Micro-environment versus Personal Monitoring: Estimation of Exposure to Carbon Monoxide

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1 INTRODUCTION

Until recently, human exposure to air pollutants could be assessed only with fixed-site ambient monitoring data. Typically, people residing in the same neighborhood near a monitoring station were treated as homogeneous receptors fixed at the location of the monitoring station. Recent field studies with personal exposure monitors (PEM) have found this approach inadequate for pollutants which are spatially variable or have nonambient sources or sinks, such as carbon monoxide. For example, during the Washington Micro-environment Study, commuters were exposed to 9 to 12 ppm CO averaged over the entire commute route, while at the same time of day fixed-site monitors in DC logged an average of about 3 ppm CO (Akland *et al.*, 1985). Nagda and Koontz (1985) observed CO concentrations generally between the MEM and PM values reported here for comparable micro-environments. Furthermore, it is important to consider population activities and mobility when assessing exposure.

Incorporation of population mobility and activities into the exposure assessment of CO became a practical reality with the development of reliable, continuous CO PEM's. There are two general approaches to assess exposure using PEM's. The first is the personal monitoring (PM) or direct approach in which human subjects are sampled from the target population and are equipped with PEM's for a defined time to measure directly their exposures. This approach was taken in the Washington Urban Scale Study. Advantages of this approach are simplicity of design and freedom from modeling assumptions. The main disadvantage is cost, which is very high for large scale investigations.

An alternative approach to assess exposure is the micro-environment type (MET) or indirect approach in which pollutant concentration data are combined with or enhanced by activity time data (Duan, 1982, 1985; Ott, 1982, 1984). The MET approach can be implemented either by the enhanced

Methods for Assessing Exposure of Human and Non-Human Biota. Edited by R.G. Tardiff and B. Goldstein

personal monitoring (EPM) method or by the micro-environment monitoring (MEM) method (Duan, 1985). The latter approach was taken in the Washington Micro-environment Study during the winter of 1983. In this approach, a number of micro-environments may be sampled in each MET, with research staff or trained technicians sent to the sampled micro-environments to monitor those areas directly.

The MET method combines MET-specified pollutant concentration data and activity time data to estimate exposures. Further discussion of the EPM and MEM methodologies is available in Duan (1982, 1985).

2 METHODS FOR ESTIMATING EXPOSURE

The MET concentration data and the activity time data can be combined in several ways to estimate exposure. For average exposure, one can use the average time-weighted summation formula:

$$\bar{E} = \Sigma_k \bar{C}_k x \bar{T}_k \tag{1}$$

where $\bar{E}$ is the average exposure, $\bar{C}_k$ is the average MET concentration for the kth MET, and $\bar{T}_k$ is the average MET time for the kth MET. This method implicitly assumes that the MET concentrations and MET times are uncorrelated, a usual implicit assumption for many models (e.g., SHAPE) of human exposure that rely on the MET approach (Ott, 1982, 1984) and the convolution method (Duan, 1982, 1985). This assumption in essence rules out responses to air pollution episodes which might cause people to stay away from MET's having high concentration during those episodes.

For most purposes, the estimation of average exposure is inadequate: rather it is necessary to define distributions of individual exposures. A simulation model such as SHAPE can be used by describing the concentration and activity data as probabilistic distributions; human activity and concentration data are simulated from those probabilistic distributions, and the simulated data are used to estimate exposures. This type of approach generally assumes that concentrations and time are independent variables.

The convolution method proposed by Duan (1982, 1985) is another approach. From the activity data base, persons are paired with days from the concentration data base to form combined units (i.e., person-days), and the exposure for each combined unit is estimated using the following time-weighted summation formula:

$$E_{im} = \Sigma_k C_{mk} T_{ik} \tag{2}$$

where E_{im} is the exposure combining the ith unit in the activity data base and the mth unit in the concentration data base, C_{mk} is the MET concentration for the mth unit in the concentration database in the kth MET, and T_{ik} is the MET time for the ith unit in the activity data base in the kth MET.

To illustrate the application of Equation (2), consider a study that has 43 days of MEM data, combined with a sample of 705 persons, each providing a diary of one day of activity. If the ith person in the activity sample spent the day according to T_i and was exposed to concentrations C_m in the MET's encountered during that day, he would receive exposure E_{im}. Since independence is assumed between the MET concentrations and times, each of the 43 concentration vectors C_m is equally likely for each of the 705 participants. With the convolution method, the exposures E_{im} are derived for each of the 30,315 pairings (43 x 705) of persons and days in the two data bases. Each such pairing forms one combined person-day.

This method requires that the concentration and time be considered independent. Under this assumption, the distribution of exposures estimated from the convolution method is an unbiased estimate of the distribution of actual exposures and is a function of the empirical cumulative distribution functions for the MET concentrations and the activity times (Duan, 1982, 1985). Because the empirical cumulative distribution function is the efficient nonparametric estimate for the true cumulative distribution function, the exposure distribution estimated by the convolution method is also efficient in the same sense.

Another method can be viewed as a hybridisation between the average time-weighted summation Equation (1) and the convolution method Equation (2). With this hybrid method, the average MET concentration is used to estimate the exposure for each unit (day or person-day) from the activity data base by

$$E_i = \Sigma_k \bar{C}_k T_{ik} \tag{3}$$

This method ignores the variability in exposures between micro-environments of the same MET. If all micro-environments belonging to the same MET have the same concentration, this method is preferable to the convolution method because of its simplicity. If the micro-environments belonging to the same MET vary substantially, this approach is likely to underestimate the variability of the exposure distribution.

3 ACTIVITY TIME DATA

A population-based study of CO exposure was conducted during the winter of 1982–83 in the Washington, DC metropolitan area (Akland *et al.* 1985).

An area probability sample of human subjects was enrolled for one day for each in this study. The participants filled out activity diaries giving the activities they were engaged in during each time period. The activities were entered in the diaries as activity segments, where each activity segment was defined to be the time period between two reported changes in activities in the activity diary. Participant exposures to CO were recorded as the average concentration over each activity segment.

The participants in the Washington Urban Scale Study were selected from a probability sample. To extrapolate from the sample to the target population, it is necessary to weight the individual observations by the sampling weights based on sampling probabilities. In a preliminary analysis, the summary statistics based on the weighted and the unweighted procedures were compared. The weighting had no major effect on the results. For example, the average time spent in car commuting differed by about 2 percent between the weighted and the unweighted estimates. Because the primary goal of the comparative study was to compare the estimated exposures based on the MEM and PM approaches for the observed sample, the extrapolation to the target population was not crucial. Therefore, to simplify the analysis, the authors decided not to weight the individual observations.

In the Washington Urban Scale Study, each participant filled out activity diaries for one day. During this sampling day, whenever there was a new activity—e.g., the participant stopped reading a newspaper in the living room (end of an old activity) and went outside for a walk (beginning of a new activity)—the participant was required to record the start time of the new activity, and to describe it. The period between two entries in the activity diary was referred to as an activity segment. Each activity segment was regarded as one micro-environment.

Based on information available, activity segments were grouped into seven MET's: parking, public transportation, private car, pedestrian, shops, offices, and other. The rest of this section gives the heuristic definitions of these MET's. Further details on these definitions and evaluation of MET classification schemes are reported in Duan (1985).

The MET parking is restricted to indoor parking, because only indoor parking concentration data are available from the CO Micro-environment Study. The MET public transportation includes both bus and metrorail. Because both buses and metrorails are monitored in the Micro-environment Study, it is possible to consider them as distinct MET's. However, in the evaluation of MET classification schemes, (Duan, 1985), it was found unproductive to distinguish between these two MET's; therefore, public transportation was considered as one MET without further refinement.

The MET private-car includes private cars, trucks, motorcycles, and vans. It is debatable whether this MET should be restricted to the narrow definition including private cars only. (Only private cars were monitored in the Micro-environment Study.) The four modes of travel were grouped into one MET for two reasons:

(1) The amount of time spent in trucks, motorcycles, and vans is very

Table 1. Activity times for modes of travel and types of shops

MET	Mode/Type	Average time (hr.)	Fraction of MET (%)
Car	Car	1.517	93.47
	Truck	0.069	4.25
	Motorcycle	0.002	0.12
	Van	0.035	3.16
	TOTAL	1.623	100.00
Pedestrian	Walking	0.254	94.42
	Jogging	0.007	2.60
	Biking	0.008	2.97
	TOTAL	0.269	100.00
Shops	Stores	0.369	96.09
	Malls	0.015	3.91
	TOTAL	0.384	100.00

small compared with the amount of time spent in private cars. The top part of Table 1 gives the average amount of time spent in each of these modes of travel. The total amount of time spent in the four modes of travel is 1.6 hours per person per day, out of which only 0.11 hours belong to the three modes other than private car, less than 7 percent of the total;

(2) The MET concentrations based on PEM for those four modes of travel are roughly similar. The top of Table 2 gives the average concentrations

Table 2. Average concentrations for modes of travel and types of shops

MET	Mode/Type	N[a]	Average conc. (ppm)	SE[b]
Car	Car	592	5.1	0.22
	Truck	22	6.3	1.67
	Motorcycle	1	3.0	
	Van	7	2.1	0.79
Pedestrian	Walking	220	2.3	0.16
	Jogging	6	2.3	0.78
	Biking	5	4.0	0.82
Shops	Stores	225	2.2	0.17
	Malls	11	1.8	0.54

[a] The number of participants who used this mode/type during the sampling period
[b] Standard error of the average concentration

with standard errors. The difference between car and truck is small (about 1 ppm) and statistically insignificant. The difference between car and van is larger (about 3 ppm) and is statistically significant, but only seven people reported using a van in their travel.

The MET pedestrian includes walking, biking, and jogging. It is debatable whether jogging and biking should be grouped with walking into one MET. Table 1 shows that the amount of time spent jogging and biking is very small. The difference is concentrations between walking and jogging is very small (less than 0.1 ppm) and statistically insignificant (t = 0.09). The difference between walking and biking is about 2 ppm and is statistically significant (t = 2.09). However, only five people reported biking during the sampling period. Therefore, they are combined into one MET.

The MET shops consist of the activity segments reported as stores, shopping malls, and theaters in malls. The amount of time spent in the malls is small (less than 5 percent) relative to the time spent in stores. The difference in concentration is very small (less than 0.5 ppm) and statistically insignificant (t = 0.65). Therefore, they are combined into one MET.

The MET offices category consists of activity segments reported as offices. The MET "other" is a residual category for activity segments not considered above. The main component of activity segments in this MET is home. Because there are no micro-environment monitoring data corresponding to these activity segments in the Micro-environment Study, this MET cannot be refined any further.

4 CO CONCENTRATION DATA

The Washington Micro-environment Study was conducted in the Washington, DC, metropolitan area during the winter of 1983. Primarily, the study focused on the measurement of commuting micro-environments, including parking garages, driving an automobile, riding a bus, riding a train, and walking. The study design and some preliminary results from the study are given in Flachsbart *et al.* (1987). Data acquisition methodology is presented in Fitz-Simons and Sauls (1984).

For automobile commutes, the study identified eight routes that "collectively extend 150 miles, about 8.1 percent of the total length (1,853 miles) of Washington's arterials and freeways." (In 1980, the Washington metropolitan area had 9,432 miles of streets and roads, including arterials, freeways, and locals). The routes were selected to "have high expected commuter CO exposure as predicted by Flachsbart's indicator" (Flachsbart *et al.*, 1987).

Although the routes might be representative of the arterials and freeways, they might not be representative of all routes traveled by the general population. The empirical analysis found that for the commuting MET's, the MET concentrations from the Micro-environment Study were substantially higher than corresponding MET concentrations based on personal monitoring from the Urban Scale Study.

A Commuter Study Links Data Base was constructed from the commuting part of the Micro-environment Study. Each commuting route was divided into links ranging from one-half to three miles, each link being a physically distinct segment of the route, and is regarded as an individual micro-environment.

For quality assurance, several commuting trips used co-located monitors or inside/outside pairs. Preliminary results on monitor accuracy and monitor precision were given in Flachsbart *et al.* (1987). In the paired situation, this study restricts attention to the primary monitor.

The ME study included monitoring on some indoor micro-environments—shopping centers and offices. Additional monitoring was conducted on walking micro-environments. The pedestrian data were combined with those from the commuting part of the study and analyzed as belonging to the same MET.

The ME study was not a comprehensive coverage of all micro-environments commonly encountered. One major exclusion was the home micro-environment. A residual MET, referred to as the MET other, consists of all micro-environments not covered in the Micro-environment Study. Since there are no MET concentration data collected for this MET in the ME study, we use the personal monitoring data from the Urban Scale Study for this MET. In other words, we treat the part of the personal monitoring data corresponding to the MET other as an additional part of the Micro-environment Study, and use these PM concentration data as the MEM concentration data for this MET.

5 OBSERVED MET CONCENTRATIONS

5.1 CONCENTRATIONS BASED ON MEM

For each MET, except the MET other, the measurements from the Micro-environment Study are aggregated into daily averages, which are used as the MET concentrations in further analysis. A total of 43 days were measured during the period from January 1 through March 18, 1983.

Table 3 gives the summary statistics for the MET concentrations for the six MET's. As expected, the concentrations in parking garages were very high. The average concentration exceeded the one-hour federal standard level of 35 ppm. The concentration in private cars was also fairly high. The average concentration exceeded the eight-hour federal standard level of 9 ppm. Public transportation, walking, and shops had moderate levels averaging about 5 ppm. Offices had low levels, averaging about 2 ppm.

Table 3. Summary statistics for CO MET concentrations based on MEM

MET	Mean[a]	SD[b]
Parking	44.55	32.36
Pedestrian	4.95	2.07
Public	5.34	3.12
Private car	11.39	3.11
Shop	4.20	1.54
Office	2.29	0.86

[a] Average of the MET concentrations given in ppm.
[b] Standard deviation of the MET concentrations given in ppm.

5.2 CONCENTRATIONS BASED ON PM

An alternative set of estimates of MET concentrations was derived from the personal monitoring data in the Urban Scale Study. For each activity segment reported, the exposure for that activity segment was computed as the product of the duration of the activity segment and its average CO concentration. For each participant and for each MET, the exposures from the activity segments belonging to that MET are summed as the total exposure for that MET. The total exposure in the MET was divided by the total amount of time (hours) in the MET to get the average MET concentration.

For certain activity segments, the CO concentrations were unavailable, possibly because of monitor failure. Those activity segments were not included in the calculation of the MET concentrations. To assess the effect of those missing data, the amount of time belonging to such activity segments was calculated for each participant and for each MET. For three MET's—namely, shops, parking, and public transportation—none of the participants had any activity segments with missing CO concentration data. For the other three MET's, some of the activity segments had no CO concentrations. However, the amount of time for those activity segments is very small. For the MET private car, the average amount of time per participant for which CO concentration was missing was 0.004 hours. This is less that one-half of 1 percent of the average time of 1.6 hours spent in this MET. For the MET office, the average amount of time without CO concentration is 0.001 hour, again very small compared with the average time of 0.269 hours in this MET. Missing concentration data are, therefore, of very little effect.

Table 4 summarises statistics for the average MET concentrations based on personal monitoring.

Table 4. Summary statistics for CO MET concentrations based on PM

MET	Mean	SD
Parking	9.60	12.6
Pedestrian	2.29	2.35
Public	3.10	2.65
Private Car	5.08	5.18
Shop	2.19	2.47
Office	1.82	2.73

5.3 COMPARISON OF MET CONCENTRATIONS

The MET concentrations based on PM were substantially lower than the corresponding MET concentrations based on MEM, especially in the commuting MET's (See Tables 3 and 4). The most dramatic difference of all was the MET parking, in which there is a fourfold difference between PM and MEM. The average MET concentration for private cars based on MEM is more than twice the corresponding average concentration based on personal monitoring. As was noted in Section 4, the lack of representativeness in the commuting routes might contribute to this discrepancy. The monitor battery run down might also be a contributing factor, as was noted in Wallace *et al.* (1988).

6 COMPARISON OF ESTIMATES OF EXPOSURE DISTRIBUTION

The comparison between the two sets of summary statistics for the estimated exposures shown in Table 5 indicates that the two distributions are substantially different. The average MEM exposure is about 40 percent higher than the average PM exposure. The difference is highly significant

Table 5. Summaries for MEM and PM exposures

Method	Mean[a]	SD[b]	Skew[c]	Kurt[d]
MEM-C[e]	2.29	2.22	9.47	175.0
MEM-H[f]	2.29	1.63	9.39	114.4
PM	1.59	1.63	3.11	16.7

[a] Average of the estimated exposures in ppm-days.
[b] Standard deviation of the estimated exposures.
[c] Skewness of the estimated exposures.
[d] Kurtosis of the estimated exposures.
[e] MEM exposure using the convolution method.
[f] MEM exposure using the hybrid method.

(t = 6.69 for the convolution method, t = 8.01 for the hybrid method). The two-sample Kolmogorov-Smirnov test (Smirnov, 1939; Massey, 1951) for the difference between the MEM and PM exposure distributions is also highly significant ($P<0.0000001$ for both methods).

The comparison between the summary statistics for the logarithm of the estimated exposures also indicates major differences between the MEM and PM exposures. The average log MEM exposure is significantly higher than the average log PM exposure.

For certain situations, such as qualifying the health effects of air pollution, it is only necessary that the estimated exposure be an accurate predictor of actual exposure. In such instances, the appropriate way to assess the validity of the estimated exposure is to examine the regression relationship between the actual and estimated exposures. The slope coefficient in the regression relationship must be significant, indicating that the estimated exposure predicts the ranking of actual exposures, even though the magnitude might be inaccurate. Furthermore, the slope coefficient should be close to one, and the intercept coefficient close to zero, implying that estimated exposures are approximately equal to actual exposures.

As usual the actual exposures are unknown; therefore, one cannot determine the relationship between the estimated exposures and the unobserved actual exposures. The PM exposure is used as a benchmark; the regression relationship between the two estimated exposures is tested, regressing the PM exposure on the MEM exposure.

The results for the regression of PM exposures on the MEM exposures are shown in Table 6. On the untransformed scale, the regression results show a very significant relationship between PM and MEM exposures. The convolution method gives a more significant slope coefficient than the hybrid method. This indicates that even though the MET concentrations from MEM and PM are substantially different, MEM exposures are still useful

Table 6. Regression of PM exposures on MEM exposures (t-statistics given in parentheses)

Method	Scale	Intercept	Slope	R^2 (Percent)
Convol	Original	0.528 (7.70)	0.466 (21.64)	39.9
	Log	−0.601 (19.35)	1.053 (33.44)	61.3
Hybrid	Original	1.011 (9.84)	0.254 (6.94)	6.4
	Log	−0.667 (7.39)	0.879 (8.02)	8.4

for predicting the ranking of PM exposures. In other words, if an individual's MEM exposure is high, it is reasonable to expect that his PM exposure would also be high. The R^2 statistic for the convolution method is about 40 percent, indicating that the MEM exposure is not only a significant predictor for the PM exposure but is also an informative one, explaining an important fraction of the variability in the PM exposure. The hybrid method has a much smaller R^2. With the convolution method, the slope coefficient is about 0.5, and the intercept coefficient is about 0.5 ppm. For simplicity, the estimated regression model may be approximated as follows:

$$\text{PM exposure} = 0.5 + 0.5 \times \text{MEM exposure} \tag{4}$$

At levels less than 1 ppm, the MEM exposure underestimates the PM exposures. For example, for an individual with MEM exposure equal to zero, the regression model predicts that his actual exposure is probably about 0.5 ppm. At levels more than 1 ppm, the MEM exposure overestimates the PM exposure. For example, for an individual with MEM exposure equal to 10 ppm, the regression model predicts that his PM exposure is probably about 5.5 ppm, substantially lower than the MEM exposure. Because the average MEM exposure is about 2 ppm, for most people the MEM exposure overestimates the PM exposure in accordance with the regression model.

On a logarithmic scale, regression results show a significant relationship between MEM exposure and PM exposure, indicating that the MEM exposures successfully predict the ranking of PM exposures (see the "log" rows in Table 6). The R^2 statistic for the convolution method is about 60 percent, indicating that the log MEM exposure is fairly powerful to explain an important fraction of the variability of the log PM exposure.

With the convolution method, the slope coefficient in the logarithmic scale regression is near one, the difference not being statistically significant at the conventional 5 percent level (t = 1.68). This indicates that the span of the MEM exposures is well-calibrated relative to PM exposures. The intercept coefficient is about -0.6 log (ppm-day), significantly less than zero, indicating that MEM exposure consistently overestimates PM exposure.

7 DISCUSSION

Methods for estimating population CO exposures using micro-environment monitoring (MEM) data, personal monitoring (PM) data, and activity data have been presented, and results compared.

MEM exposures averaged about 40 percent higher than exposures estimated by the PM method. The observed difference in the estimated distributions is probably specific to these data, and might not be generalizable.

Given problems in sampling micro-environments and those associated with personal monitoring, it is remarkable that MEM exposure is a successful predictor of PM exposure. The convolution method is preferable to the hybrid method for these data due to the high variability of MET concentrations.

For future studies applying the MEM approach, probabilistic sampling techniques are necessary to select micro-environments in each MET to be monitored. For some MET's such as homes and shops, standard area probability samples would be sufficient. For some MET's such as commuting routes, the appropriate sampling techniques remain to be developed. It is also crucial that the MET definitions in the activity pattern data and the MET concentration data match closely. For example, if the MET private vehicle in the activity pattern data included both sedans and bikes, the MET concentration data should be collected for both. Otherwise, say if concentration is only collected for sedans, the micro-environments monitored for this MET would be biased: i.e., some micro-environments (bikes) in this MET are excluded from the sampling frame. Both the failure to use probabilistic sampling techniques and the mismatch in MET definitions are plausible factors resulting in the discrepancy between the MEM and PM exposure estimates. The mismatch in MET definitions are minor; therefore, sampling bias, especially in the MET parking and MET private-car, might be more important.

In summary, exposure estimates based on monitoring carbon monoxide in micro-environments were compared to exposure estimates based on personal monitoring. Methods of estimation were reviewed and discussed, and results of estimation presented. These data indicated that population exposure estimates based on data from the Washington Microenvironment Study, combined with people's activity data from the Washington Urban Scale Study, were about forty percent higher than estimates based on personal monitoring data from the Urban Scale Study. The former set of exposure estimates was found to be a good predictor of the latter.

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