A RAND NOTE

Comparison of Microenvironment Monitoring with Personal Monitoring in Estimating Population Exposure to Carbon Monoxide

Naihua Duan, Harold Sauls, David Holland

September 1988

40 Years 1948-1988

RAND

The research described in this report was supported by a grant from the SIAM Institute for Mathematics and Society (SIMS), and by The RAND Corporation using its own research funds.

Published by The RAND Corporation
1700 Main Street, P.O. Box 2138, Santa Monica, CA 90406-2138

A RAND NOTE

N-2811-SIMS/RC

Comparison of Microenvironment Monitoring with Personal Monitoring in Estimating Population Exposure to Carbon Monoxide

Naihua Duan, Harold Sauls, David Holland

September 1988

Prepared for
The SIAM Institute for Mathematics and Society

40 Years 1948-1988

RAND

PREFACE

This Note was prepared for the Fifth SGOMSEC Workshop held in Mexico City, Mexico, August 12-16, 1985, and will appear in the workshop proceeding. It should be of interest to researchers who want to apply the microenvironment monitoring approach to assess human exposure to air pollution. Further technical background is available in N. Duan, "Models for Human Exposure to Air Pollution," *Environment International*, Vol. 8, No. 305, 1982, and N. Duan, *Application of the Microenvironment Monitoring Approach to Assess Human Exposure to Carbon Monoxide*, R-3222-EPA, The RAND Corporation, January 1985.

SUMMARY

Exposure estimates based on monitoring carbon monoxide in microenvironments are compared to exposure estimates based on personal monitoring. Methods of estimation are reviewed and discussed, and results of estimation are presented. These data indicate that population exposure estimates based on data from the Washington Microenvironment Study, combined with people's activity data from the Washington Urban Scale Study, are about 40 percent higher than estimates based on personal monitoring data from the Urban Scale Study. The former set of exposure estimates is found to be a good predictor of the latter. Nevertheless, generalizations of these findings to other data bases might not be valid.

CONTENTS

TABLES

I. INTRODUCTION

Because of high costs, equipment requirements, and people-related difficulties associated with personal exposure monitoring, it is highly desirable to develop a methodology with which to estimate population exposure to air pollution without directly monitoring individuals sampled from the population. Knowledge of pollutant concentrations in microenvironment types (METs) plus information about the activities and mobility of a population under study can be used to produce a valid estimate of overall population exposure, known as the indirect approach (Duan, 1982). Variability of pollutant concentrations and activity times are the principal limiting factors of the reliability of the indirect approach.

This study applies an indirect approach, the microenvironment monitoring (MEM) approach, to estimate human exposure to carbon monoxide (CO), using activity time data from the Washington Urban Scale Study (Akland et al., 1985) and CO concentration data from the Washington Microenvironment Study (Flachsbart et al., 1987). The estimated exposures based on the MEM approach are then compared with estimated exposures based on the direct approach, namely, the personal monitoring (PM) approach.

For the specific data used in this study, the MEM exposures are about 40 percent higher than the PM exposures. However, despite this discrepancy, the MEM exposure is found to be a powerful predictor for the PM exposure. On the log scale, the MEM exposure has the correct span relative to the PM exposure; the relationship between the two sets of exposure estimates is found to be a constant drift.

Several factors offer some explanation of the observed difference between the MEM and the PM exposures. The two data-collecting activities were not designed primarily for comparative analysis. Therefore, the microenvironments are imperfect matches with the reported activities. The commuting routes of the CO Microenvironment Study were selected as having "high expected commuter CO exposure" (Flachsbart et al., 1987), and were sampled only during the rush hour periods. The PM study sampled travel in private cars at any time it occurred. Also, Wallace et al. (1988) noted that carboxyhemoglobin (COHb) levels estimated from breath measurements were higher than those estimated from PM observations. It is believed that readings decline as the monitor battery discharges. Monitors were used for much shorter periods with more frequent calibrations during the CO Microenvironment Study than in the PM Study.

Given the exploratory nature of the data used in this Note, the results reported here should be considered as illustrative and should be generalized only with caution to future exposure studies. Based on the experience from this study, in future comparative exposure studies more emphasis must be placed on statistical methodology in selecting samples of microenvironments and on matching the microenvironments of the MEM study to the activities of the PM study.

II. EXPOSURE ASSESSMENT

Until recently, human exposure to air pollution 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 (PEMs) have found this approach inadequate for pollutants that are spatially variable or have nonambient sources or sinks, such as carbon monoxide. During the Washington Microenvironment Study, commuters were exposed to 9-12 ppm CO averaged over the entire commute route, whereas at the same time of day fixed-site monitors in Washington, D.C., logged an average of about 3 ppm CO. Nagda and Koontz (1985) observed CO concentrations generally between the MEM and PM values reported here for comparable microenvironments. Obviously it is important to consider population activities and mobility when assessing exposure.

Incorporation of population mobility and activities into the CO exposure assessment process became a more practical reality with the development of reliable, continuous CO PEMs. There are two general approaches to assess exposure using PEMs. The first is the PM approach, also called the direct approach, in which human subjects are sampled from the target population and are equipped with PEMs for a certain time period to measure their exposures directly. 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, too high for large-scale investigations.

An alternative approach to assess exposure is the MET approach, also called the 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 personal monitoring (EPM) method or by the MEM method (Duan, 1985). The latter approach was taken in the Washington Microenvironment Study during the winter of 1983. In this approach, a number of microenvironments may be sampled in each MET, with research staff or trained technicians sent to the sampled microenvironments to monitor those microenvironments directly.

The MET method combines MET-specified pollutant concentration data and activity time data to estimate exposures. This approach incorporates information about the mobility of the population under study. Further discussion of the EPM and MEM methodologies appears in Duan (1982, 1985).

III. METHODS FOR ESTIMATING EXPOSURE

The MET concentration data and the activity time data can be combined in several ways to estimate exposure. If one is interested only in average exposure, one can use the average time-weighted summation formula and estimate average exposure by

$$\bar{E} = \Sigma_k \bar{C}_k \times \bar{T}_k \quad , \tag{1}$$

where $\bar{E}$ is the average exposure, $\bar{C}_k$ is the average activity concentration for the k^{th} MET, and $\bar{T}_k$ is the average MET time for the k^{th} MET. This method implicitly assumes that the MET concentrations and MET times are uncorrelated. The assumption that MET concentrations and MET times are uncorrelated is not unusual. It is implicitly assumed in many models for human exposure using the MET approach, including SHAPE (Ott, 1982, 1984) and the convolution method (Duan, 1982, 1985). The assumption in essence rules out responses to air pollution episodes that might cause people to stay away from high concentration METs during such days.

For most purposes the mere estimation of average exposure is inadequate, and it is necessary to estimate exposure distribution or individual exposures. One way of doing this is to use a simulation model such as SHAPE in which the concentration and activity data are summarized by 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 the concentration and time are independent.

Another approach is the convolution method proposed in Duan (1982, 1985). Units (e.g., persons) from the activity data base are paired with units (e.g., days) from the concentration data base to form combined units (e.g., person-days), and the exposure for each combined unit is estimated using a time-weighted summation formula similar to Eq. (1):

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

where E_{im} is the exposure combining the i^{th} unit in the activity data base and the m^{th} unit in the concentration data base in the k^{th} MET, and T_{ik} is the MET time for the i^{th} unit in the activity data base in the k^{th} MET.

To illustrate the application of Eq. 2, consider a study that has 43 days of MEM data, combined with a sample of 705 persons, each tracking one day of activity in a diary. If the i^{th} person in the activity sample spent the day according to T_i and was exposed to concentrations C_m in the METs encountered during that day, he would receive exposure E_{im}. As 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 43 x 705 = 30,315 pairings 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 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 hybridization between the average time-weighted summation formula Eq. (1) and the convolution method Eq. (2). With this hybrid method, the average MET concentration in each MET is used to estimate the exposure for each unit (day or person-day) from the activity data base by

$$E_i = \Sigma_k \bar{C}_k \times T_{ik} \quad .$$

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

IV. ACTIVITY TIME DATA

A population-based study of CO exposure was conducted during the winter of 1982-83 in the Washington, D.C., metropolitan area. Details on this study are available in 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. The participants' exposures to CO were measured using PEMs, which recorded 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 preliminary analysis, the summary statistics based on the weighted and the unweighted procedures were compared. The weighting did not have a major effect on the results. For example, the average time spent in car commuting differs by about 2 percent between the weighted and the unweighted estimates. Because the primary goal of the comparative study is to compare the estimated exposures based on the MEM and PM approaches for the observed sample, the extrapolation to the target population is not crucial. Therefore, to simplify the analysis it was 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 describe it. The period between two entries in the activity diary is referred to as an activity segment. Each activity segment is regarded as one microenvironment.

Using available information, activity segments are grouped into seven METs: parking, public transportation, private car, pedestrian, shops, offices, and other. The rest of this section gives the heuristic definitions of these METs. 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 Microenvironment Study. The MET public transportation includes both bus and metrorail. Because both buses and metrorails are monitored in the Microenvironment Study, it is possible to consider them as distinct METs. However, in the evaluation of MET classification schemes (Duan, 1985), it was found unproductive to distinguish between these two METs; therefore, public transportation is 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 Microenvironment 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 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 1.623 hours per person per day, out of which only 0.106 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 similar. The top part of Table 2 gives the average concentrations along with the standard errors for the averages. The difference between car and truck is small (about 1 ppm) and statistically insignificant. The difference between car and van is not small (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 again 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 (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* consists of the activity segments reported as stores, shopping malls, and theaters in malls. The amount of time spent in the malls is small relative to the time spent in stores (less than 5 percent). 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* 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 microenvironment monitoring data corresponding to these activity segments in the Microenvironment Study, this MET cannot be refined any further.

V. CO CONCENTRATION DATA

The Washington Microenvironment Study was conducted in the metropolitan area during the winter of 1983. Primarily the study focused on the measurement of commuting microenvironments, 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% 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 METs, the MET concentrations from the Microenvironment Study are 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 Microenvironment 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 microenvironment.

For quality assurance, several commuting trips used collocated 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 microenvironments--shopping centers and offices. Additional monitoring was conducted on walking microenvironments. The pedestrian data are 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 microenvironments commonly encountered. One major exclusion was the home microenvironment. A residual MET, referred to as the MET *other,* consists of all microenvironments not covered in the Microenvironment 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 Microenvironment Study, and use these PM concentration data as the MEM concentration data for this MET.

VI. OBSERVED MET CONCENTRATIONS

CONCENTRATIONS BASED ON MEM

For each MET except the MET *other,* the measurements from the Microenvironment 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 METs. As expected, the concentrations in parking garages are very high. The average concentration exceeds the one-hour federal standard level of 35 ppm. The concentration in private cars is also fairly high. The average concentration exceeds the eight-hour federal standard level of 9 ppm. Public transportation, walking, and shops have moderate levels averaging about 5 ppm. Offices have low levels, averaging about 2 ppm.

CONCENTRATIONS BASED ON PM

An alternative set of estimates of MET concentrations can be derived from the personal monitoring data in the Urban Scale Study. For each activity segment reported, the exposure for that activity segment is 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 is divided by the total amount of time (hours) in the MET to get the average MET concentration.

For certain activity segments, the CO concentrations are not available, possibly because of monitor failure. Those activity segments are 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 is calculated for each participant and for each MET. For three METs--namely, *shops, parking, and public transportation*--none of the participants had any activity segments with missing CO concentration data. For the other three METs, some of the activity segments did not have 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 is missing is 0.004 hours. This is less than one-half of 1 percent of the average time of 1.623 hours spent in this MET. For the MET *office,* the average amount of time without CO concentration is 0.001 hours, 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 gives the summary statistics for the average MET concentrations based on personal monitoring.

COMPARISON OF MET CONCENTRATIONS

The MET concentrations based on PM are substantially lower than the corresponding MET concentrations based on MEM, especially in the commuting METs. (See Tables 3 and 4.) The most dramatic difference of all is 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 Sec. I, 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).

VII. COMPARISON OF EXPOSURE DISTRIBUTION ESTIMATES

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 ($t = 6.69$ 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 a good 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 off. Furthermore, the slope coefficient should be close to one, and the intercept coefficient close to zero, implying that the estimated exposures are approximately equal to the 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 the benchmark and 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 the PM and the 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, the MEM exposures are still useful for predicting the ranking of the PM exposures. In other words, given that a certain individual's MEM exposure is high, it is reasonable to expect that his PM exposure is also 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 predictor, 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 in this regression is about 0.5, substantially smaller than one, and the intercept coefficient is about 0.5 ppm, significantly larger than zero. For simplicity the estimated regression model may be approximated as follows:

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

At low 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 higher 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 according to the regression model.

On the logarithmic scale, too, the regression results show a significant relationship between the MEM exposure and the PM exposure, indicating that the MEM exposures successfully predict the ranking of the 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 in explaining an important fraction of the variability of the log PM exposure.

With the convolution method, the slope coefficient in the logarithmic scale regression is very close to 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 the PM exposures. The intercept coefficient is about -0.6 log(ppm-day), significantly less than zero, indicating that the MEM exposure consistently overestimates the PM exposure.

VIII. DISCUSSION

Methods for estimating population CO exposures using MEM data, PM data, and activity data have been presented and results compared.

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

Given the problems in the sampling of microenvironments and problems associated with personal monitoring, it is impressive that the MEM exposure is a successful predictor of PM exposure, especially on the log scale on which the MEM exposure derived by the convolution method has the correct span relative to the PM exposure and the drift is constant over the range. The convolution method is preferable to the hybrid method for this data set because of the high variability within the MET concentrations.

For future studies applying the MEM approach, it is crucial to use probabilistic sampling techniques to select the microenvironments in each MET to be monitored. For some METs such as homes and shops, standard area probability samples would be sufficient. For some METs 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 includes both sedans and bikes, the MET concentration data should also be collected for both. Otherwise, for instance, if concentration data are only collected for sedans, the microenvironments monitored for this MET would be biased: Some microenvironments (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. As was discussed in Sec. IV, the mismatch in MET definitions is minor, therefore, the sampling bias, especially in the METs *parking and private car*, might be more important.

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	0.268	100.00
Shops	Stores	0.369	96.09
	Mall	0.015	3.91
	Total	0.384	100.00

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	NA
	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.

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.

Table 4

SUMMARY STATISTICS FOR CO MET CONCENTRATIONS BASED ON PM[a]

MET	Mean	SD
Parking	9.60	12.60
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

[a] The summary statistics are based on 705 participants in the Urban Scale Study.

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.

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

REFERENCES

Akland, G. G., T. D. Hartwell, T. R. Johnson, and R. W. Whitemore, "Measuring Human Exposure to Carbon Monoxide in Washington, D.C., and Denver, Colorado during the winter of 1982-1983," *Env. Sci. Technol.,* Vol. 19, 1985, pp. 911-918.

Duan, N., "Model for Human Exposure to Air Pollution," *Env. Intl.,* Vol. 8, 1982, p. 305.

Duan, N., *Application of the Microenvironment Monitoring Approach to Assess Human Exposure to Carbon Monoxide,* The RAND Corporation, R-3222-EPA, January 1985.

Fitz-Simons, T., and H. Sauls, "Using the PH-41CV Calculator as a Data Acquisition System for Personal Carbon Monoxide Exposures Monitors," *J. Air Pollut. Contr. Assoc.,* Vol. 34, 1984, p. 954.

Flachsbart, P. G., G. A. Mack, J. E. Howes, and C. E. Rodes, "Carbon Monoxide Exposures of Washington Commuters," *J. Air Pollut. Contr. Assoc.,* Vol. 37, 1987, pp. 135-142.

Massey, F. J., Jr., "The Distribution of the Maximum Deviation between Two Sample Cumulative Step Functions," *Ann. Math. Statistics,* Vol. 22, 1951, pp. 125-128.

Nagda, N. L., and M. D. Koontz, "Microenvironmental and Total Exposures to Carbon Monoxide for Three Population Subgroups," *J. Air Pollut. Contr. Assoc.,* Vol. 35, 1985, p. 134.

Ott, W. R., "Concepts of Human Exposure to Air Pollution," *Env. Int.,* Vol. 7, 1982, pp. 179-186.

Ott, W. R., "Exposure Estimates based on Computer Generated Activity Patterns," *J. Toxicol. - Clin. Toxicol.,* Vol. 21, No. 142, 1984, pp. 97-128.

Smirnov, N., "On the Estimation of the Discrepancy between Empirical Curves of Distribution of Two Independent Samples," *Bulletin Mathematique de l'Universite de Moscou,* Vol. 2, fasc., 1939, p. 2.

Wallace, L. A., J. Thomas, D. T. Mage, and W. R. Ott, "Comparison of Breath CO, CO Exposure, and Coburn Model Predictions," *Atom. Env.,* Vol. 22, forthcoming, 1988.

RAND/N-2811-SIMS/RC