS exposure model we will be using treats multizonal pollutant and human location dynamics by incorporating dynamic pollutant emissions and household dispersion and the complex spatial trajectories of smoking and nonsmoking household members. In keeping with the fundamental exposure formulation presented above, the occurrence of an exposure event depends on the concurrence in time and space of pollutant concentrations and a human being.

Our model incorporates a dynamic mass-balance indoor air quality (IAQ) model that accounts for (1) airborne particle emissions from smoking activity in any room at any moment in time, (2) outdoor air exchange rates, (3) transport of particles between rooms, (4) particle removal via outdoor air exchange, (5) and particle loss through surface deposition.³ The central assumption of the indoor air model is instantaneous mixing of airborne particles within each room. While the model includes consideration of natural leakage ventilation through building cracks and air flow across interior doorways, it does not consider air flow across open windows or changes in air flow due to the operation of a central air handling system.

The input parameter values for the model have been selected so that they fall approximately in the middle range of values reported in the scientific literature. The hypothetical house, whose layout is pictured in Figure 1, has five zones on a single-level with a total volume of 220 m³, which is a little smaller than the average size of houses in the US (about 300 m³). In this house, the hallway mediates air flow between each of the three main rooms, and the bathroom is connected only to the bedroom. The whole-house leakage air exchange rate is 0.5 h⁻¹, and air flow rates through open and closed doors are assumed to be 100 and 1 m³ h⁻¹, respectively. The size-integrated deposition rate for SHS particles, which adhere irreversibly to household surfaces, is 0.1 h⁻¹. The duration of each cigarette smoked in the house is assumed to be 10 min, with each cigarette having 10 milligrams of total particle emissions.

Although the above physical input parameter values are held fixed, pollutant emissions and house air flow characteristics can change over time due to the behavior of household occupants, who may smoke cigarettes in different rooms and close doors of rooms they occupy. To supply realistic movement patterns for people in the house, a pair of time-location profiles, corresponding to a smoker and a nonsmoker, were randomly sampled from an empirical activity pattern diary data set (these data are described in Section 4). The pair of occupants are assumed to be spouses who sleep together in the bedroom.

³The IAQ model is defined by a set of n coupled differential equations, one corresponding to each room. The differential equations are solved numerically using a Runge-Kutta algorithm to obtain dynamic airborne particle concentrations in each room of the house.

Hypothetical Five-Zone House

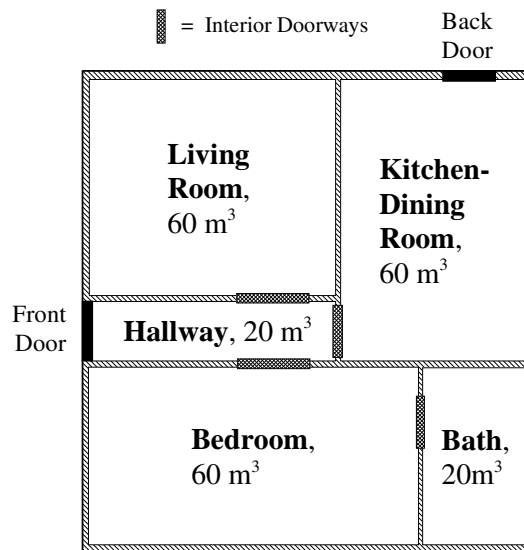


Figure 1: Floorplan for a hypothetical five-zone house, which provides the environment for an illustrative simulation of secondhand tobacco smoke room and personal exposure. The house has three main rooms of equal size plus a master bathroom and a hallway. The main rooms are interconnected via doorways to the centrally located hallway. See Figures 2 and 3 for the simulation results.

In this example simulation, the smoker consumes 15 cigarettes in the main rooms of the house between about 7:00 AM and 8:00 PM. The SHS particle concentration time profiles in each room of the house resulting from these cigarettes are presented in Figure 2 for the case when doors are generally left open in the house, except during time spent sleeping in the bedroom or in the bathroom (the *door-open* case). Figure 3 shows the case for when the smoking room door is closed during smoking episodes in which the nonsmoker and smoker occupy separate rooms (the *door-closed* case). In addition to room concentrations, each figure also shows the time-location patterns and exposure profiles of the smoker and nonsmoker house occupants and the smoker's active cigarette profile.

For the door-open case, the 24-hour average SHS particle concentrations are highest in the living room and kitchen-dining room (69 and 49 $\mu\text{g m}^{-3}$, respectively), where most of the cigarettes are smoked. The SHS exposure of the smoker (not including his/her direct exposure from smoking the cigarettes) is comparable to the 24-hour concentrations in the rooms with the most smoking (57 $\mu\text{g m}^{-3}$). In contrast, the nonsmoker spends part of the time either out of the house or in rooms away from active smoking, so his/her 24-hour SHS particle exposure is significantly lower than that of the smoker (38 $\mu\text{g m}^{-3}$). For

different nonsmoker time-location patterns where a person might spend either more or less time in the same room as the smoker, exposure can approach or exceed those of the smoker, or perhaps be much lower.

For the door-closed case, where doors to rooms are closed when the active smoker is alone in the room where he smokes (in this case the living room), the 24-hour average living room concentration is much higher than before ($91 \mu\text{g m}^{-3}$), whereas all of the other rooms have lower average concentrations. This situation arises because the living room is the location where the smoker spends most of his/her time alone. The smoker's average exposure increases dramatically from 57 to $81 \mu\text{g m}^{-3}$ with respect to the door-open case due to the significant amount of time he/she spends in a room with practically no air exchange with other parts of the house. The nonsmoker also experiences elevated levels close to $400 \mu\text{g m}^{-3}$ upon entering the smoke-filled living room, which contributes to their higher average exposure relative to the door-open case (42 versus $38 \mu\text{g m}^{-3}$).

These simulation results illustrate how the zonal character of a house can result in quite different SHS concentration in different rooms and significant differences in 24-hour exposures for different household occupants. Taking the simulation approach a few steps further, it would be possible to explore how changes in multiple door and window positions, central air handling, and active filtration can affect residential SHS exposure. Using time-diaries of household occupants sampled from a real population, one can estimate frequency distributions of exposure for typical time-location patterns.

4 HUMAN ACTIVITY PATTERN DATA

The strong influence of human activity patterns on exposure is evident from Equation 1 and the results of the example exposure simulation presented above, where the movement of house occupants between different rooms has a sizeable impact on 24-hour average exposures. Human activity data are routinely collected as part of individual exposure assessment studies. Several large-scale human activity pattern databases are also available for populations in North America. To provide the reader with more background on human activity patterns, which are critical to all types of exposure simulation, this section presents detailed information from a recent nationally representative human activity pattern survey.

The most detailed and representative human activity and location study conducted for the US population is the National Human Activity Pattern Survey (NHAPS), which was sponsored by the US Environmental Protection Agency (USEPA) and carried out in the early-to-mid 1990's [Klepeis et al., 2001]. Both NHAPS, and the subsequent Canadian Human Activity Pattern Survey

(CHAPS) [Leech et al., 1996], were patterned after a set of studies conducted in California [Jenkins et al., 1992; Wiley et al., 1991a,b]. The USEPA's consolidated human activity database (CHAD) contains readily available data from many recent human activity surveys, including NHAPS [McCurdy et al., 2000].⁴

The NHAPS respondents comprise a representative cross-section of 24-hour daily activity patterns in the contiguous US.⁵ The 9,386 NHAPS respondents, who were interviewed by telephone, gave a minute-by-minute diary account of their previous day's activities, including the places they visited and the presence of a smoker in each location.⁶ Detailed information was provided on the rooms that each respondent visited while in residences, whether their own or one they were visiting. Since NHAPS contains the precise sequence and duration of human locations for a large sample of people, with room-specific categories for time spent at home, it presents a rich resource for use in understanding the frequency distribution of exposures to a variety of pollutants for which a single 24-hour period is an appropriate time scale, e.g., for secondhand smoke exposure in the residential indoor environment.

Figure 4 illustrates the character of the NHAPS time-location data using plots of stacked timelines across different residential locations. The plot shows 25 randomly sampled NHAPS respondent diaries, each represented by a horizontal strip with different patterns and shades designating the different rooms the respondent was reported to visit. The timelines are sorted from bottom to top by the total amount of time spent at home. The four residential locations depicted in this figure are a reduced but exhaustive set derived from the 15 total residential locations that were coded for each NHAPS respondent. White space corresponds to locations outside or away from the residence.

Figure 5 contains a plot of the time-location profiles for 25 randomly sampled participants from the USEPA's PTEAM study conducted in Riverside, CA [Özkaynak et al., 1996, 1993]. This study was an exposure monitoring study, which was not focused on the gathering of time-activity patterns, but which provides another example of empirical activity pattern data. As before, the data are sorted from bottom to top by the total amount of time each subject spent at home. However, unlike in Figure 4, the locations categories shown in Figure 5 span time spent

⁴The NHAPS data are also available at the ExposureScience.Org website, <http://exposurescience.org>, along with other exposure-related materials, including research articles and modeling software.

⁵Note that NHAPS is biased because it undersamples people who are homeless, on vacation, or who may be institutionalized or in the military.

⁶The time reported in the presence of a smoker may be a biased predictor of actual secondhand tobacco smoke exposure, because of complications surrounding awareness of smokers, smoke persistence, and proximity to smokers.

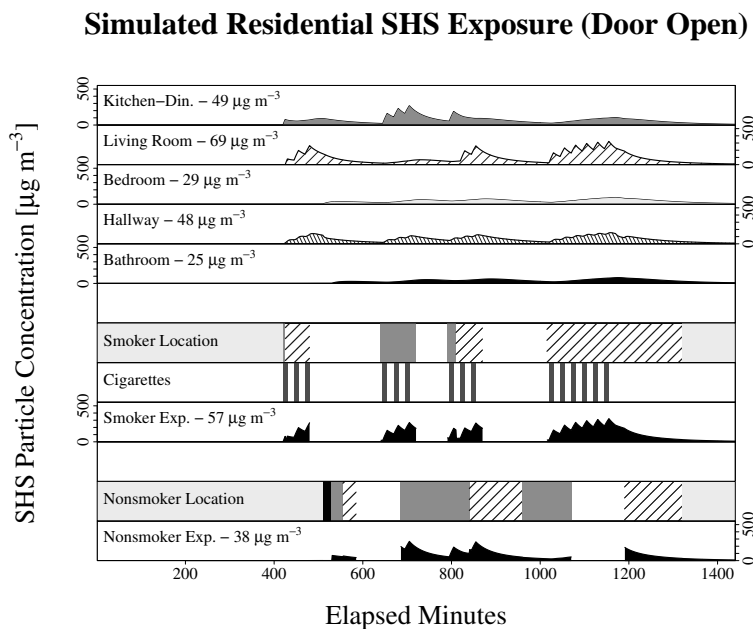


Figure 2: Example simulated 24-hour time-profiles for room particle concentrations [$\mu\text{g m}^{-3}$] (top panels), selected occupant-specific behavior patterns, and occupant exposure [$\mu\text{g m}^{-3}$] (middle and bottom panels) for the case when doors are left open in the house, except when occupants are sleeping or in the bathroom. Each profile starts and ends at midnight. Occupant-specific activity profiles are included for the cigarette and location behavior of a single smoker and nonsmoker pair. The 24-hour average room and exposure are included in the appropriate panels. The simulated exposure profile for each person is positioned below each group of behavior profiles. The grayscale shading and hatch patterns that have been used to draw each room concentration match the fill patterns used in the location profiles. White space in the activity profiles corresponds to “absent from house” and “inactive” conditions for location and cigarette profiles, respectively. Filled segments correspond to the opposite condition.

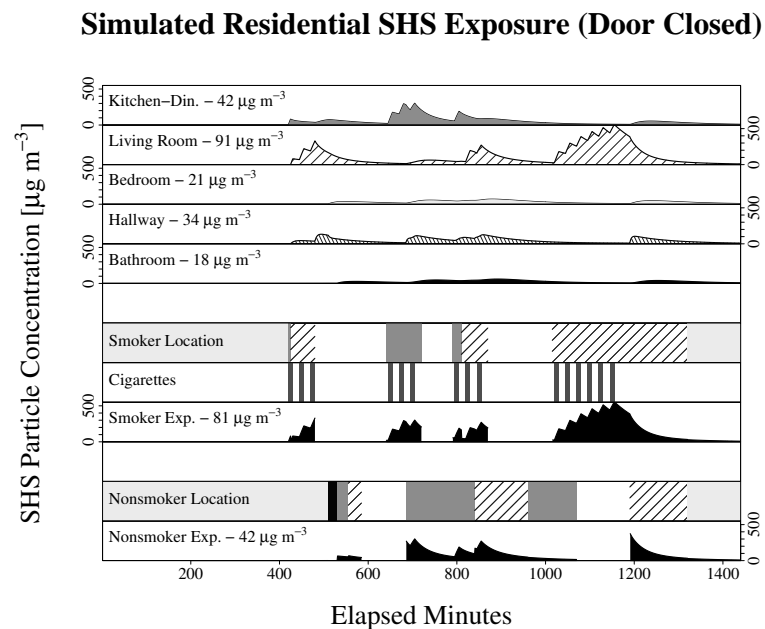


Figure 3: Example simulated 24-hour time-profiles for room particle concentrations [$\mu\text{g m}^{-3}$] (top panels), selected occupant-specific behavior patterns, and occupant exposures [$\mu\text{g m}^{-3}$] (middle and bottom panels) for the case when doors are closed in smoking rooms during smoking episodes when the smoker and nonsmoker are in separate rooms, i.e., the door is left open during smoking episodes only when the smoker and nonsmoker are in the same room. See Figure 2 and its caption for more information on the plot and for simulation results when the smoker’s door is always left open during smoking episodes. Notice how the concentration in the living room, during times when the active smoker is alone, are much higher when the doors are closed. Consequently, when the nonsmoker enters the living room soon after smoking has stopped, he/she receives a higher exposure than if the door had been open for the entire smoking episode.

both at home and away from home.

The most striking feature of the time-location plots in Figures 4 and 5 is the overwhelming amount of time spent at home over a 24-hour time block. Even the 50% of each sample that spent the least amount of time at home still spent the bulk of the 12-hour period between 8 PM and 8 AM at home.

Aggregate statistics for comprehensive time spent by NHAPS respondents in six locations over the 24-hour day are given in Table 1. These include the overall average time spent in each location taken across all of the NHAPS respondents, the overall average percentage of time spent in each location, the percentage of respondents that reported being in each location, i.e., the *doers*, and the average time spent by the doers in each location. More analysis of the NHAPS diary, disaggregated by demographic and health variables, is available from Klepeis et al. [2001, 1996] and Tsang and Klepeis [1996]. The results presented here indicate that over 90% of time is spent indoors or in a vehicle and that the home is undeniably the location where one spends the bulk of one's life. All but a very small percentage of sampled Americans spent time in their own home on the day just before they were interviewed, being at home for an average time of more than 16 hours, or $\frac{2}{3}$ of the day.

A standout feature of the time spent in different rooms of detached homes by NHAPS respondents, as evident from the per-room statistics presented in Table 2, is that almost 98% of interviewed Americans spend time in the bedroom for more than 9 hours, on average, which is 58% of the time spent, on average, in any location in or around the house. Taken together, the kitchen, living room, and bedroom account for over 85% of the total time spent at home, with 5% taken up with time reported as *moving from room-to-room*, which may have been a fallback category for some respondents, and less than 5% for any other house location.

Figure 6 presents the fraction of NHAPS respondents that spent the bulk of each hour of the day in different rooms of their detached house, focusing on the most predominant rooms, i.e., kitchen and/or dining room, living room, and bedroom. From this figure, it is apparent that the largest fraction of individuals are in the bedroom until about 9 AM and after 11 PM, as might be expected. During the middle of the day, and especially between 6 PM and 10 PM, more Americans are in the kitchen and living room than in any other room of the house, although about 40–60% of Americans are away from home between the hours of 9 AM and 6 PM.

Although NHAPS offers a rich and representative human activity pattern data set, the data are somewhat limited for use in understanding exposures occurring in complex environments, such as a household ecology. The interaction of individuals in a house environment can-

Time Spent at Home Every Hour (US)

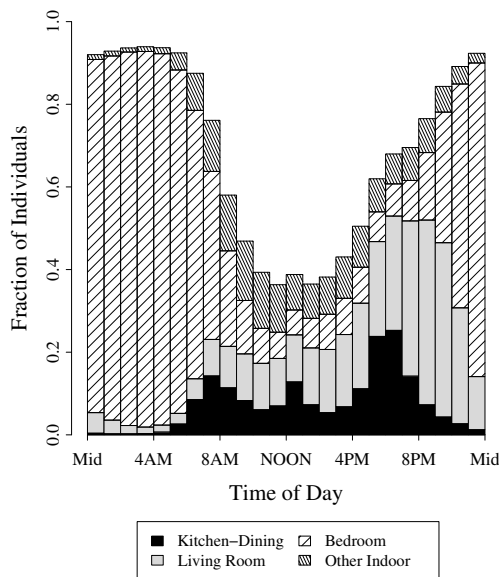


Figure 6: Stacked bar chart showing the overall fraction of NHAPS respondents living in detached houses who spent time in various locations in their home during each hour of the day.

not be fully characterized by independent activity profiles from unassociated individuals, such as those collected as part of NHAPS. In addition, the NHAPS time-diary data do not contain information on activities that are likely to affect pollutant emission or removal in a given location, such as the operation of appliances, the smoking of cigarettes, filtration practices, or flow-related activities involving windows, doors, or mechanical air handling. Nevertheless, NHAPS, and similar databases, can be used to explore frequency distributions of residential exposure occurring in multiple-person households by superimposing hypothetical or separately observed window, door, ventilation, and source-related activity patterns onto time-location patterns, and by matching individual time-location diaries for persons in a hypothetical household based on selected temporal or demographic characteristics, such as age, gender, or day of the week. This general approach for a single pair of matched NHAPS respondents was used in the example simulations presented above in Section 3.

5 PRACTICAL USES OF EXPOSURE MODELING

Who uses exposure models? Are they really helpful to professionals in the health and environment fields? To help shed light on these questions, consider the following:

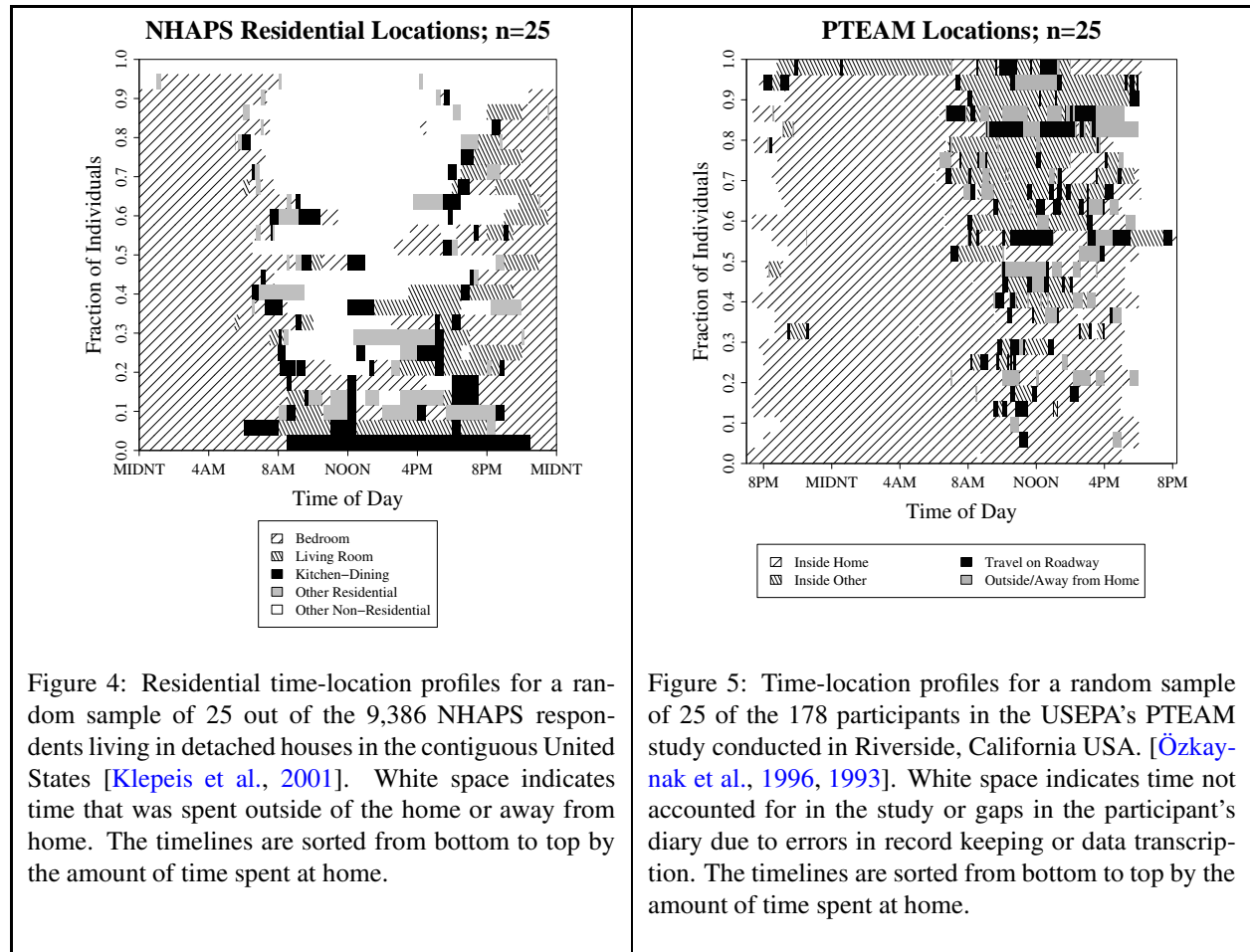


Figure 4: Residential time-location profiles for a random sample of 25 out of the 9,386 NHAPS respondents living in detached houses in the contiguous United States [Klepeis et al., 2001]. White space indicates time that was spent outside of the home or away from home. The timelines are sorted from bottom to top by the amount of time spent at home.

Figure 5: Time-location profiles for a random sample of 25 of the 178 participants in the USEPA’s PTEAM study conducted in Riverside, California USA. [Özkaynak et al., 1996, 1993]. White space indicates time not accounted for in the study or gaps in the participant’s diary due to errors in record keeping or data transcription. The timelines are sorted from bottom to top by the amount of time spent at home.

Table 1: Overall Weighted Statistics for Time Spent by NHAPS Respondents in Six Different Grouped Locations Over a 24-hour Period^a

| Location | Average Time [min] | Average ^b Time % | Doer % | Doer Average Time [min] |
|-----------------------------|--------------------|-----------------------------|--------|-------------------------|
| In a Residence ^c | 990 | 68.7 | 99.4 | 996 |
| Office-Factory | 78 | 5.4 | 20.0 | 388 |
| Bar-Restaurant | 27 | 1.8 | 23.7 | 112 |
| Other Indoor | 158 | 11.0 | 59.1 | 267 |
| In a Vehicle | 79 | 5.5 | 83.2 | 95 |
| Outdoors | 109 | 7.6 | 59.3 | 184 |

^aMeans and percentages have been calculated using sample weights.

^bThe overall average percentage time spent was calculated by dividing the mean number of minutes spent by NHAPS respondents in each location by the total time spent on the diary day, i.e., 24-hour = 1440 min.

^cThe *In a Residence* category includes time spent in one’s own home or in another person’s home.

Table 2: Overall Statistics for Time Spent by NHAPS Respondents Living in Detached Homes in Different Rooms of Their Residence Over a 24-hour Period^a

| Location | Average Time [min] | Average Time ^b % | Doer % | Doer Average Time [min] |
|---------------------------|-----------------------|--------------------------------|-----------|----------------------------|
| Kitchen | 75.3 | 7.2 | 77.2 | 97.6 |
| Living, Family, Den | 199.5 | 19.3 | 81.4 | 245.2 |
| Dining Room | 13.8 | 1.3 | 19.5 | 70.6 |
| Bathroom | 24.5 | 2.7 | 70.9 | 34.5 |
| Bedroom | 547.4 | 58.0 | 97.6 | 560.6 |
| Study, Office | 9.8 | 0.9 | 4.3 | 227.1 |
| Garage | 3.2 | 0.3 | 2.7 | 117.2 |
| Basement | 5.2 | 0.5 | 3.7 | 141.4 |
| Utility, Laundry | 3.9 | 0.4 | 5.3 | 72.7 |
| Pool, Spa | 1.0 | 0.1 | 1.0 | 98.4 |
| Yard, Outdoors | 40.2 | 3.6 | 28.7 | 140.1 |
| Room to Room ^c | 54.6 | 5.0 | 40.6 | 134.5 |
| In and Out of House | 6.3 | 0.6 | 6.6 | 94.5 |
| Other, Verified | 1.9 | 0.2 | 1.5 | 129.1 |
| Refused to Answer | 0.3 | 0.0 | 0.3 | 131.4 |

^aAll statistics are unweighted.

^bThe overall average percentage time spent was calculated by averaging the individual percentages of time spent in each residential location, which are taken over the total time spent by each individual in all residential locations. The total time spent in residential locations varied from individual to individual.

^cThe *room-to-room* location was likely a fallback for respondents who were unsure where they were, or who visited many rooms over a short time period.

1. You are an academic researcher involved in a large European health study where you must estimate the exposure of persons in different European cities to airborne particulate matter using only projected concentrations in different fixed locations based on a relatively small number of measurements and data on human travel habits between homes and work or school.
2. You are a scientist working with the US Environmental Protection Agency (USEPA) and you need to estimate the exposure of Americans to airborne toxic metals as part of a risk assessment that will determine whether or not a product can be marketed, although unfortunately you do not have the budget for a multi-million dollar personal monitoring survey.
3. You are a graduate student in epidemiology who is studying respiratory disease in rural Indian villages, but you only have enough resources to measure average particle concentrations in selected locations and to gather crude activity diaries from the village residents.

In these three situations, direct information on exposure is lacking, and, therefore, the characterization of potential exposures for each group of affected people requires one to synthesize available information on airborne pollutant concentrations and human behavior patterns. By

using an exposure model, the investigator in each of these cases can quantify the exposure distribution of study subjects and examine the likely influence of each location and other exposure factors. Conversely, without making use of an exposure model, only broad inferences could be made about potential exposures.

Although exposure models do not contain any data on the probability of ill health, and they do not assess the acquired dose of particular chemical species, they are still useful to health researchers, practitioners, and the general public. The rest of this section discusses specific areas in public health where inhalation exposure modeling can be useful. A summary is given in Table 3.

One of the most important uses of exposure modeling in environmental health is the identification and exploration of physically effective means to mitigate exposure to toxic species. Once a link has been established between typical exposure levels and disease, models can be used to establish situations where unhealthful conditions might arise. Exposure modeling results can be used to make public information brochures or reference documents for the public and health researchers alike. Apart from the effectiveness of specific physical measures, successful interventions also depend on changes in human behavior patterns. The knowledge imparted by the modeling of exposure lends itself to critical discussions between family members or coworkers that evaluate specific

Table 3: Specific Public Health Uses of Inhalation Exposure Models

| Area | How Exposure Model Results Are Used |
|------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Epidemiology | As epidemiologists try to establish links between exposure to toxic pollutants and specific disease outcomes, they are assisted in the construction of questionnaires and diaries by accurate and reliable information on how exposure occurs and which exposure variables are most important |
| Education | The results of exposure models can be used to educate the general public on how much exposure to toxic air pollutants they may receive in a variety of everyday situations. |
| Intervention | Efforts by health practitioners to intervene in unhealthy situations where persons are being exposed to toxic agents benefit from data on effective exposure reduction measures. This information can be used in ongoing dialogs with family members to facilitate the empowerment of individuals and to accentuate their involvement in reducing exposure. |
| Risk Assessment | When estimating the health risk of populations who are exposed to specific kinds of toxic air pollutants the exposure for the affected population must be estimated before being combined with toxicological data. Models are an inexpensive and flexible way to provide the exposure data for a wide variety of situations. |
| Air Quality Guidelines | The modeling of exposure to air pollutants has a large role in establishing guidelines for acceptable indoor and outdoor levels of pollution that rely on the estimation of health risk associated with air pollutants for different likely scenarios. |

mitigation strategies, which may be especially practical or attractive to particular households or workplaces.

Links between acute and chronic adverse health effects and exposure to toxic airborne pollutants are established by environmental epidemiologists and toxicologists. Epidemiological studies typically rely on questionnaires or diaries that could be revised and expanded in light of sophisticated model-based information on how exposure occurs in homes and other locations. The same kind of exposure information, combined with data on a compound's toxicity, can be used in health risk assessments, which estimate the probability of ill health resulting from typical uses of common products.

Using the results of risk assessment, governmental agencies, such as the US Environmental Protection Agency (USEPA) and the California Air Resources Board (CARB), work to establish standards for levels of ambient air pollution, which are designed to protect the health of persons in the US, particularly those who live in cities suffering from motor-vehicle induced smog.⁷ Unfortunately, these ambient air quality standards were not designed to be applicable to the range and intensity of the toxic constituents in indoor air pollution or air pollutant emissions from short-lived local outdoor sources. Beyond the technical difficulties of characterizing indoor

exposure patterns, the enactment of explicit indoor air quality standards is fairly problematic from a policy perspective, likely because of issues related to jurisdiction and enforcement.

However, building standards for *indoor ventilation* have already been established by the American Society of Heating, Refrigerating, and Air Conditioning Engineers (ASHRAE). These standards can be used as a basis for designing healthy homes. In addition, indoor air concentration guidelines have already been successfully established for the case of lung cancer risk due to radon gas. These guidelines were created using estimates of risk based on established health and exposure data.⁸ In the future, formal concentration, building, and product use guidelines might be set by the USEPA, or some other regulatory agency, for other specific types of indoor air pollution, such as secondhand smoke, through the use of exposure simulation. By applying the machinery of a sophisticated exposure model, the likelihood of exceeding a particular indoor air quality concentration could be associated with specific building conditions and human behavior patterns.

6 REVIEW OF SOME EXISTING INHALATION EXPOSURE MODELS

At this point, we have seen that exposure models can be useful to scientists studying the interaction between hu-

⁷Carbon monoxide (CO) and particulate matter are two of the USEPA's *criteria pollutants* considered harmful to public health and the environment, for which National Ambient Air Quality Standards (NAAQS) have been established in accordance with the 1990 Clean Air Act. The 24-hour NAAQS for PM_{2.5} is currently 65 $\mu\text{g m}^{-3}$ and the annual NAAQS for PM_{2.5} is 15 $\mu\text{g m}^{-3}$. The 1-hour NAAQS for CO is 10,000 $\mu\text{g m}^{-3}$ and the 8-hour standard is 40,000 $\mu\text{g m}^{-3}$.

⁸See http://www.epa.gov/radon/risk_assessment.html and <http://www.epa.gov/radon/pubs/> for more information on residential radon guidelines.

man health and the human environment. But what are some examples of real models that currently exist? In this section, we introduce some of the more well-developed exposure models for airborne contaminants that have appeared in the scientific literature or that are currently undergoing active use and refinement. All of these exposure models apply the basic exposure formula given in Equation 1 in which airborne pollutant concentrations and receptor movements are superimposed, revealing patterns in human exposure.

Although all of the models use a common formula, the inputs required by each different model for assigning or simulating pollutant concentrations and human activity patterns may be quite different. Two elements that most current models have in common are (1) they derive outdoor concentrations from raw empirical levels of ambient air pollution measured at fixed sites and (2) they use time-location profiles obtained from empirical human activity pattern data. Raw activity patterns are sometimes manipulated to artificially generate long-term (multi-day) time profiles or profiles for multiple associated persons.

When treating indoor exposure, some models draw from empirical distributions of indoor concentrations while others use a single or multizone indoor air quality model to predict indoor levels, as for the example presented in Section 3. Indoor air quality models are capable of simulating time-varying or time-averaged room concentrations using specified indoor source emission rates and the physical characteristics of a building, such as the air flow rates between rooms, the rate of air exchange with the outdoors, room volumes, and rates of chemical or physical transformation. These models generalize knowledge of the physical and chemical behavior of pollutants to arbitrary buildings and environmental conditions, which, while adding another level of overall model complexity, can be convenient when exploring the determinants of exposure.

The many inhalation exposure models currently under development can be crudely divided into two camps, the “exploratory” and the “regulatory”, according to their primary intended purpose. Table 4 lists a number of existing inhalation exposure models, categorizing them by their general status in either camp. Seigneur et al. [2002] and Price et al. [2003] both present fairly in-depth descriptions of many of these listed models as well as others. The entries in the table reflect significant efforts by a regulatory agency or efforts that have an associated article in the refereed scientific literature, or both. As a whole, they are reasonably reflective of the current state of inhalation exposure modeling, including efforts by government, academia, and industry. Most of the models listed are or have been made available in distributable (executable) form.

The first camp is comprised of models that are ex-

ploratory and limited in scope, focusing on a particular domain of exposure scenarios. Their purpose is primarily in developing methods or approaches, establishing mechanisms of exposures, empirically testing model assumptions, and exploring model predictions as part of a formal sensitivity and/or uncertainty analysis. For this camp, the prediction of exposures for arbitrary populations is less a priority than is understanding how exposure occurs in a given setting. The essence of the exploratory approach is to conduct carefully controlled computer-based simulation experiments to isolate the effects of a small number of key variates on the outcome variate of interest. Some of the earliest examples of exploratory models are those by Sparks et al. [1993], Sparks [1991], Koontz and Nagda [1991], and Wilkes et al. [1992], which track the behavior of household occupants and follow pollutant concentrations between rooms, incorporating detailed physical mechanisms of emissions and pollutant dynamics.

The second camp of models has a much broader scope and is intended to support regulatory mandates, such as the estimation of population health risk. Those who use these models are generally interested in applying them to large groups of people, and therefore they may incorporate sophisticated sampling techniques, e.g., Monte Carlo or Latin Hypercube sampling, and stratification of model inputs and outputs according to geographic or demographic characteristics. They likely describe multiple sources of pollution and a range of different settings where exposure can occur.

In recent years, there has been an emphasis on the regulatory type of model with organizations such as the USEPA investing considerable resources in its NEM, HAPEM, SHEDS, and APEX series of models [McCurdy, 1995; Rosenbaum, 2002; Burke et al., 2001; Richmond et al., 2002]. Because inhalation is likely the most important exposure route for many toxic chemicals and is mechanistically one of the simplest routes of exposure, and since extensive air quality regulations are already concerned with air quality (e.g., the US Clean Air Act), these inhalation exposure models are among the most well-developed, especially by in-house or contracted researchers at regulatory agencies (e.g., USEPA or CARB). They tend to be statistically based, sampling from empirical or parameterized distributions of observed air concentrations and aggregate times spent in broad location categories (e.g., home, outdoors, or automobile).

There exists a massive database of ambient air quality data to support regulatory and other predictive population exposure models, as mandated under regulations such as the US Clean Air Act. There is also a growing data base of personal inhalation exposure monitoring data from studies such as EXPOLIS, NHEXAS, TEAM, PTEAM [Koistinen et al., 2001; Sexton et al., 1995; Pellizzari et al., 1995; Wallace, 1987; Özkaynak et al., 1996], and oth-

Table 4: Examples of Some Existing Regulatory and Exploratory Inhalation Exposure Models

| Reference | Acronym | Class ^a | Developed By ^b | Full Name or Description |
|------------------------------------------------------------------------|----------------|--------------------|---------------------------|----------------------------------------------------------------------------------------------------------------------------------|
| Ott et al. [1988]; Ott [1984] | SHAPE | Expl | EPA | Simulation of Human Activity Patterns and Exposure |
| McKone [1987] | – | Expl | LLNL | Residential inhalation exposure model for volatile compounds in tap water |
| Traynor et al. [1989] | – | Expl | LBNL | A “macromodel” for indoor exposure to combustion products |
| Sparks [1988, 1991]; Sparks et al. [1993] | RISK | Expl | USEPA | Descendant of EXPOSURE and INDOOR models; simulates multi-zone indoor air concentrations, individual exposure, and risk |
| Koontz and Nagda [1991] | MCCEM | Expl | – | Multichamber Chemical Exposure Model |
| Wilkes et al. [1992, 1996, 2002] | MAVRIQ/TEM | Expl | Carnegie-Mellon | Model for Analysis of Volatiles and Residential Indoor Air Quality / Total Exposure Model |
| McCurdy [1995] | NEM-pNEM | Reg | USEPA | (Probabilistic) National Exposure Model; criteria pollutants |
| Macintosh et al. [1995] | BEADS | Reg | Harvard | Benzene Exposure and Absorbed Dose Simulation |
| Koontz et al. [1998]; Koontz and Niang [1998]; Rosenbaum et al. [2002] | CPIEM | Reg | CARB | California Population Indoor Exposure Model |
| Burke et al. [2001] | SHEDS-PM | Reg | USEPA | Stochastic Human Exposure Dose Simulation – Particulate Matter |
| Rosenbaum [2002] | HAPEM | Reg | USEPA | Hazardous Air Pollutant Exposure Model; mobile source air toxics |
| Dols and Walton [2002] | CONTAM | Expl | NIST | Multizone simulation of air flows, contaminant concentrations, and personal exposure. |
| Richmond et al. [2002] | APEX/TRIM Expo | Reg | USEPA | Air Pollutants Exposure Model and Total Risk Integrated Methodology Exposure Event Module; criteria and hazardous air pollutants |
| Kruize et al. [2003]; Hänninen et al. [2003] | EXPOLIS | Reg | EXPOLIS | European population particle exposure model |
| de Bruin et al. [2004] | EXPOLIS | Reg | EXPOLIS | European population carbon monoxide exposure model |
| Briggs et al. [2003] | – | Expl | Northampton | Residential Radon exposure model |

^aRegl: Regulatory models used for development or enforcement of government regulations or for related risk assessments. These models are typically applied to large populations and require extensive data inputs that are representative of the population being modeled; Expl: Exploratory models used for intensive scientific study of particular exposure scenarios. These models typically treat an individual or narrowly-defined cohort of people and have facilities for a detailed treatment of residences or some other specific microenvironment.

^bUSEPA: US Environmental Protection Agency, Washington, D.C. USA; NIST: National Institute of Standards and Technology, Gaithersburg, MD USA; CARB: California Air Resources Board, Sacramento, CA USA; EXPOLIS: European Exposure Assessment Project; LLNL: Lawrence Livermore National Laboratory, Livermore, CA USA; LBNL: Lawrence Berkeley National Laboratory, Berkeley, CA USA; Northampton: Contributed by academic researchers in Northampton, UK.

Information and downloads for the APEX, TRIM, HAPEM, and HEM regulatory models for criteria pollutants and air toxics can be accessed from the EPA website at the following URL: <http://www.epa.gov/ttn/fera/>

ers, and a large database of microenvironmental inputs, including indoor air quality model parameters, to support the scope of regulatory modeling efforts. The American Chemistry Council has funded two recent in-depth reviews of data sets and reports having relevance to exposure modeling [Koontz and Cox, 2002; Boyce and Garry, 2002]. The USEPA's "Exposure Factors Handbook" and "Exposure Factors Handbook for Children" are two fairly comprehensive resources of appropriate inputs for predictive exposure models [USEPA, 1997, 2002]. An online European Exposure Factors Sourcebook, called *Expofacts*, provides access to electronic data sets containing exposure-related information for many different European countries.⁹

7 ADVANCING THE SCIENCE OF EXPOSURE

7.1 MODELS AS THEORY

Exposure models exist because they are of practical value in estimating the health impact of particular products or behavior patterns. But more fundamentally, the development and application of models forms the basis for advancement in exposure theory.

Any given empirical survey of human exposure can only address a limited domain of possible exposures and scenarios over a restricted period of time. On the other hand, models, such as the residential exposure model described in Section 3, are well-equipped to describe the complex interaction between elements of exposure, including environmental characteristics, human behavior, and pollutant dynamics, and their evolution in time. Exposure models generalize experimental findings across a range of complicated and arbitrary scenarios and time scales, encapsulating the current state of scientific knowledge related to a particular environmental health problem. They consolidate a wide range of submodels, survey data, and expert opinions into an adaptable quantitative framework, which can be used to explore relationships between various exposure factors, e.g., as part of a formal *sensitivity analysis*.

Because they can predict exposures for arbitrary situations and human populations, models facilitate the generation of testable hypotheses concerning the mechanisms by which exposure occurs and, therefore, fulfill a need of the utmost importance in any field of science. Whether conceptual or quantitative, models provide direction for future studies, and therefore the driving force for scientific advancement. In this way, the development and application of exposure models lie at the heart of exposure science. Once model predictions are compared to empirical data, the model assumptions can be revised and the-

oretical mechanisms of exposure can be updated, thereby completing the cycle of scientific inquiry.

7.2 THE VANGUARD OF EXPOSURE MODELING

As evidenced by the material presented, exposure modeling is already in a fairly advanced state of development. However, as with any scientific endeavor, there are many remaining frontiers and areas of uncertainty that need further investigation. The following subsections contain discussion of three possible topic areas that are at the edge of exposure modeling research, and therefore of exposure research in general. These areas are (1) the direct evaluation of predictive exposure models, (2) the improved characterization of the dispersion of indoor and outdoor pollutant concentrations, and (3) the inclusion of more detailed human social factors into exposure model design. Some specific topics associated with these areas are also summarized in Table 5.

7.2.1 DIRECT EVALUATION OF MODEL PREDICTIONS

While models are very useful for exploring the effect of different variables on human exposure to air pollution, it is important to have knowledge about their limitations in predicting real exposure for individual cases or for populations. The evaluation of exposure models can be conducted on several levels. For example, one could proceed by validating the different component elements of an exposure model. How accurate are its predictions of pollutant concentrations or human time-location patterns? Or, most directly, the exposure metrics produced by models could be compared with empirical surveys of exposure that make use of personal monitoring devices. A careful comparison of the distribution of simulated and observed exposures, taking into account specific housing characteristics and occupant behavior patterns, allows for an evaluation of the general performance of the model, as well as calibration of the model input parameters and the interpretation of features in the empirical exposure frequency distribution.

Currently, there have not been very many attempts to compare the output of population exposure models with the results of personal exposure surveys. One problem is that few large-scale exposure surveys exist. Another problem is that surveys, because of limited time and fiscal budgets, tend to measure less detailed information than is typically used as input for exposure models, making it difficult to gain insight into the causes of discrepancies between theory and experiment. Nevertheless, it is still possible to gauge the overall accuracy of exposure models using available survey data.

As part of the USEPA's PTEAM study [Özkaynak et al., 1996, 1993], which is representative study of personal

⁹See <http://www.ktl.fi/expofacts/> for more information on *Expofacts*.

Table 5: Future Directions in Exposure Modeling Research

| Area | General Problem Description |
|------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Direct Model Evaluation | There is currently a need for more direct evaluation of exposure predictions against the results of empirical personal exposure surveys. Ideally, these new surveys would collect data expressly for the purpose of testing the performance of exposure models, including relevant and complete data on houses, air flow parameters, and human activity patterns. |
| Indoor Air Modeling | Because indoor air quality modeling is central to many inhalation exposure models, efforts should be made to test and parameterize these models in a variety of situations that are relevant to specific sources, human behavior, and environmental conditions. |
| Mixing and Proximity Effects | The nonuniform mixing (dispersion and dilution) of air pollutants in both indoor and outdoor settings for times when a proximate source is active can lead to elevated exposures for persons spending time near the active source. This effect needs more study. Dispersion of hazardous chemical and biological agents, perhaps from intentional and malevolent releases, is an especially pressing area of study. |
| Longitudinal Activity Patterns | There is currently a dearth of multi-day human activity pattern data. Most activity data are limited to a single 24-hour period. It is currently unclear how much human location and activity for a given person change with time. |
| Multi-Person Household Activity Patterns | Most available human activity data are limited to a single person per household. Since the interaction between persons in a household are likely to impact exposure, surveys of multiple persons in a population of homes should be conducted. |
| Detailed Activity Categories | Activity pattern studies are sometimes designed under limited budget circumstances or for use in a large variety of modeling analyses. For best use in characterizing specific types of exposure, activity pattern surveys should use focused location and activity categories, such as information on source proximity, room size and type, window and door position, and use of household pollutant sources. |
| Time Series Analysis | Exposure models must be applied across a variety of time scales. More work needs to be done in understanding how concentrations and human activities, and therefore human exposures, vary in time. How the distribution of exposure changes as a function of averaging time and the correlation of exposure in time, i.e., its autocorrelation, are two issues that deserve attention. |
| Social Ecologies | Exposure models currently treat the ecology of a household or other exposure environment in a fairly distracted way, focusing more on pollutant levels and cross-sectional time-location patterns. For the purpose of identifying both technologically and socially effective means to reduce exposure, modelers should consider the complex, nonlinear social dynamics of persons having different roles and demographics in each modeled environment. |

particle exposures for persons residing in a city in California in the early 1990's, and other monitoring studies [e.g., Williams et al., 2003a,b; Wallace et al., 2003; Liu et al., 2003; Allen et al., 2003], some of the necessary variables to facilitate a comparative analysis were recorded, e.g., house air exchange rates, time spent by individuals at home, smoking activity, cooking activity, cleaning activity, and approximate house size and room types. Unfortunately, specific information on the timing of sources either in or out of the house were not collected. In spite of these deficiencies, a systematic comparison between the results of the simulation model and the results of intensive monitoring studies would be desirable.

Additional exposure surveys for the purpose of validating an exposure model should be conducted. A large validation study with a more complete set of variables, similar to or exceeding the level of the PTEAM effort, is expected to be very expensive and time-consuming. A more manageable approach might involve using carefully scripted location and activity profiles for a small number of houses, where the level of information detail could be expanded, including the use of real-time, or nearly real-time, monitoring of room concentrations, personal exposures, personal activities, house configuration, and environmental characteristics. An improvement over most time-activity diaries that are administered to study participants would be to include greater resolution in time and space on the locations and activities of subjects in their homes, including the rooms that were visited, the positions of doors and windows, as well as the use of combustible products and other sources of air pollution. With a systematic analysis across these study factor combinations, an airborne exposure simulation model could be thoroughly tested across a variety of important scenarios.

7.2.2 UNDERSTANDING THE LOCAL DISPERSION OF INDOOR AND OUTDOOR POLLUTANTS

Although some recent efforts, such as those by Ribot et al. [2002], involve modeling the distribution of indoor pollutants in single rooms using computational fluid dynamics (CFD), the central assumption of many zonal indoor air quality models is that of uniform mixing of pollutants in individual rooms. Under this assumption, any emitted pollutant is instantaneously mixed throughout the zone of release. The implications of this assumption are that concentrations in a particular room are considered the same everywhere. In reality, it takes a finite amount of time for emissions to mix within a room so that the average exposure one receives while immediately next to an active pollutant source may be larger than the average exposure at a more distant location, such as on the other side of the room.

It may be possible that one's average exposure over a

sufficiently long period is not much different than the theoretical well-mixed case. Based on a number of published studies that have evaluated the performance of multizone indoor air models and/or investigated the phenomena of indoor mixing and source proximity (Table 6), the general behavior of indoor models seems accurate, although under some air flow conditions or when the human receptor and source are in close proximity, the assumption of uniform mixing may break down. This possibility deserves more attention. A careful investigation into the proximity effect for emissions from an assortment of household products, especially one that characterizes the distribution of exposures as a function of distance and averaging time, is warranted.

The modeling of concentrations and exposures near active outdoor pollutant sources is expected to be even more complex than for indoor sources. Unlike for indoor settings, the persistence of local pollutant emissions in outdoor settings is very short. Therefore, there is no build-up or homogenization of emissions as there is indoors, and the forces of mixing and dispersion, driven from wind and turbulent air currents, are of key importance in determining local concentrations. Proximate exposure to local outdoor sources of air pollution is an emerging area of study with respect to common pollutants, such as tobacco smoke, but also with respect to releases of hazardous chemical and biological agents, perhaps due to deliberate destructive intent.

7.2.3 HUMAN FACTORS

The nature of human activities makes up half of the exposure equation (Equation 1). However, this critical aspect of exposure modeling has thus far received relatively little attention as compared to that given to the measurement and modeling of environmental concentrations. For example, there is currently insufficient information available on human activity patterns on the household level. Two large-scale activity patterns conducted across the US and in California have produced timelines of human movement for broad location outside of their home and between specific rooms of their houses (see Section 4). Although several recent exposure assessment studies have incorporated multi-day activities in their design [For example: Liu et al., 2003; Wallace et al., 2003; Wallace and Williams, 2005], there have not appeared any studies for large populations that have collected multi-day human activity pattern data simultaneously for two or more members of a household.

To fully understand how exposure to residential air pollutants, such as secondhand smoke, occurs, it is important to consider dependencies among members of a household, and possible changes in activity patterns from day to day, perhaps in response to particular exposure-relevant

Table 6: Studies Evaluating Models of Residential Multi-Zone Transport of Indoor Air Pollutants, Single-Zone Mixing, and Source-Proximity Effects

| Study | Source | Method | Conclusions/Results |
|--------------------------------------------------|---------------------------------------------------------------------------------------|-----------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| De Gids and Phaff [1988] | Tracer gas | Real-time CO monitoring in a house | Good agreement between measured and modeled CO |
| Sparks et al. [1991] | Moth cakes, kerosene heater, dry cleaned clothes, aerosol spray, applied wet products | VOC and particle samples in a house | Multizone model does a good job of predicting indoor pollutant concentrations |
| Miller et al. [1997]; Miller and Nazaroff [2001] | Cigarettes and tracer gas | Real-time tracer and particle monitoring in a house | Good agreement between two-zone model and measurements |
| Ott et al. [2003] | Cigarettes | Real-time particle and CO monitoring in a house | Good agreement between measurements and two-zone model parameterized from same experiment; error surface shows relative insensitivity to flow parameters |
| Baughman et al. [1994] | Tracer gas | Grab sampling of SF ₆ at 41 points in a chamber | Mixing times range from 7 to 15 min under natural convection in which heat was added from solar radiation or an electrical heater |
| Drescher et al. [1995] | Tracer gas | Real-time monitoring of CO at 9 points in a chamber | Mixing times range from 2 to 15 min for forced convection |
| Mage and Ott [1996] | Cigarettes and tracer gas | Real-time particle and CO monitoring in a tavern and house | Use of a uniformly mixed assumption to determine average exposures is generally valid for an intermittent source if the source-off well-mixed time period is large compared to the source-on plus mixing time periods |
| Klepeis [1999] | Cigarettes and tracer gas | Real-time particle and CO monitoring in a house, tavern, and smoking lounge | Mixing of air pollutant in medium to large rooms is fairly rapid in real locations under typical conditions on the order of 12–15 min before average concentrations at separated points are within 10% of the room mean |
| Furtaw et al. [1996] | Tracer gas | Real-time SF ₆ monitoring in a chamber | Average concentration at a distance of 0.4 m from the source was double the theoretical well-mixed concentration for typical flow rates |
| McBride et al. [1999] | Tracer gas and incense stick | Real-time CO and particle monitoring | Proximity to active particle sources of 1 m resulting in mean concentrations averaging 3 times higher than those at a fixed distant location. Proximate CO concentration were also much higher than distant ones during source-on periods. |

initiatives or changing source behaviors. The amount of time that occupants spend together and in which rooms, and what activities are performed together or apart, coupled with the time-dependent nature of particular pollutant generating patterns, e.g., smoking, cooking, cleaning, and door, window, and centralized air handling configurations, will all affect exposures. Careful consideration of relative movements for occupants of different ages and relationships, e.g., child and caregiver, would allow for a better understanding of how different demographic groups are exposed.

In addition to a lack of longitudinal data for multiple household members, much of the activity pattern data collected to date consists of fairly crude location and activity categories. Future exposure studies should be focused on specific types of exposure and measure as detailed information on exposure-related human activities events as possible. The use of detailed microenvironment and behavior categories results in a record of the micro-level behavior of human beings, which can play a critical role in how exposure occurs and help to identify new and better strategies for reducing or eliminating exposure. The collection of detailed information may be prohibitive for large studies, although the advent of sophisticated electronic monitoring equipment may facilitate data gathering and management. Modern information technology, including microsensors and remote digital loggers, holds the promise of the more efficient collection of real-time activity patterns and other exposure-related data. The use of geographic information systems (GIS), which can track health, demographic, and environmental data could be used to manage and facilitate the analysis of exposure variation for households across neighborhoods, cities, regions, and nations.

As mentioned earlier, the identification of effective mitigation strategies for exposure is an important application of exposure modeling. However, while strategies for reducing exposure may at times appear to be straightforward from a technological or logistical perspective, there may be sizeable hurdles to overcome in terms of house roles, personalities, habits, and scheduling. For public health intervention projects focusing on households, as with urban planning or peace and nation-building efforts that have significantly larger scope, a roadmap for improvement or recovery handed down “from above” is not enough, and is likely to fail. The people who live in the households (or cities) must desire the change. Ideally, they understand the process, and are fully informed and involved, as it progresses.

For example, for the case of residential secondhand smoke (SHS) exposure, it is likely not enough that SHS has known adverse health effects and that strategies such as isolating smokers, opening windows, or using filtration devices may be effective means of removing indoor air

pollutants. When this knowledge is fed into the ecology of a smoking household by health care workers, the media, or other elements of society, it may or may not have any lasting and beneficial effect. Nonlinear effects related to social pressure on smokers, interpersonal roles, personal empowerment, and feelings of involvement in evaluating, identifying, or implementing effective means of decreasing SHS exposure are likely to play important roles in the eventual reduction or elimination of exposure.

In the next phase in exposure science, physical models of pollutant dynamics might be fused with informed social models of human dynamics. New developments in quantitative social science, including techniques of agent-based modeling [Epstein and Axtell, 1996], show promise as a means of understanding the complex, changing relationships in human ecologies. Some exposure modelers are beginning to recognize that life-stage and life-role variables must be included in studies of human activity in order to sufficiently explain and understand the variation in human behavior that impacts exposure [Graham and McCurdy, 2004]. Exposure science could benefit by drawing from fields such as cognitive psychology, sociology, and geography, which are focused on human behavior and the interactions amongst individuals and between individuals and the environment. The enhanced use of social variables in theoretical descriptions of exposure would allow exposure assessors to study how factors such as roles, empowerment, knowledge, perception, and beliefs contribute to a particular exposure landscape, and could help facilitate the identification of both physically and socially practical means for reducing or eliminating dangerous exposures.

QUESTIONS

1. What are four specific uses of exposure models in public health?
2. Make a diary of the locations you visit over the course of a full day, including the times you enter and leave each location. Calculate the percentage of time spent in each type of location. What is the location in which you spent the most amount of time? The least? How do you think these percentages might change from day to day? Are these percentages likely to be different for other members of your family?
3. When designing a household activity pattern survey for the purpose of gathering data that will be used in modeling human exposure, describe four important design considerations.
4. Given the table of average airborne particle concentrations for different locations provided below, calculate your 24-hour average exposure to airborne par-

ticles based on the activity patterns you recorded for question 2.

| Location | Ave. Airborne Particle Conc. [$\mu\text{g m}^{-3}$] |
|----------------|----------------------------------------------------------|
| Home | 90 |
| Office-Factory | 40 |
| Bar-Restaurant | 200 |
| Other Indoor | 20 |
| In a Vehicle | 45 |
| Outdoors | 35 |

- Derive the time-average canonical exposure formula (Equation 1) from the semi-continuous dynamic formula (Equation 3).
- Derive the population version of the canonical exposure formula (Equation 4).
- Given the average time spent by Americans in different locations presented in Table 1 and the average airborne particle concentrations in each location given in question 4, calculate the 24-hour average exposure of Americans to airborne particles. What specific assumptions are inherent in this calculation?
- What are two major assumptions that are typically made when modeling indoor exposure to airborne pollutants?
- Discuss at least three strategies for reducing exposure to secondhand tobacco smoke in the home. Which strategies do you think would be the least and the most effective? Describe specific simulation experiments you might use to explore the effectiveness of different mitigation strategies.

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