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# Assessment of Inter-Individual and Geographic Variability in Human Exposure to Fine Particulate Matter in Environmental Tobacco Smoke

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## Abstract

Environmental tobacco smoke (ETS) is a major contributor to indoor human exposures to fine particulate matter of 2.5 microns or smaller ($PM_{2.5}$). The Stochastic Human Exposure and Dose Simulation for Particulate Matter (SHEDS-PM) model developed by the US Environmental Protection Agency estimates distributions of outdoor and indoor $PM_{2.5}$ exposure for a specified population based on ambient concentrations and indoor emissions sources. A critical assessment was conducted of the methodology and data used in SHEDS-PM for estimation of indoor exposure to ETS. For the residential microenvironment, SHEDS uses a mass-balance approach which is comparable to best practices. The default inputs in SHEDS-PM were reviewed and more recent and extensive data sources were identified. Sensitivity analysis was used to determine which inputs should be prioritized for updating. Data regarding the proportion of smokers and "other smokers," and cigarette emission rate were found to be important. SHEDS-PM does not currently account for in-vehicle ETS exposure; however, in-vehicle ETS-related $PM_{2.5}$ levels can exceed those in residential microenvironments by a factor of 10 or more. Therefore, a mass-balance based methodology for estimating in-vehicle ETS $PM_{2.5}$ concentration is evaluated. Recommendations are made regarding updating of input data and algorithms related to ETS exposure in the SHEDS-PM model. Inter-individual variability for ETS exposure was quantified. Geographic variability in ETS exposure was quantified based on the varying prevalence of smokers in five selected locations in the U.S.

### Keywords

exposure; fine particulate matter; environmental tobacco smoke; modeling; variability

## 1. INTRODUCTION

Epidemiological studies of health effects associated with $PM_{2.5}$ typically use ambient concentration as a surrogate for human exposures.(1-3) Therefore, health effects are often estimated based on concentration-response (C-R) relationships derived from such studies.(4-6) However, because most people spend the majority of their time indoors, the use of ambient data does not accurately represent the concentrations to which people are actually exposed. Hence, there is growing recognition of the need to quantify human exposure to $PM_{2.5}$ as an alternative basis for characterizing associated health effects.(7)

Total personal exposure to $PM_{2.5}$, including both indoor and ambient exposures, is significantly associated with daily mortality.(8) Air pollution epidemiology and exposure studies have identified Environmental Tobacco Smoke (ETS) as a major contributor to indoor air concentrations and human exposure to $PM_{2.5}$.(9-10) Smoking is associated with significantly increased risk of heart disease, stroke, lung and chronic lung diseases.(11-13) Exposure to second-hand smoke by children is associated with reduced cognitive ability, and increased risk of serious respiratory problems and middle ear infections.(14-16) Therefore, it is necessary to account for the contribution of smoking to indoor $PM_{2.5}$ when estimating total exposures to $PM_{2.5}$.

A scenario-based inhalation exposure simulation model is intended to estimate exposures to simulated individuals by estimating the movement of such individuals through a series of microenvironments, each with its own air pollutant concentration.(17) The exposure of an individual during a day is based on the time-weighted concentration from the microenvironments in which the individual spent time. Examples of such models that incorporate ETS are the Simulation of Human Activity and Pollutant Exposure (SHAPE) model, Total Human Exposure Model (THEM), Air Pollution Exposure (APEX) model, and Stochastic Human Exposure and Dose Simulation model for Particulate Matter (SHEDS-PM).(18-21)

The objective of SHEDS-PM is to predict total personal exposures to $PM_{2.5}$. SHEDS-PM uses a probabilistic approach to estimate inter-individual variability in distributions of outdoor and indoor $PM_{2.5}$ exposure for a population of simulated individuals based on ambient $PM_{2.5}$ concentrations and sources of indoor $PM_{2.5}$ emissions. Currently, SHEDS accounts for ETS exposure for home, restaurant, and bar microenvironments.

The objectives of this paper are to answer four key questions:

- What are the spatial and temporal trends in factors affecting ETS exposure?
- What are the key factors to which exposure is sensitive for ETS in different microenvironments?
- What are the key factors leading to geographic and inter-individual variability in ETS exposure?

## 2. MODELING OF ENVIRONMENTAL TOBACCO SMOKE EXPOSURE

Figure 1 illustrates the main inputs and key algorithms in SHEDS-PM for calculating indoor $PM_{2.5}$ concentrations contributable to ETS. Input data include demographic data, ambient $PM_{2.5}$ concentration, and human activity data. The demographic data used in SHEDS-PM were obtained from the US Census for the year 2000. The daily average ambient $PM_{2.5}$ concentration for each census tract for the geographic area of interest is input by the user based on ambient monitoring or air quality modeling data. The Consolidated Human Activity Database (CHAD) is comprised of U.S. human activity pattern diary data compiled based on a variety of activity studies.(22-26)

SHEDS-PM selects the US Census data for user specified census tracts and randomly generates demographically representative individuals by age and gender. The number of individuals simulated, and the distribution of age and gender, is specified by the user. Each simulated individual is randomly assigned an activity diary record from CHAD based on age and gender and other user specified matching criteria (e.g., housing type, employment status, and smoking status). A cross-sectional simulation is based on a different random sample of individuals each day, whereas a longitudinal simulation is based on one random set of individuals each of whose activity pattern is simulated from day-to-day, thereby taking into account daily dependence in activities.(27) All simulations reported here are based on longitudinal simulation.

For the residential microenvironment, ETS-related inputs include the cigarette emission rate, proportions of smokers and "other smokers," and the number of cigarettes smoked. Emissions from cigarette smoking include: (1) emissions from smoking by someone who is a smoker; and (2) emissions to which a non-smoker is exposed because of smoking by others, who are referred to as "other smokers." These support assessments of ETS-based $PM_{2.5}$ exposures for smokers and non-smokers, respectively.(21)

In the restaurant and bar microenvironments, the ETS-related inputs are Active Smoking Count (ASC) and the average incremental increase in indoor $PM_{2.5}$ concentration caused by smoking one cigarette smoking ($C_{ets}$). ASC is the average number of cigarettes actively smoked during a defined time interval.(28)

A mass balance approach is applied in the residential microenvironment based on the assumption of a single steady-state zone, and on parameters for penetration of outdoor $PM_{2.5}$, air exchange rate, deposition rate, and indoor volume. The assumption is not strictly satisfied in most cases, however, in many situations the equation provides good estimates.(29-32) Exposure events are simulated for exposure time periods of typically minutes to hours, according to the duration of time spent in a microenvironment per diary sampled from CHAD.

SHEDS-PM estimates the indoor $PM_{2.5}$ concentration including ETS but does not estimate direct inhalation by a smoker from active smoking. $PM_{2.5}$ concentrations in the residential microenvironment are estimated by a mass balance: (31-32)

$$C_{\text{Home}}=\frac{P\cdot a}{a+k}C_{\text{ambient}}+\frac{E_{cig}N_{cig}+E_{\text{cook}}t_{\text{cook}}+E_{\text{clean}}t_{\text{clean}}+E_{\text{other}}t_{\text{other}}}{(a+k)\,VT} \quad (1)$$

Where,

a = air exchange rate ($h^{-1}$);

$C_{Home}$ = $PM_{2.5}$ concentration in the home (μg/$m^3$);

$C_{ambient}$ = ambient outdoor $PM_{2.5}$ concentration (μg/$m^3$);

$E_{cig}$ = emission rate for cigarette smoking (μg/cig);

$E_{cook}$ = emission rate for cooking (mg/$m^3$);

$E_{clean}$ = emission rate for cleaning (mg/$m^3$);

$E_{other}$ = emission rate for all other activities (mg/$m^3$);

k = deposition rate ($h^{-1}$);

$N_{cig}$ = number of cigarettes smoked during model time step (cig);

P = penetration factor (unitless);

T = model time step (min);

$t_{cook}$ = duration of time spent cooking during model time step (min);

$t_{clean}$ = duration of time spent cleaning during model time step (min);

$t_{other}$ = duration of time spent doing other activities during model time step (min);

V = volume of microenvironment ($m^3$).

The indoor $PM_{2.5}$ concentration attributable to penetration of ambient $PM_{2.5}$ is estimated based on a penetration factor, deposition rate, air exchange rate, and indoor volume. The second term in Equation (1) describes the contribution from indoor emission sources, including smoking, cooking, cleaning, and other sources.

Parameter values for Equation (1) can be assigned fixed quantities or frequency distributions. The model time step ( $T$ ) is the duration of a diary event. The emission generating durations ($t_{cook}$, $t_{clean}$, $t_{other}$) are obtained from the CHAD database for each simulated individual. Several steps are used to calculate the number of cigarettes ($N_{cig}$) smoked. The daily total numbers of cigarettes smoked in the residence are assigned to an individual who is a smoker or other smoker, based on the user-specified proportions for the number of cigarettes smoked by smokers and by others, respectively. The rate of smoking in the home is based on the number of cigarettes smoked at home divided by time spent at home while not sleeping. For each diary event at home, the hourly rate is multiplied by the duration of the event in hours to estimate an average number of cigarettes.(27)

Due to lack of data needed to apply Equation (1) to the restaurant and bar microenvironments, a simplified approach is used instead. The simplified approach is based ona linear regression to estimate indoor concentration based on outdoor concentration, incremental impact on indoor air quality from cigarette smoking, and indoor background concentration. The indoor $PM_{2.5}$ concentration for the restaurant and bar microenvironments is (28):

$$C_{\text{rest/bar}}=B+r_{I/O}\cdot C_{\text{ambient}}+ASC\cdot C_{ets} \quad (2)$$

Where,

ASC = active smoking count, the average number of cigarettes being actively smoked in the microenvironment in a defined time interval (cig);

B = background indoor $PM_{2.5}$ concentration from indoor $PM_{2.5}$ sources (μg/$m^3$);

$C_{rest/bar}$ = $PM_{2.5}$ concentration for of restaurant or bar microenvironment (μg/$m^3$);

$C_{ambient}$ = ambient outdoor $PM_{2.5}$ concentration (μg/$m^3$);

$C_{ets}$ = incremental $PM_{2.5}$ concentration caused by smoking a cigarette during a defined time interval [μg/($m^3$.cig)];

$r_{I/O}$ = ratio of indoor concentration associated with penetration of outdoor concentration.

The first term of Equation (2) describes the non-ambient contribution to indoor $PM_{2.5}$ concentration except for ETS. The second term describes the contribution from outdoor $PM_{2.5}$. The $PM_{2.5}$ concentration attributable to ETS is described by the last term.

# 3. METHODOLOGY

The methodology includes: (1) review literature for ETS data and algorithms used in SHEDS-PM; (2) sensitivity analysis to identify the key factors to which exposure is sensitive for ETS in selected microenvironments; (3) assessment of the effect of updated data on estimated exposures; and (4) characterization of inter-individual and geographical variability associated with ETS exposure.

## 3.1 Review of Inputs and Algorithms

The review of existing inputs and algorithms in SHEDS-PM for estimating $PM_{2.5}$ concentration associated with ETS is based on: (a) detailed review of the SHEDS-PM model, its user guide, and the literature cited as the basis for default input assumptions; (b) published peer reviewed papers regarding SHEDS-PM and similar models; and (c) databases of the U.S. Department of Health and Human Services (DHHS) and the Substance Abuse & Mental Health Services Administration (SAMHSA).

## 3.2 Sensitivity Analysis

An overview of sensitivity analysis methods is given by Frey and Patil.(33) Differential Sensitivity Analysis (DSA) is applicable to linear models for which there are no nonlinear interactions between terms, as is the case for the ETS aspects of SHEDS-PM. DSA evaluates the effect on model outputs exerted by individually perturbing only one of the model inputs, while holding all other inputs at their nominal or base-case values.(34) Sensitivity in a model output is represented as a positive or negative percentage change compared to the nominal solution. This type of sensitivity analysis provides a measure of model responsiveness to a unit change in an input. In separate analyses, inter-individual variability in exposure is estimated based on simultaneous variation in multiple model inputs over their plausible ranges of variability.

In the DSA, selected inputs were varied by plus or minus 10 percent, which is well within the plausible range of values. In subsequent probabilistic simulations, these inputs are varied over plausible ranges. The differential sensitivity of estimated exposure for selected indoor microenvironments is based on the time-weighted daily average $PM_{2.5}$ exposures for the $50^{th}$, $90^{th}$, and $99^{th}$ percentile of simulated individuals. Because only a small fraction of the simulated population spent time in the restaurant and bar microenvironments, the sensitivity analysis for these microenvironments focuses on the $99^{th}$ percentile.

## 3.3 Assessment of Updated Inputs and Algorithms

The assessment of the effect of updated input data on estimated exposures are based on running SHEDS-PM with default data, with updated data for ETS-related inputs, and comparison of the two sets of results. Ambient $PM_{2.5}$ air quality data, demographic data, sample size, and algorithms are kept the same in both sets of simulations. Frequency distributions of air exchange rate, penetration factor, and deposition rate are used for the residential microenvironment. Vehicle air exchange rates have much more variability than those in a residential microenvironment. Therefore, a mass balance model for estimating in-vehicle microenvironment $PM_{2.5}$ concentration is separately evaluated based on sensitivity to air exchange rates.

### 3.4 Inter-individual Variability in Residential Exposures

To explore variability in exposure in the residential microenvironment, exposures are estimated and compared for specific sources of $PM_{2.5}$ including: (a) infiltration of outdoor air; (b) indoor sources other than smoking; and (c) ETS from smoking. Updated data regarding the proportion of smokers and "other" smokers, and cigarette emission rate, are used in the simulation.

### 3.5 Geographic Variability in Exposures

Smoking prevalence, housing types, and demographic factors (i.e. age, gender) vary among geographic areas. In order to assess the geographic variability in estimated exposure, five locations were selected as a basis for comparisons from U.S. states that span the lowest to highest range of smoking prevalence. Utah has only 9.3 percent proportion of smokers compared to Kentucky, with 25.2 percent, based on 2008 data. California (14.0%), New York (16.8%), and North Carolina (20.9%) are examples of varying proportions between the lowest and highest.(35) For each state, the county with the highest population was selected as the basis for case studies, with an assumption that the county and state smoking prevalence are the same. For each county, ten census tracts were selected at random. Two case studies were conducted for each area: (1) base case without ETS; and (2) with ETS. Updated data were used for $E_{cig}$, ASC, and $C_{ets}$. To focus on the role of ETS without confounding effects of differences in actual ambient $PM_{2.5}$ concentrations, the daily average ambient $PM_{2.5}$ concentration for each census tract was assigned the same constant value of 10 μg/m$^3$ over space and time for each area, and analysis of results focused on the incremental contribution of ETS to daily exposure.

## 4. RESULTS

Results for updated inputs and algorithms are given. An algorithm for ETS exposure in the in-vehicle microenvironment is evaluated using sensitivity analysis. Inter-individual and geographic variability in ETS-related exposure is evaluated.

### 4.1 Evaluation of ETS-Related Input Data

The default data in SHEDS related to smoking prevalence is representative of 1995 and 1993, for adults 18 years and older and adolescents from 12 to 17 years old, respectively. More recently available U.S. data, representative of 2007 and 2006 for adults and adolescents, respectively, on the proportion of smokers at home is lower than that of the default data, especially for adolescents aged from 12-17, because of declining trends in smoking prevalence. From 2000 to 2007, the U.S. nationwide prevalence of smoking decreased from 23.2 to 18.4%.(36) The default and updated inputs are compared in Table I.

There are no recent data regarding the proportion of "other smokers" by gender. However, updated data are available for age categories. SHEDS takes into account other smokers for persons older than 12 years old for three age groups. The default proportion of persons exposed to other smokers varies from 4 to 49 percent depending on the age group. However, SHEDS does not currently estimate exposures of children 11 years of younger to other smokers. An estimated 24.9% of children in this age group are exposed to cigarette smoking at home.(40)

The available data regarding smoking prevalence are on an individual basis.(36) However, there are no available data on the proportion of residences in which smoking occurs.

The default input for the cigarette emission rate in SHEDS-PM is 10.9 mg per cigarette. Özkaynak *et al*. estimated a cigarette emission rate of 14 ± 4 mg/cig by fitting a nonlinear regression model to average $PM_{2.5}$ concentrations for 178 homes in Riverside, CA.(31) The mean value of $PM_{2.5}$ emission rate among the 50 top brands of cigarettes is 13.8 mg/cig, with a standard deviation of 3.1 mg/cig and a range of 8 to 23 mg/cig based on a sample size of 111.(41) Based on a summary of 14 papers, Nazaroff and Klepeis reported a mean $PM_{2.5}$ emission rate of 13.7 mg/cig.(29) Thus, the default input is lower than the mean value of cigarette emission rate based on various studies. An updated emission rate of approximately 13.8 mg/cig, which is 27 percent higher than the default, with a range from 8 to 23 mg/cig, is used here.

In 1993, an average smoker smoked 19.6 cigarettes per day (cpd), with a mean of 21.3 cpd for men and 17.8 cpd for women. In 2004, the mean was 16.8 cpd, with 18.1 cpd for men and 15.3 cpd for women.(42) Thus, over an 11 year period, the number of cigarettes smoked declined on average by 14 percent for women and 15 percent for men. However, updated data are not available for specific gender and age cohorts. Therefore, the default inputs used in SHEDS-PM based on NHAPS are retained. However, to assess the implications of possible reductions in cpd, a sensitivity case was conducted using the example of Wake County in which a 15 percent reduction was applied for all cohorts.

As a default, ASC for the restaurant and bar microenvironments has a uniform distribution of 0 to 3. ASC ranged from 0 to 4 cigarettes per hour with an average of 1.3 cigarettes per hour based on 1993 to 1994 data.(28) Assuming 16 hours of smoking per day, the ASC in 2004 is approximately 1.05 cigarettes per hour per smoker, based on 2004 data. The value of ASC appears to be decreasing with time.

The SHEDS-PM default for $C_{ets}$ is a triangular distribution with a minimum of 32 μg/m$^3$, best estimate or mode of 40.4 μg/m$^3$, and a maximum of 50 μg/m$^3$ per cigarette per hour for both restaurants and bars. Ott *et al*. used a mass balance approach to estimate an incremental $PM_{2.5}$ concentration in a tavern of 42.5 μg/m$^3$ based on a cigarette emission rate of 2.4 mg/min, and an ASC of 1.17 cigarettes.(28) Based on the range of cigarette emission rate from 8 to 23 mg/cig, and assuming the duration of one cigarette smoking is 10 minutes, the estimated $C_{ets}$ ranges from 14 to 40 μg/m$^3$, which overlaps with the range of defaults used in SHEDS-PM.

Based on CHAD data, the time people spend in a vehicle is almost 10 times less than that at home. However, in-vehicle $PM_{2.5}$ concentrations associated with smoking have been measured or estimated to be as high as 658 μg/m$^3$, depending on the status of vehicle windows and air conditioning system.(43) Vehicles have a wider range of air exchange rates compared to those measured in homes. The relatively high ETS $PM_{2.5}$ concentrations inside a vehicle can be attributed to the smaller interior volume.(43)

### 4.2 Sensitivity Analysis

To compare the sensitivity of estimated exposure to each of several ETS-related inputs, a typical case study was developed based on ten randomly selected census tracts in Wake County, North Carolina. For each census tract, 10,000 individuals were simulated. For each of the residential, restaurant and bar microenvironments, sensitivity analysis was conducted based on default inputs.

Seven inputs were varied, including: (1) proportions of smokers and other smokers, cigarette emission rate, and number of cigarettes, for the residential microenvironment; and (2) ASC and $C_{ets}$ for the restaurant and bar microenvironments. One simulation was conducted for default inputs in all three microenvironments, and 14 simulations were conducted for the upper and lower bound of each of the 7 inputs except the number of cigarette. One sensitivity case was conducted for the number cigarettes smoked per day based on 15% reduction of the default inputs. Each model run was conducted on a Windows XP Pentium 4 computer and had an approximate runtime of 400 minutes. The results for the residential microenvironment are given in Table II. The results for restaurants and bars are given in Table III.

Over 99 percent of the simulated population spent time in the residential microenvironment. Based on the default inputs, about 40 percent of people were estimated to be exposed to ETS. Because ETS concentration is a linear function of proportion of smokers and cigarette emission rate, therefore, the 90$^{th}$ and 99$^{th}$ percentiles of inter-individual variability in exposure vary plus or minus 10 percent for a plus or minus 10 percent variation in proportion of smokers or cigarette emission rate. For an estimated 15 percent decrease in the average cpd over time, the 90$^{th}$ and 99$^{th}$ percentiles of exposure also decrease by 15 percent. The 50$^{th}$ percentile of exposure is less sensitive to ETS-related inputs.

Only 22 and 4 percent of the simulated population spent time in the restaurant and bar microenvironments, respectively. According to Equation (2), the concentrations inside the restaurant and bar are linearly proportion to the product of ASC × $C_{ets}$. Therefore, the exposure at the 99$^{th}$ percentile is equally sensitive to relative variations of plus or minus 10 percent to either of these two inputs.

### 4. 3 Assessment of the Effect of Updated Inputs and Algorithms

Comparison of estimated daily average exposures to individuals based on updated data to that based on default data is given in Table IV. For the residential microenvironment inputs, a lognormal distribution was used for air exchange rate, with geometric mean of 0.56 and geometric standard deviation of 1.84. Normal distributions were used for penetration factor and deposition rate, with means of 0.91 and 0.79, standard deviation of 0.1 and 0.31, respectively. The updated data include circa 2006 to 2007 proportions of smokers and nonsmokers, with $E_{cig}$ = 13.8 μg/m$^3$, versus default circa 1995 data on the proportion of smokers and non-smokers and $E_{cig}$ = 10.9 μg/m$^3$. The mean exposures, and standard deviation based on updated data are 8 and 31 percent higher, respectively, than those based on defaults. Although the mean values of updated proportion of smokers and “other” smokers are 32% and 5% lower, respectively, than the defaults, the updated mean cigarette emission rate is 27% higher than the default. The overall increase in the estimated exposure despite the lower proportions of smokers and other smokers is consistent with the results of sensitivity analysis, which indicates that exposure is equally sensitive to the proportion of smokers and “other smokers,” and cigarette emission rate.

### 4.4 In-Vehicle Exposure to ETS

Turk developed a mass balance equation which contains both indoor and outdoor emission sources for calculating concentrations in a chamber.(44) Ott *et al*. summarize previous studies, and describe and evaluate a mass balance equation used in a chamber.(30) Examples of exposure models using mass balance approaches are SHAPE, THEM, APEX, Sequential Cigarette Exposure Model (SCEM),(30) Multi-Chamber Concentration and Exposure Model (MCCEM),(45) and European Population Particle Exposure Model (EXPOLIS).(46)

Ott *et al*. evaluates a linear regression equation for estimation of indoor respirable suspended particle (RSP) concentration based on penetration of ambient RSP.(30) They conclude that the linear regression approach can be applied to estimate RSP concentrations from ETS in similar taverns.

A typical mass balance approach for estimation in-vehicle concentration is available in SCEM. SCEM was developed for predicting the time series of concentration in a well-mixed vehicle for any cigarette smoking activity pattern. Ott *et al*. observe that time series of carbon monoxide and particle concentration agree well (within 5 percent) with the time series predicted by the model.(30) The mass balance model is:

$$C_{In-Vehicle}=\frac{R_{cig}\cdot E_{cig}\cdot t}{a\cdot V\cdot T} \quad (3)$$

Where,

a = air exchange rate (h$^{-1}$);

$C_{\text{In-Vehicle}}$ = $PM_{2.5}$ concentration for the in-vehicle microenvironment (μg/m$^3$);

$E_{cig}$ = emission rate for cigarette smoking (μg/cig);

$R_{cig}$ = average smoking rate (cig/h);

t = duration of active smoking of an individual (min);

T = duration of diary event in the vehicle (min);

V = vehicle interior cabin volume ($m^3$).

This model is similar to the second term of Equation (1), except it does not account for deposition rate.

For the in-vehicle microenvironment, results of sensitivity analysis of Equation (3) are given in Table V. The air exchange rate was varied, holding other inputs at their default values. The estimated in-vehicle $PM_{2.5}$ concentrations range from 8 to 201 μg/$m^3$ based on air exchange rates ranging from 79 to 3.0 $h^{-1}$. When all the windows are closed, and with the air conditioner operated in the "max" AC setting with recirculation, the $PM_{2.5}$ concentration reached the largest estimated value. At a vehicle speed of 20 mph, opening a single window from 3 inches to fully open decreased the estimated concentration by fourfold. Air exchange rate is more sensitive to the ventilation system status than to the window status and vehicle speed. With the vehicle speed at 60 mph, windows closed, switching from AC Max (with recirculation of interior air) to AC Regular (with intake of fresh air) leads to an eightfold increase in the air exchange rate, and an eightfold decrease in the in-vehicle $PM_{2.5}$ concentration. At a speed of 20 mph and with AC off, adjusting the window from 3 inches to fully open leads to a fourfold increase in the air exchange rate and decrease in in-vehicle $PM_{2.5}$ concentration. With one window open 3 inches and the AC off, increasing the vehicle speed from 20 mph to 60 mph leads to a threefold increase in the air exchange rate and decrease in in-vehicle $PM_{2.5}$ concentration.

### 4.5 Inter-individual Variability in Residential $PM_{2.5}$ Exposure with Default Inputs

Simulated cumulative frequency distributions (CDF) of inter-individual variability in daily average $PM_{2.5}$ exposures based on selected scenarios for the residential microenvironment are given in Figure 2. In order to focus comparisons among the exposures attributable to different emission sources, ambient $PM_{2.5}$ concentration is set to 10 μg/$m^3$ for 24 hours and kept constant for each simulated day. Updated inputs are used in the simulation. The $PM_{2.5}$ sources considered are ETS only, cooking only, and infiltration of ambient air only. A comparison of these three scenarios provides insight regarding their relative importance to exposure.

About 25 percent of simulated individuals are exposed to ETS in the residential microenvironment. The CDF attributable to only ETS has a mean of 7.0 μg/$m^3$, with a range of 0 to 519 μg/$m^3$, and a standard deviation of 20 μg/$m^3$. For an ambient concentration of 10 μg/$m^3$, the average exposure associated with infiltration of outdoor air is 2.4 μg/$m^3$. The average exposure from cooking is 1.6 μg/$m^3$. Hence, unless ambient concentration is very high, ETS is likely to contribute a plurality or majority of the average residential indoor exposure in homes where smoking occurs. However, the contribution of ETS to individual exposure is much higher for some individuals, and is zero for households without any smoking.

### 4.6 Geographic Variability in Daily Average ETS-related $PM_{2.5}$ Exposure

There are geographic differences in factors such as the distribution of smoking prevalence by age and gender, distribution of the population by age and gender, and the distribution of housing stock, which affect comparisons of estimated concentrations. The variation in these factors among geographic areas is shown in Table VI. These data are among the inputs to SHEDS-PM.

The average proportion of smokers, including all age groups and both genders, ranges from 9.3 to 25.2 percent among the selected geographic areas, with Jefferson County, KY being the highest and Salt Lake County, UT being the lowest. Jefferson County generally has the highest smoking prevalence for all age groups between ages 14 to 64 for both male and female compared to the other four geographic areas, with the exception of male smokers in Wake County, NC aged 45 to 64.

The average age of the population in Wake County, NC and Los Angeles, CA is slightly younger than in the other areas, whereas the other three areas have similar average ages. For Wake and Los Angeles, approximately 54 percent of the population is aged 12 to 34, versus only 42 percent for Jefferson County. In Jefferson County, taking into account the distribution of both smoking prevalence and of the population by age and gender, the cohorts that typically contribute the most to smoking are for ages 35 to 44 for both genders, with a nearly similar contribution from the 45 to 64 age cohorts. Although New York and Salt Lake Counties have a similar proportion of the population in the 45 to 64 age groups as Jefferson County, there is a lower contribution of these groups to ETS exposure because of lower smoking prevalence.

The distribution of housing stock varies geographically. Larger houses are estimated to have lower indoor concentrations of ETS for the same air exchange rate and emission rate compared to smaller houses. Single family homes, whether detached or attached (e.g., townhouses), tend have larger interior volumes than either multiple family homes (apartments) or mobile homes. Los Angeles, Salt Lake, and Jefferson Counties have 67 to 71 percent single family housing, versus only 46 percent for New York County. Conversely, New York County has the highest proportion of smaller homes, at 54 percent.

Results of estimated incremental daily average $PM_{2.5}$ exposure attributable to ETS are summarized in Table VII. These average exposures range from 4.6 to 7.7 μg/m$^3$ among the five analyzed geographic areas. The mean exposure to ETS increases monotonically with respect to the average proportion of smokers, a metric that takes into account both the population distribution and the smoking prevalence for individual age and gender cohorts. However, housing stock is also an influential factor. For example, even though New York County has a smoking prevalence approximately one-third lower than for Jefferson County, the average ETS exposure is only 12 percent lower at least in part because of the generally smaller housing volumes.

## 5. CONCLUSIONS

SHEDS-PM default inputs regarding the proportion of smokers and “other smokers” should be updated to account for the desired time period for which exposures are simulated, since there are significant differences in these proportions over time. The default data regarding cigarette emission rate is low compared to average emission rates estimated from several studies, and thus should be updated. Furthermore, emission rates vary by approximately a factor of three among cigarettes. This variability can be accounted for as part of a probabilistic simulation of exposure. Data on the market-share weighted distribution of variability in cigarette emission rate are needed in order to allow better estimation of the contribution of ETS to indoor air. The algorithms used for ETS exposure in the residential, restaurant, and bar microenvironments are generally based on best practice.

ETS-related $PM_{2.5}$ exposure is sensitive to the proportion of smokers and “other smokers,” and cigarette emission rate for the residential indoor microenvironment, and to the incremental increase in indoor $PM_{2.5}$ concentration associated with smoking a cigarette during an hour in the residential and bar microenvironments. Hence, these inputs and parameters are the ones that merit the most attention when developing input data.

For the in-vehicle microenvironment, the most sensitive parameter is the air exchange rate, which in turn depends on the status of windows, the air conditioning and heating system, and vehicle speed. An implication of the sensitivity analysis results is that in-vehicle exposure to ETS can be very high particularly in warm weather for drivers who use air conditioning on recirculation with windows closed. For some individuals, in-vehicle exposures to ETS could be a significant component of daily average exposure even though the time spent in vehicle is less than that of other indoor microenvironments.

For a population of individuals, exposure to ETS can be the largest single contributor to daily average exposure to fine particulate matter, even though only a portion of all individuals are exposed to ETS. For those who are exposed to ETS, there is a wide range of variability in such exposures.

Geographic variability in the prevalence of smokers and demographic factors such as the distribution of the population by age and gender are among factors that lead to geographic variability in daily average $PM_{2.5}$ exposures attributable to ETS. Thus, area-specific data for the proportion of smokers and for demographics should be used.

There are some limitations in available data and models that lead to recommendations for future efforts to improve ETS exposure modeling. Even though the proportion of smokers and the number of cigarettes smoked per smoker per day appear to be declining with time in the U.S., they are still significant and should be tracked consistently over time by age and gender. Some demographic factors that affect smoking prevalence, such as education or socioeconomic status, are not incorporated into existing exposure models. Exposure of young children to ETS and data on the proportion of households in which smoking occur merit quantification. Data are not currently available for avoidance behaviors, such as a non-smoker who avoids proximity to a smoker during a smoking event. Furthermore, changes in smoker activity patterns due to bans on smoking in public indoor spaces, such as whether the rate of smoking is differentially affected in other microenvironments, are not yet quantified.

Despite a variety of actions and messages aimed at reducing the prevalence of smoking, smoking nonetheless continues to be a significant source of exposure to fine particulate matter. The residential and in-vehicle microenvironments in particular are conducive to potentially high exposure concentrations.

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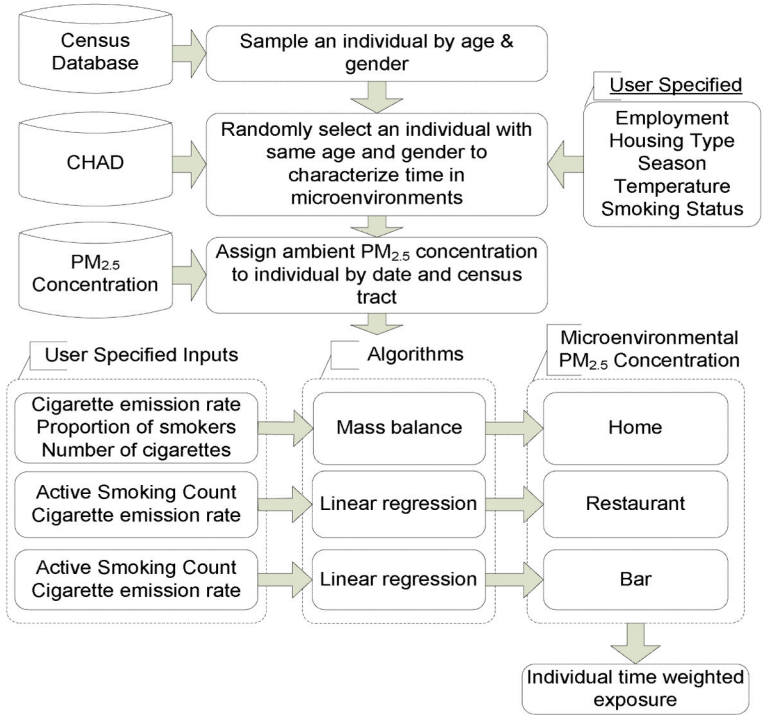


**FIGURE 1.**

Conceptual Diagram of the Components of the Stochastic Human Exposure and Dose Simulation Model for Particulate Matter (SHEDS-PM) Relevant to Environmental Tobacco Smoke (ETS)

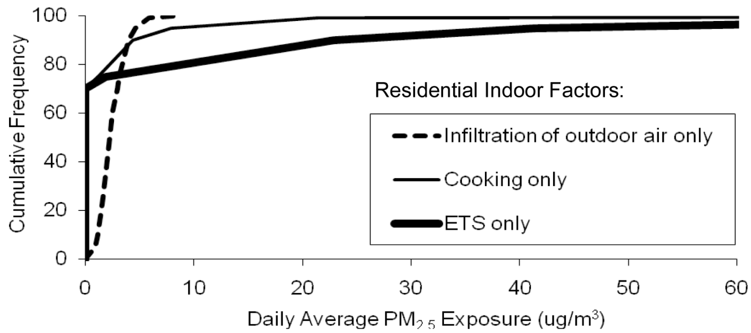


**FIGURE 2.**

Comparison of Cumulative Frequency Distributions of Estimated Daily Average $PM_{2.5}$ Exposures ($\mu g/m^3$) in the Residential Microenvironment

*Note:* Simulation assumptions: 100,000 individuals, 10 census tracts in Wake County, NC. Same random seeds are used in each simulation Emission Rate: 13.8 mg/cig. Ambient $PM_{2.5}$ concentration: 10 $\mu g/m^3$.

## Table I

Default and Updated National Average Inputs for the Proportion of smokers and "Other smokers" by age and Gender in the Stochastic Human Exposure and Dose Simulation Model for $PM_{2.5}$[a]

| Proportion of Smokers (%) | | | | | Proportion of "Other Smokers" (%) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Default[b] | | Updated[c] | | | | Default[e] | | Updated[f] | |
| Age Group | Male | Female | Male | Female | Smoking Status | Age Group | Male | Female | Male | Female |
| 12-13 | 10.0 | 10.0 | 1.80 | 1.80 | | 12-17 | 73 | 89 | 49 | 62 |
| 14-15 | 20.1 | 20.1 | 8.40 | 8.40 | | | | | | |
| | | | | | Smoker | 18-64 | 35 | 38 | 37 | 55 |
| 16-17 | 29.3 | 29.3 | 18.9 | 18.9 | | >64 | 16 | 28 | 32 | 39 |
| 18-24 | 28.4 | 23.9 | 28.5 | 19.3 | | | | | | |
| 25-34 | 31.5 | 28.7 | 27.4 | 21.5 | | 0-11 | n/a | n/a | 22 | 35 |
| 35-44 | 32.4 | 27.3 | 24.8 | 20.6 | Non-smoker | 12-17 | 31 | 35 | 17 | 23 |
| 45-64 | 28.9 | 24.5 | 24.5 | 19.3 | | 18-64 | 10 | 12 | 5.0 | 9.0 |
| >64 | 14.8 | 11.4 | 12.6 | 8.30 | | >64 | 4.0 | 5.0 | 4.0 | 6.0 |

[a] Data are based on household interviews of a sample of the civilian noninstitutionalized population.

[b] DHHS (1998)(37): adults 18 years and older; SAMSHA (1996)(38): adolescents 12-17 years old.

[c] DHHS (2008)(36): adults 18 years and older; SAMSHA (2008)(39): adolescents 12-17 years old.

[d] Klepeis and Tsang (1996).(22)

[e] DHHS (2007).(40)

[f] According to DHHS (2007), the proportion of other smokers for male continues to be lower than that for females, but available data are not reported by gender. However, ranges are given. To be consistent with the expected trends, the lower bound of the range of the proportion of other smokers is assigned to males, and the upper bound is assigned to females.

## Table II

Results of Sensitivity Analysis of Total Daily Exposure for SHEDS-PM for the Residential Microenvironment[a]

| Input Assumption | 50th Percentile $PM_{2.5}$ Exposure ($\mu g/m^3$) | 90th Percentile $PM_{2.5}$ Exposure ($\mu g/m^3$) | 99th Percentile $PM_{2.5}$ Exposure ($\mu g/m^3$) | %Change in 50th Percentile | % Change in 90th Percentile | % Change in 99th Percentile |
|---|---|---|---|---|---|---|
| Default Inputs | 4.4 | 41 | 105 | / | / | / |
| Proportion of Smokers +10%[b] | 4.7 | 45 | 116 | 6 | 10 | 10 |
| Proportion of Smokers −10%[b] | 4.2 | 37 | 95 | −6 | −10 | −10 |
| Proportion of "Other Smokers" +10%[c] | 4.7 | 45 | 116 | 6 | 10 | 10 |
| Proportion of "Other Smokers" −10%[c] | 4.2 | 37 | 96 | −6 | −10 | −10 |
| Emission Rate +10%[d] | 4.8 | 45 | 116 | 8 | 10 | 10 |
| Emission Rate −10%[d] | 4.1 | 37 | 95 | −8 | −10 | −10 |
| Number of Cigarette −15%[e] | 4.1 | 36 | 96 | −9 | −15 | −15 |

[a] Simulation assumptions: 100,000 individuals, 10 randomly selected census tracts in Wake County, NC; same random seeds are used in each simulation; ambient $PM_{2.5}$ concentration: 10 $\mu g/m^3$; emission rate: 13.8 mg/cig.

[b] The proportion of smokers given in Table I for each gender and age group was multiplied by 1.1 for the +10% case and by 0.9 for the −10% case.

[c] The proportion of other smokers given in Table I for each smoking status, age group, and gender was multiplied by 1.1 for the +10% case and by 0.9 for the −10% case.

[d] The emission rate was varied from 12.4 mg/cig (−10) to 15.2 mg/cig (+10%).

[e] The average number of cigarettes smoked, as given in (Burke, 2001) (27), is reduced by 15 percent.

## Table III

Results of Sensitivity Analysis of Total Daily Exposure for SHEDS-PM for the Restaurant and Bar Microenvironment[a]

| Input Assumption | Restaurant | | Bar | |
|---|---|---|---|---|
| | 99th Percentile $PM_{2.5}$ Exposure (μg/$m^3$) | % Change in 99th Percentile | 99th Percentile $PM_{2.5}$ Exposure (μg/$m^3$) | % Change in 99th Percentile |
| Default Inputs | 12 | / | 10 | / |
| ASC +10% | 13 | 10 | 13 | 10 |
| ASC −10% | 11 | −10 | 11 | −10 |
| $C_{ets}$ +10% | 13 | 10 | 13 | 10 |
| $C_{ets}$ −10% | 11 | −10 | 11 | −10 |

[a]Simulation assumptions: 100,000 individuals, 10 census tracts in Wake County, NC; same random seeds are used in each simulation; ambient $PM_{2.5}$ concentration: 10 μg/$m^3$; ASC = 1.05 cigarette; $C_{ets}$= 40.4 μg/$m^3$ in restaurant and bar.

[b]ASC was varied from 0.95 to 1.16 cig/hr.

[c]Cets was varied from 36.4 to 44.4 μg/$m^3$.

## Table IV

Inter-individual Variability in Estimated Residential Microenvironmental Exposures for Default and Updated Data for Smoking Prevalence and Cigarette Emission Rate[a]

| Input Data | SHEDS-PM Model Output for Inter-Individual Variability in Daily Average Exposure to $PM_{2.5}$ | | | | |
|---|---|---|---|---|---|
| | 50th Percentile ($\mu g/m^3$) | 90th Percentile ($\mu g/m^3$) | 99th Percentile ($\mu g/m^3$) | Mean ($\mu g/m^3$) | Std.Dev. ($\mu g/m^3$) |
| Default Inputs[b] | 6.7 | 29 | 79 | 12 | 16 |
| Updated Inputs[c] | 6.0 | 31 | 100 | 13 | 21 |

[a] Simulation assumptions: 100,000 individuals, 10 census tracts in Wake County, NC; same random seeds are used in both simulations; ambient $PM_{2.5}$ concentration data were based on hourly data from July 1, 2002 to July 30, 2002 from the output of the CMAQ air quality model.

[b] The proportions of smokers and “other smokers” in 1995 are approximately 23% and 31%, respectively. Ecig=10.9 mg/cig.

[c] The proportions of smokers and “other smokers” in 2007 are approximately 18% and 28%, respectively. Ecig=13.8 mg/cig.

## Table V

Estimated In-vehicle $PM_{2.5}$ Concentrations for Selected ETS Exposure Scenarios[a]

| Speed (mph) | Windows | Ventilation System | Air Exchange Rates[b] ACH ($h^{-1}$) | Predicted $PM_{2.5}$ Concentrations[c] ($\mu g/m^3$) |
|---|---|---|---|---|
| 20 | One fully Open | AC Off | 78.6 | 8 |
| 60 | One Open 3 inches | AC Off | 56.4 | 11 |
| 60 | All Closed | AC Regular | 38.6 | 16 |
| 20 | One Open 3 inches | AC Off | 20.9 | 29 |
| 0 (parked) | One Fully Open | AC Off | 19.2 | 31 |
| 60 | All Closed | AC Max | 5.1 | 118 |
| 20 | All Closed | AC Max | 3.0 | 201 |

[a]Simulation assumptions: $V = 4\ m^3$, $E_{cig} = 13800\ \mu g/cig$, $R_{cig} = 1.05\ cig/h$, $t = 10$ min, $T = 60$ min, and ACH as shown.

[b]Air exchange rates were obtain from Ott *et al*. (2008).(43)

[c]$PM_{2.5}$ concentrations are calculated based on the mass balance Equation (3).

## Table VI

Factors Affecting Geographic Variability in Daily Average $PM_{2.5}$ Exposure Associated with ETS

**Distribution of Smoking Prevalence by Gender (%)[a]**

| | Jefferson, kY | | Wake, NC | | New York, NY | | Los Angeles, CA | | Salt Lake, UT | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Age** | **Male** | **Female** | **Male** | **Female** | **Male** | **Female** | **Male** | **Female** | **Male** | **Female** |
| 12-13 | 4.1 | 4.1 | 4.0 | 4.0 | 5.1 | 5.1 | 4.1 | 4.1 | 3.1 | 3.1 |
| 14-15 | 14.4 | 14.4 | 12.0 | 12.0 | 11.6 | 11.6 | 10.6 | 10.6 | 4.4 | 4.4 |
| 16-17 | 27.9 | 27.9 | 21.0 | 18.0 | 18.1 | 18.1 | 17.1 | 17.1 | 7.9 | 7.9 |
| 18-24 | 32.7 | 30.6 | 31.3 | 20.9 | 19.3 | 17.3 | 20.0 | 13.5 | 10.1 | 7.5 |
| 25-34 | 33.6 | 31.5 | 29.0 | 20.6 | 20.4 | 18.4 | 19.9 | 13.6 | 10.9 | 8.3 |
| 35-44 | 28.8 | 26.7 | 26.4 | 16.0 | 18.1 | 16.0 | 18.4 | 11.9 | 12.5 | 9.9 |
| 45-64 | 25.7 | 23.6 | 26.8 | 16.4 | 20.0 | 18.1 | 17.1 | 10.6 | 11.9 | 9.3 |
| >64 | 11.9 | 9.8 | 14.5 | 4.1 | 8.9 | 6.9 | 9.8 | 3.3 | 4.7 | 2.1 |

**Distribution of Age by Gender (%)[a]**

| | Jefferson, KY | | Wake, NC | | New York, NY | | Los Angeles, CA | | Salt Lake, UT | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Age** | **Male** | **Female** | **Male** | **Female** | **Male** | **Female** | **Male** | **Female** | **Male** | **Female** |
| 12-13 | 3.6 | 3.4 | 4.5 | 4.8 | 3.8 | 3.9 | 4.7 | 4.6 | 3.1 | 2.9 |
| 14-15 | 3.5 | 3.3 | 4.9 | 4.3 | 3.7 | 3.9 | 4.6 | 4.4 | 3.7 | 3.3 |
| 16-17 | 3.5 | 3.5 | 4.6 | 4.7 | 3.5 | 3.7 | 4.6 | 4.5 | 4.1 | 3.9 |
| 18-24 | 3.2 | 3.2 | 4.5 | 5.5 | 3.5 | 3.6 | 4.5 | 4.5 | 5.4 | 5.6 |
| 25-34 | 7.4 | 7.6 | 8.5 | 8.5 | 6.8 | 7.5 | 9 | 8.6 | 7.5 | 7.5 |
| 35-44 | 10 | 11 | 6.3 | 5.9 | 9.7 | 11.1 | 8.7 | 8.3 | 8.1 | 7.9 |
| 45-64 | 10.9 | 11.9 | 9.6 | 9.4 | 11.2 | 12 | 9.5 | 9.5 | 11.5 | 11.5 |
| >64 | 6 | 8 | 6.9 | 7.1 | 5.6 | 6.5 | 5.2 | 4.8 | 7.2 | 6.8 |

**Distribution of Housing Types, Percent[b]**

| | Jefferson, kY | Wake, NC | New York, NY | Los Angeles, CA | Salt Lake, UT |
|---|---|---|---|---|---|
| Single Family Detached | 66 | 58 | 30 | 64 | 65 |

**Distribution of Housing Types, Percent**[b]

| | Jefferson, kY | Wake, NC | New York, NY | Los Angeles, CA | Salt Lake, UT |
|---|---|---|---|---|---|
| Single Family Attached | 1 | 2 | 16 | 7 | 6 |
| Multiple Family | 32 | 31 | 53 | 27 | 27 |
| Mobile Family | 1 | 9 | 1 | 2 | 2 |

[a]DHHS (2008)(36): adults 18 years and older; SAMSHA (2008)(39): adolescents 12-17 years old.

[b]U.S. Census 2000.

**Table VII**

Simulated Incremental Daily Average $PM_{2.5}$ Exposures Associated with ETS for Selected Geographic Areas[a]

| Location (County, State) | Proportion of Smokers (%) | 50th Percentile[b] ($\mu g/m^3$) | 90th Percentile ($\mu g/m^3$) | 99th Percentile ($\mu g/m^3$) | Mean ($\mu g/m^3$) | Std.Dev.[c] ($\mu g/m^3$) |
|---|---|---|---|---|---|---|
| Jefferson, KY | 25.2 | 1.8 | 22 | 71 | 7.7 | 20 |
| Wake, NC | 22.1 | 1.4 | 21 | 72 | 7.0 | 20 |
| New York, NY[d] | 16.8 | 1.6 | 20 | 69 | 6.8 | 21 |
| Los Angeles, CA[d] | 14.0 | 1.3 | 17 | 61 | 6.0 | 18 |
| Salt Lake, UT | 9.3 | 1.1 | 13 | 45 | 4.6 | 14 |

[a]Simulation assumptions: 10,000 individuals per census tract, 10 census tracts simulated for each of Jefferson County (KY), Wake County (NC), New York County (NY), Los Angeles County (CA), and Salt Lake County (UT); ambient $PM_{2.5}$ concentration: 10 $\mu g/m^3$; proportions of smokers are different for each state based on (CDC, 2009).(35)

[b]For each percentile and for the mean, incremental exposure is calculated by the difference between exposures with and without smoking.

[c]Incremental standard deviation is calculated by the square root of the difference between the variance of exposure with and without smoking.

[d]Smoking was banned in restaurants and bars in NY and CA before 2008; therefore, ETS was not modeled in these two geographic areas in restaurants and bars.