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EVALUATION OF EMISSION INVENTORY METHODOLOGIES FOR THE RAPS PROGRAM

.S. ENVIRONMENTAL PROTECTION AGENCY

Office of Air and Waste Management

Office of Air Quality Planning and Standards

Research Triangle Park, North Carolina 27711

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by

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16. ABSTRACT

The general objective of the work described here is the evaluation and quantification of the methodology being developed and used for the Regional Air Pollution Study (RAPS) emissions inventory. Improved emission methodologies are one of the RAPS objectives. However, they are essential to the realization of one of the other principal objectives--namely, the evaluation of mathematical air quality simulation models. The output of any such simulation model is only as good as the input emissions data supplied to it. The thrust of this work is to evaluate the individual emissions models and relate them to their application to air quality models.

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I SUMMARY AND CONCLUSIONS

A. Introduction

The overall objective of the work described in this report is the evaluation and quantification of the methodology being developed and used for the Regional Air Pollution Study (RAPS) emissions inventory. Improved emission methodologies are one of the RAPS objectives. However, they are essential to the realization of one of the other RAPS principal objectives: the evaluation of mathematical air quality simulation models. The output of any such simulation model is only as good as the input emissions data supplied to it. The thrust of this work is to evaluate the individual emissions models and relate them to their application to air quality models. This project encompassed four major elements:

- An in-depth review of emission models and procedures used in the total context of the RAPS emissions inventory, to ensure that together they provide a well-balanced approach to the overall objective.
- An evaluation of the effectiveness of the emission models to ensure an accuracy commensurate with the needs of the RAPS program.
- The identification of possible modifications to the emission models and procedures.
- Design of an experimental verification program that could be conducted in St. Louis. This program would validate the various emission models to fulfill an objective of RAPS as well as for more general use.

During the development of validation procedures for the emissions modules, benefit-cost ratios were determined. The recommended validation program was developed under this contract and is reported separately (Shelar et al., 1976).

B. Conclusions

Sections V through VIII contain an evaluation of the various emission inventory methodologies. With the exception of the methodologies for sulfur dioxide, enough data are not generally available to support objective conclusions. A number of recommendations are made concerning possible improvements or validation of various emission estimates. Areas that need the most further effort include:

- Highway source inventory--validation is needed for both model input data and the emission methodology (see Section VII).
- Point source inventory--additional stack tests are warranted for nitrogen oxides (see Section V.B).
- Fugitive dust--further work is needed to validate existing results and to separate particles into size categories (see Section VIII.A).

Sections X and XI estimate the effect of emission inventory errors on air quality model performance. Analysis shows that the sulfur dioxide inventory is the most accurate and most suitable for air quality modeling purposes. Further validation work is needed to support any firm conclusions about hydrocarbons and carbon monoxide. More research on fugitive dust is required to support particulate modeling efforts.

Although there are limitations in the accuracy of the RAPS inventory, the inventory is a definite asset. More significantly, it is the most comprehensive inventory available to support air quality modeling objectives. Significant improvements could be realized with nominal future expenditures. The data system is flexible enough to allow refinements in input data such as emission factors, fuel consumption, and land use.

II TECHNICAL BACKGROUND

A. Overview of RAPS Emission Inventory

The RAPS emission inventory is the most comprehensive in existence. It was assembled primarily to support the development and verification of air quality models. Generally, the previous inventories fell short of providing the requisite accuracy and resolution (spatial and temporal). For the RAPS inventory, the air quality modelers had an input to the requirements prior to the collection activity (Littman et al., 1974).

In response to air quality modeling requirements, EPA adopted a program to acquire the most responsive data and develop the best available methodology within the budget constraints of the program. This report assesses the adequacy of the resulting product.

B. Identification of Important Parameters

The inventory is comprised of three general source types: point, line, and area. For point sources, emission parameters consist of:

- Emission rate
- Location (UTM coordinates)
- Stack parameters
  - Height
  - Diameter
  - Gas exit velocity
  - Gas exit temperature.

Line source parameters involve only emission rate and coordinates of the endpoints of each line segment (link). Area sources are represented by a grid, one kilometer square, or an even multiple thereof. In addition to emission rate, area source parameters are the grid size and the coordinates given for the lower left (southwest) corner. Nominal emission release heights are also needed for both line and area sources.

Emissions, in this evaluation study, are considered for the primary pollutants: sulfur dioxide (SO_2), carbon monoxide (CO), total hydrocarbons (THC), nitrogen oxides (NO_x), and particulates. Some discussion addresses the breakdown of hydrocarbons and particulates (size distributions).

The temporal resolution of the emission data base is one hour. The RAPS data handling system accesses the raw input data (fuel consumption, automobile traffic data, and so forth), applies the appropriate emission factors, and computes the emissions. Improvements in input data and emission factors (models) can readily be incorporated into the data handling software. In some cases, for large point sources, raw process data was compiled hourly from January 1975 through March 1977. In other cases, hourly rates were estimated on the basis of available data.

C. Quantification of Inventory Errors

1. Previous Studies

The effects of emission inventory errors on the prediction of ambient air pollution concentrations have been evaluated in previous studies. One of these studies (Koch et al., 1971), had a significant bearing on the RAPS emission inventory methodology. Some of the more relevant Koch study findings were:

- Averaging area source emission rates over areas larger than 1 square mile can lead to significant errors in estimated pollutant concentrations.
- Treating area sources as emitting from the same height does not significantly affect estimated pollutant concentrations.

The Koch study also addressed the sensitivity of certain meteorological parameters.

In another study (Hilst, 1970), a steady-state Gaussian model was demonstrated to be relatively insensitive to random errors in the specification of source strength. Hilst concluded that, among multiple sources, random errors tend effectively to cancel. Of course, it was recognized that systematic emission errors lead to systematic errors in predicted concentrations.

The SRI study (Littman et al., 1974) addressed the accuracy requirements for source coordinates. Their sensitivity analysis showed that large sources should be located within 10 meters of their true coordinate.

2. Discussion

While the studies just mentioned (Littman, Koch, and Hilst) provide valuable insight toward the specification of inventory parameters, they did not address the specific problem associated with RAPS. Namely, is the RAPS inventory accurate enough such that it does not significantly hinder efforts in the model development and evaluation process? To answer this question, we must examine the other constraints that limit the accuracy of prediction: errors in the meteorological input data, and errors in the model formulation itself. Since model error is subject to improvement over the years, our approach has been to quantify errors induced by emission inventory inaccuracies in relation to those induced by inaccuracies in the meteorological input parameters.

III EMISSION INVENTORY EVALUATION PROCEDURE

A. General Sensitivity Analyses Procedure

Common to the emission inventory evaluation process is the application of a sensitivity analysis procedure to the various components of the RAPS emissions and air quality models. Sensitivity is formally defined as the partial derivative of the output of a model to the input parameter(s) in question. In the case of complex models, it is more appropriate to consider incremental changes in output resulting from incremental changes in input because the determination of the analytical expressions for partial derivatives becomes too cumbersome.

One of the primary objectives of this work is to determine the sensitivity of the air quality model output as a function of various emission inputs in relation to meteorological inputs. Quantifying the potential sources of error (output) in this manner gives the air quality modeler a better understanding of the limitations on model performance and identifies those types of input data that most need improvement.

The air quality model output, χ, can be represented as some function of emissions inputs, Q, and meteorological inputs G as follows:

$$[\chi]_{t,s} = f\left\{[Q]_{t,s}, [G]_{t,s}\right\} + [\chi'_{err}]_{t,s} \qquad (1)$$

where χ, χ'_{err}, Q, and G are vectors in time (t) and space (s). The χ'_{err} term* represents an error in the formulation, which is only a mathematical approximation to the physics and chemistry of the atmosphere. For our purposes, it is assumed that the χ'_{err} term represents a random error not

---

*In the notation used here, the prime will be used to designate errors caused by the model formulation; unprimed error terms will designate the total error.

related to the Q and G arrays. The sensitivity of any element in the χ array to any element in either the Q or G arrays is given by

$$\frac{\partial \chi_i}{\partial Q_j} = \frac{\partial f\left\{[Q]_{t,s}, [G]_{t,s}\right\}}{\partial Q_j}$$

or (2)

$$\frac{\partial \chi_i}{\partial G_j} = \frac{\partial f\left\{[Q]_{t,s}, [G]_{t,s}\right\}}{\partial G_j} \quad .$$

However, Q's and G's are also only mathematical approximations or measurements subject to error. These are expressed as

$$[Q]_{t,s} = [Q]_{t,s} + [Q_{err}]_{t,s}$$

and (3)

$$[G]_{t,s} = [G]_{t,s} + [G_{err}]_{t,s} \quad .$$

The variations in the Q_{err} and G_{err} terms are numbers that can be used to quantify air quality model errors by substitution for incremental changes in Q_j and G_j in the discretized approximation of Equation (2).

The G_{err} terms can be estimated from reports of previous meteorological studies. Parameters such as wind and diffusion coefficients are approximated in some manner before they are used in an air quality model. They are derived from measured data of questionable adequacy. In the RAPS study, meteorological data available for model input are quite comprehensive. However, significant errors will still arise.

The Q_{err} terms were estimated after conducting a separate sensitivity analysis for the relevant emission model. The emission variable can be expressed as:

$$[Q]_{t,s} = g[P]_{t,s} + [Q'_{err}]_{t,s} \tag{4}$$

where g represents the emission model, and P represents the input parameters; Q'_{err} represents the model formulation error.

The sensitivity analysis for the emissions model is analogous to that for the air quality model. Errors in the input parameters, P_{err}, are used to quantify emissions errors.

B. Application to the RAPS Inventory

In Sections V through IX, Q_{err} is estimated for all significant source types. For some large point sources, source test statistics are used to quantify Q_{err}. For other sources, we subjectively evaluate the term on the basis of assumed accuracies.

Estimation of the G_{err} term is described in Section XI. Then, the relative effects of G_{err} and Q_{err}, as they impact model pollutant concentration predictions, are presented.

IV EVALUATION CRITERIA FOR THE RAPS EMISSION METHODOLOGIES

A. Overview

Adequate validation data are the key to the successful evaluation of any emission model methodology. In the presence of such data, statistical tests can quantify the model performance. Ideally, one would like to have such data for each major source or, at the very least, each major source type. Furthermore, ideally, these test data should be comprehensive enough to constitute a statistically valid sample.

Unfortunately, validation data rarely exist in sufficient quantity. Therefore, a truly objective methodology assessment is difficult. Nevertheless, a "semiobjective" evaluation is possible for the RAPS inventory. The level of objectivity varies according to the source type and size.

In this report, various source types are evaluated relative to each of the major pollutants--SO_2, CO, NO_x, hydrocarbons (HC), and particulates. For the latter two pollutants, reactive versus nonreactive HC and particulate size distributions are briefly considered also. Approximate magnitudes* by category for point and area source emissions are presented in Table 1. These estimates are used as a guide in the remainder of the report.

Emission factors are the basis for converting a source activity level to pollutant-specific emission rates. The activity level is described in parameters that are readily measured (or estimated) for the type of source. As an example, for power plants, fuel consumption rate is commonly used to describe an activity level. To calculate the emission rate for sulfur dioxide, one can multiply the activity rate by the fuel sulfur content and the emission factor.

---

*Courtesy of J. Piere, Rockwell International.

Table I

ESTIMATES OF RAPS SOURCE EMISSIONS (TONS/YEAR)--1975
(Courtesy of Rockwell International)

	Particulate (TSP)	SO_X	NO_X	HC	CO
Area Sources					
River Vessels	196	458	3,353	688	1,319
Fugitive Dust					
Unpaved roads	458,605	0	0	0	0
Agricultural tilling	60,244	0	0	0	0
Wind erosion	524,583	0	0	0	0
Construction	138,156	0	0	0	0
Aggregate storage	937	0	0	0	0
Unpaved airstrips	470	0	0	0	0
Paved roads	64,464	0	0	0	0
Highways					
Area sources	704	302	5,856	12,376	120,081
Line sources	6,278	2,347	67,185	99,990	1,033,770
Railroads	878	2,001	11,960	4,229	4,360
Stationary Residential and Commercial					
Residential fuel oil	547	1,573	655	164	273
Residential natural gas	432	25	3,453	345	863
Residential LPG	386	1	1,623	163	406
Residential coal	2,079	9,873	312	2,079	9,355
Commercial fuel oil	895	6,676	3,000	149	199
Commercial natural gas	218	12	2,612	174	435
Commercial LPG	0	0	0	0	0
Commercial coal	1,608	5,457	529	115	414
Evaporation from HC	0	0	0	3,807	0
Evaporation from HC-automatic tanks	0	0	0	13,650	0
Evaporation from HC-dry cleaning	0	0	0	645	0
Structural fires	306	18	115	574	1,625
Solid waste disposal	127	14	24	102	206
Off-Highway Mobile					
Motorcycles	3	1	2	220	421
Lawn and garden equipment	32	8	124	1,530	11,927
Farm equipment	390	277	3,287	1,951	23,148
Construction equipment	964	983	12,652	1,893	19,508
Industrial equipment	734	679	8,765	3,056	66,085
Outboard motors	0	45	46	7,799	23,474
Stationary Industrial Sources	133	58	149	106	20
Airports	65	48	555	1,467	2,969
Total Area Sources	1,264,434	30,856	126,257	157,272	1,320,858
Point Sources					
Fuel Combustion	11,165	805,262	275,687	2,422	7,931
Industrial Process	31,884	96,293	13,404	45,216	130,238
Solid Waste Disposal	319	227	182	136	3,180
Total Point Sources	43,368	901,782	289,273	47,774	141,349
Grand Total (all sources)	1,307,802	932,638	415,530	205,046	1,462,207

For point sources, emission factors have been classified into source classification codes (SCC). Each SCC represents a particular source type and, consequently, has its own emission factor. These factors are based on pre-RAPS data and have been published in AP-42,[*] Supplement 5. As part of the RAPS program, new source test data were acquired for many of the point sources in the St. Louis area. For these tested sources, new emission factors were established when the test results did not verify the old (Supplement 5) factors. Consequently, the RAPS point source inventory relies on a mixture of emission factors based on (1) stack test results for the source in question, or, when not available, (2) AP-42, Supplement 5.

Extensive evaluation of the AP-42 emission factors was undertaken by PEDCO Environmental (Gibbs et al., 1974). Results of this EPA-commissioned study form one of the foundations for the analysis presented in this report. More recently, Littman et al. (1977), at Rockwell International, performed an evaluation for a few of the large point sources in the RAPS inventory. Verification studies for the mobile and area source inventories, however, do not currently exist.

Some summary statistics from the PEDCO study are presented in Table 2. Average precision[†] is a measure of the variation among stack test results according to pollutant. For SO_2, the statistical interpretation is that about 68% of the results fall within 17.7% of the mean or average; for CO, about 68% would fall within 32.1% of the mean. Therefore, the average precision can be thought of as being a measure of the repeatability of stack measurements. This repeatability is inversely proportional to the precision value. This concept is further illustrated in later sections.

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[*] EPA Publication AP-42 with Supplements, "Compilation of Air Pollutant Emission Factors."

[†] Ratio of the standard deviation to the mean of the test results--averaged over SCC codes by pollutant.

Table 2

PEDCO AVERAGE PRECISION DATA

Pollutant	Average Precision of Test Data
Particulate	0.196
SO_2	0.177
NO_x	0.134
HC	0.203
CO	0.321

B. Evaluation Criteria

The analysis errors in the inventory will be assumed to follow a Gaussian distribution as shown in Figure 1. The symbols in the figure indicate the error parameters of interest. The distribution of errors about the true emission rate, T, is subject to bias (b) and variability. Precision, σ_e, is a measure of the variability of the distribution.

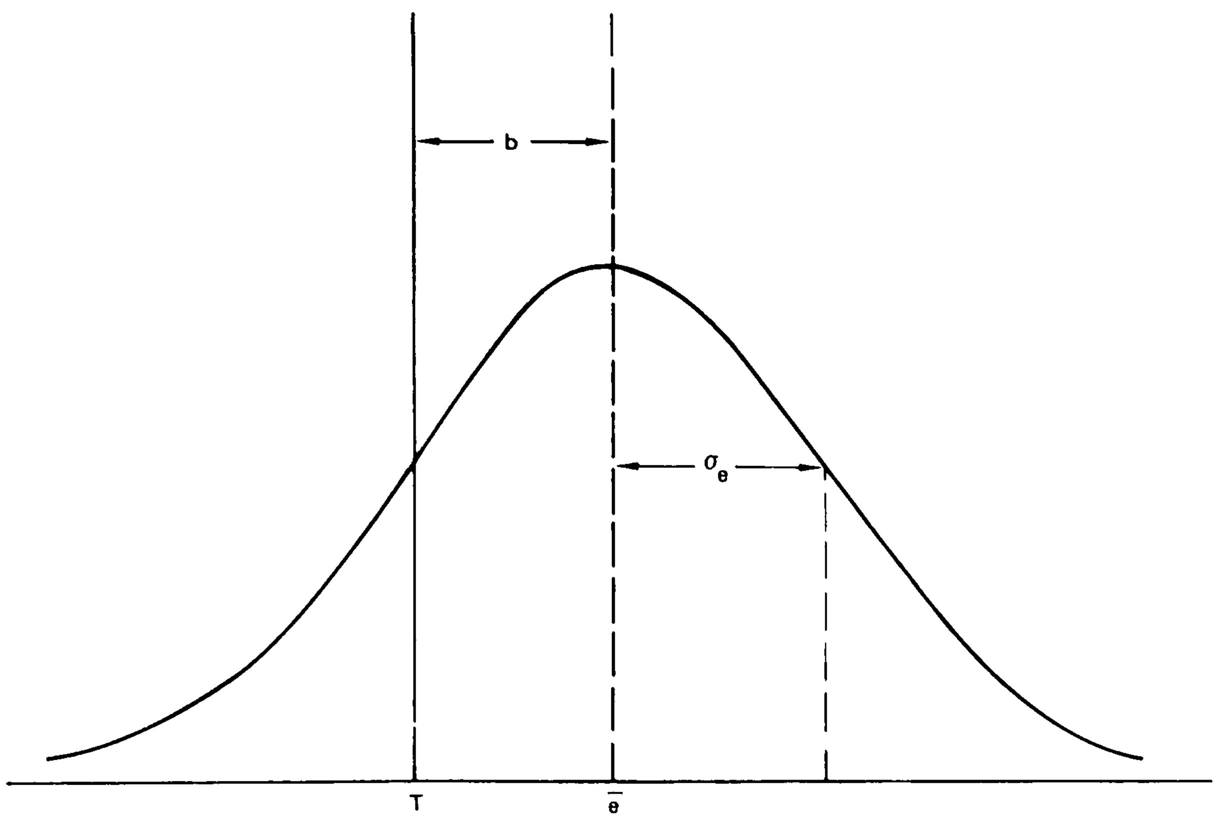

FIGURE 1 ASSUMED DISTRIBUTION OF ERROR

For the ideal emission model, b and σ_e are both zero. Where possible in the analyses to follow, limits are estimated for these parameters. The effect of such errors on the performance of air quality models is evaluated later in Sections X and XI.

V EVALUATION OF STATIONARY POINT SOURCE EMISSIONS

The methodology for stationary point sources is based on the application and verirication of standard EPA emission factors. As described by Littman (1974), the RAPS inventory is distinguished from previous inventories by three factors:

- Accuracy
- Space resolution
- Time resolution.

As a quantitative measure of overall accuracy and probable error, consider the Weighted Sensitivity Analysis Program (Ditto et al., 1973). Although this program does not supply any estimates on the absolute accuracy, it does help evaluate the maximum permissible error of any part of the inventory, if provided with a maximum permissible error for the whole system. In its evaluation, the program keeps the inventory at an equivalent level of accuracy and points out areas where accuracy has to be improved to provide a desired overall accuracy. In addition, it also provides an approach to establish confidence levels for the emission inventory.

The first step of the method is based on the following linear model:

$$Q^2\theta^2 = \sum_{k=1}^{N} Q_k^2\,\sigma_k^2 \qquad (5)$$

where

Q = Total amount of pollutant emitted

$100\ \theta$ = Percentage error associated with Q

Q_k = Amount of pollutant emitted by subclass k

$100\ \sigma_k$ = Percentage error associated with Q_k.

This linear model is postulated as an appropriate model to analyze the propagation of error through the emission inventory. If each subclass contributes to the error an amount proportional to its relative physical contribution, it can be shown for each k that

$$\sigma_k = \theta \sqrt{\frac{Q}{Q_k}} \quad . \tag{6}$$

The analysis demonstrates that to obtain a predetermined level of precision for a source class, not all subclasses need to be measured with the same precision; the greater the ratio of $Q:Q_k$, the greater the allowable value of σ_k. Conversely, σ_k approaches the value of θ as the ratio approaches unity. Equation (6) allows calculation of allowable inventory error per category, σ_k, after specification of allowable total error, θ. Confidence in the values for θ and σ_k is quantified by a second step as described in the following paragraph.

By using Chebyshev's inequality, the second step allows one to establish probabilistically the confidence level for the inventory; i.e., what is the probability that the actual overall error in emissions will not exceed θ. Ditto et al. (1973) provide a complete treatment of the theory. Using results from this reference, Table 3 shows the interrelationships among overall emission inventory error, confidence level, and θ. As an interpretation, Table 3 indicates that, for the emission inventory to be accurate within 10% of the true value at a 95% confidence level, θ must be 2.24% (or less).

Table 3

VALUES OF θ FOR SELECTED INVENTORY ERRORS AND CONFIDENCE LEVELS

Inventory Error (%)	Confidence Level (%)		
	90	95	99
5	1.58	1.12	0.5
10	3.16	2.24	1.0
20	6.32	4.47	2.0

A 10% overall inventory accuracy specification was deemed reasonable by Rockwell International. (Ideally, the specification should reflect requirements of the air quality modeling community.) They used values from the 1973 NEDS inventory to calculate the allowable error for point source classes of various sizes, which are given in Table 4.

Table 4

MAXIMUM ALLOWABLE ERROR σ_k FOR POINT SOURCES OF VARIOUS SIZE*
(Acceptance Interval 10%, Confidence Level 95%, θ = 2.24%)

Pollutant	Total Point Source Emissions, Q (tons/yr)†	Allowable Error σ_k for Point Source of		
		(100 ton/yr)	(1,000 ton/yr)	(10,000 ton/yr)
SO_2	1,187,296	244%	77%	24%
CO	1,684,794	290%	92%	29%
NO_x	310,993	125%	40%	--
HC	78,474	63%	20%	--
Particulate	323,952	127%	40%	--

*Reprinted from Littman et al. (1974).

†Source: NEDS December 1973, except for CO, which is given in NEDS at 2,836,270 before correcting to the value shown in this table.

The allowable error results served as the foundation for the point source data collection strategy. Sulfur dioxide (SO_2) was the pollutant emphasized initially in the inventory because it occupied the position of highest priority within the RAPS. Therefore, SO_2 emissions will be discussed first.

A. Sulfur Dioxide

1. Background

The SO_2 point source inventory and its verification are described in detail by Littman, Griscom, and Klein (1977). For sources emitting at least 1000 tons of SO_2 per year, hourly fuel consumption data were acquired. For smaller point sources (less than 1000 ton/year), hourly data were derived from annual data plus a detailed operating pattern. This approach is consistent with the results of the weighted sensitivity analysis.

2. Evaluation

Calculation of the SO_2 emission rate from the process data is based on the following equation:

$$Q = W \cdot EF$$

$$Q = W \cdot EF = W \cdot K \cdot S \qquad (7)$$

where

Q = The emission rate

W = The fuel consumption rate

EF = The emission factor (normally $EF = K \cdot S$)

S = The percentage of sulfur in the fuel

K = An emission constant.

For air quality modeling purposes, it is assumed that a temporal resolution of one hour is sufficient. For sources emitting at least 1000 ton/year, W is acquired on an hourly basis. These large sources are considered first.

3. Large Point Sources

As a first approximation, the error is related to the product of S and K. S is measured directly, but not on an hourly basis. More typically it is measured weekly or monthly. Emission factors have been experimentally verified. Based on the PEDCO report (Gibbs et al., 1974), the precision of measuring the sulfur content is generally less than 0.1, depending on the type of fuel. The daily variability of the sulfur content can be at least that great.

Assessment of the precision of emission factors can only be semiquantitative. While the PEDCO report does present precision and accuracy (bias) calculations for a wide variety of source types, these calculations are based on source test data that are subject to inaccuracies. In recognition of this, EPA commissioned Rockwell International to conduct emission factor verification studies in the St. Louis area. These have been reported by Littman, Griscom, and Klein (1977).

The Rockwell International report concluded that some previous stack tests were suspect, particularly those that relied on stack gas velocity measurements such as used in EPA Method 2. Upon reviewing these measurements, Rockwell found that stack flow values were high by varying but substantial amounts. They further verified these conclusions using fuel consumption rates.

Based on their most recent mass flow data, Rockwell concluded that AP-42 emission factors for SO_2 were reasonably accurate. In a private communication,* Littman estimated the general precision of the RAPS SO_2 emission factors to be within 0.15 with no significant bias. (This roughly corresponds to a "typical error" of 15%.) The precision estimate is supported by the PEDCO analysis (see Table 2).

The overall precision of the emissions model is the square root of the sum of the square for the individual precisions based on: (1) emission factors† and (2) the daily variability of the sulfur content Mathematically,

$$\sigma_e = P\sqrt{(0.15)^2 + (0.15)^2} = 0.225 \qquad (8)$$

where σ_e is defined in Figure 1. For purposes of this evaluation, σ_e will be approximated at 0.2 for future calculations. Further it is assumed that the bias, b, is negligible for these major SO_2 sources. The Rockwell studies tend to verify this assumption.

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*Dr. F. E. Littman, Rockwell International, private communication, 1976.

†The precision of the sulfur content is inherent in the emission factor precision.

4. Small Point Sources

Statements made in the previous subsection (3) concerning the accuracy of emission factors and sulfur measurements still apply here. However, for small point sources, hourly process data are not collected. Instead, annual data are acquired and modified by a detailed operating pattern. Sufficient data are not on hand to validate the accuracy of these operating patterns. For the purposes of future analyses, we will assume a precision of 0.4 and negligible bias.

B. Nitrogen Oxides

In the PEDCO report, the precisions of NO_x measurements (by SCC code) are, on the average, comparable to those for SO_2. However, a substantial bias appears because emission factors for combustion sources are too high. The Rockwell verification study corroborates the PEDCO results. Their experimentally obtained factors ranged from a low of 7.7% to 72% of the applicable AP-42 factors.

The RAPS data handling system allows for the input of plant specific emission factors. Standard AP-42 emission factors are being used at untested sites. It is reasonable to assume that these sites will also be represented by emission factors that are too high. This will result in the inventory being biased accordingly.

The amount of inventory bias is a function of the number of sources verified, as described above. If we assume one-half of the emission factors are corrected, then it would appear that the other half is biased by 7.7 to 72%, or, on the average, 40%. The total inventory then will be biased by one half that amount--20%.

If we assume precisions comparable to those for SO_2, a very tentative estimate of NO_x emission inventory errors follows:

- Large point sources:

$$b = +0.2\ T$$

$$\sigma_e = 0.2 \quad .$$

- Small point sources:

$$b = +0.2\ T$$

$$\sigma_e = 0.4 \quad .$$

The impact of such errors on air quality predictions is discussed in Sections X and XI. The relative importance of these point source data is evident in Table 1, which shows the dominant effect of point sources accounting for almost 70% of NO_x emissions.

C. Carbon Monoxide

As shown in Table 1, point source CO emissions account for only a few percent of the total inventory. As with NO_x, CO emissions cannot be verified through material balance calculations. The Rockwell tests indicate experimental emission factors much lower than those given in AP-42. The PEDCO report does not contain sufficient data to enable any general conclusions to be made. Therefore, we will assume that the precision and bias are comparable to those for NO_x.

D. Hydrocarbons

Point source emissions make up about 25% of the total HC inventory. For HC, point sources consist of those emissions released through a stack or vent, resulting from either fuel combustion or evaporation.

Rockwell has been delegated the responsibility of measuring HC components, both reactive and nonreactive. Primarily, the efforts were in separating out methane and nonmethane components with a particular emphasis on accurately measuring the nonmethane components. Littman, Griscom, and Seeger (1977) describe a chromatographic technique that is linear with respect to carbon number and HC concentration up to 3.5×10^3 per carbon number. Griscom (1977) also estimated HC emissions by category. (The categorizing of HC components in the inventory is an important input in photochemical air quality simulation models.) This topic is discussed more thoroughly in Sections VIII.F and XI.C. Our evaluation here is limited to total hydrocarbons (THC).

The Rockwell approach consists of modifying emission factors for tested sources only. Other sources are estimated using AP-42 factors. The process data are collected hourly for major combustion sources. For evaporative sources, which account for about 40% of the point source inventory, data are presented annually. Therefore, the hour-to-hour variability will be another source of inaccuracy.

All the above factors must be taken into account in estimating precision and bias. For combustible sources, these parameters should be about the same as for NO_x and CO. For evaporative sources, for which annual fuel loss data are used, the long-term bias should be negligible, but the precision should be high because no corrections are made for loss as a function of time. Our estimate of the composite of the above cases is a bias of +0.1 T and a precision of 0.4.

E. Particulates

Based on the figures in Table 1, ground level TSP measurements should be dominated by fugitive dust sources. However, the dominance is primarily caused by the mass of large inert particles (diameters above 2 μm). Other source types may be dominant emitters of the smaller (resperable) particles or chemically active particles. Hence, accurate particulate data from nonfugitive dust sources are essential.

Previous inventories focused on TSP, but the RAPS inventory separates particulate data by particle size categories. In general,

$$E_i = W \cdot EF \cdot (1 - C_i) \cdot F_i \cdot P \qquad (9)$$

where

E_i = Emission rate for particles in category i
W = Mass flow rate
EF = Emission factor
F_i = Fraction of particles in category i
C_i = Efficiency of control system for particles in category i
P = Percentage of production subject to control.

Rockwell was commissioned to assemble and verify the point source particulate inventory (both by TSP and size category). The work is described by Littman, Griscom, and Wang (1977). Some emission factors, by particle size, were derived from the Rockwell stack test data. Others were based on other factors experimentally derived by Midwest Research Institute (Weast et al., 1974).

The frequency categorization and control device efficiency are two additional sources of inaccuracy in determining total emissions. Sufficient data do not exist to allow us to make a reasonable estimate on the bias and precision of these parameters and, hence, the particulate point source inventory as a whole.

VI EVALUATION OF STATIONARY AREA SOURCE EMISSIONS

Unlike the point source inventory, where emission estimates can be evaluated by testing a relatively small number of sources, stationary area sources can be numbered in the hundreds of thousands. Broadly speaking, there are three basic categories of stationary area sources: residential, commercial, and industrial. The emissions from any one source under varying conditions can be estimated within an assumed accuracy. However, the complete characterization of every small source is a monumental task well beyond the scope (and budget) of the RAPS survey. Therefore, the general approach has been to derive fuel consumption, land use, and other algorithms to estimate hourly emission rates per unit area.

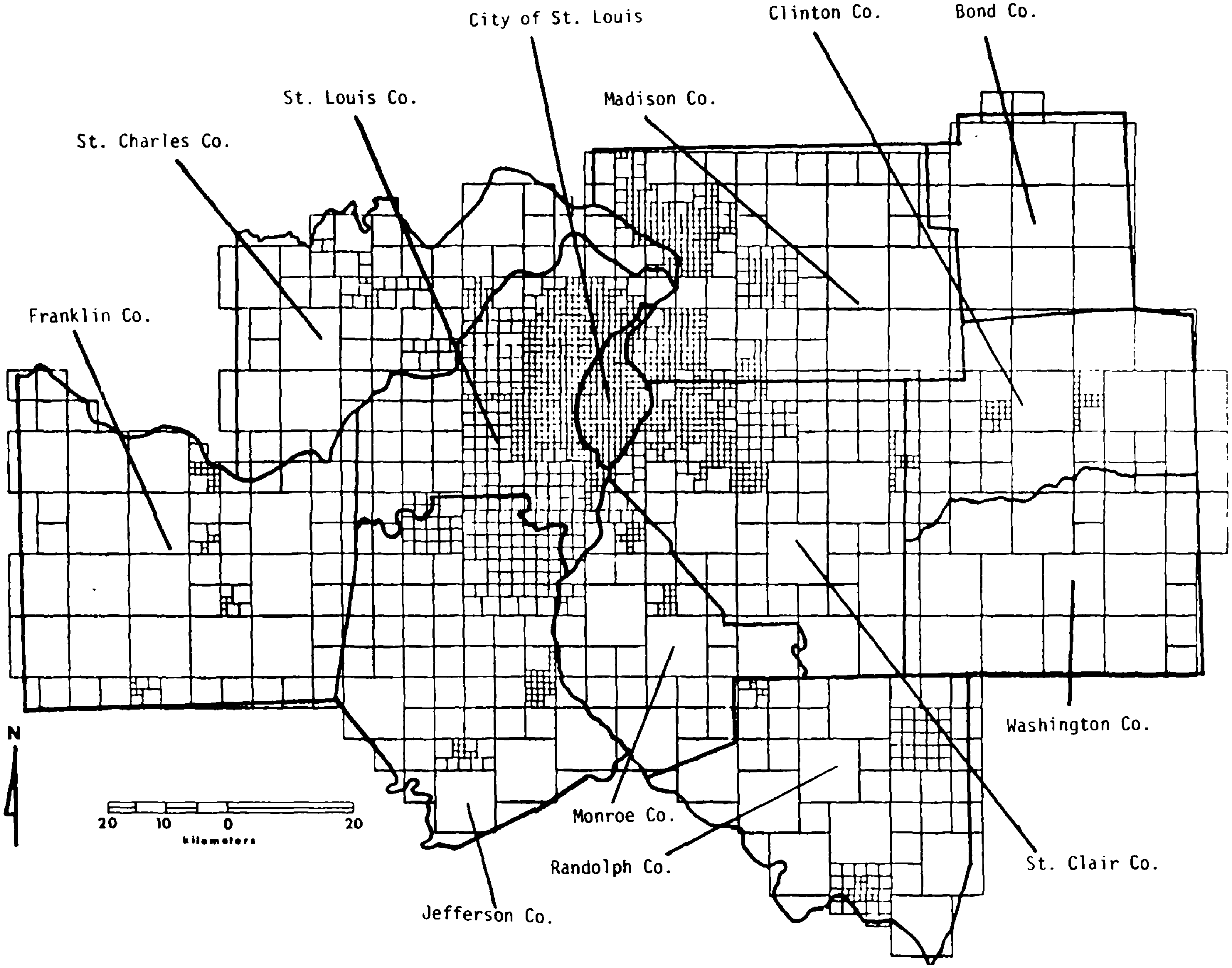
The minimum size for an area source is a 1 km by 1 km square grid with larger grid sizes being even multiples. Figure 2 illustrates the RAPS grid system. In general, areas of heavy emissions and large spatial variability are represented by the smaller grids and the more rural areas (with low emission density) are represented by larger grids. The RAPS grid system is consistent with requirements of most air quality models.

With the exception of evaporative hydrocarbon emissions, stationary area source emissions are predominantly the result of demand fuel usage. For commercial and residential sources, the emissions methodology was developed by Environmental Science and Engineering, Inc. (Holden, 1975); the industrial sources were estimated by Rockwell International (Littman and Isam, 1977). These industrial sources are insignificant and, for our purposes, can be neglected. Therefore, the focus of the section is the commercial and residential area sources.

In the methodology, spatial allocations to the RAPS grid system was based on census data* for residential estimates and land use data† for

*Bureau of Census, Population Estimates and Projections for 1972-73.

†The East-West Gateway Coordinating Council, 1971-72 Existing Land Use Update and Analysis.



City of St. Louis
Clinton Co.
Bond Co.
St. Louis Co.
Madison Co.
St. Charles Co.
Franklin Co.
Washington Co.
Monroe Co.
Randolph Co.
St. Clair Co.
Jefferson Co.
N
20 10 0 20
kilometers

commercial estimates. Temporal distributions were derived from demand fuel records. The 1973 NEDS inventory was the source of annual emissions estimates.

The adequacy of any of the techniques is largely a function of the pollutant and the currency of the basic data. The basic data are three to five years old and should be updated. In the following two subsections, spatial and temporal distribution methodologies are discussed. Then each of the critical pollutants is evaluated separately.

A. Estimation of Spatial Resolution

Environmental Science and Engineering Inc. (ESE) distinguished between residential and commercial land use. Quantification of residential areas was based on the U.S. Bureau of Census Fourth Count Computer Summary Tables, which contain data on: size and nativity of families, education, employment status, age of home, and fuel usage for space-heating, water heating, and cooking for census tracts, county subdivisions, and counties. The determination of the spatial distribution of residential fuel usage was estimated from the data on these tapes for the tracts in the St. Louis Standard Metropolitan Statistical Area (SMSA).

1. Residential Sources

ESE developed a methodology to equate the Census data to the RAPS grid system (Figure 2). In essence, their procedure involved an overlay of the RAPS grid system on tract maps. Each grid square was assigned a visually estimated land area percentage of the total tract. Allowances were made for special terrain and land use effects (along the banks of the Mississippi River; near Forest Park; and so forth). ESE then checked results to ensure that 100% of each tract had been apportioned among the grid system.

Specifically, the census data provided information on the number of housing units using: (1) natural gas, (2) bottled (LP) gas, (3) electricity, (4) fuel oil, (5) coal or coke, (6) wood, (7) other, and (8) none. It became possible for ESE to determine annual tract fuel usages by the following formula:

$$\frac{\text{Number of homes in tract heated by fuel type i}}{\text{Number of homes in county heated by fuel type i}} \times \text{annual county residential area source use of fuel type i}$$

The annual county residential area source fuel usage of each fuel type was available from the EPA NEDS Stationary Source Fuel Summary Reports for the respective counties.

2. Commercial Sources

Land use for commercial sources was resolved in a similar manner as that for residential sources, only the basic reference was different. In this case, the East-West Gateway Coordinating Council report (previously cited) became the basic reference. However, this report did not include the type of fuel used. Therefore, this methodology assumes that the relative fuel type distribution is the same as that for residential space heating in the same area.

3. General Comments

The ESE technique of spatially distributing area source emissions is comprehensive and technically sound. For RAPS purposes, the basic data sources should be updated and verified. Although St. Louis is not a rapidly growing area, it is growing and the spatial distribution of its population and commercialization is changing.

B. Estimation of Temporal Resolution

For the sake of discussion, this area source inventory can be divided into three categories: demand fuel usage, evaporative hydrocarbon emissions, and solid waste disposal-structural fire activities. These topics are discussed in the following paragraphs.

1. Fuel Usage

Data supplied by Laclede Gas Company formed the basis for the ESE temporal distribution algorithm. The data itself concerned natural gas usage, but ESE generalized the analysis for other space heating fuels.

The Laclede data included over a year of hourly gas flow and a number of meteorological parameters (wind speed and direction, temperature, and solar radiation).

Based on the LaClede statistics, ESE empirically derived flow equations for natural gas usage as a function of temperature and wind speed for times of space heating demand. In this analysis, space heating was assumed to be in demand when temperatures were below 68°F (20°C). When temperatures exceed 68°F (20°C), the ESE algorithm projects a baseline value independent of the meteorological parameters. Estimates were also corrected for time of day. The natural gas algorithm for space heating is also applied to other fuels. Therefore, strictly for space heating, emissions for these fuels are estimated as zero when temperatures exceed 68°F (20°C).

The fuel demand algorithms are an effective way of temporally distributing emissions. They are based on a large enough data base to be realistic. There are bound, however, to be some inaccuracies. For instance, the discontinuity of the equations at 68°F (20°C) is too abrupt to be real. Nevertheless, the results should provide good estimates.

2. Evaporative Hydrocarbon Losses

Hydrocarbon emissions result from evaporation of dry cleaning fluids, solvents from paint, and gasoline at service stations. The temporal distribution of dry cleaning emissions was assumed uniform over normal working hours. Paint emissions were similarly assumed to be uniform.

Gasoline emissions occur in two ways: filling losses from underground storage tanks, and filling losses and spillage from the filling of vehicle tanks. The former distribution was assumed uniform over the normal working day. The latter was assumed to be related to automobile traffic patterns as estimated by Ludwig and Dabberdt (1972). In Figure 3, these diurnal traffic patterns are illustrated for weekend and weekday. Both types of gasoline emissions are adjusted as a function of month (based on marketing information).

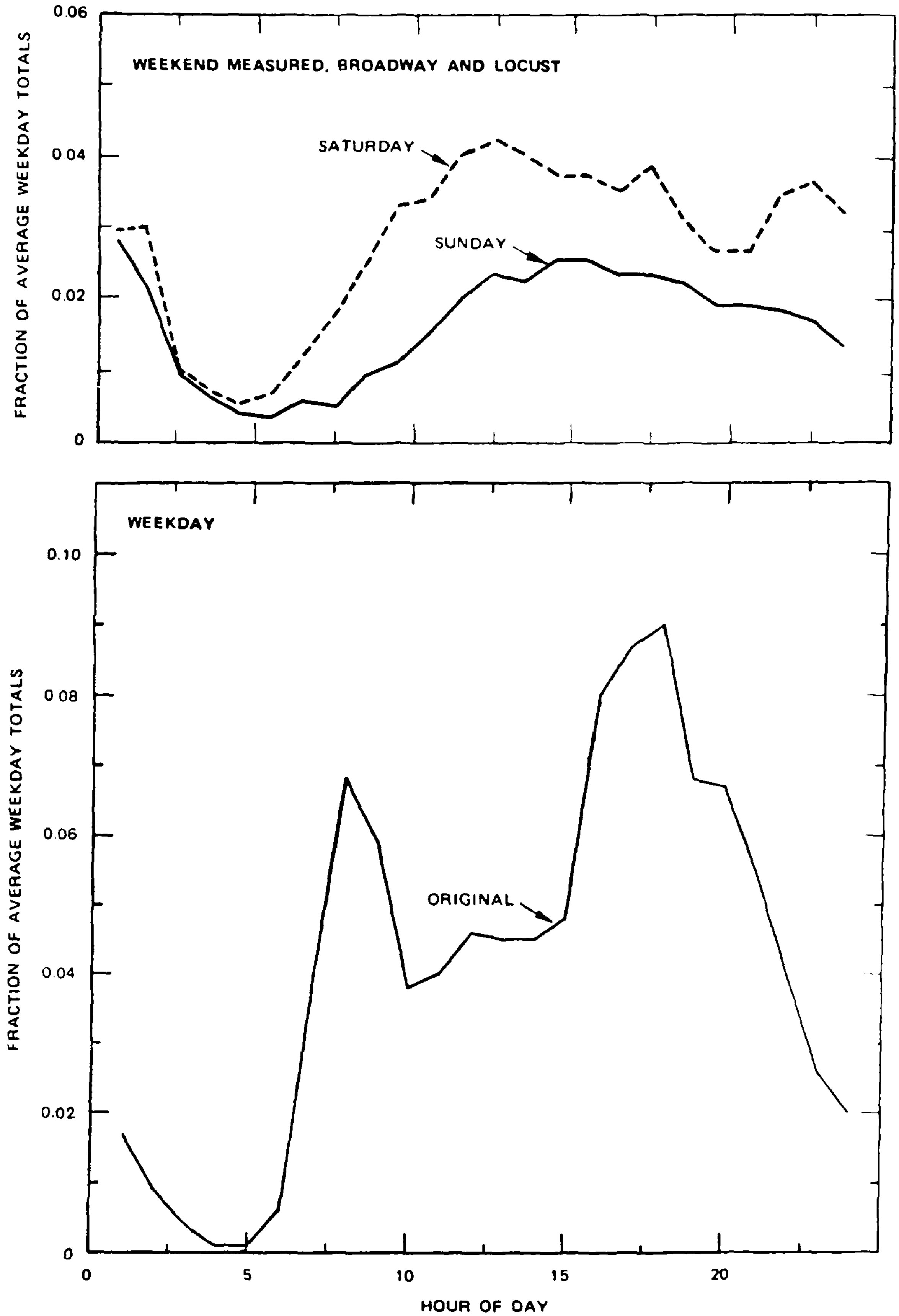


FIGURE 3 WEEKEND AND WEEKDAY DIURNAL PATTERNS FOR MOTOR VEHICLES

In Table 1, it can be seen that the most critical estimate is that for evaporative losses from automobile gas filling and spillage. Appropriately, ESE derived a comprehensive estimate for this case. Use of the diurnal traffic patterns is, perhaps, the best criteria. However, a composite pattern from a number of locations should be used. In the analysis, data from one downtown location was used, which may or may not be representative.

3. Solid Waste Disposal--Structural Fires

Emissions from solid waste disposal through open burning and incineration were taken from an inventory prepared by St. Louis County. Temporal allocation was based on an 8:00 a.m. to 5:00 p.m. workday. Structural fires, on the other hand, occur randomly and, temporally, the resulting emissions are assumed to be uniformly distributed over the year. Generally, emissions in this category are insignificant on an annual basis.

C. Discussion of Area Sources by Pollutant

In the following paragraphs, each of the criteria pollutants is discussed separately.

1. Sulfur Dioxide

Space heating requirements almost totally account for area source SO_2 emissions. Fuel oil and coal are the primary fuels here. The consumption of these fuels can be estimated accurately for a year. The unknowns are the fuel sulfur content, the temporal distribution, and the spatial distribution. All of these parameters can be estimated or modeled (as discussed previously).

There are probably compensating factors (offsetting errors) that should be taken into consideration. For instance, an underestimation of a spatial allocation in one grid may be offset somewhat by an overestimation in an adjacent grid, or fuel with a below average sulfur content from one area may be offset by an above average sulfur content in another area--and so forth.

In general, with some checking of the yearly fuel consumption data and sampling of fuels (for sulfur content) the methodology should produce negligible annual bias. The emission factors should be as accurate as those for point sources. Nevertheless, the accuracy of the emission estimate from any particular grid at a specified time is probably subject to a high degree of variability. For the sake of future discussion, we will estimate that the precision is approximately 0.75 and the bias is negligible.

2. Nitrogen Oxides

The problems in estimating NO_x are much the same for area sources as they were for point sources once the effects of spatial and temporal distribution are factored out. Spatial allocations are much the same as they were for SO_x. Temporal allocations are also much the same. The Laclede Natural Gas data are, if anything, more accurate here since NO_x emissions from natural gas are prominant.

For the purposes of our evaluation, we will again estimate the precision at 0.75. This time we should acknowledge that a bias probably exists. The PEDCO report, in analyzing the precision of area sources, relies heavily on precisions computed for point source emission factors. Using this rationale, the bias could average on the order of +0.4 T.

3. Carbon Monoxide

For lack of better data, the accuracy of CO emission estimates should be comparable to those for NO_x .

4. Hydrocarbons

Evaporative sources dominate the inventory. Therefore, the bias should be negligible for these sources since they are based on fuel balance estimates. The precision should be comparable to that for other pollutants.

5. Particulates

Except for fugitive dust, particulate emissions from area sources are rather small when compared to other sources. Emissions predominantly are a function of space-heating requirements. Precision and bias estimates should be comparable to those for NO_x and CO.

D. Summary of Quality of Stationary Area Source Methodology

The general methodology proposed by ESE should adequately fulfill the accuracy requirements of the RAPS inventory. Improvements can be realized in a number of areas such as:

- Improvement of verified emission factors for point sources could be applied to area sources using the same processes.
- A random analysis of fuels should be conducted to verify ash and sulfur content.
- Verification of fuel use data-records from major fuel suppliers should be checked.

In general, the temporal and spatial allocation of the emissions should be sufficient. However, the diurnal pattern assumed for evaporative emissions for hydrocarbons should be updated. This would almost automatically result from a similar analysis needed in the mobile source inventory.

VII EVALUATION OF HIGHWAY SOURCE EMISSIONS

A. Evaluation of Highway Source Inventory

As shown in Table 1, emissions from conventional highway sources dominate the inventory for two pollutants (CO and HC) and significantly effect the third (NO_x). Yet, no St. Louis field test data (comparable to stack test data) exist. Hence, any evaluation will lack objectivity. Lack of these field test data is the most serious deficiency in the entire RAPS inventory. To fulfill this need, a field test plan was developed as part of this contract and is reported separately (Shelar et al., 1976).

In the absence of data to corroborate estimated emissions, we must rely on a subjective evaluation of the quality of the input data. Even in this respect, accuracy of most input parameters is not known. For instance, the 58 second-by-second speed and time profiles are basic input data to the RAPS highway (modal) model. Though these are based on actual measurements, the sample size is relatively small. Therefore, the representivity of these speed and time profiles should be determined through further tests.

The discussion in this section is minimal on explicit treatment of traffic volume. The number and type of vehicles on the road at any given time are crucial. Since emissions are estimated on an hourly basis, the diurnal traffic variations must be defined throughout the RAPS area. For vehicle mix, local vehicle registration data are used. The resulting mix (percent) is assumed as uniform in time and space. In reality, vehicle mix is related to economic and social issues which vary from one part of the area to another. On the average, this variability might be negligible. However, this should be confirmed by random field tests.

The number of vehicles on the road at any specified hour (of the year) is based on 1975 ADT estimates adjusted by a temporal distribution algorithm. The traffic volume is adjusted for:

- Month of the year through evaluation of gasoline sales records
- Day of the week, weekend versus weekday as shown in Figure 3.
- Hour of day, as shown in Figure 3.

The latter two factors are based on site specific data that are several years old. Such data should be sampled in various parts of the city on different highway types. The resulting analysis should then be used to determine whether one diurnal cycle is sufficient.

Potential inaccuracies in all model input parameters must be determined through field test data. Model performance should also be determined through field tests. Only then can an accuracy assessment be made on the highway source emission inventory. As the inventory exists now, it is probably the best of its type in existence. However, an estimation of bias and precision, as per Figure 1, is not too meaningful at this time. Nevertheless, to carry the analysis further will estimate bounds on the precision (σ_e) as 1.0.

About 80% of the highway emissions are represented by line sources (links). The remainder are allocated to grid squares as area sources as shown in Figure 2. This allocation of highway emissions to grids and lines is consistent with requirements of air quality models (line and area source types). As part of the quality assurance program, the accuracy of road coordinates were verified through random sampling.

B. Highway Emission Models

The previous discussion has focused on the need to verify highway model input parameters. The sensitivity of two models is treated in the next subsection. Although the modal model is used for the RAPS highway inventory, we were commissioned to compare its sensitivity and estimates to those generated by an alternative model--based on the Federal Test Procedure (FTP).

Emission models play an important role in the determination of mobile source emission inventories. First, the choice of the emission model to be used must be made, considering both the accuracy of the model and the difficulty and cost of obtaining the input data required by the model. Second, once a model has been selected, its sensitivity to errors in the input data must be assessed to determine the effects of such errors on emission estimates. In fact, the model sensitivity to input may be a factor in the model selection process.

For the RAPS evaluation, two emission models were considered: (1) the methodology presented in AP-42, Supplement 5, and (2) the modal emission model (Kunzelman, et al., 1974). The following subsections briefly describe these models. A comparison was made of the emissions produced by the two models over a wide range of model input. The results of this comparison are discussed in Section VII.E. The results of an analysis of the sensitivity of each model to errors in the input data are described in Sections VII.F and VII.G.

C. FTP Emission Model

The emission factor methodology described in AP-42, Supplement 5 (referred to here as the FTP emission model), enables prediction of emission factors for CO, HC, and NO_x. These basic emission factors for light-duty vehicles (LDV) and light-duty trucks (LDT) were derived from measurements made on a variety of vehicles operating over the Federal Test Procedure (FTP) driving sequence. The conditions present for the FTP driving cycle tests are: (1) the cycle has an average route speed of 19.6 mph, and (2) the ambient air temperature is approximately 75°F (24°C). The emission factors presented in Supplement 5 represent a combination of 20% of the vehicles operating in a cold condition, 27% in a hot start-up condition, and 53% in a hot stabilized condition. The emission factors vary for each model year and the age of the model year at the time of interest.

To compute emission factors for speeds, temperatures, and percentages of cold and hot starting vehicles other than those given above, correction factors are applied to the basic emission factors using the following equation:

$$e_{npstwx} = \sum_{i=n-12}^{n} c_{ipn} m_{in} v_{ips} z_{ipt} r_{iptwx} \tag{10}$$

where

e_{npstwx} = Composite emission factor for LDV and LDT for calendar year n, pollutant p, average speed s, ambient temperature t, percentage cold operation w, and percentage hot start operation x (g/mi)

c_{ipn} = FTP mean emission factor for the ith model year during calendar year n for pollutant p (g/mi)

m_{in} = Fraction of annual travel by the ith model year during calendar year n

v_{ips} = Speed correction factor for the ith model year for pollutant p and average speed s

z_{ipt} = Temperature correction factor for the ith model year for pollutant p and ambient temperature t

r_{iptwx} = Hot/cold vehicle operation correction factor for the ith model year for pollutant p, ambient temperature t, percentage cold operation w, and percentage hot start operation x.

Speed correction factors apply to speeds between 5 and 45 mph, with the end point value used for a speed outside the range. Temperature dependent correction factors apply to a temperature range of 20 to 80°F (-6.7 to 26.7°C), with the end-point value used for a temperature outside the range. The above equation applies to both LDV and LDT, although the values of the parameters differ for the two types of vehicles.

Heavy-duty gasoline truck (HDG) and heavy-duty diesel truck (HDD) emission factors are based on the San Antonio Road Route test and assume 100% warmed-up vehicle operation at an average route speed of approximately 18 mph. To adjust these emission factors for other average route speeds, a speed correction factor is applied according to the following equation:

$$e_{nps} = \sum_{i=n-12}^{n} c_{ipn} m_{in} v_{ips} \tag{11}$$

where

e_{nps} = Composite emission factor for HDG and HDD for calendar year n, pollutant p, and average speed s (g/mi)

c_{ipn} = Test procedure emission factor for pollutant p for the ith model year in calendar year n (g/mi)

m_{in} = Fraction of annual travel by the ith model year during calendar year n

v_{ips} = Speed correction factor for the ith model year for pollutant p and average speed s.

Equation 11 applies to both HDG and HDD, although the values of the parameters differ for the two types of vehicles.

In addition to exhaust emission factors, the FTP methodology provides for computation of evaporative and crankcase hydrocarbon emission factors for LDV, LDT, and HDG. Composite crankcase and evaporative HC emission factors are determined using the equation:

$$f_n = \sum_{i=n-12}^{n} h_i m_{in} \tag{12}$$

where

f_n = Combined evaporative and crankcase HC emission factor for calendar year n (g/mi)

h_i = Combined evaporative and crankcase HC emission factor for the ith model year (g/mi)

m_{in} = Fraction of annual travel by the ith model year during calendar year n.

Of course, each of the above parameters differ for the three vehicle types.

Once exhaust and, for hydrocarbons, evaporative and crankcase emission factors have been computed for all types of vehicles, the emission factor for each vehicle type is weighted according to the percentage of the total vehicle population of that vehicle type. The weighted factors are summed to obtain a composite emission factor.

D. Modal Emission Model

The automobile exhaust emission modal analysis model was developed to reproduce light-duty vehicle exhaust emissions over any specified driving sequence containing accelerations, decelerations, steady-speed operation, and idling for CO, HC, NO_x, and CO_2. A functional form for the emission rate function for steady-speed cases and for acceleration and deceleration cases was determined from test data recorded over the Surveillance Driving Sequence. The steady speed emission rate function is given by:

$$\dot{e}_s(v) = S_1 + S_2 v + S_3 v^2 \tag{13}$$

where

v = Speed

S_1, S_2, S_3 = Constants.

For nonzero accelerations and decelerations, the emission rate function is given by:

$$\dot{e}_A(v,a) = b_1 + b_2 v + b_3 a + b_4 av + b_5 v^2 + b_6 a^2 + b_7 v^2 a + b_8 a^2 v + b_9 a^2 v^2 \tag{14}$$

where

a = Acceleration (or deceleration)

b_1 to b_9 = Constants.

The instantaneous emission rate function for a given vehicle and pollutant is given by:

$$\dot{e}(v,a) = h(a)\dot{e}_s(v) + [1 - h(a)]\dot{e}_A(v,a) \tag{15}$$

where h(a) is a weighting function dependent upon acceleration and bounded by the values of 0 and 1, which allow for a smooth, continuous transition from steady speed to acceleration and deceleration emission rate functions.

The emission rate function for a group of vehicles has been determined by averaging the coefficients that make up the emission rate functions of each vehicle in the group. The average vehicle response is obtained by integrating its rate function over the second-by-second speed-time curve specified by the driving sequence. The emission response of the group during any driving sequence is determined by multiplying the average vehicle response by the number of vehicles in the group. These emissions are then added to the emissions computed for the other groups that form the total vehicle population on the highway.

Temperature and percent cold-start vehicle correction factors originally used in the modal model were those given in AP-42, Supplement 5 for model years prior to and including 1971. The coefficients, S_1, S_2, S_3, and b_1 to b_9, however, have been updated and, as now used, relate to vehicles of model years prior to and including 1975. Light-duty vehicle modal emissions may be projected to years beyond 1975 by applying the ratio of future year emissions to those of the 1975 FTP emission factors for LDV for the appropriate pollutant.

E. Emission Model Comparison

Emission predictions resulting from the FTP and modal models were compared to determine whether the collection of the detailed input data required by the modal model is warranted or whether the FTP methodology, with its somewhat simpler input data, predicts emissions with sufficient accuracy for RAPS purposes.

1. Model Input Data

The input data required by the two models are listed in Table 5. To include all possibilities likely to be encountered in the RAPS highway network, the CO, HC, and NO_x emission factors were computed with each model for a wide range of input conditions. We chose the following input conditions: two calendar years, three temperatures, three percentages of cold-start vehicles (with associated percentages of hot-starting vehicles), 25 speed and time profiles (for the FTP model, corresponding average route speeds, computed by taking a simple average of

Table 5

EMISSION MODEL INPUT DATA

FTP Model Required Input	Modal Model Required Input
Pollutant type	Pollutant type
Calendar year	Calendar year
Ambient temperature	Ambient temperature
Percentages cold-starting and hot-starting vehicles	Percentage cold-starting vehicles
Average route speed	Second-by-second speed and time profile over the route
Fraction of total vehicles of each vehicle type	--
Fraction of annual travel driven by each model year of each vehicle type during the calendar year of interest	Fraction of annual travel driven by LDV of each model year during 1971
Traffic volume	Traffic volume

the second-by-second speeds). Values of each variable were selected so that the range of values for each variable allowed by the emission models was represented. Table 6 lists the values of the variables used in emission model computations. Emissions were computed for all combinations of these values, with the exception of those that are not physically realistic. The exceptions will be discussed later. The total number of possible cases for the various combinations of input variable values is 1350.

The speed and time profiles were based on data obtained by the Department of Transportation (DOT). Of the 25 speed and time profiles used in the modal computations, 24 are the results of a study made by Washington University for EPA in which an attempt was made to isolate "representative" profiles for the various roadway types in the St. Louis area. In this study, three roadway type descriptors were defined: roadway function, average daily traffic (ADT), and volume to capacity (V/C) ratio. For each descriptor, classes were defined as shown in Table 7. There are 48 different combinations of classes for the three descriptors

Table 6

EMISSION MODEL INPUT DATA USED FOR MODEL COMPARISON RUNS

Variable	Values of Variable Used	
	FTP Model	Modal Model
Calendar year	1975, 1977	1975, 1977
Temperature °F (°C)	20,50,80 (-6.7,10,26.7)	20,50,80 (-6.7,10,26.7)
Percentage cold starting and hot starting vehicles*	0/0,50/10,100/0	0,50,100
Pollutant	CO, HC, NO_x	CO, HC, NO_x
Vehicle speed	Average route speed corresponding to each of 25 speed/time profiles	25 speed/time profiles†
Fraction of total vehicles of each vehicle type	National average‡ vehicle type mix	
Fraction of annual travel driven by each model year of each vehicle type	National average‡ model year mixes	1971 national average‡

*Correction factors involving hot-starting vehicles apply only to the FTP model.

†See text for description of speed/time profiles used.

‡Taken from AP-42, Supplement 5. See text and Table 8.

(and thus 48 different roadway types), but only 29 of the types actually exist in the St. Louis Area.

In the study, speed/time profiles for both peak and off-peak hours were chosen that were considered "representative" of each of the 29 roadway types. The 58 second-by-second profiles chosen are of various durations in time and cover different lengths of roadway. Examination of the 58 profiles revealed that for the purpose of emission model comparison it is possible to eliminate ADT as a descriptor. In general, for each combination of functional class of roadway and V/C ratio class, roadways

Table 7

ROADWAY DESCRIPTOR CLASSES

Descriptor	Descriptor Classes
Roadway function	1 = freeway 2 = principal arterial 3 = minor arterial
Average daily traffic (ADT)	Freeway 1 = <40,000 vehicles 2 = 40,000-60,000 3 = 60,000-80,000 4 = >80,000 Principal arterial 1 = <10,000 2 = 10,000-20,000 3 = 20,000-30,000 4 = >30,000 Minor arterial 1 = <5,000 2 = 5,000-10,000 3 = 10,000-15,000 4 = >15,000
Volume to capacity (V/C) ratio	1 = <0.3 2 = 0.3-0.6 3 = 0.6-0.9 4 = >0.9

exist for only two or three of the ADT classes. The variation among each of these sets of two or three profiles was found to be minimal, so one profile was chosen to represent each combination of roadway function class and V/C ratio class. Since there are 3 roadway function classes and 4 V/C ratio classes, 12 peak hour and 12 off-peak hour speed and time profiles were selected for use in the model comparison.

As shown in Table 7, the roadway function classes are freeway, principal arterial, and minor arterial. Among the original 58 speed and time profiles there were no freeway cases that were congested, even the peak hour case having V/C ratio class 4 and ADT class 4 (see Table 7). In fact, the lowest average route speed for freeways was 50.0 mph with a standard deviation of speed over the profile of 1.42 mph. Since the

DOT study in the St. Louis area did not contain a congested freeway profile during peak travel hours, it was felt one should be added to the data set used for emission model comparison. Therefore, a speed and time profile was fabricated from a travel distance and travel time study conducted on a section of Interstate 80 near Berkeley, California. This was a very congested case, with an average route speed of 4.6 mph.

A further note is in order about the speed and time profiles for the 29 roadway types. For most cases, comparison of off-peak hour profiles and peak hour profiles, with identical roadway descriptors, shows only slight differences in average route speed or the standard deviation of average route speed over the profile. There are a few notable exceptions. For many of the roadway types in the St. Louis area, variation between peak and off-peak hour profiles would be expected. This fact, as well as the absence of a congested freeway case, was discussed with the investigators who performed the speed and time profile study. The explanation given for these factors is that the data sample from which the 58 "representative" speed and time profiles were chosen is limited. The entire data sample contained no congested freeway cases, and the cases chosen as representative are the most representative of the data that was available.

As mentioned above, emissions were computed using both the FTP and modal models for all combinations of 2 calendar years, 3 temperatures, 3 percentages of cold-starting vehicles, 3 pollutants, and 25 average route speeds or speed and and time profiles, with the exception of those cases that were not physically realistic.

The cases considered unrealistic are the following: (1) the 162 cases having 100% cold-start vehicles on freeways; (2) the 144 cases having 100% cold-start vehicles on principal arterials; and (3) the 144 cases having 0% cold-start vehicles on minor arterials. Thus, of the 1350 possible combinations, 900 cases (300 for each pollutant) were considered realistic and were used in the model comparison computations.

Other input data required by the FTP model include the fractions of total vehicles of each vehicle type and the fractions of annual travel driven by each model year of each vehicle type. The vehicle type mix used in model calculations is the national average vehicle type mix: 80.4% LDV, 11.8% LDT, 4.6% HDG, and 3.2% HDD. The national average model year mixes used in FTP emission computations for 1971, 1975, and 1977, are listed in Table 8.

Table 8

FRACTION OF ANNUAL TRAVEL BY VEHICLE AGE*

Vehicle Age (years)	Fraction of Annual Travel						
	Calendar Year 1971			Calendar Years 1975 and 1977			
	LDV	LDT	HGT	LDV	LDT	HGT	HDT
1	.116	.094	.062	.112	.094	.062	.096
2	.135	.138	.111	.143	.141	.124	.169
3	.125	.127	.117	.130	.132	.117	.168
4	.122	.131	.122	.121	.123	.110	.164
5	.106	.098	.093	.108	.098	.093	.110
6	.086	.083	.080	.094	.083	.080	.080
7	.083	.076	.066	.079	.076	.066	.067
8	.072	.057	.057	.063	.057	.057	.048
9	.051	.044	.047	.047	.044	.047	.034
10	.037	.032	.040	.032	.032	.040	.018
11	.023	.023	.031	.019	.023	.031	.011
12	.012	.016	.021	.013	.016	.021	.007
13+	.033	.081	.153	.039	.081	.153	.029

*Taken from AP-42, Supplement 5.

The modal model also requires input of the fraction of annual travel driven by each LDV model year. Since the coefficients used in computations with the modal model are derived from calendar year 1971 data, the national average model year mix for 1971, listed in Table 8, was used as model input. To project modal emissions to future years (in this study, years 1975 and 1977), the future year FTP emission factor for the case being modeled is computed using the vehicle model year mix for that year. The 1971 FTP emission factor is also computed, using the 1971 vehicle model year mix. Then, the ratio of the FTP future year to FTP

1971 emissions is applied to the 1971 modal LDV emissions to project the modal LDV emissions to a future year.

2. Method for Determination of Composite Emission Factors

The emission factor methodology in AP-42, Supplement 5, allows computation of CO, HC, and NO_x exhaust along with HC evaporative and crankcase emission factors for LDV, LDT, HDG, and HDD. Each of these emissions is weighted according to the fraction of the total vehicle population belonging to that vehicle type; then the weighted factors are summed to produced a composite emission factor for the highway.

The modal emission model allows for computation only of LDV exhaust emission factors. To compare the output of the two models, LDV modal emissions were converted to a composite emission factor. This was done using the following method: (1) the ratio of the composite FTP exhaust emission factor to the FTP LDV exhaust emission factor was computed for each case; (2) the modal LDV exhaust emission factor was multiplied by this ratio; and (3) for HC, the FTP evaporative and crankcase composite emission factor was added to the result of (2) above. The emission factor computed using this procedure is considered to be a composite modal emission factor. The basic assumptions of the procedure are: (1) the functional form of LDT, HDG, and HDD emissions over the driving sequence is the same as the functional form of LDV emissions over the sequence; (2) the ratio of composite exhaust emissions to LDV exhaust emission is the same for both the FTP and modal models; and (3) for HC, the functional forms of exhaust emissions and of evaporative and crankcase emissions are not the same.

3. Results

CO, HC, and NO_x emission factors were computed with the two emission models for each of the 300 cases. For each pollutant, the 300 modal emission values were plotted against the corresponding FTP emission values. The range of emission values was such that when all 200 points were plotted on the same figure, individual points could not be distinguished in areas where points were clustered. Therefore, to gain sufficient resolution so that individual points could be distinguished, the plots presented in Figures 4 to 6 include only those points within a limited range. The range was chosen so the region where the majority of points was clustered could be shown in detail. Figure 7 is an enlargement of a portion of Figure 4. The regression lines on Figures 4 to 7 are a best fit to each of the entire 300 point data sets.

Various statistical quantities were computed from the emission factors for each pollutant. The quantities computed include: (1) the correlation coefficient and linear regression constants (FTP emission = A X Modal emission + B) for the modal versus FTP emission factors; and

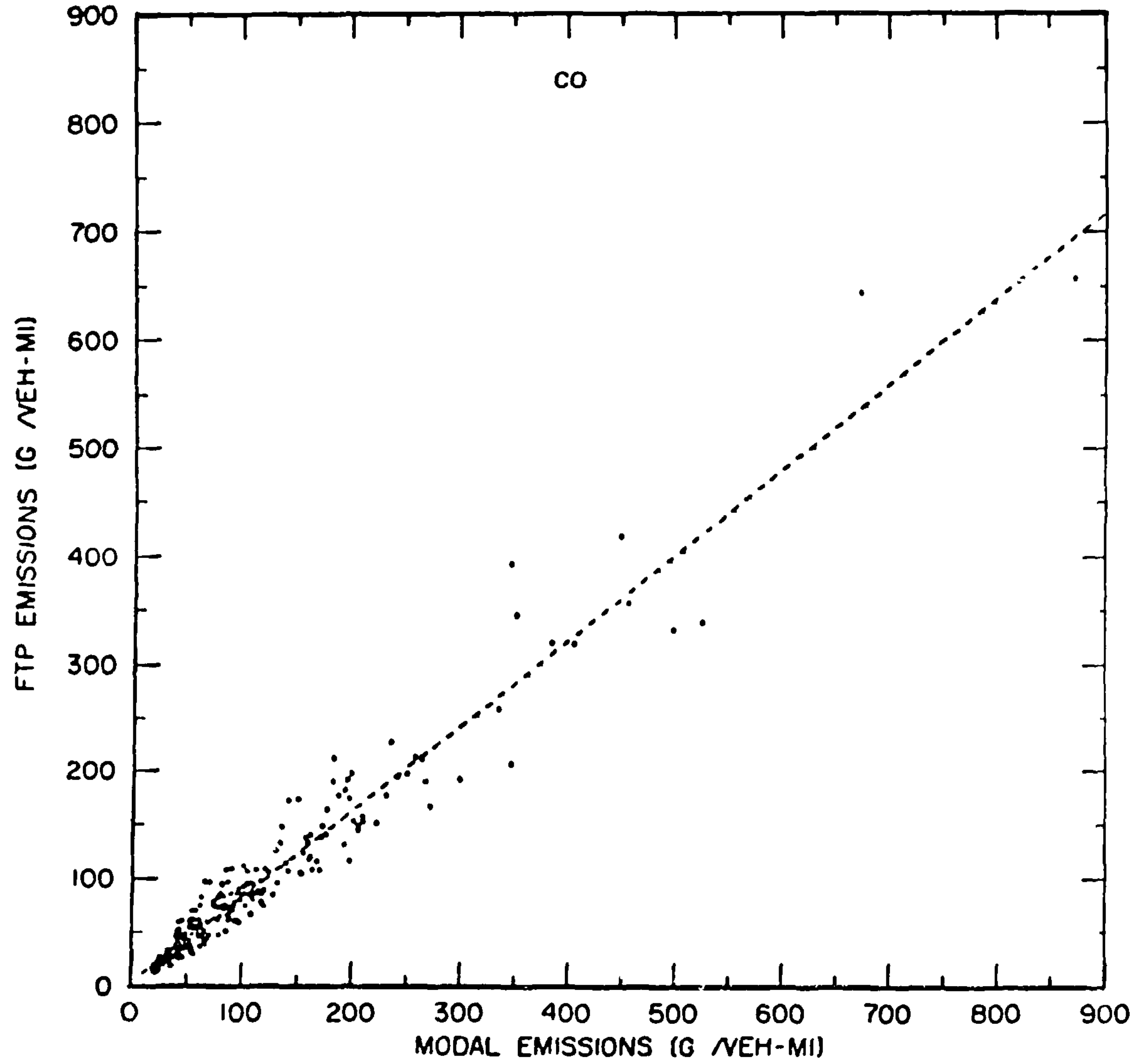


FIGURE 4 PLOT OF CO EMISSIONS COMPUTED WITH FTP METHODOLOGY AND WITH MODAL MODEL FOR CASES WITH EMISSIONS LESS THAN 900 g/veh-mi

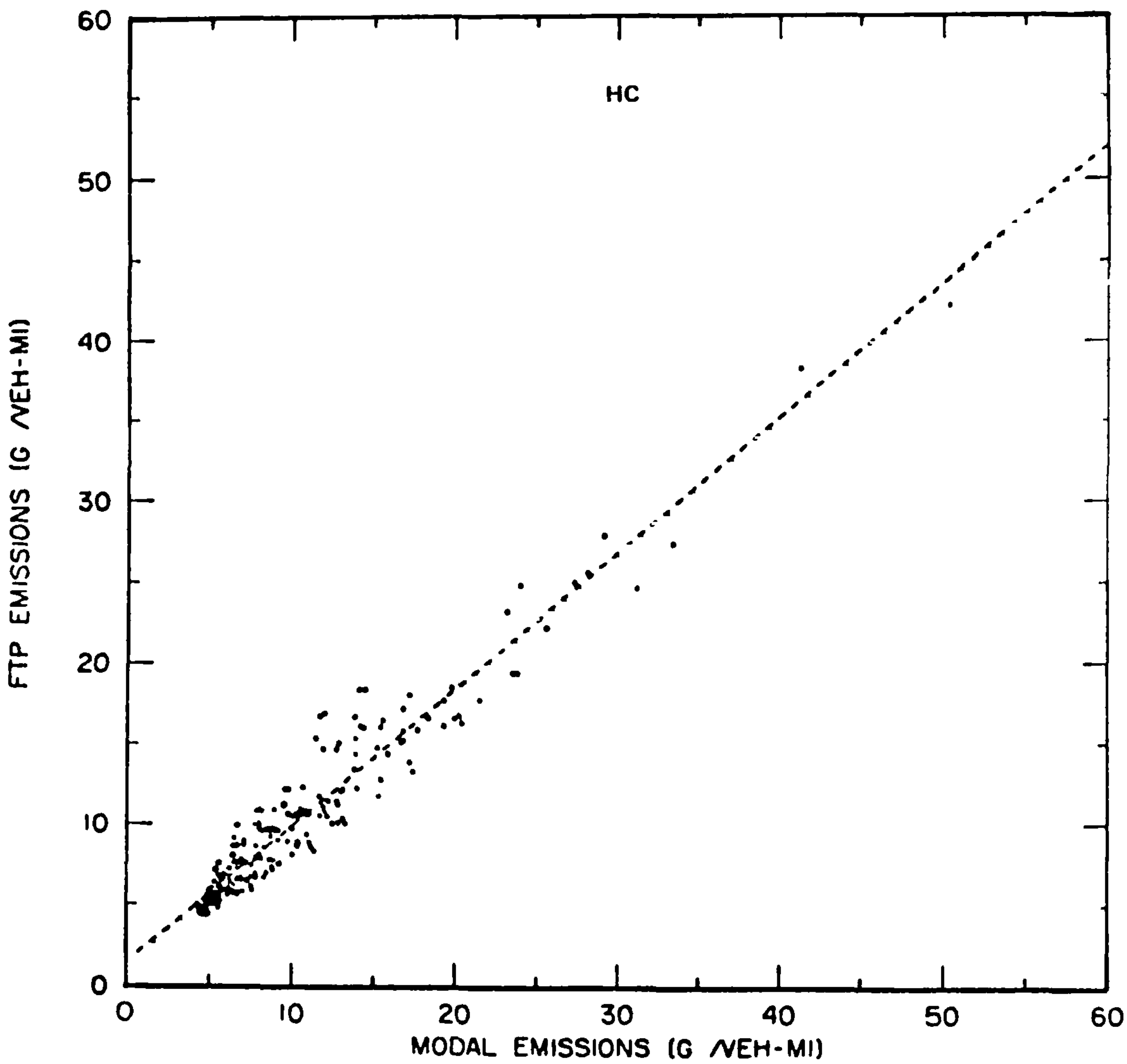


FIGURE 5 PLOT OF HC EMISSIONS COMPUTED WITH FTP METHODOLOGY AND WITH MODAL MODEL FOR CASES WITH EMISSIONS LESS THAN 60 g/veh-mi

(2) the averages and standard deviations of the modal emissions and of the FTP emissions. These statistics were computed for several subsets of the total sample of 300 cases as well as for the total sample. Those subsets are comprised of all cases having in common a particular value of input data. The input data values that delineate the subsets are: 1975; 1977; freeways; principal arterials; minor arterials; peak hours; off-peak hours; congestion; no congestion; 20°, 50°, and 80°F (-6.7, 10, and 26.7°C) temperatures; and 0, 50, and 100% cold-start vehicles. The values of the statistical quantities listed above for the total sample and for the subsets are given for each pollutant in Tables 9 to 11.

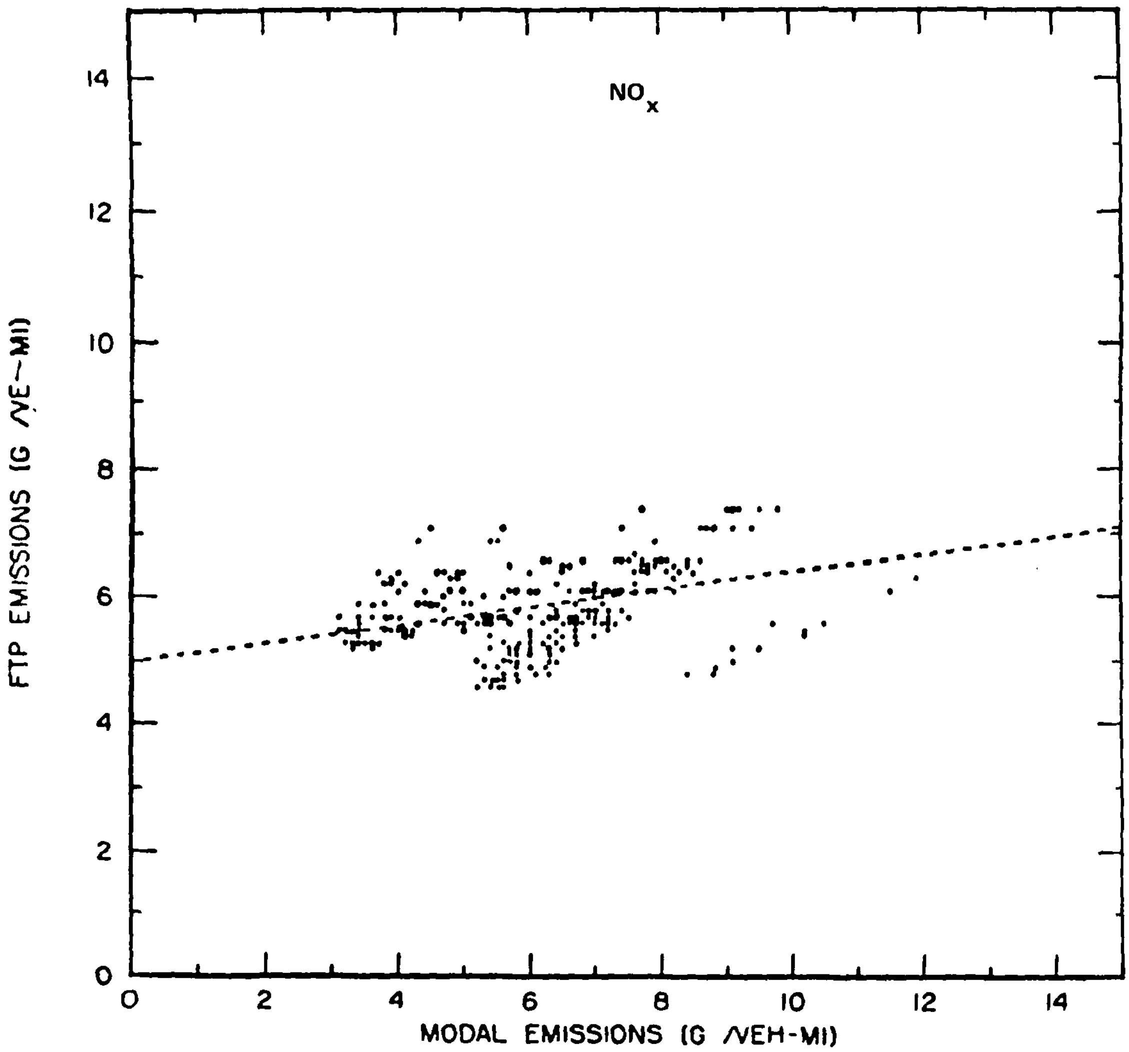


FIGURE 6 PLOT OF NO_x EMISSIONS COMPUTED WITH FTP METHODOLOGY AND WITH MODAL MODEL FOR CASES WITH EMISSIONS LESS THAN 15 g/veh-mi

The correlation between the modal and FTP emission models for CO and HC is very high, as shown in Tables 9 and 10. For both pollutants the correlation coefficients for all cases and for each subset of cases are greater than 0.9. Also, the fits of the regression lines are good, as seen in Figures 4 and 5. The correlations of the subsets were computed and compared to determine which cases correlated the best and which cases had the poorest correlation. A test was applied to the correlation coefficients of the subsets which were being compared to determine whether the differences between them are statistically significant. A test statistic, z, was computed according to the following equations:

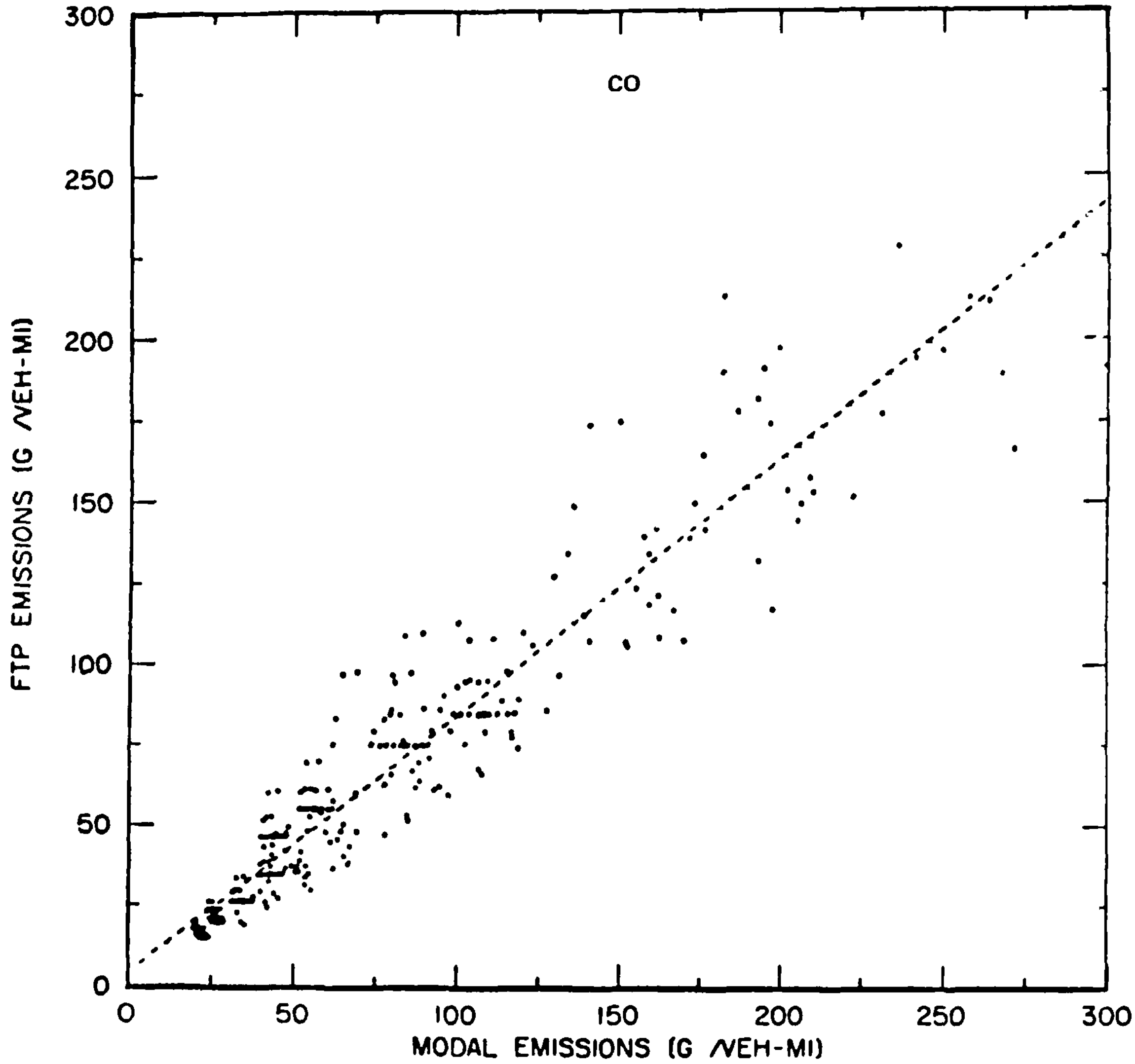


FIGURE 7 PLOT OF CO EMISSIONS COMPUTED WITH FTP METHODOLOGY AND WITH MODAL MODEL FOR CASES WITH EMISSIONS LESS THAN 300 g/veh-mi

$$Z_1 = 1/2 \ln \left[\frac{1 + r_1}{1 - r_1} \right] \qquad (16)$$

$$Z_2 = 1/2 \ln \left[\frac{1 + r_2}{1 - r_2} \right] \qquad (17)$$

$$z = \frac{Z_1 - Z_2}{\sqrt{\frac{1}{N_1 - 3} + \frac{1}{N_2 - 3}}} \qquad (18)$$

where

r_1, r_2 = The two correlation coefficients being compared

N_1, N_2 = The sizes of the samples from which the correlation coefficients were computed.

Table 9

MODEL COMPARISON STATISTICS FOR CO

Cases	Number of Cases in Sample	Correlation Coefficient	Linear Regression Constants		Modal		FTP	
			A	B	Average	Standard Deviation	Average	Standard Deviation
All cases	300	.9714	.793	4.39	94.0	100.6	78.9	82.1
1975	150	.9793	.730	7.51	105.3	111.9	84.4	83.4
1977	150	.9762	.908	-1.70	82.7	86.3	73.4	80.3
Freeway	108	.9874	.849	0.12	75.7	119.8	64.4	103.0
Principal arterial	96	.9697	.785	1.70	101.7	90.1	81.5	72.9
Minor arterial	96	.9412	.665	21.55	106.9	82.3	92.6	58.1
Peak hour	156	.9748	.802	1.91	112.7	121.6	92.3	100.0
Off-peak hour	144	.9549	.773	7.42	73.7	65.3	64.4	52.9
Congested	84	.9722	.815	-3.22	174.6	145.8	139.1	122.3
Noncongested	216	.9354	.779	6.66	62.7	47.8	55.5	39.8
20° temperature	100	.9736	.772	4.08	140.9	139.3	112.8	110.5
50° temperature	100	.9758	.933	2.76	78.4	69.2	75.9	66.2
80° temperature	100	.9847	.731	2.05	62.8	52.3	48.0	38.9
0% cold starts	102	.9823	.753	0.40	48.7	42.3	37.0	32.4
50% cold starts	150	.9754	.806	4.98	112.6	117.5	95.8	97.1
100% cold starts	48	.9390	.648	29.51	132.2	96.9	115.2	66.9

Table 10

MODEL COMPARISON STATISTICS FOR HC

Cases	Number of Cases in Sample	Correlation Coefficient	Linear Regression Constants		Modal		FTP	
			A	B	Average	Standard Deviation	Average	Standard Deviation
All cases	300	.9635	.842	1.55	9.10	5.86	9.21	5.12
1975	150	.9694	.809	1.80	9.89	6.37	9.80	5.31
1977	150	.9582	.896	1.17	8.32	5.19	8.62	4.85
Freeway	108	.9894	.851	1.14	8.21	7.03	8.13	6.05
Principal arterial	96	.9621	.830	1.30	9.73	5.09	9.37	4.39
Minor arterial	96	.9253	.818	2.51	9.47	4.95	10.26	4.37
Peak hour	156	.9781	.842	1.38	10.28	7.02	10.04	6.04
Off-peak hour	144	.9174	.869	1.51	7.82	3.88	8.30	3.67
Congested	84	.9803	.855	..694	14.40	7.94	13.00	6.92
Noncongested	216	.9313	1.04	.419	7.04	2.84	7.73	3.17
20° temperature	100	.9643	.825	2.12	11.91	7.76	11.94	6.64
50° temperature	100	.9690	.880	1.71	8.13	4.22	8.87	3.83
80° temperature	100	.9795	.703	1.71	7.27	3.58	6.81	2.57
0% cold starts	102	.9801	.757	1.32	7.07	3.66	6.68	2.83
50% cold starts	150	.9784	.824	1.91	9.95	6.66	10.10	5.60
100% cold starts	48	.9266	.810	3.07	10.77	5.83	11.79	5.09

Table 11

MODEL COMPARISON STATISTICS FOR NO_x

Cases	Number of Cases in Sample	Correlation Coefficient	Linear Regression Constants		Modal		FTP	
			A	B	Average	Standard Deviation	Average	Standard Deviation
All cases	300	.3669	.140	5.00	6.13	1.65	5.86	0.63
1975	150	.4154	.163	4.86	6.26	1.67	5.88	0.65
1977	150	.3108	.116	5.15	5.99	1.62	5.84	0.60
Freeway	108	.5838	.220	4.78	6.89	1.47	6.29	0.55
Principal arterial	96	.0071	.003	5.60	6.47	1.68	5.62	0.59
Minor arterial	96	.1547	.070	5.27	4.92	1.00	5.62	0.46
Peak hour	156	.3845	.181	4.71	6.06	1.40	5.81	0.66
Off-peak hour	144	.3618	.113	5.22	6.20	1.87	5.91	0.58
Congested	84	.0640	.020	5.28	6.50	1.82	5.41	0.56
Noncongested	216	.6853	.248	4.56	5.98	1.55	6.04	0.56
20° temperature	100	.4039	.136	5.43	6.67	1.85	6.34	0.62
50° temperature	100	.2251	.067	5.45	6.13	1.56	5.86	0.46
80° temperature	100	-.0240	-.007	5.42	5.58	1.30	5.39	0.36
0% cold starts	102	.3451	.152	5.07	7.05	1.68	6.14	0.74
50% cold starts	150	.1290	.047	5.52	5.98	1.39	5.80	0.51
100% cold starts	48	-.1420	-.058	5.71	4.62	0.87	5.44	0.36

The test statistic is then compared with the confidence coefficients corresponding to the 95 and 99% confidence levels to determine whether the differences in the correlation coefficients are significant at the 95 or 99% confidence level. Table 12 lists the results of the significance tests.

The significance tests show that the correlation between emission model results are equally good for emissions from the 1975 vehicle mix and the 1977 vehicle mix. The freeway cases are better correlated than the principal or minor arterial cases, and the principal arterial cases are better correlated than the minor arterial cases. However, peak-hour cases show better correlation than do nonpeak hour cases, and congested cases are better correlated than noncongested cases. The congested and noncongested results seem inconsistent with the correlations found for the three highway-type subset comparisons. Since all except one of the freeway cases are noncongested and over half of the principal arterial cases are congested and those cases comprise 71% of the congested cases, it would appear that the principal arterial cases should have better correlation than the freeway cases. This apparent inconsistency has not been resolved. Since the peak-hour cases are better correlated than the off-peak hour cases and most of the congested cases are for the peak hour, the peak and off-peak hour and the congested and noncongested results appear consistent.

The cases having an ambient air temperature of 80°F (26.7°C) are better correlated than those having a temperature of 20°F (-6.7°C). The poorer correlation of the 20°F cases is probably a result of error introduced by the temperature correction factors of the emission models. The temperature at which the basic emission factor measurements were made was near 75°F (25°C). Thus, for the 80°F cases, the effect of the temperature correction factors was minimal since the factors for 80° are near unity; for the 20° cases, however, the factors are large.

The correlation of cases having 0% cold-start vehicles is significantly better than the correlation of cases having 100% cold-start vehicles. Also, cases with 50% cold-start vehicles show better correlation than cases with 100% cold-start vehicles. The explanation for this

Table 12

RESULTS OF TESTS FOR SIGNIFICANCE OF DIFFERENCES BETWEEN CORRELATION COEFFICIENTS OF VARIOUS SUBSETS OF THE DATA SAMPLE

Pollutant	Cases for Which Correlation Coefficients are Being Compared		Significance	Cases Showing Highest Correlation
HC and CO	1975	1977	Not significant	
HC and CO	Freeway	Principal arterial	Significant at a 99% confidence level	Freeway
HC and CO	Freeway	Minor arterial	Significant at a 99% confidence level	Freeway
HC and CO	Principal arterial	Minor arterial	Significant at a 95% confidence level	Principal arterial
HC and CO	Congested	Noncongested	Significant at a 99% confidence level	Congested
HC and CO	20°	50°	Not significant	
HC and CO	20°	80°	Significant at a 95% confidence level	80°
HC and CO	50°	80°	Not significant	
HC and CO	0% cold starts	50% cold starts	Not significant	
HC and CO	0% cold starts	100% cold starts	Significant at a 99% confidence level	0%
HC and CO	50% cold starts	100% cold starts	Significant at a 99% confidence level	50%
HC	Peak hour	Off-peak hour	Significant at a 99% confidence level	Peak hour
CO	Peak hour	Off-peak hour	Significant at a 95% confidence level	Peak hour

is similar to that for temperature: error is probably introduced by the correction factors--in this case, the cold-start correction factors. The basic emission factors used in the FTP model assume 20% cold-start vehicles; the modal model coefficients, however, are based on 0% cold-start vehicles. Thus, for percentages of cold-start vehicles greater than the assumed base levels, the influence of the correction factors is greater and correlation between the models is reduced.

It is probable that the poorer correlation of the 100% cold-start cases is a major influence on the correlation of the minor-arterial cases, compared with the other highway type subsets. One-half of the minor arterial cases have 100% cold-start vehicles; the freeway and principal arterial cases include only 0 and 50% cold-start cases, respectively. Since the 100% cold-start cases show poorer correlation than do the 0 and 50% cases, the correlation of the minor arterial cases, compared with freeway and principal arterial cases, would be reduced.

Examination of Table 11 reveals that correlation between the emission models for NO_x is poor. Figure 6 shows that the variation among modal NO_x emission values for the test cases is considerably greater than the variation among FTP emission values for the same test cases. Table 11 gives the standard deviation of modal emissions for the 300 test cases as 1.65 g/veh-mi and the FTP standard deviation as 0.63 g/veh-mi. This large difference is due to the data bases from which the emission models were derived. The emission values from which the modal coefficients, described in Section VII.D, were computed were not corrected for humidity; the FTP emission factors were corrected. It is believed that for NO_x, the FTP methodology is a more accurate means of computing emissions.

F. FTP Model Sensitivity Analysis

The input data required by the FTP methodology are listed in Table 5. An analysis was performed to assess the error that would be introduced into the emission factors if there were an error in estimating the input data. First, the analysis was centered on determination of relative error resulting from error in a single input variable. Then, based on the results of this analysis, relative error resulting from error in two input parameters was determined.

1. Sensitivity to Error in a Single Input Parameter

For each pollutant, the sensitivity to error in each of the following four input parameters was determined: average route speed, ambient temperature, percentage of cold-start vehicles, and traffic volume. It was assumed that the other input parameters, such as calendar year, vehicle type mix, and model year mix, could be accurately assessed. The national average vehicle type mix and model year mix were used in the calculations.

Speed Sensitivity Analysis--In the speed sensitivity analysis, relative error caused by erroneous speed was computed for each of three roadway types: freeways, principal arterials, and minor arterials. Several assumptions were made to distinguish the roadway types. It was assumed that average route speeds on freeways vary from 5 to 45 mph; speeds on principal arterials vary from 5 to 40 mph, and speeds on minor arterials vary from 5 to 35 mph. The following were assumed for all roadway types: (1) a speed of 5 mph can be as much as +10 mph in error; (2) a speed of 10 mph can be as much as +10 or -5 mph in error; (3) speeds from 15 to 35 mph can be as much as +10 or -10 mph in error. In addition, it was assumed that a speed of 40 mph on a principal arterial or a freeway can be as much as +5 or -10 mph in error, and a speed of 45 mph on a freeway can be as much as -10 mph in error.

Emission factors were computed for all combinations of 2 calendar years, 3 temperatures, 3 percentages of cold-start vehicles, and 9 average route speeds. Table 13 lists the values of these parameters used in the analysis. For each roadway type, the average relative error in estimating emission factors caused by errors of +5, -5, ±5, +10, -10, and ±10 mph in speed was computed for each pollutant, considering the assumptions listed above. The results of these computations are shown in Table 14. As could be expected, the larger the magnitude of the error in speed, the greater the relative error in the emission factor. For HC

Table 13

VALUES OF INPUT PARAMETERS ASSUMED IN FTP MODEL SINGLE PARAMETER SENSITIVITY ANALYSIS

Parameter	Units	Values Assumed
		Speed Sensitivity Analysis
Speed	mph	5,10,15,20,25,30,35,40,45
Calendar year	--	1975, 1977
Temperature	°F	20,50,80
Cold starts	%	0,50,100
		Temperature Sensitivity Analysis
Temperature	°F	20,21,22,38,39,40,41,42,58,59,60, 61,62,78,79,80
Calendar year	--	1975, 1977
Cold starts	%	0,50,100
Speed	mph	5,15,25,35,45
		Cold-Start Sensitivity Analysis
Cold starts	%	0,5,10,15,20,25,30,35,40,45,50, 55,60,65,70,75,80,85,90,95,100
Calendar year	--	1975, 1977
Temperature	°F	20,50,80
Speed	mph	5,15,25,35,45

and CO, underestimated speeds produce larger errors then do overestimated speeds of the same magnitude. This is because of the exponential form of the speed correction factor functions. For NO_x, the slight difference in relative error between cases with underestimated and overestimated speeds of the same magnitude is not significant; it results from the choice of cases used to compute the average relative error. From the HC and CO results, it appears that, for these two emission types, it is better to overestimate average route speed than it is to underestimate it.

The fractional error caused by a particular amount of error in speed is least for freeways and greatest for minor arterials. The

Table 14

AVERAGE FRACTIONAL ERROR IN FTP EMISSION FACTORS RESULTING FROM ERROR IN A SINGLE INPUT PARAMETER

Pollutant	Facility Type	Error in Average Route Speed (mph)					
		+10	-10	±10*	+5	-5	±5*
HC	Freeway	.24	.35	.29	.14	.18	.16
CO	Freeway	.37	.69	.53	.22	.31	.26
NO_x	Freeway	.08	.08	.08	.05	.05	.05
HC	Principal arterial	.24	.40	.31	.14	.20	.17
CO	Principal arterial	.37	.77	.55	.22	.34	.28
NO_x	Principal arterial	.08	.09	.08	.05	.05	.05
HC	Minor arterial	.24	.45	.32	.15	.22	.18
CO	Minor arterial	.37	.85	.57	.24	.38	.30
NO_x	Minor arterial	.08	.09	.09	.05	.06	.05

Pollutant	Error in Ambient Temperature (°F)					
	+2	-2	±2*	+1	-1	±1*
HC	.02	.02	.02	.01	.01	.01
CO	.03	.03	.03	.01	.02	.01
NO_x	.00	.01	.01	.00	.00	.00

Pollutant	Error in Percentage Cold-Starting Vehicles (%)						
	±50†	+20	-20	±20*	+10	-10	±10*
HC	.37	.16	.13	.15	.08	.07	.07
CO	.77	.37	.24	.30	.18	.12	.15
NO_x	.06	.02	.02	.02	.01	.01	.01

*The average fractional error in emission factors resulting from input parameter error of ±X may or may not be the simple average of the fraction error caused by input parameter error of +X and -X, since in some cases different sample sizes were used in computing the +X and -X errors.

†Errors of +50 and -50 were grouped together because the sample size was small.

differences arise from the assumptions made about what average route speeds occur on the different roadway types. The differences in fractional error of emission factors among the roadway types suggest that the error is smaller when high speeds are misestimated than when the low speeds are misestimated; the exponential nature of the speed correction function causes less sensitivity to error at the higher speeds. The maximum error computed for HC is 45%, for CO is 85%, and for NO_x is 9%.

Temperature Sensitivity Analysis--To perform an analysis of the sensitivity of FTP emission factors to temperature, the emission factors for all combinations of the 2 calendar years, 3 percentages of cold-starting vehicles, 5 average route speeds, and 16 temperatures listed in Table 13 were computed. For each pollutant, the sensitivity of the emission factors to errors of +2, -2, ±2, +1, -1, and ±1 degrees Farenheit was assessed; the results appear in Table 14. The largest emission factor error results from the cases with the largest error in temperature. Temperature can be measured quite accurately, so it is doubtful that it will be in error by more than 2°F (1°C). Since the largest relative error computed for any pollutant is less than three percent, even for 2°F temperature error, the sensitivity of the FTP methodology to erroneous temperature is virtually negligible.

Cold-Start Vehicle Sensitivity Analysis--Table 13 lists the values for the 2 calendar years, 3 temperatures, 5 average route speeds, and 21 percentages of cold-start vehicles used in the analysis of FTP emission factor sensitivity to error in estimating the percentage of cold-start vehicles. The average relative errors in emission factors resulting from cold-start errors of ±50, +20, -20, ±20, +10, -10, and ±10% were computed and are given in Table 14. As expected, the larger the magnitude of the error in percent cold-start vehicles, the larger the error in the emission factor. For HC and CO, overestimating the percent of cold-start vehicles produces larger error than underestimating it by the same magnitude. This is due to the functional form of the cold-start correction factor. On the average, for CO, 77% error in emission factor is introduced by underestimating or overestimating the percent cold-start vehicles by 50% or more. Less than 6% error in NO_x emission factors results from even a 50% error in percent of cold-start vehicles. The HC emission factor error is as large as 37% when the cold-start factor is in error by 50%.

Traffic Volume Sensitivity Analysis--Since pollutant emissions are directly proportional to the volume of vehicles on a roadway, an error in volume of a particular magnitude produces a corresponding error in emission factor. This will hold true as long as the roadway is uncongested. However, if the volume is in error and the average route speed is therefore estimated erroneously, the resultant error in emissions would not be directly proportional to the volume error. An analysis of error introduced by congested conditions is considered beyond the scope of this study.

2. Sensitivity to Error in Two Input Parameters

The results of the single parameter sensitivity tests show that FTP emission factors are relatively insensitive to the error in temperature measurements likely to be encountered in RAPS. Therefore, the sensitivity of emission factors to temperature error in conjunction with error in another input parameter was not considered. The two parameter sensitivity analysis was conducted for: error in speed and volume; percent cold-start vehicles and volume; and speed and percent cold-start vehicles.

Rather than compute emission factors for various combinations of volume error and speed or cold-start error to obtain average relative error caused by error in volume and speed or cold starts, an equation was derived to compute the relative error. This is possible because of the direct proportionality of volume error to emission factor error. Let v be the correct volume and v′ be the amount by which the volume is in error, positive or negative. Let E be the correct emission factor and E′ be the positive or negative amount the emission factor is in error because of error in speed or percent cold-start vehicles. Then the relative error is given by

$$\text{error} = \left| \frac{vE - (v + v') (E + E')}{vE} \right| \qquad (19)$$

Reorganizing and reducing,

$$\text{error} = \left| \frac{v'}{v} + \frac{E'}{E}\left(1 + \frac{v'}{v}\right)\right| \tag{20}$$

But the quantity v'/v is the fractional amount the volume is in error. Therefore, for any fraction of volume error, the total relative error caused by error in both volume and a second input parameter is a simple function of the fractional error due to error in the second input parameter. Equations with the same form as Eqs. (19) and (20) were used in the speed and volume and cold-start and volume sensitivity analyses.

Speed and Volume Sensitivity Analysis--Table 15 lists the values of speed, calendar year, temperature, and percent cold-start vehicles used in the speed and volume sensitivity analysis. This analysis was performed using speeds ranging from 5 to 45 mph. Computations were made for volume error of +20, -20, +10, -10, +5, -5, ±20, ±10, and ±5% and for speed error of +5, -5, ±5, +10, -10, and ±10 mph. The relative error resulting from all combinations of volume and speed error classes for each pollutant are given in Table 16. The largest error results when the effect of the errors in both volume and speed produces emission factor errors of the same sign.

For HC and CO, the largest error occurs when volume is overestimated and speed is underestimated, or when volume is underestimated and speed is overestimated. In these cases, when there is an error in either the speed or volume parameter, the emission factor error will become larger as the magnitude of the error in the other parameter is increased. However, when volume and speed are both either underestimated or overestimated, the emission factor error introduced by error in one of the input parameters has the opposite sign of the emission factor error caused by error in the other input parameter. The net effect is a varying degree of error cancellation, depending on the magnitude of the error in each input parameter. For a given amount of error in volume, the larger the magnitude of the error in speed, the larger the emission factor error. But for a given amount of error in speed, as the magnitude of the volume error decreases the emission factor error may either (1) increase, or (2)

Table 15

VALUES OF INPUT PARAMETERS ASSUMED IN FTP MODEL TWO PARAMETER SENSITIVITY ANALYSES

Parameter	Units	Values Assumed
		Speed and Volume Sensitivity Analysis
Speed	mph	5,10,15,20,25,30,35,40,45
Calendar year	--	1975, 1977
Temperature	°F	20,50,80
Cold starts	%	0,50,100
		Cold-Start and Volume Sensitivity Analysis
Cold starts	%	0,5,10,20,25,30,35,40,45,50,55,60, 65,70,75,80,85,90,95,100
Calendar year	--	1975, 1977
Temperature	°F	20,50,80
Speed	mph	5,15,25,35,45
		Speed and Cold-Start Sensitivity Analysis
Speed	mph	5,10,15,20,25,30,35,40,45,
Cold starts	%	0,5,10,15,20,25,30,35,40,45,50,55, 60,65,70,75,80,85,90,95,100
Calendar year	--	1975, 1977
Temperature	°F	20,50,80

decrease and then increase. Thus, in some cases, for a given amount of speed error, the total emission factor error is smaller for a large volume error than it is for a small volume error. This occurs because the emission factor errors related to speed and a larger volume error more nearly cancel than do the errors related to speed and a smaller volume error.

For NO_x when speed and volume are both overestimated or underestimated, they produce emission factor errors of the same size. However, the emission factor error resulting from underestimated volume and overestimated speed, or from overestimated volume and underestimated speed

Table 16

AVERAGE FRACTIONAL ERROR IN FTP EMISSION FACTORS RESULTING FROM ERROR IN BOTH SPEED AND VOLUME

Pollutant	Error in Speed (mph)	Error in Volume (%)								
		+20	-20	+10	-10	+5	-5	±20*	±10*	±5*
HC	+5	.11	.31	.08	.22	.10	.18	.21	.15	.19
	-5	.42	.13	.30	.10	.24	.12	.27	.20	.18
	±5	.26	.22	.19	.16	.17	.15	.24	.17	.16
	+10	.12	.39	.16	.31	.20	.27	.26	.24	.24
	-10	.62	.15	.49	.22	.42	.29	.39	.36	.35
	±10	.37	.27	.32	.27	.31	.28	.32	.30	.29
CO	+5	.11	.37	.14	.30	.18	.26	.24	.22	.22
	-5	.57	.13	.44	.18	.38	.25	.35	.31	.31
	±5	.34	.25	.29	.24	.28	.25	.30	.27	.26
	+10	.24	.49	.30	.43	.33	.40	.37	.37	.37
	-10	1.03	.36	.86	.52	.78	.61	.69	.69	.69
	±10	.63	.42	.58	.48	.55	.50	.53	.53	.53
NO_x	+5	.21	.20	.11	.09	.08	.04	.20	.10	.06
	-5	.20	.20	.10	.10	.05	.07	.20	.10	.06
	±5	.20	.20	.10	.10	.06	.06	.20	.10	.06
	+10	.23	.18	.15	.08	.11	.06	.21	.11	.08
	-10	.18	.22	.08	.14	.07	.11	.20	.11	.09
	±10	.21	.20	.11	.11	.09	.08	.20	.11	.09

*The average fractional error in emission factors resulting from input parameter error of ±X may or may not be the simple average of the fractional error caused by input parameter error of +X and -X, since in some cases different sample sizes were used in computing the +X and -X errors.

have opposite signs and have a cancelling effect. For a given speed error, larger volume error produced larger emission factor error. This is also true for cases in which emission factor errors resulting from speed error and volume error both have the same sign. But when these errors have opposite signs for a given amount of volume error, the resultant emission factor error from a smaller amount of speed error may be larger than the emission factor error from a larger amount of speed error.

The magnitude of the emission factor error resulting from error in both volume and speed varies among the pollutants. The maximum error for all three pollutants occurs when speed is underestimated by 10 mph and volume is overestimated by 20%. The maximum errors are: HC, 62%; CO, 103%; and NO_x, 23%.

Cold-Start and Volume Sensitivity Analysis--Table 15 lists the values of percent of cold-start vehicles, calendar year, temperature, and speed used in the cold-start and volume sensitivity analysis. Volume errors were computed for +20, -20, +10, -10, +5, -5, ±20, ±10, and ±5%; cold start errors were computed for +10, -10, ±10, +20, -20, ±20, and ±50%. The average relative errors in emission factors for each pollutant resulting from all combinations of the above classes of volume and cold-start errors are given in Table 17.

For HC and CO, the largest emission factor error results when cold starts and volume are both either underestimated or overestimated. For these cases, for a given amount of error in one input parameter (cold starts or volume), the emission factor error will become larger as the magnitude of the error in one input parameter (volume or cold starts) is increased. When cold starts are underestimated and volume is overestimated or when cold starts are overestimated and volume is underestimated, the emission factor errors resulting from error in volume and from error in cold starts partially cancel. For these cases, for a given amount of volume error, the emission factor error will become larger as the magnitude of the error in cold starts becomes larger. However, for a given amount of error in cold starts, the emission factor error will (1) decrease, (2) decrease and then increase, or (3) increase as the volume error magnitude decreases. The reason such effects are observed was discussed previously in this report.

For NO_x, emission factor errors are additive and therefore largest when cold start is overestimated and volume is underestimated, or when cold start is underestimated and volume is overestimated. For these cases, for a given error in one of the input parameters being tested, the emission factor error decreases as the magnitude of the error in the other input parameter decreases. When error in cold start and volume are both either underestimated or overestimated, the emission factor error resulting

Table 17

AVERAGE FRACTIONAL ERROR IN FTP EMISSION FACTORS RESULTING FROM ERROR IN BOTH COLD STARTS AND VOLUME

Pollutant	Error in Cold Start (%)	Error in Volume (%)								
		+20	-20	+10	-10	+5	-5	±20*	±10*	±5*
HC	+10	.30	.14	.19	.05	.14	.04	.22	.12	.09
	-10	.12	.25	.05	.16	.03	.11	.19	.10	.07
	±10*	.21	.20	.12	.11	.08	.08	.20	.11	.08
	+20	.39	.11	.28	.08	.22	.11	.25	.18	.16
	-20	.09	.31	.07	.22	.09	.17	.20	.14	.13
	±20*	.24	.21	.18	.15	.15	.14	.22	.16	.15
	±50†	.48	.31	.42	.32	.39	.35	.39	.37	.37
CO	+10	.42	.12	.30	.08	.24	.12	.27	.19	.18
	-10	.08	.30	.05	.21	.08	.16	.19	.13	.12
	±10*	.25	.21	.17	.15	.16	.14	.23	.16	.15
	+20	.64	.14	.50	.23	.43	.30	.39	.37	.37
	-20	.11	.39	.16	.32	.20	.28	.25	.24	.24
	±20*	.37	.27	.33	.27	.32	.29	.32	.30	.30
	±50†	.94	.60	.86	.69	.81	.73	.77	.77	.77
NO_x	+10	.19	.21	.09	.11	.04	.06	.20	.10	.05
	-10	.21	.19	.11	.09	.06	.04	.20	.10	.05
	±10*	.20	.20	.10	.10	.05	.05	.20	.10	.05
	+20	.17	.22	.08	.12	.03	.07	.20	.10	.05
	-20	.23	.18	.13	.08	.08	.03	.21	.10	.05
	±20*	.20	.20	.10	.10	.05	.05	.20	.10	.05
	±50†	.20	.20	.10	.11	.07	.07	.20	.11	.07

*The average fractional error in emission factors resulting from input parameter error of ±X may or may not be the simple average of the fractional error caused by input parameter error of +X and -X, since in some cases different sample sizes were used in computing the +X and -X errors.

†Errors of +50 and -50 were grouped together because the sample size was small.

from error in one input parameter has the opposite sign to the emission factor resulting from error in the other input parameter. For a given value of error in cold start, the emission factor error decreases as the magnitude of error in volume decreases. But for a given amount of error in volume, the emission error increases as the magnitude of cold-start error decreases.

The number of cases with cold starts underestimated or overestimated by 50% were few enough that it was felt that these cases should be combined to be statistically significant. The behavior of the emission factor error as the error in volume changes is evident from Table 17.

The magnitude of emission factor error resulting from error in both cold start and volume is greatest for CO and least for NO_x. The maximum HC and CO emission factor error occurs when cold starts are ±50% in error and volume is overestimated by 20%. The maximum value for HC is 48% and for CO is 94%. For NO_x the maximum error of 23% occurs when cold starts are underestimated by 20% and volume is overestimated by 20%.

Speed and Cold-Start Sensitivity Analysis--Table 15 lists the values of speed, percent cold-start vehicles, calendar year, and temperature used in the speed and cold-start sensitivity analysis. Computations were made for speed error of +5, -5, ±5, +10, -10, and ±10 mph and for cold-start error of +10, -10, ±10, +20, -20, ±20, and ±50%. The average fractional error in emission factor resulting from all combinations of the above error classes are given for each pollutant in Table 18.

The largest emission factor errors for HC and CO occur when speed is overestimated and cold start is underestimated or when speed is underestimated and cold start is overestimated. For these cases, for an error in one input parameter (speed or cold start), emission factor increases with increasing error magnitude in the other input parameter. When speed error and cold-start error are both underestimated or overestimated, for a given value of cold-start error, emission factor error increases as the magnitude of speed error is increased. But for a given amount of speed error, emission factor error may increase or decrease as cold-start error magnitude increases.

For NO_x, emission factor error is largest when speed is overestimated and cold start is underestimated, or when speed is underestimated and cold start is overestimated. For a given amount of error in speed, emission factor error changes little as cold-start error magnitude increases. Since the sample sizes are not large, the differences in emission factor errors are considered negligible. For a given value of

Table 18

AVERAGE FRACTIONAL ERROR IN FTP EMISSION FACTORS RESULTING FROM ERROR IN BOTH SPEED AND PERCENT COLD STARTS

Pollutant	Error in Speed (mph)	Error in Cold Starts (%)						
		+10	-10	±10*	+20	-20	±20*	±50†
HC	+5	.10	.19	.15	.11	.25	.18	.33
	-5	.28	.12	.20	.38	.11	.24	.46
	±5*	.19	.16	.17	.24	.18	.21	.40
	+10	.18	.29	.23	.16	.33	.25	.34
	-10	.47	.28	.37	.58	.21	.40	.59
	±10*	.32	.28	.30	.37	.27	.32	.47
CO	+5	.15	.31	.23	.21	.40	.30	.64
	-5	.57	.19	.38	.82	.17	.49	1.07
	±5*	.36	.25	.30	.52	.28	.40	.86
	+10	.27	.44	.36	.25	.51	.38	.57
	-10	1.02	.51	.76	1.35	.36	.86	1.47
	±10*	.65	.47	.56	.80	.44	.62	1.02
NO_x	+5	.04	.06	.05	.04	.06	.05	.08
	-5	.06	.04	.05	.06	.04	.05	.08
	±5*	.05	.05	.05	.05	.05	.05	.08
	+10	.08	.09	.08	.07	.10	.08	.10
	-10	.09	.08	.08	.09	.07	.08	.10
	±10*	.08	.08	.08	.08	.09	.08	.10

*The average fractional error in emission factors resulting from input parameter error of ±X may or may not be the simple average of the fractional error caused by input parameter error of +X and -X, since in some cases different sample sizes were used in computing the +X and -X errors.

†Errors of +50 and -50 were grouped together because the sample size was small.

cold-start error, emission factor error increases as the magnitude of speed error is increased. These two trends also apply to cases where speed error and cold-start error are both either underestimated or overestimated.

The error in CO emission factors resulting from error in speed and percent of cold-start vehicles is the largest error of the three pollutants. The largest errors in both HC and CO emission factors occur when cold start is 50% in error and the speed is underestimated by 10 mph;

the maximum values are 59% for HC and 147% for CO. NO_x error is smaller, not exceeding 10%.

3. Conclusions

It has been shown that relatively large error in FTP emission factors are produced when model input parameters are measured or estimated erroneously. To illustrate more clearly the effect of input error, an arbitrary threshold value of 20% was chosen, and a table was made to show which input parameter error classes or combination of parameter error classes would produce emission factor error exceeding the threshold value. Table 19 shows which error classes exceed the threshold value for each pollutant.

Cold-start error of 20% or greater produces emission factor error greater than 20% for CO; for HC, the threshold value is not exceeded unless cold-start error is about 50%. NO_x emission factor error is less than 20% even when cold-start error is as large as 50%.

Error in emission factors caused by temperature error of a magnitude likely to be encountered in RAPS data has been determined to be negligible; this was discussed in the preceding section.

For HC and CO, most of the speed-error classes produced errors exceeding the emission threshold value. However, NO_x emission factors were in error by less than 20% for all of the speed-error values.

Error in both volume and speed cause the HC emission factor error to exceed the threshold value for several combinations of values of speed error and volume error, as seen in Table 19. CO emission factors are slightly more sensitive than the HC factors. The only error classes causing NO_x emission factor error to exceed the threshold value are those with 20% volume error.

The results of the volume and cold-start analysis appear in Table 19. They are very similar to those described above for the volume and speed analysis.

The HC emission factor error resulting from error in both speed and cold start exceeds the threshold value for many of the combinations

Table 19

INPUT PARAMETER ERROR VALUES THAT CAUSE FTP EMISSION FACTOR ERROR TO EXCEED 20%

Pollutant	Error in Cold Start (%)				
	+10	-10	+20	-20	±50
HC					X
CO			X	X	X
NO_x					

Pollutant	Error in Minor Arterial Speed (mph)			
	+5	-5	+10	-10
HC		X	X	X
CO	X	X	X	X
NO_x				

Pollutant	Error in Speed (mph)	Error in Volume (%)					
		+5	-5	+10	-10	+20	-20
HC	+5				X		X
	-5	X		X		X	
	+10		X		X		X
	-10	X	X	X	X	X	
CO	+5		X		X		X
	-5	X	X	X		X	
	+10	X	X	X	X	X	X
	-10	X	X	X	X	X	X
NO_x	+5					X	
	-5						
	+10					X	
	-10						X

Table 19 (Concluded)

Pollutant	Error in Cold Start (%)	Error in Volume (%)					
		+5	-5	+10	-10	+20	-20
HC	+10					X	
	-10						X
	+20	X		X		X	
	-20				X		X
	±50	X	X	X	X	X	X
CO	+10	X		X		X	
	-10				X		X
	+20	X	X	X	X	X	
	-20		X		X		X
	±50	X	X	X	X	X	X
NO_x	+10						X
	-10					X	
	+20						X
	-20					X	
	±50						

Pollutant	Error in Speed (mph)	Error in Cold Start (%)				
		+10	-10	+20	-20	±50
HC	+5				X	X
	-5	X		X		X
	+10		X		X	X
	-10	X	X	X	X	X
CO	+5		X	X	X	X
	-5	X		X		X
	+10	X	X	X	X	X
	-10	X	X	X	X	X
NO_x	+5					
	-5					
	+10					
	-10					

of speed error and cold-start error. CO emission factors are in error by more than 20% for almost all combinations of speed error and cold-start error tested. However, NO_x error was under the threshold value for all error classes tested.

In general, CO emission factors are most sensitive to error in input parameters, and NO_x emission factors are the least sensitive to errors in input parameters. HC emissions are somewhat less sensitive than CO emissions, but are considerably more affected by input parameter error than are NO_x emission factors.

G. Modal Model Sensitivity Analysis

The input parameters required by the modal model are listed in Table 5. The modal model sensitivity analysis was centered on assessment of emission factor error introduced by error in each of three input parameters: temperature, percent of cold-start vehicles, and traffic volume. Based on the model sensitivity to error in a single input parameter, an analysis of emission factor error introduced by error in two parameters was performed.

It was assumed that calendar year, vehicle type mix, and model year mix could be accurately assessed. Assessment of the effects of error in the second-by-second speed and time profiles was considered beyond the scope of this study.

1. Sensitivity to Error in a Single Input Parameter

Since modal temperature and cold-start correction factors are not dependent on vehicle model year, the effect of error in either of these parameters on the emission factor can be assessed independent of the value of the uncorrected emission factor. This is also true for error in traffic volume. The following equations illustrate the independence:

$$\text{error} = \left| \frac{aE - a'E}{aE} \right| \quad . \tag{21}$$

Reducing,

$$\text{error} = \left| 1 - \frac{a'}{a} \right| \qquad (22)$$

where

a = The correction factor for the correct temperature or cold start or the correct volume

a′ = The correction factor for the erroneous temperature or cold start or the erroneous volume

E = The uncorrected modal emission factor.

Equation (22) was used to assess the sensitivity of modal emission factors to error in temperature, cold start, and volume.

Temperature-Sensitivity Analysis--All combinations of the values of temperature and percent of cold-start vehicles listed in Table 20 were used in the temperature-sensitivity analysis. For each pollutant, the sensitivity of the emission factors to errors of +2, -2, ±2, +1, -1, and ±1 degree Farenheit was assessed; the results appear in Table 21. Since temperature error is not likely to be greater than 2°F (1°C), and the maximum emission factor error computed was 3%, it appears that modal model sensitivity to error in temperature is not significant.

Cold-Start Sensitivity Analysis--Table 20 lists the percent of cold-start vehicles and the temperatures used in the modal cold-start sensitivity analysis. For each pollutant, the average errors in emission factor resulting from cold-start error of +10, -10, ±10, +20, -20, ±20, and ±50% were computed. In general, the greater the magnitude of the cold-start error, the greater the error in emission factors. The maximum error occurs when cold-start is 50% in error; the error value for HC is 49%, for CO it is 82%, and for NO_x it is 13%.

Traffic Volume Sensitivity Analysis--The effect on emission factors of error in traffic volume is the same for both the modal and the FTP emission models. See the discussion for the FTP model in Section VII.F.

Table 20

VALUES OF INPUT PARAMETERS ASSUMED IN MODAL MODEL SENSITIVITY ANALYSES

Parameter	Units	Values Assumed
		Temperature Sensitivity Analysis
Temperature	°F	20,21,22,28,29,30,31,32,38,39,40,41,42,48, 49,50,51,52,58,59,60,61,62,68,69,70,71,72, 78,79,80
Cold starts	%	0,20,40,60,80,100
		Cold-Start Sensitivity Analysis
Cold starts	%	0,5,10,15,20,25,30,35,40,45,50,55,60,65,70, 75,80,85,90,95,100
Temperature	°F	20,30,40,50,60,70,80
		Cold-Start and Volume Sensitivity Analysis
Cold starts	%	0,5,10,15,20,25,30,35,40,45,50,55,60,65,70, 75,80,85,90,95,100
Temperature	°F	20,30,40,50,60,70,80

2. Sensitivity to Error in Two Input Parameters

As was the case in the FTP model temperature sensitivity analysis, the modal model is relatively insensitive to error in temperature. Therefore, emission factor sensitivity to temperature error in conjunction with error in another input parameter was not considered. Therefore, the modal model two parameter sensitivity analysis was performed only for error in both cold start and volume. The following equation describes the emission factor error:

$$\text{error} = \left| \frac{vaE - (v + v')\,a'E}{vaE} \right| . \tag{23}$$

Reducing,

$$\text{error} = \left| 1 - \frac{a'}{a}\left(1 + \frac{v'}{v}\right) \right| \tag{24}$$

Table 21

AVERAGE FRACTIONAL ERROR IN MODAL EMISSION FACTORS RESULTING FROM ERROR IN A SINGLE INPUT PARAMETER

Pollutant	Error in Ambient Temperature (°F)					
	+2	-2	±2*	+1	-1	±1*
HC	.03	.02	.03	.01	.01	.01
CO	.03	.03	.03	.02	.01	.01
NO_x	.01	.01	.01	.00	.00	.00

Pollutant	Error in Percent Cold-Start Vehicles (%)						
	+10	-10	±10*	+20	-20	±20*	±50†
HC	.11	.08	.10	.22	.16	.19	.49
CO	.20	.12	.16	.39	.24	.31	.82
NO_x	.03	.03	.03	.05	.05	.05	.13

*The average fractional error in emission factors resulting from input parameter error of ±X may or may not be the simple average of the fractional error caused by input parameter error of +X and -X, since in some cases different sample sizes were used in computing the +X and -X errors.

†Errors of +50 and -50 were grouped together because the sample size was small.

where

a = The correction factor for the correct percent of cold starts

a′ = The correction factor for the erroneous percent of cold starts

E = The temperature-corrected emission factor

v = The correct volume

v′ = The amount by which the volume is in error.

Again, the emission factor error is independent of the value of the temperature-corrected emission factor.

The sensitivity of modal emission factors was computed for all combinations of cold-start error of +10, -10, ±10, +20, -20, ±20, and ±50% and for volume error of +20, -20, +10, -10, +5, -5, ±20, ±10, and ±5%. The results of the analysis appear in Table 22.

Table 22

AVERAGE FRACTIONAL ERROR IN MODAL EMISSION FACTORS RESULTING FROM ERROR IN BOTH VOLUME AND COLD-START

Pollutant	Error in Cold Start (%)	Error in Volume (%)								
		+20	+10	+5	-5	-10	-20	±20*	±10*	±5*
HC	+10	.33	.22	.17	.06	.05	.12	.23	.14	.11
	-10	.11	.04	.04	.13	.17	.26	.19	.11	.08
	±10*	.22	.13	.10	.09	.11	.19	.21	.12	.10
	+20	.47	.34	.28	.16	.11	.10	.28	.23	.22
	-20	.07	.08	.12	.20	.25	.33	.20	.16	.16
	±20*	.27	.21	.20	.18	.18	.21	.24	.19	.19
	±50†	.59	.54	.51	.46	.44	.39	.49	.49	.49
CO	+10	.43	.31	.26	.14	.09	.11	.27	.20	.20
	-10	.08	.04	.07	.16	.21	.30	.19	.12	.12
	±10*	.26	.18	.16	.15	.15	.20	.23	.16	.16
	+20	.67	.53	.46	.32	.25	.15	.41	.39	.39
	-20	.10	.16	.20	.28	.31	.39	.24	.24	.24
	±20*	.38	.35	.33	.30	.28	.27	.33	.31	.31
	±50†	.98	.90	.86	.77	.73	.65	.82	.82	.82
NO_x	+10	.17	.07	.02	.07	.12	.22	.20	.10	.15
	-10	.23	.13	.08	.03	.08	.18	.21	.10	.05
	±10*	.20	.10	.05	.05	.10	.20	.20	.10	.05
	+20	.14	.05	.02	.10	.15	.24	.19	.10	.06
	-20	.26	.16	.11	.02	.05	.16	.21	.11	.06
	±20*	.20	.10	.06	.06	.10	.20	.20	.10	.06
	±50†	.22	.15	.14	.12	.13	.19	.20	.14	.13

*The average fractional error in emission factors resulting from input parameter error of ±X may or may not be the simple average of the fractional error caused by input parameter error of +X and -X, since in some cases different sample sizes were used in computing the +X and -X errors.

†Errors of +50 and -50 were grouped together because the sample size was small.

For HC and CO, the largest emission factor error results when cold start and volume are both either underestimated or overestimated. For these cases, for a given value of error in one input parameter (cold start or volume), the emission factor error increases as the magnitude of the error in the other input parameter is increased. When cold starts are underestimated and volume is overestimated or when cold starts are overestimated and volume is underestimated, for a given value of error in one input parameter, the emission factor may (1) increase, (2) decrease, or (3) decrease and then increase as the magnitude of the error in the other input parameter is increased. As in the FTP sensitivity analysis, this is a result of a varying degree of cancellation of the error introduced by error in the two input parameters.

For NO_x, the largest emission factor error results when volume is overestimated and cold starts are underestimated, or when volume is underestimated and cold starts are overestimated. For these cases, for a given amount of error in one input parameter, emission factor error increases as the magnitude of the error in the other input parameter is increased.

When errors in cold starts and volume are both either underestimated or overestimated, for a given amount of cold-start error, the emission factor error increases as the magnitude of volume error increases. But for a given amount of volume error, the emission factor error may decrease or remain constant as the magnitude of cold-start error is increased.

For HC and CO, the largest emission factor error occurs when volume is overestimated by 20% and the percent of cold starts is in error by 50%. The maximum HC error is 59%, and the maximum CO error is 98%. The maximum NO_x emission factor error of 26% occurs when volume is overestimated by 20% and cold starts are underestimated by 20%.

The sample of cases having cold-start error of 50% was small, so both underestimated and overestimated cases were combined. It is probable that error resulting from a larger sample of cases having either 50% overestimated or 50% underestimated cases alone may be higher than the error computed when all 50% cases are combined. Therefore, worst-case error would probably occur for cases with 50% overestimated or underestimated cold-start error.

3. Conclusions

As was seen in the preceding sections, emission factor error introduced by error in some input parameters can be appreciable, particularly for HC and CO. There is considerable variation between pollutants as to the magnitude of error produced by various input parameter errors and as to what value or pair of values of input parameter errors produce a given level of emission factor error. As in the FTP model analysis, an arbitrary value of emission factor error (20%), was selected as a threshold error value. Table 23 shows what values of input error will produce emission factor error exceeding the threshold value.

For HC and CO, 10% cold-start error does not exceed the threshold, but for the most part, 20 and 50% cold-start errors do exceed it. However, as much as 50% cold-start error does not produce more than 20% NO_x emission factor error. The preceding sections showed that error in temperature produces negligible emission factor error.

For HC, any of the chosen values of cold-start error in combination with at least one of the volume error classes exceeds the threshold, and vice versa. There are even fewer combinations of error classes that do not produce more than 20% CO emission factor error. NO_x emission factor error is less than 20% for most combinations of error classes, except for those with 20% volume error.

Table 23

INPUT PARAMETER ERROR VALUES THAT CAUSE MODAL EMISSION FACTOR ERROR TO EXCEED 20%

Pollutant	Error in Cold Start (%)				
	+10	-10	+20	-20	±50
HC			X		X
CO			X	X	X
NO_x					

Pollutant	Error in Cold Start (%)	Error in Volume (%)					
		+5	-5	+10	-10	+20	-20
HC	+10			X		X	
	-10						X
	+20	X		X		X	
	-20				X		X
	±50	X	X	X	X	X	X
CO	+10	X		X		X	
	-10				X		X
	+20	X	X	X	X	X	
	-20		X		X		X
	±50	X	X	X	X	X	X
NO_x	+10						X
	-10					X	
	+20						X
	-20					X	
	±50					X	

VIII EVALUATION OF OTHER TYPES OF SOURCES OF EMISSIONS

A. Fugitive Dust

Fugitive dust is perhaps the most difficult type of emission to quantify. Midwest Research Institute (Cowherd and Guenther, 1976) compiled the inventory for the following sources: (1) unpaved roads, (2) agricultural land tilling, (3) wind erosion of agricultural land, (4) construction sites, (5) aggregate storage piles, and (6) unpaved airstrips. Rockwell International (Littman and Isam, 1977) has estimated fugitive dust emissions from paved roads.

For each of the over 2000 area sources, data were compiled on annual emissions of fugitive dust. Hourly apportioning factors were derived to account for emission variations by hour of the day, day of the week, and season of the year. Total particulate emissions (particles smaller than 30 μm) from categories (1) through (6) listed above, were about 1,183,000 tons/year. It was assumed that 20% of the emissions involved particle sizes smaller than 5 μm. Therefore, for these smaller particles, TSP emissions are about 237,000 tons/year. (The fugitive dust estimated in Table 1 include all particle sizes.)

As can be seen in Table 1, fugitive dust emissions dominate the particulate inventory. Dust from unpaved roads and wind erosion of agricultural land is the major source of fugitive dust emissions.

Midwest Research Institute (MRI) estimated relative errors for each of the source categories. These are represented in Table 24. These errors, corresponding to a 90% confidence level, were determined by a progressive analysis of errors associated with each calculation step. One could conclude that estimates for paved roads should be somewhat better than those for unpaved roads. Traffic volumes and vehicle speed should be much better known for paved roads. In view of all the uncertainties, the estimates in Table 4, appear somewhat optimistic, particularly for the "hourly adjustment factors."

Table 24

MRI ESTIMATES OF FUGITIVE DUST INVENTORY ACCURACY
(Estimated Relative Error)

Source Category	Source Extent	Corrected Emission Factor	Hourly Adjustment Factor
Unpaved roads	±5%	±20%	±15%
Agricultural tilling	±15%	±30%	±20%
Wind erosion	±30%	±20%	±15%
Construction	±35%	±30%	±20%
Aggregate storage	±25%	±30%	±20%
Unpaved airstrips	±15%	±25%	±20%

In general, the fugitive dust inventory is probably somewhat less accurate than those inventories that depend on fuel consumption data. Furthermore, information on the size distribution from fugitive dust sources is virtually nonexistent. Some field data should be collected to (1) give breakdowns by particle size and (2) verify assumptions inherent in the MRI methodology.

B. Aircraft

The aircraft emission inventory was developed by GCA Corporation (Patterson et al., 1974). Even in the Lambert Field area, aircraft (and support vehicles) account for only modest emissions of the criteria pollutants. The maximum emissions found in any grid within the Lambert Field vicinity is 793 tons per year of carbon monoxide (grid 523). Emissions for the other pollutants were less. For the area as a whole, aircraft emissions account for a very small portion of the emissions burden (less than 1%).

Sources of emissions include airctaft operation, engine maintenance testing, ground support vehicles, and fuel storage and handling. Three types of airports were considered: municipal, military, and civilian. For each airport, the number, type, and operating patterns of the aircraft were considered. Ground support vehicle and fuel handling emissions are related to the volume and type of aircraft activity at each airport. GCA applied aircraft emission rate data which was compiled by Cornell Aeronautical Laboratory. These data are summarized in AP-42. Various modes of aircraft operation were considered: idle, taxi, take-off, landing, climb-out, and approach.

The number and type of aircraft operating out of each airport is fairly well known. For Lambert Field, scheduled airline data are known accurately. GCA gathered data from the Official Airline Guide, the Federal Aviation Authority, and the airport managers office. Similar data are available from other airports. The number and types of sources generally are quite well known. The validity of the emission factors would appear to be the most questionable item.

In general, the aircraft sources are specified with better accuracy than other mobile sources, with the possible exception of railroads. For our purposes, we will assume negligible bias and a precision of unity.

C. Off-Highway Mobile Sources

The off-highway mobile source emission inventory was compiled by Rockwell International (Littman and Isam, 1977), using in part methodologies developed by Hare and Springer (1974). Six categories have been calculated for the 1989 RAPS grid squares. These categories included: motorcycles, lawn and garden equipment, industrial equipment, construction equipment, farm equipment, and outboard motorboats. From Table 1, it can be seen that all categories, except motorcycles, account for modest quantities of pollutants (CO, NO_x and HC) normally attributed to mobile sources.

Temporal apportionments were made on the basis of seasonal activity and normal daily operating estimates. Emissions were distributed uniformly over the operating period. For instance, industrial equipment was assumed to operate year round from 8:00 a.m. to 6:00 p.m.; lawn and garden equipment was assumed to operate from April through September, 9:00 a.m. to 7:00 p.m.

The primary problem is lack of accurate background data on which to base emission calculations. Although emission factors are known to be within typical precisions (0.1 to 0.3), the number, type, and operating patterns of most off-highway equipment are not known well. Each type, except motorcycles, are considered separately below.

1. Lawn and Garden Equipment

The lawn and garden equipment category includes riding mowers, walking mowers, garden tractors, and motor tillers. There are registration data to quantify numbers of these devices. Therefore, Rockwell acknowledges that emission figures at the grid level are meant solely to give an "order-of-magnitude" calculation.

The emission estimates were based on U.S. Census data on the distribution and types of houses, emission factors, an assumed linear correspondence between one-unit housing structures and small utility engines, and a seasonal utilization factor. While this approach does serve to quantify emissions, the bias and precision could be quite high. In absence of any verification data, we will assume a bias of 0.5 and precision of 2.0.

2. Construction Equipment

The major sources of data on construction equipment are national figures on units shipped per year, annual usage, total horsepower in use, load factors, and duty cycles. Rockwell apportioned national data to the RAPS area based on a ratio of national-to-state construction volumes and state-to-county populations.*

Composite nationwide emission factors for an assumed distribution for each of ten construction categories were compiled for the nation as a whole and then apportioned to the RAPS area in the manner based on a ratio of national-to-state construction volumes. Grid emissions were

*Illinois and Missouri construction volumes were not available by the county.

based on a ratio of grid construction acreage to county construction acreage. The accuracy of the construction inventory should be comparable to that for lawn and garden equipment.

3. Industrial Equipment

The industrial equipment category includes fork lifts, utility carts, small tractors and wheel loaders, quarrying machinery, portable generators, and so forth. Rockwell categorized these devices into small-utility and heavy-duty engines. The methodology for industrial equipment is similar to that used for construction equipment. National emissions data serve as the starting point. County emission estimates were derived from a ratio of national industrial activity to county industrial activity. Grid apportionments were based on locations of industrial plants on a grid basis. Again, accuracies are probably comparable to the other off-highway mobile source inventories.

4. Farm Equipment

Farm equipment includes farm tractors, garden tractors, self-propelled combines, forest harvesters, balers, irrigation pumps, and auxiliary engines. Background data on equipment population was available through 1969 Census of Agriculture estimates. Based on EPA usage estimates and emission factors, county emissions were compiled.

Emissions were then appropriated by grid based on farm acreage data prepared by MRI in compiling the fugitive dust inventory. In general the farm equipment inventory is more accurate than the construction and industrial equipment inventory.

5. Outboard Motorboats

From Table 1 it can be seen that emissions are modest for two pollutants (HC and CO) and negligible for others. Emission factors are low for typical outboard operation because a certain portion of the exhausts are removed in the water (exhaust outlets are normally below water level). Boat registration data was the basis for calculations. Annual usage and EPA emission factors were applied to compile the regional inventory. Spatial apportionments were made on the basis of navigable water ratios (county-to-state, grid-to-county). The accuracy of this inventory is about the same as that for industrial equipment.

6. Summary

As stated in the Rockwell report, this inventory provides "order-of-magnitude" estimate only. Also, the applied background data in many cases is several years old. Therefore, the overall accuracy is much a question mark. For our purposes, we will assume an overall bias of ±0.5 T and precision of 2.

D. River Vessels

Emissions from river vessels are dominated by towboat traffic. Estimates of emissions from towboats have been prepared by the Department of Transportation (Sturm, 1976). As shown in Table 1, emissions from river vessels are almost insignificant, accounting for less than one percent of the total. The DOT report accurately quantifies the yearly estimates, based on current emission factors. However, the report concludes that hourly emissions are not worth the effort to accurately quantify, given their low contribution to the total. Therefore, in this report, we will assume a bias of T and coefficient of precision of 2.

E. Railroads

Railroad emissions are more substantial than river vessel emissions, but do not contribute signficantly to the total. They are large enough to be observable locally in the vicinity of railroad tracks during active periods. Railroad emissions were compiled by Walden Research (Wiltsee et al., 1977). Walden developed separate methodologies to compile emissions from two types of rail activity: line-haul operations and switch yard activity. The study inventoried emissions only from diesel locomotive operations since other type emissions were deemed insignificant.

Features of the Walden methodology include:

- Department of Transportation (DOT) compilations of:
  - Routing, runtime, and locomotive information for each train in the study area
  - Total active and idle hours and locomotive information for each rail yard in the AQCR
  - Interyard transfer routing and runtime.
- A system of links simulating the rail network.
- Classification of locomotives into the five engine categories specified in AP-42.
- Derivation of active and idle load factors for switch and road locomotives.
- Characterization of a "typical" transfer engine used in the St. Louis AQCR.

In general, the Walden methodology appears thorough in estimating annual emissions and spatial apportioning. The main inaccuracy appears to be that of time distinction. In general, this problem could be overcome by collecting minimal data on diurnal variation. On an annual basis, the railroad inventory should be somewhat better than conventional highway sources. For our purposes, we will assume that bias is negligible and coefficient of precision is 0.75.

F. Separation of Hydrocarbon Emissions into Classes

Once total hydrocarbon emissions were determined for each source, a classification scheme was applied to estimate the proportion of these emissions contributed by the following classes: nonreactive, paraffins, olefins, aromatics, and aldehydes (Griscom, 1977). Emission factors by hydrocarbon type were established for each source category. These factors were based on an earlier study which consisted of compositional analyses on organic emissions in Los Angeles (Trijonis and Arledge, 1975). As Rockwell noted, there were three limitations in applying the Los Angeles results to St. Louis:

(1) The classification scheme (e.g., olefins) required for RAPS was somewhat different than that used in the Los Angeles study.

(2) The compositions of petroleum products and solvent usage may be different between Los Angeles and St. Louis.

(3) Certain source types existing in St. Louis were not considered in the Los Angeles study.

In spite of the above limitations, Rockwell was able to make some reasonable assumptions by augmenting the Los Angeles results with those from a host of other studies. (See the Griscom report, 1977, cited above.)

For point sources, emission factors, by hydrocarbon type, were developed for each SCC. Area sources were generally described according to the source types listed in Table 1. One exception is the highway sources, which were separated into LDV, HDG, and HDD classes. (Separate factors for exhaust and evaporative losses were used for LDV and HDG.) The accuracy of the emission factors, by hydrocarbon class, cannot reliably be estimated since verification data are not available. In view of the limitations stated above and assumptions made in both the Griscom and Trijonis studies, it is clear that the accuracy in the emission estimates by class is substantially less than that for total hydrocarbons.

IX COST BENEFIT ANALYSIS

The lack of field validation data precludes a completely objective analysis of cost and benefits. However, based on the background and information presented in our previous discussion on bias and coefficient of precision, we can make some relative estimates. These estimates in turn, can be used to provide insight on (1) the effectiveness of monies already spent and (2) where future improvements can best be applied.

The emissions inventory is summarized in terms of: emission totals, estimated accuracy, and costs. The totals are derived from Table 1. The estimated accuracy relates to combined coefficient of precision and bias estimates previously discussed in the various emission evaluations. The cost estimates were provided by EPA.* The total inventory budget, exclusive of the data handling system, was about $870,000. This was divided as shown in Table 25.

The classification of the inventory by pollutant is shown in Table 25. Exclusive of TSP, the point source inventory made up 49.8% of all the totals; the highway inventory made up 37.9%; and so forth. The accuracy ranking shows that by far the point source inventory is the most accurate with an average coefficient of precision-bias of 0.275. (This may be taken generally to be the sum of the estimated coefficient and one-half the bias.) The most outstanding figure corresponds to the accuracy of the highway (mobile source) inventory. It is about the same as it is for those inventory types (airports, railroads, and so forth) contributing much less to the total inventory budget. This is the most outstanding inconsistency in the accuracy of the inventory. (Accuracy should be proportional to percent of the emission inventory budget.)

---

*Masser, C. (private communication, July 1977).

Table 25

INVENTORY SUMMARY: TOTALS, ACCURACY, AND COST

Inventory	Percent of Total Emissions						Accuracy Ranking							Percent Cost
	SO_x	NO_x	CO	HC	Particulate*	$(Avg)_4$†	SO_x	NO_x	CO	HC	Particulate*	$(Avg)_4$†	Order‡	
Point Source	96.7	69.6	9.7	23.3	3.3	49.8	0.20	0.30	0.30	0.30	0.30	0.275	1	44.4
Highways	0.3	17.5	78.9	54.8	0.5	37.9	1.0	1.0	1.0	1.0	1.0	1.0	4	25.3
Stationary, residential and commercial	2.5	3.0	0.9	10.7	0.5	4.3	0.75	0.95	0.95	0.95	0.95	0.90	3	6.9
Stationary, industrial	--	--	--	--	--	0.0	--	--	--	--	--	--	--	2.6
Off highway mobile	0.2	6.0	9.9	8.0	0.2	6.0	2.0	2.0	2.0	2.0	2.0	2.0	--	4.6
Railroads	0.2	2.9	0.3	2.1	0.1	1.4	0.75	0.75	0.75	0.75	0.75	0.75	2	2.9
River vessels	--	0.8	0.1	0.3	--	0.3	2.0	2.0	2.0	2.0	2.0	2.0	5	2.9
Airports	--	0.1	0.2	0.7	--	0.3	1.0	1.0	1.0	1.0	1.0	1.0	4	7.5
Fugitive dust	--	--	--	--	95.4*	--	--	--	--	--	--	--	--	3.4

*For information only; these figures are not used in calculating averages.

†$(Avg)_4$ denotes the average of the four gaseous pollutants (SO_x, NO_x, CO, and HC).

‡The inventories (e.g., point source, highways) are ordered from 1 to 5 from the most accurate to the least accurate.

To an extent, the same type of inconsistency appears in the percent cost category. For the smaller inventories, anywhere from 3.4 to 6.9% of the budget was expended. This is reasonable since it requires a minimal amount (about $30,000) to quantify any of these smaller inventories. Although their individual contributions might be negligible, this would not be known until the study has been completed. The highway inventory, however, constitutes almost 40% of the emissions budget (excluding TSP), but only about 25% of the cost budget. If we are to assume that the accuracy of the point source inventory is adequate, than a similar accuracy should be the goal of future highway inventories.

X EFFECTS OF EMISSION PARAMETER INACCURACIES ON AIR QUALITY MODEL PREDICTIONS

The objective of the analysis in this section is the characterization of the effects of emission parameter errors when they are used as input to air quality simulation models. In the analysis to follow, steady-state Gaussian diffusion models are used. Of course, the final RAPS models will be more sophisticated. However, the results generated herein are easily extended to these more sophisticated models within the accuracy constraints of the analytical techniques applied.

A. Quantification of Errors in the Meteorological Input Parameters

One of the primary objectives of this work was to determine the sensitivity of the air quality model output as a function of various emission inputs in relation to the sensitivity as a function of the meteorological input parameters. Quantifying potential sources of error in this relative manner allows the air-quality modeler to gain a better understanding of the limitations on model performance and identifies those types of input data that need to be improved.

The air quality model output X can be represented as some function of emissions input Q and meteorological input G. Thus,

$$[X]_{t,s} = f\left\{(Q)_{t,s}\ ,\ (G)_{t,s}\right\} \tag{25}$$

where X, Q, and G are vectors in time (t) and space (s). Any element in the X array is sensitive to variations of any element in both Q and G arrays and to errors in the measurement of these elements. In this section we examine the accuracy of measuring the meteorological elements that are used to derive meteorological input parameters for the models.

In the sensitivity analyses to follow, Gaussian plume models are used. Accordingly, our discussion here relates to input parameters for Gaussian plume models. However, we do not imply here that the Gaussian plume formulation will appear in the final versions of any of the RAPS models. In fact, a RAPS modeling objective is to improve on the Gaussian model. Nevertheless, we believe that the utility of the formulation in our sensitivity analysis will produce representative values.

Most Gaussian plume models that are used to analyze pollutant concentrations in an urban environment require the following meteorological parameters as input:

- Wind speed and direction
- Diffusion parameters, both crosswind (σ_y) and vertical (σ_z)
- Vertical mixing ceiling (height).

Major differences among model applications pertain to the degree of detail of meteorological input data and the averaging time periods of the data. For example, whereas some models hypothesize the existence of mean meteorological conditions, others use the joint frequency distribution of meteorological parameters, including wind direction, speed, and stability class. At least one model (APRAC-1A) uses wind data from airport weather stations and estimates mixing layer ceilings from the nearest radiosonde data and maximum afternoon temperature.

The meteorological measurements needed to determine the meteorological input parameters in air quality models may be listed as:

- Wind speed and direction
- Solar radiation
- Cloud cover and types
- Vertical temperature profiles/height of mixing layer.

As mentioned earlier, the wind measurements are used directly as input parameters in the air quality models; other parameters are derived. The accuracy and variations of wind consequently have a direct bearing on the performance of air quality models.

The airflow over a metropolitan area is a critical factor in air quality since it is the medium that transports many effluents. Also, transport occurs throughout the depth of mixed layer; therefore, wind through the planetary boundary layer, rather than only the surface wind, is a relevant parameter. The variations of wind over the RAPS area have been verified by special field experiments. It has been found that:

- Airflow over RAPS area is modified to heights well above 300 meters.
- Wind speeds, varied by 20 to 30%, and wind direction by 20 to 30 degrees near the metropolitan area (Ackerman, 1974).

These findings have a significant bearing on the sensitivity analysis of air quality models. If the accuracies of wind measuring instruments and of pilot balloon observations are considered, the complexity of performing the analysis becomes more evident. For example, it is very difficult to predict the accuracy obtainable from a pilot balloon ascent in which the most important source of error is the uncertainty in the rate of ascent of the balloon. Even if two theodolites are used, no great precision should be expected, and it has been estimated that even the best observations at low altitudes do not give a true wind more closely than ± 2 degrees in direction and ± 1 mps in speed (Middleton and Spilhaus, 1953). These errors are comparable to those that occur in surface-based instruments, especially the errors in measuring the direction.

The mixing ceilings are estimated from vertical temperature profile measurements. The instruments used to measure temperatures at network sites, because of their limited range, are inadequate for this purpose. If radiosonde temperatures are used (as in the case of APRAC-1A), then errors in measurements can play a significant role in the prediction of concentrations. Errors caused by lag of a radiosonde thermometer at 300 m range from 2°C to 7°C as reported by Middleton and Spilhaus (1953, Figure 185).

The estimated diffusion parameters that depend on measurements of solar radiation and observations of cloud cover can be affected not only by instrumental errors, but also by human errors in estimating cloud cover. Other techniques of estimating these parameters depend on wind or temperature measurements, and they are sensitive to those errors just described above.

The meteorological network and instruments used in the RAPS study are described by Myers and Reagan (1975). Besides air quality measurements made at 25 sites, meteorological measurements were also made as part of the data base for the modeling work. In addition, solar and sky radiation, temperature gradients, and turbulence measurements were made at some sites.

For the radiation measurements, comparisons were made between urban and rural, and upwind and downwind. For the turbulence measurements, values were obtained for different types of surface roughness and thermal characteristics. The vertical temperature difference between 5- and 30-meter levels was measured. Table 26 shows some of the pertinent characteristics, including accuracy, of the instruments used for measuring meteorological elements. In addition to the measurements made at the network of stations, special upper air observations were made by pilot balloon and radiosonde techniques.

B. Case Study for a Single Point Source

Prior to considering the RAPS emission inventory as a whole, a single source sensitivity analysis is presented. The purpose of this analysis is to demonstrate how input data errors change the magnitude and spatial distribution of the predicted air pollution concentrations. This insight will facilitate the interpretation of the regional sensitivity analysis to follow.

1. Problem Formulation

A case study was conducted for one of the Union Electric power plants in St. Louis. The Sioux power plant was selected because its stack flow maximum values are similar to those of a TVA plant for which more complete characteristics are available. A steady-state Gaussian plume model was used to calculate SO_2 concentrations downwind of the

Table 26

CHARACTERISTICS OF METEOROLOGICAL MEASUREMENTS AT 25 SITE LOCATIONS IN RAPS AREAS

Meteorological Element	Manufacturer	Range	Starting Threshold (i,e., sensitivity)	Accuracy	Remarks
Wind speed	MRI	0 to 22 mps	0.22 mps	±0.17 mps or 1% whichever is greater	Range in specific instances is not adequate because winds in excess of 25 mps occur in St. Louis
Wind direction	MRI	0 to 540 deg	0.3 mps	±2.5 deg	
Temperature	MRI	-20 to +50°C	--	Not known	
Temperature gradient	MRI	-5 to +5°C	--	Not determined	Subject to excessive drift and malfunction
Dew point	EG&G	-40 to +50°C	--	1°C, normal	Meaningful data for only 30 to 40% of the time
Solar radiation	Eppley Lab	0 to 4 cal cm^2/min	--	--	
Turbulence	R. M. Young Co.	0 to 22 mps	0.22 mps	--	Operated only during intensive field investigations of RAPS
Pressure	MRI	914 to 1067 mb	<0.2%	0.02%	

Sioux plant for various perturbations in meteorological and emission inputs.

In the Gaussian formulation, the ground level concentration (χ) is:

$$\chi = \frac{Q}{\pi \sigma_y \sigma_z U} \exp - \frac{1}{2} \left[\left(\frac{y}{\sigma_y} \right)^2 + \left(\frac{H}{\sigma_z} \right)^2 \right] \qquad (26)$$

where:

U = the mean wind speed, which will be allowed to vary between 2 and 8 m/s

σ_y, σ_z = the Pasquill (Slade, 1968) horizontal and vertical dispersion coefficients, a function of downwind distance and stability class

y = the lateral distance to the plume centerline

Q = the source strength

H = the effective plume height

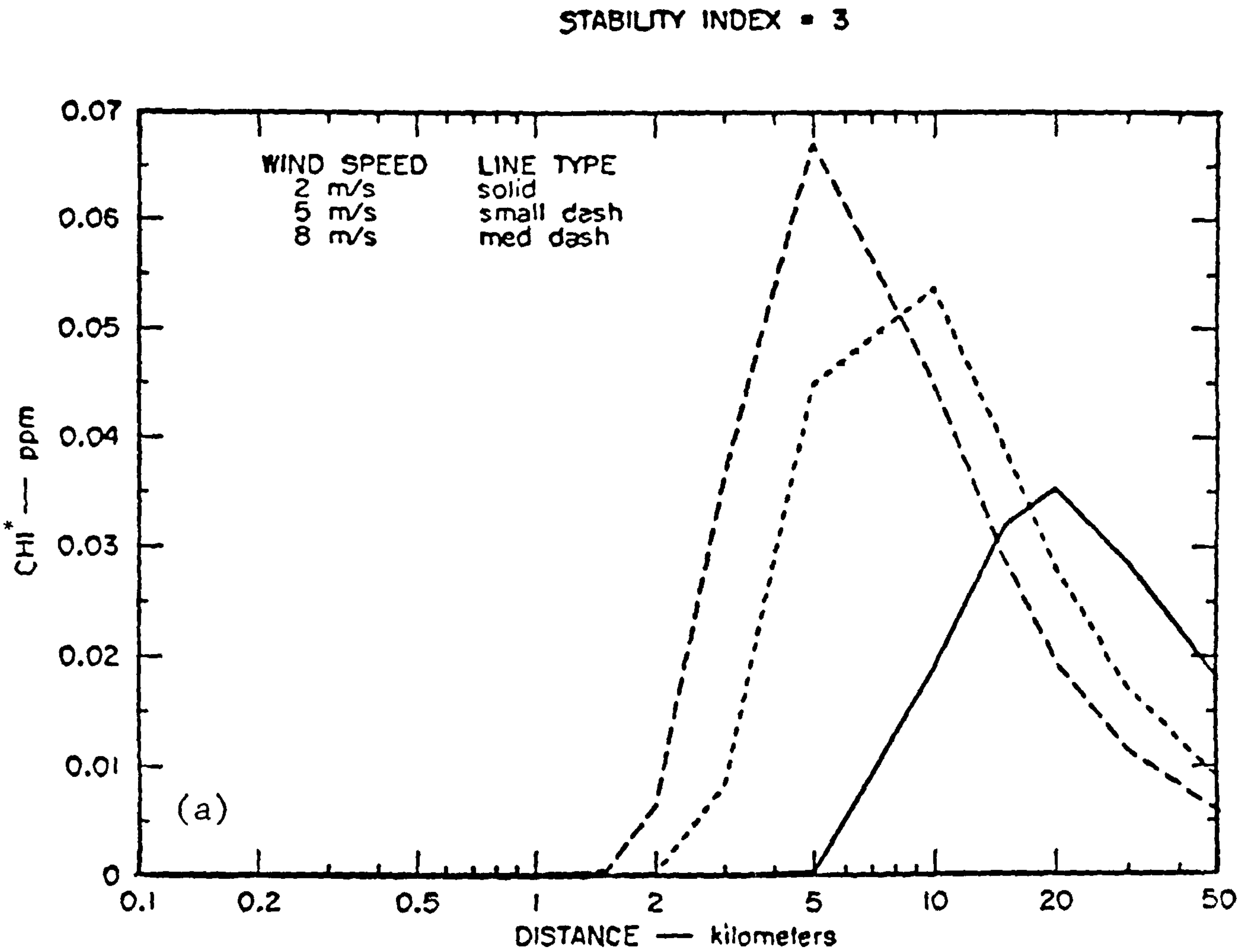
The plume rise is a function of the stack flow parameters (exit velocity and temperature) and the prevailing atmospheric conditions. The plume rise formulas chosen were proposed by Briggs (1971, 1972) and are currently being used in EPA point source models (Turner and Busse, 1973).

2. Results

The maximum steady-state downwind concentrations for nine different atmospheric conditions are illustrated in Figure 8. The concentrations were calculated for maximum plant capacity (Q = 1760 g/h) and a receptor located in the lateral centerline of the plume (y = 0). Reductions in plant load to half capacity and the effects of the reductions on the downwind concentrations were then calculated for three sets of exit temperature (T_e) and volumetric velocity (V_e) conditions:

(1) Both T_e and V_e were assumed to be unaffected by the load change (i.e., their maximum values were used).

(2) The maximum value for T_e was used; V_e was made directly proportional to the load (one-half maximum in this case). This technique is referred to as the "proposed RAPS" method.



* Note: The Greek symbol, χ, used throughout the text was not an allowable output character in the computer-generated plots for Figures 8, 9, and 10. Hence, the phonetic term "CHI" was used to represent the concentration of SO_2 in ambient air.

FIGURE 8 DOWNWIND CONCENTRATIONS FROM UNION ELECTRIC COMPANY SOUIX PLANT AT VARIOUS STABILITIES

STABILITY INDEX = 4

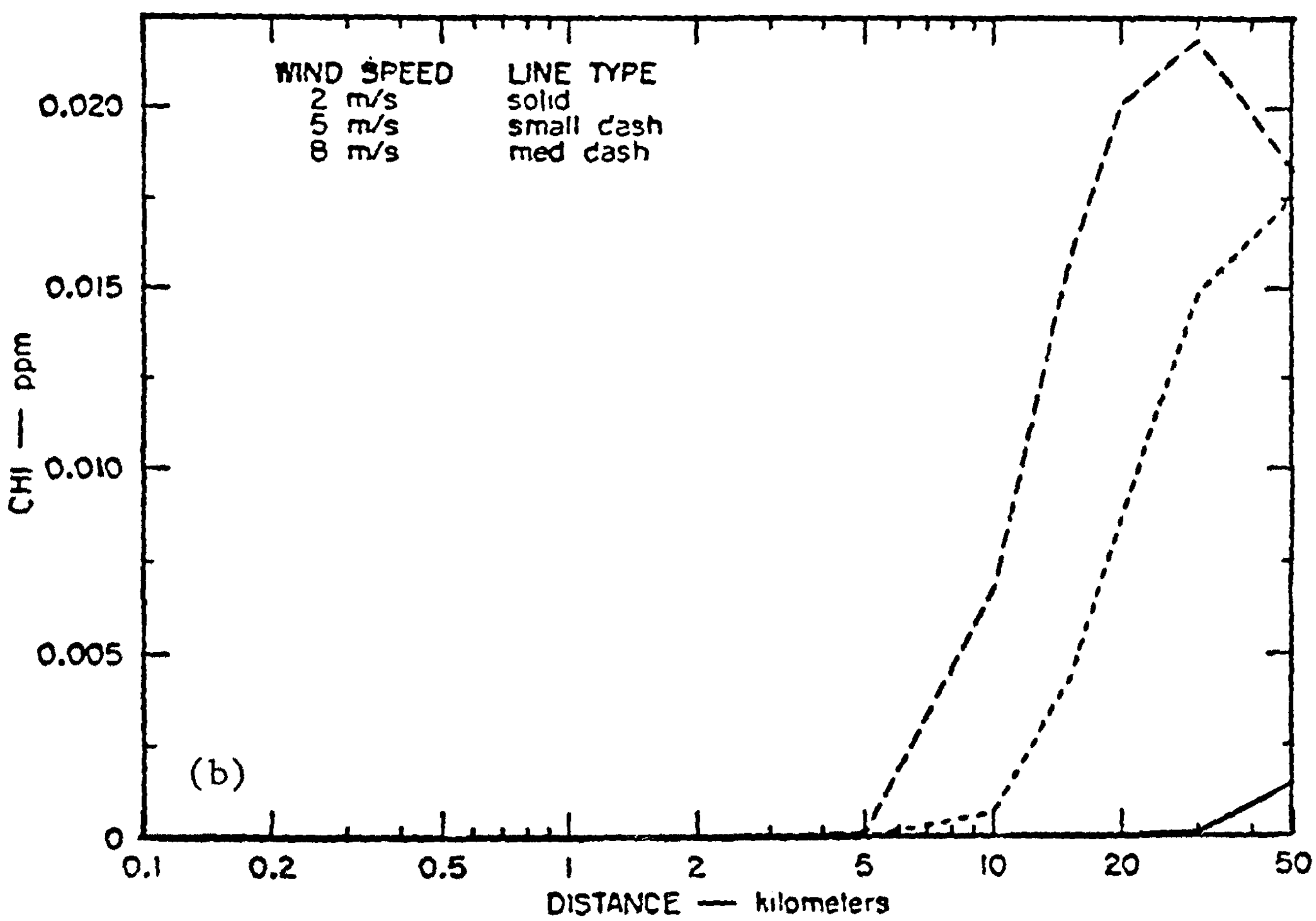


FIGURE 8 (Continued)

STABILITY INDEX = 5

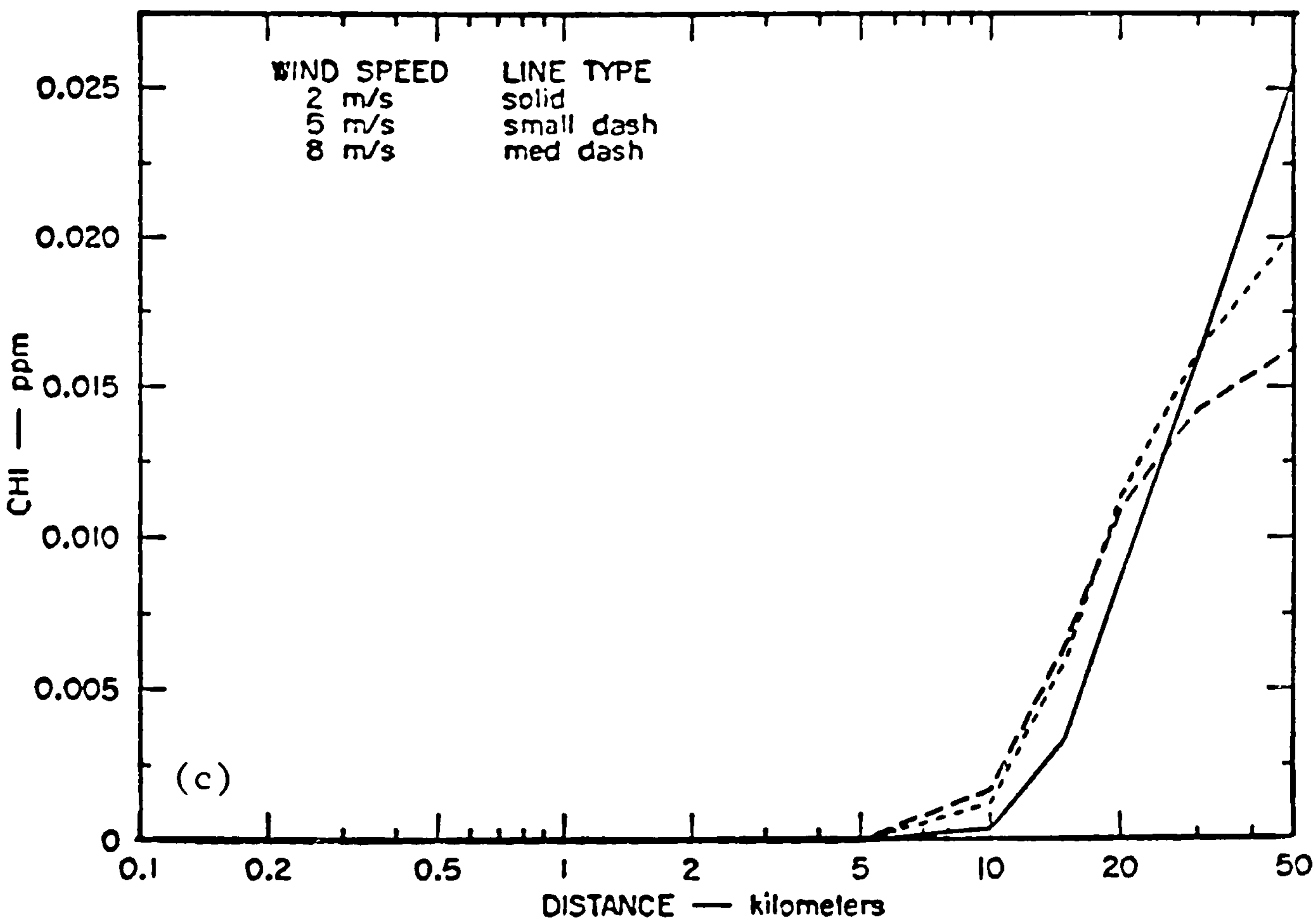


FIGURE 8 (Concluded)

(3) Both T_e and V_e were assumed to follow a relationship of the form A·L + B, where L is the load, and A and B are the proportionality and offset conditions, respectively. The actual numbers were taken from a relationship empirically derived for a similar Tennessee Valley Plant in Kingston, Tennessee (Ruff et al., 1976).

The actual numbers are summarized in Table 27. The Gaussian model was run for a few different atmospheric conditions, using the three sets of flow parameters shown. Figure 9 shows the downwind concentrations that result from different flow parameter selection strategies.

Table 27

FLOW PARAMETERS FOR THREE CASES
(Union Electric, Sioux Plant--50% Capacity)

Case	$V_e(m^3/s)$	$T_e(^oK)$
Maximum	483	435
Proposed RAPS	236	435
Actual (modeled from TVA data)	277	416

Clearly, use of the maximum values provides unacceptable errors of 100% and greater.* The RAPS technique produces maximum errors on the order of 15% for this case. This low figure is a result of offsetting errors, in that T_e is overestimated while V_e is underestimated. If the errors from either parameter are considered separately, the concentration error will increase by a factor of about two.

To place the errors just described in perspective with those of meteorological origin, perturbations in the Gaussian diffusion coefficients (σ_z, σ_y) were considered. These coefficients are generally derived from primary meteorological measurements, such as vertical temperature or velocity profiles, solar raidation and wind speed, or wind fluctuations. While the RAPS data base is rich in such measurements, the current state of the art permits generalizing such measurements into only six broad categories of atmospheric stability. In our analysis, we allow a deviation of one-quarter of the difference between category values as being representative of a coefficient standard deviation (typical error). We feel such an approach in estimating likely errors is a reasonable one and allows for improvements in the technique of estimating such parameters. This statement holds for both the current Gaussian models and the more complex K-theory formulations.

*Errors in the context here are comparable to a standard deviation of calculated values divided by a reference (true) value expressed in percent.

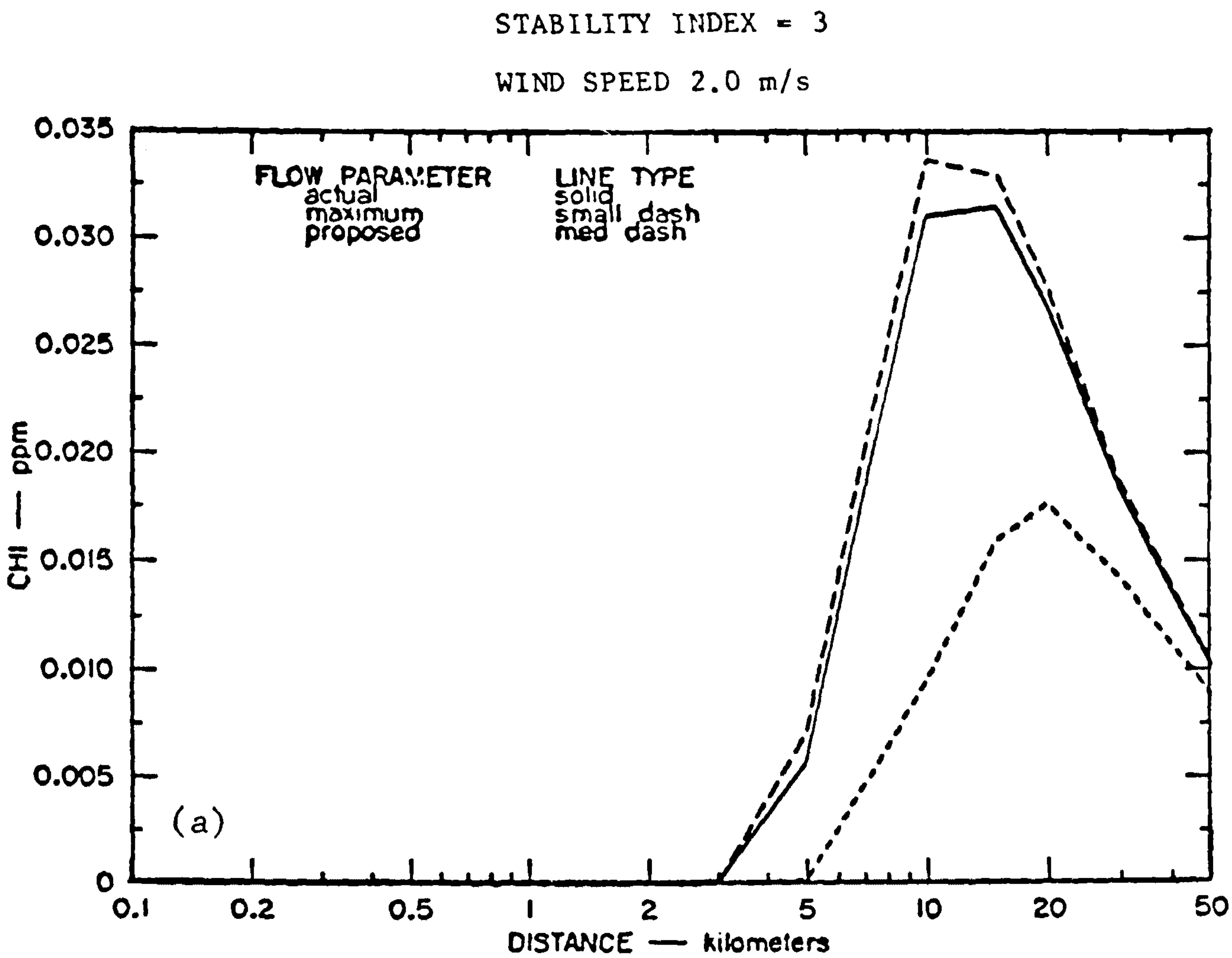


FIGURE 9 SENSITIVITY OF CONCENTRATIONS TO FLOW PARAMETER VARIATION (Souix Plant)

STABILITY INDEX = 3

WIND SPEED 5.0 m/s

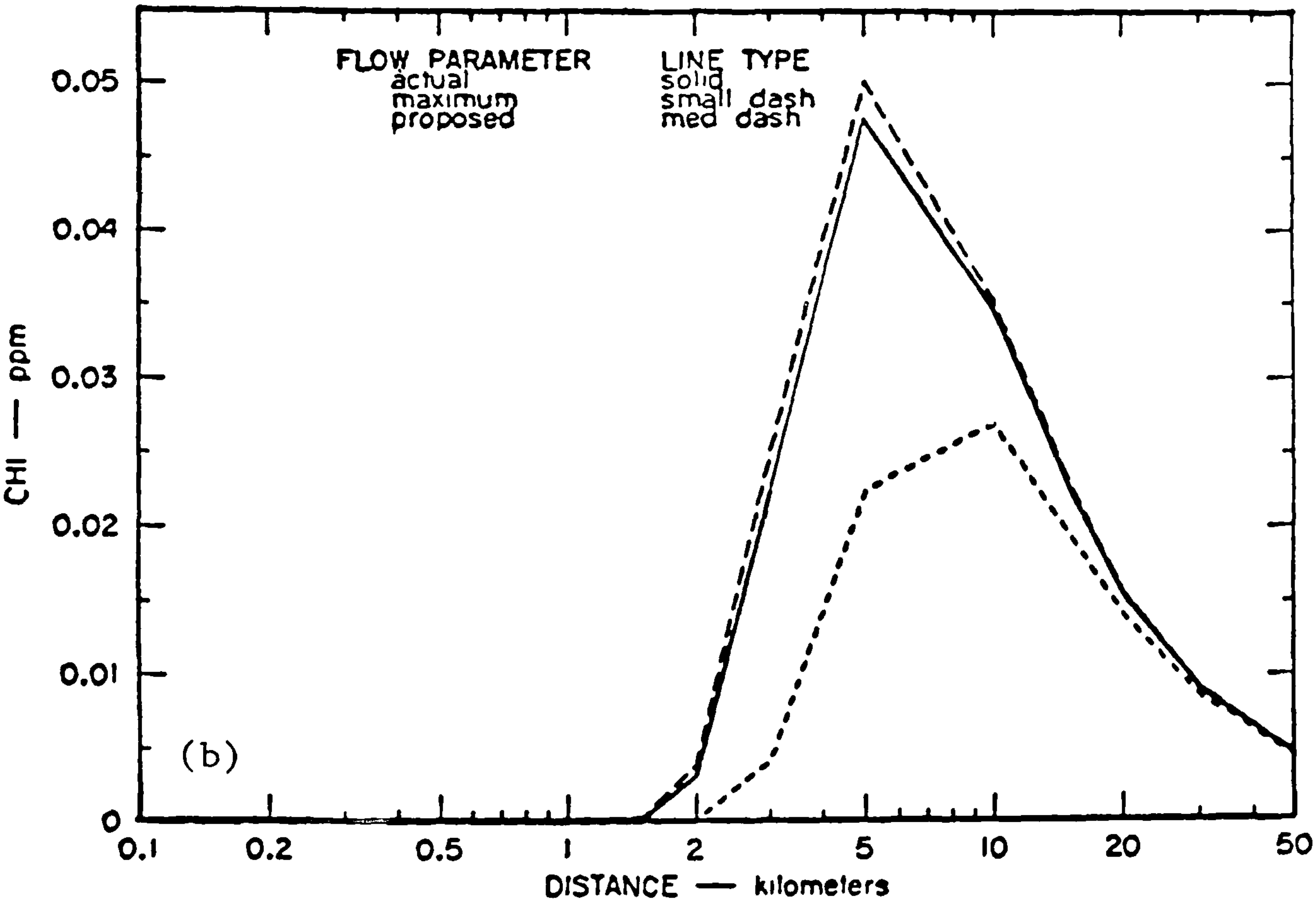


FIGURE 9 (Continued)

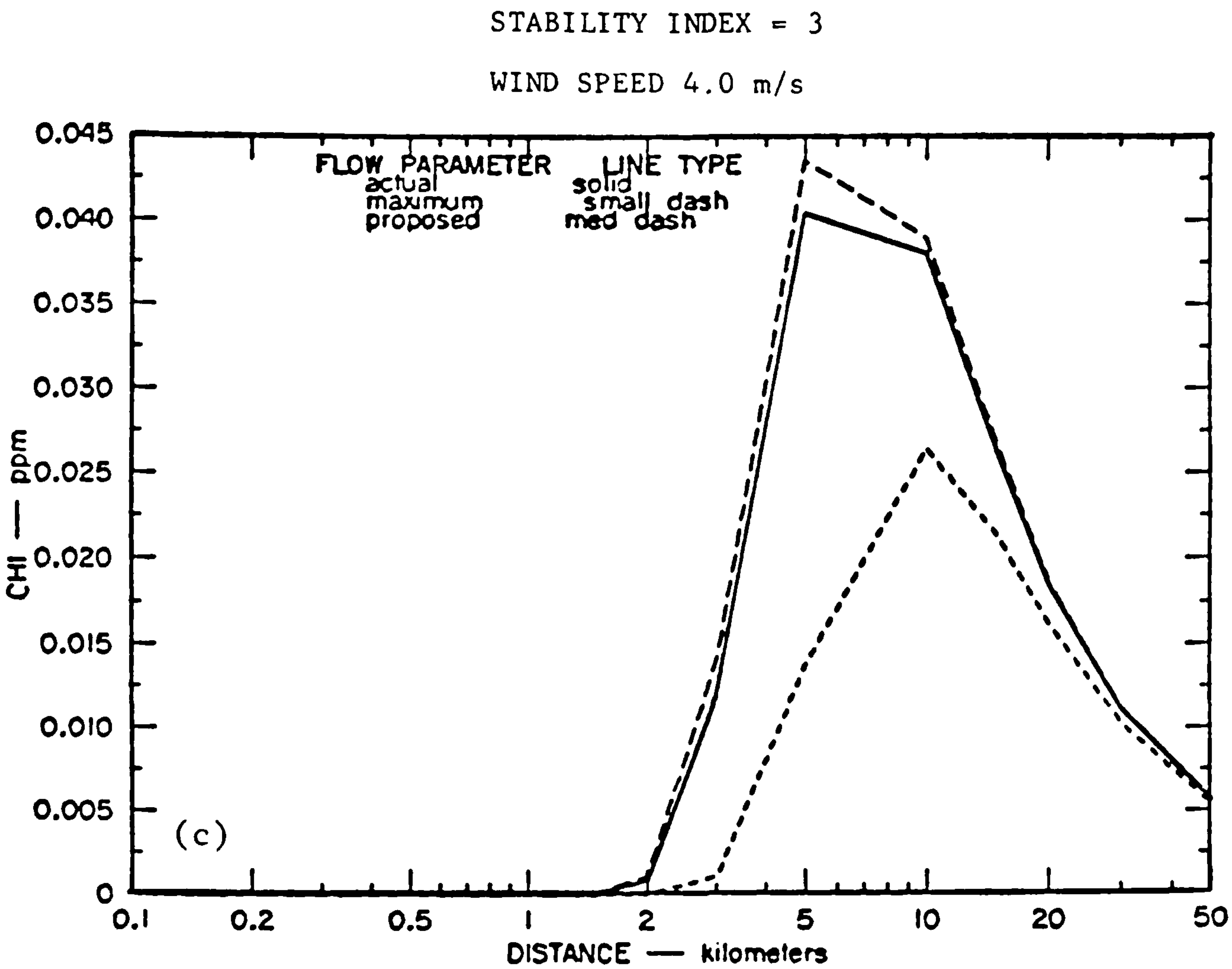


FIGURE 9 (Concluded)

The effect of allowing the Gaussian diffusion coefficients to assume values that deviate from their categorical standards is shown in Figure 10. Consider Figure 10(a): an interpretation is that the true values could correspond to stability indexes of 2.75 or 3.25, which are represented by the dashed lines. However, owing to the inherent limitations in determining the stability class to that precision, those cases would be placed in Class 3 (the solid line). The differences between the dashed and the solid lines are indicative of the errors that result. These differences are quite pronounced in this case.

It should be noted that the accuracy of the stability parameters decreases with the distance from the source. Turner indicated that errors

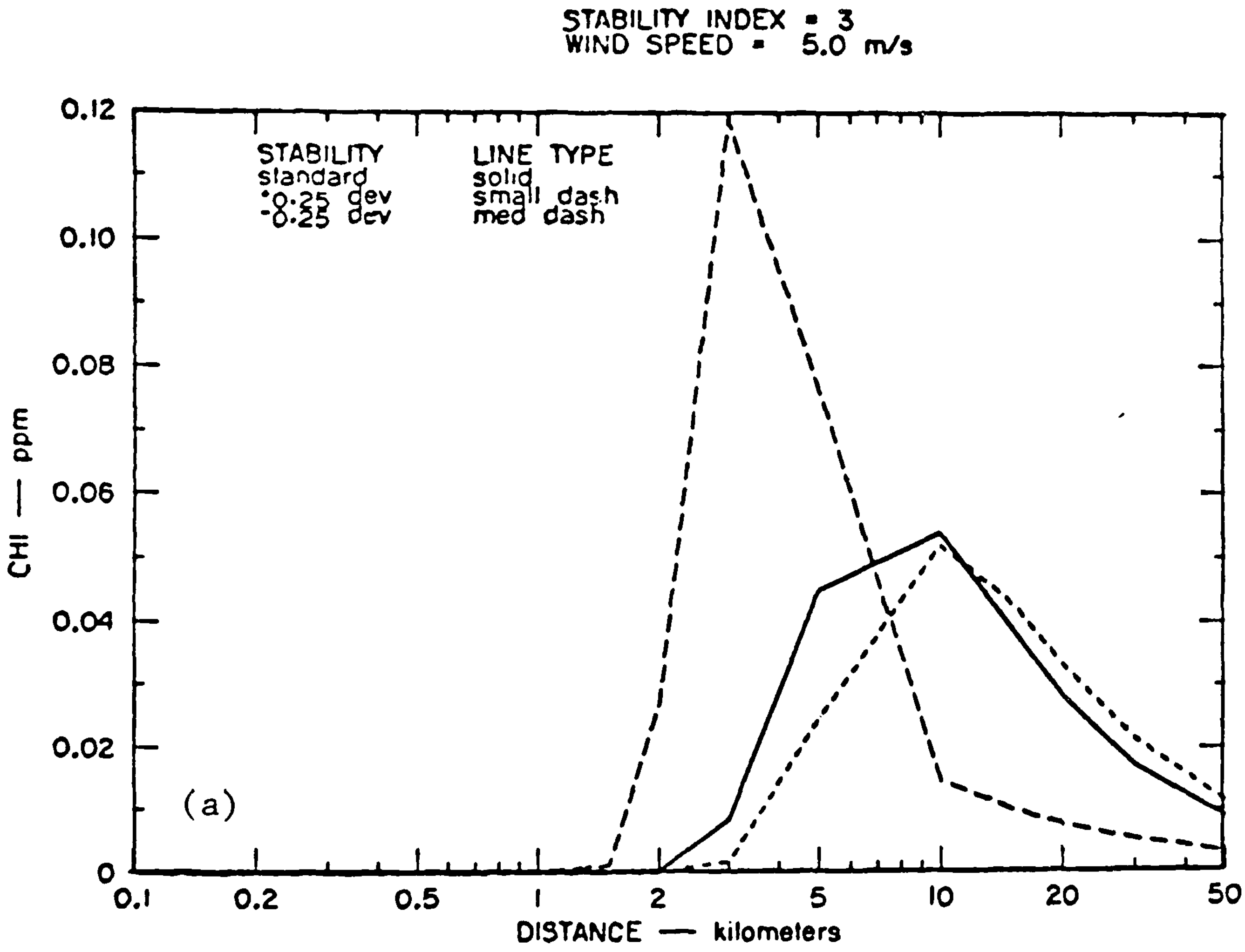


FIGURE 10 SENSITIVITY OF CONCENTRATIONS TO DIFFUSION FLOW COEFFICIENT VARIATIONS (Souix Plant)

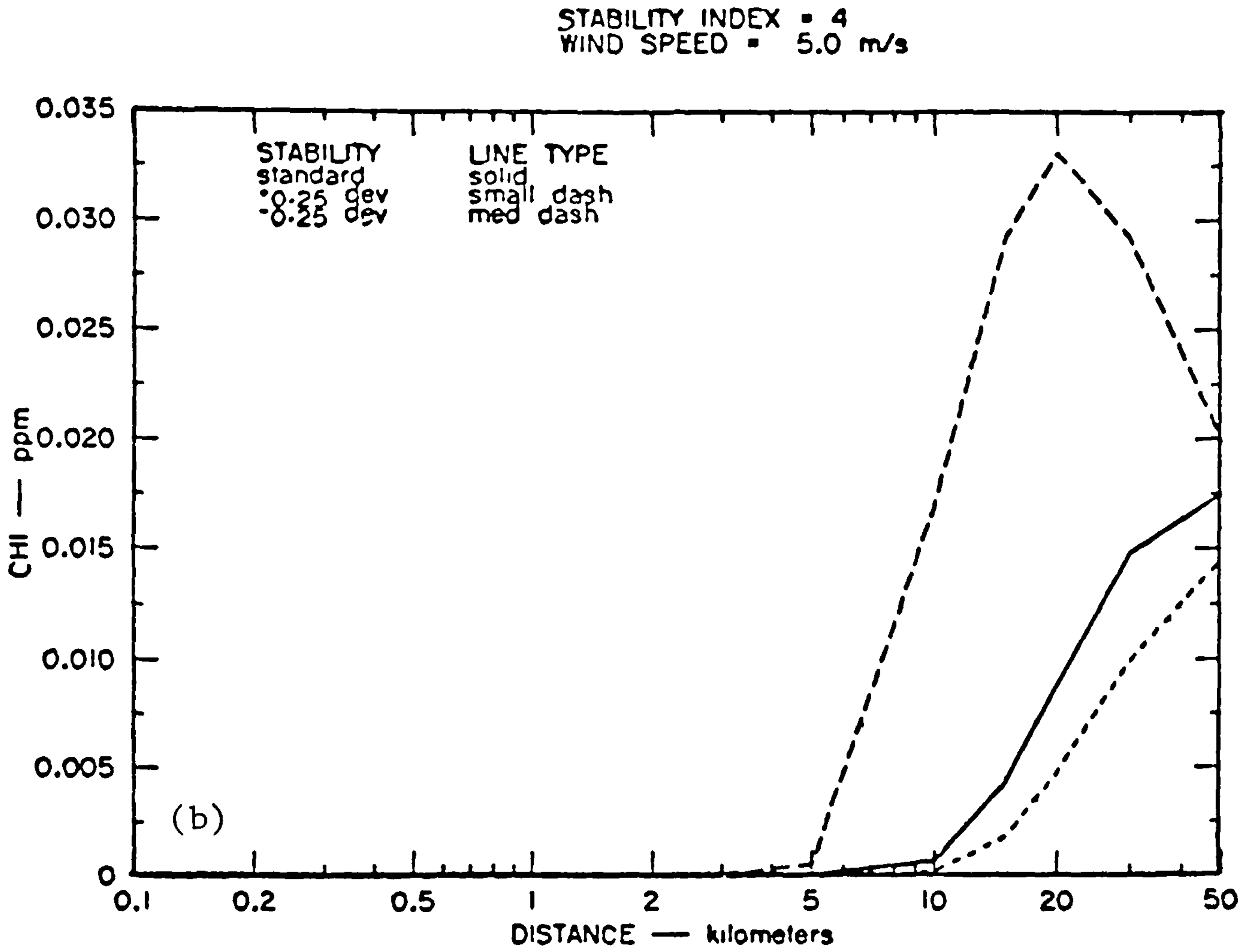


FIGURE 10 (Continued)

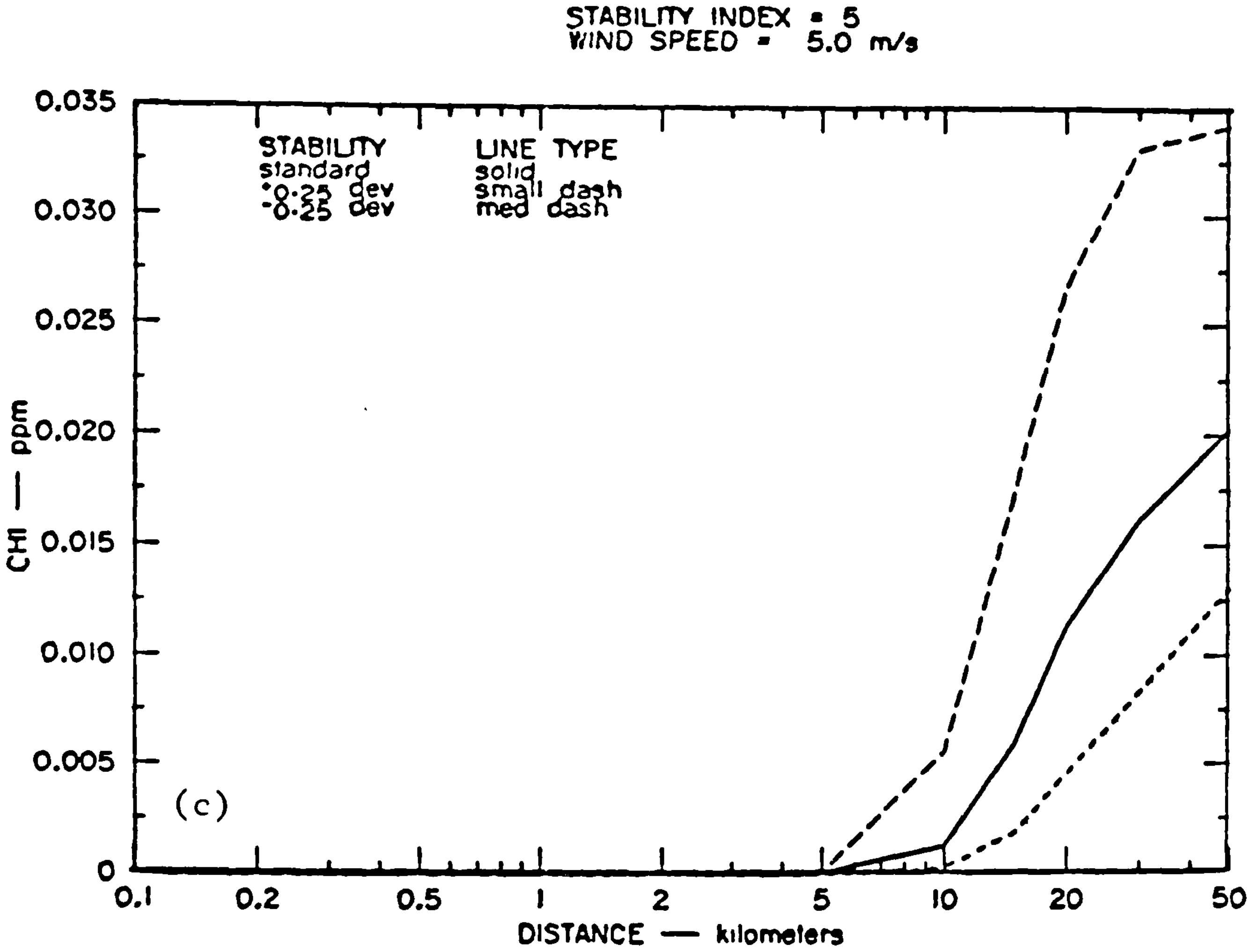


FIGURE 10 (Concluded)

may be severalfold, in some cases reducing to factors of two within a few hundred meters of the source. Our estimates are conservative compared to those of Turner (1970).

The accuracy of the emission factor, on the basis of recent stack tests by Rockwell International appears to be quite good. Littman estimated the standard error at five percent.* The daily fluctuation from the mean of the fuel sulfur content is assumed to be 10% or less.

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*The PEDCO analysis does not support this optimistic figure; however, the Rockwell International stack tests are more current.

This is analyzed and reported on a monthly basis. Therefore, the calculation of the emission parameter, Q is normally within 15% of the actual value.

The approximate errors for the Union Electric Sioux plant are summarized in Table 28. We emphasize that this is a study of only one case for a few meteorological and emission rate conditions. Nevertheless, it illustrates the effects of not altering the flow parameter estimates with varying plant loads. We recommend the use of simple models of the stack exit volumetric flow and temperature. Such models should be based on data from the plants, when available. When the data are not available, the "proposed RAPS" technique of scaling back the volumetric flow with constant stack temperature should be used. By reducing errors in all emission parameters to within 15%, modelers can focus on improvement on the atmospheric portion of the models.

Table 28

TYPICAL ERRORS IN SIGNIFICANT DOWNWIND CONCENTRATIONS

Sensitivity Parameter	Error (%)
Emission rate	15
Flow parameters (maximum values at half capacity)	> 100
Flow parameters (proposed RAPS at half capacity)	15
Dispersion coefficients	> 100

*The PEDCO analysis does not support this optimistic figure; however, the Rockwell International stack tests are more current.

XI EFFECTS OF RAPS EMISSION INVENTORY ERRORS

A. Point Source Dominated Inventory (SO_2)

1. Discussion

As discussed in Section III, the air quality model output, X, can be represented as some function of emissions inputs, Q, and meteorological input G as follows:

$$[X]_{t,s} = f\left\{[Q]_{t,s}\ [G]_{t,s}\right\} + [X'_{err}]_{t,s} \qquad (27)$$

where X, X'_{err}, Q, and G are vectors in time (t) and space (s). The X'_{err} term* represents an error in the formulation that is only a mathematical approximation to the physics and chemistry of the atmosphere. For our purposes, it is assumed that the X'_{err} term represents a random error not related to the Q and G arrays. The sensitivity of any element in the X array to any element in either the Q or G arrays is given by

$$\frac{\partial X_i}{\partial Q_j} = \frac{\partial f\left\{[Q]_{t,s},\ [G]_{t,s}\right\}}{\partial Q_j}$$

or

$$\frac{\partial X_i}{\partial G_j} = \frac{\partial f\left\{[Q]_{t,s},\ [G]_{t,s}\right\}}{\partial G_j} \quad . \qquad (28)$$

---

*In the notation used here, the prime will be used to designate errors due to the model formulation, unprimed error terms will designate the total error.

The variations in the Q_{err} and G_{err} terms are numbers that can be used to quantify air quality model errors by substitution for incremental changes in Q_j and G_j in the discretized approximation of Eq. (28).

Our sensitivity analysis to date has consisted of evaluating individual Q_j and G_j parameters in relation to their effect on X_i. The parameters involved are summarized as follows:

X_1 = ground level SO_2 concentrations ($\mu g/m^3$)

Q_1 = SO_2 emission estimate (g/s)

Q_2 = Stack gas exit parameters (temperature ^oK; volume flow m^3/s)

G_1 = Wind direction (degrees)

G_2 = Wind speed (m/s)

G_3 = Atmospheric stability (six classes derived from the atmospheric lapse rate in $^oC/100$ m).

Using our simulated RAPS inventory and the CDM (Busse and Zimmerman, 1973), the following reference set of meteorological parameters were chosen:

- Wind direction sectors: NNW (70%); NW (30%)
- Wind speed average: U3 (4.43 m/s)
- Atmospheric stability: Class 4.

This set of parameters is typical of winter conditions in the St. Louis area. The ground-level concentrations classified by area, small point, and large point sources were calculated for six downwind locations corresponding to RAPS monitoring stations. Results of the reference run are presented in Table 29.

First let us examine the sensitivity of ground-level concentration to errors in the wind direction input, G. If we assume an instrument and interpolation error in degrees, we must relate this to a frequency distribution as required by the CDM. It must also be noted that the CDM requires uniform wind fields, although more current models might require complex wind fields. Nevertheless, our analysis is valid and applicable

Table 29

GROUND-LEVEL SO_2 CDM REFERENCE CASE
(in $\mu g/m^3$)

Coordinates			Area Source	Small Point	Large Point	Total
Station	UTMX	UTMY				
104	747.31	4277.30	33	5	0	38
109	755.80	4279.89	4	10	741	755
110	747.21	4272.21	25	10	50	86
115	757.11	4297.80	1	2	148	151
117	760.56	4272.82	6	10	322	338
123	777.32	4286.38	1	17	57	75

in both cases since we are assuming that the true wind for our reference case is uniform (spatially) throughout the region.

In our analysis, we assume that wind direction error will result in an incorrect wind category 10% of the time. This is traceable to an estimated wind direction error of 2.5 degrees. The assumed erroneous distribution is:

- NNW: 60%
- NW: 30%
- WNW: 10%

Table 30 summarizes the results of the computer analysis including estimates of ground-level concentrations, individual errors, average error, and average significant error. Individual errors are the percentage difference between the Table 30 totals and those for the reference case (Table 29). The average significant error is the mean error for stations with concentrations over 100 $\mu g/m^3$.

A typical erroneous wind speed distribution is estimated in a manner similar to that described for wind direction above and is summarized in Table 31. Results for the run below are displayed in Table 32.

The third meteorological parameter, G_3, considered was atmospheric stability. This parameter is not measured directly and must be

Table 30

SENSITIVITY OF SO_2 ESTIMATES TO WIND DIRECTION ERRORS
(in $\mu g/m^3$)

Station	Area Source	Small Point Source	Large Point Source	Total	Error (%)
104	31	6	7	44	16
109	5	10	643	658*	13
110	24	8	43	75	13
115	1	1	128	130*	14
117	6	9	279	294*	13
123	1	15	64	80	7

Average error = 13; average significant error = 13.

*Used to calculate average significant error (for totals greater than 100 $\mu g/m^3$.

Table 31

ERRONEOUS WIND SPEED DISTRIBUTION

Wind Speed Category Distribution (%) (Mean Wind Speed in mps)				
Class	2	3	4	Total
Sector	(2.46)	(4.47)	(6.93)	
NNW	10	50	10	70
NW	5	20	5	30

Table 32

SENSITIVITY OF SO_2 ESTIMATES TO WIND SPEED ERRORS

Station	Area Source	Small Point Source	Large Point Source	Total	% Error
104	35	5	0	40	5
109	5	11	765	780*	3
110	27	11	51	88	2
115	1	2	145	148*	2
117	7	10	329	345*	2
123	1	18	56	74	1

Average error = 3; Average significant error = 2.

*Used to calculate average significant error.

derived from other measurements. For this sensitivity analysis, atmospheric stability is assumed to be determined solely by the average thermal lapse rate. We emphasize that all assumed errors are based on conservative estimates of instrument interpolation and interpretation accuracies. The assumed stability erroneous distribution is shown in Table 33. Results for this run are displayed in Table 34.

So far, we have considered estimates of errors for meteorological inputs used with CDM. We have chosen those conditions under which CDM is most accurate (steady-state conditions, uniform wind fields, moderate wind speeds). Our assumption is that variations in the meteorological variables occur over a short undefined period and manifest themselves in a sequence of discrete steady-state conditions. Our error estimates have been on the conservative side. There are occasions when more severe errors are encountered. As an example, atmospheric stability could be completely misclassified. This condition is illustrated in Table 35, which indicates the results of misclassifying stability to the next lower level. Even if RAPS achieves its objectives, errors such as these will

Table 33

ERRONEOUS ATMOSPHERIC STABILITY DISTRIBUTION

Atmospheric Stability Distribution (%)		
Sector	Class 3	Class 4
NNW	14	56
NW	6	24

Table 34

SENSITIVITY OF SO_2 ESTIMATES TO TYPICAL ATMOSPHERIC STABILITY ESTIMATION ERRORS

Station	Area Source	Small Point Source	Large Point Source	Total	% Error
104	30	6	0	36	5
109	4	9	647	660*	13
110	23	9	45	77	10
115	1	2	138	141*	7
117	6	9	277	292*	14
123	1	15	51	67	11

Average error = 10; Average significant error = 11.

*Used to calculate average significant error.

still occur, but they should be infrequent. We choose to consider the results presented in Tables 30, 32, and 34 as being more typical.

The sensitivity analysis for the emission parameters, Q_1 and Q_2, depends upon a random error about the mean estimate. The error follows a Gaussian distribution. A standard deviation of error is estimated. The model (CDM) uses emission parameter values that vary from the control case according to the equation

Table 35

SENSITIVITY OF SO_2 ESTIMATES TO
WORST CASE ATMOSPHERIC STABILITY ESTIMATION ERRORS

Station	Area Source	Small Point Source	Large Point Source	Total	% Error
104	19	11	0	30	21
109	3	4	270	277*	66
110	16	4	23	42	51
115	1	1	99	100*	51
117	6	3	98	107*	68
123	1	6	29	36	52

Average error = 52; Average significant error = 62.

*Used to calculate average significant error.

$$\sum_{k=1}^{k} Q_k' = \sum_{k=1}^{k} Q_k + \epsilon_k \tag{30}$$

where

Q_k' = The actual value of the parameter for source k

Q_k = The estimated emissions value for source k

ϵ_k = The error which is randomly selected but follows a normal distribution.

In the first sensitivity analysis for emission rate variations, Q, standard deviations for the different types of sources were assumed as follows:

- Large point: $0.2Q_k$
- Small point: $0.4Q_k$
- Area: $0.75Q_k$.

An interpretation for large point sources is that the standard deviation for the error, ϵ_k, is 20% of the estimated value. Assuming a normal distribution, approximately 68% of the sources will have errors within 20% of the estimated value, 95% of the sources will have errors with 2 standard deviations (40%), and so forth. A random number generator is called for each source in the CDM run. The actual value, ϵ_k, for that source is a function of the random number, which is part of a normally distributed set. The results of the sensitivity analysis for Q_1 are given in Table 36.

Table 36

SENSITIVITY OF SO_2 ESTIMATES TO TYPICAL RANDOM ERRORS IN EMISSION RATE

Station	Area Source	Small Point Source	Large Point Source	Total	% Error
104	31	6	0	37	3
109	4	13	684	701*	7
110	26	11	47	83	3
115	2	1	156	159*	5
117	7	11	300	317*	6
123	1	17	60	79	5

Average error = 5; Average significant error = 6.

*Used to calculate average significant error.

In the second sensitivity analysis for emission rates we assumed a worst case standard deviation for random error as follows:

- Large point: $0.4Q_k$
- Small point: $0.8Q_k$
- Area: $1.5Q_k$

The results of this sensitivity analysis are presented in Table 37.

Table 37

SENSITIVITY OF SO_2 ESTIMATES TO WORST CASE RANDOM ERRORS IN EMISSION RATE

Station	Area Source	Small Point Source	Large Point Source	Total	% Error
104	44	6	0	49	29
109	4	4	902	911*	21
110	35	7	45	87	1
115	2	2	121	124*	18
117	7	6	379	392*	16
123	1	18	52	72	4

Average error = 15; average significant error = 19.

*Used to calculate average significant error.

A similar sensitivity analysis was conducted for variations in Q_2, the stack flow parameters (exit temperature and volumetric flow). In this analysis we assumed standard deviations for both parameters as follows:

- Temperature: 0.1 T
- Volume flow: 0.2 VF

where T and VF represent the estimated values for exit temperature and volume flow, respectively.

In this analysis, variations in the Q_2 parameters are assumed, equal for small and large point sources and are not a factor for area sources. Results of this sensitivity run are given in Table 38.

2. Summary

The results of our sensitivity analysis for SO_2 are summarized in Tables 39 and 40.

The actual numbers in the two summaries are representative, but they are subject to wide variations, depending on the exact meteorology

Table 38

SENSITIVITY OF SO_2 ESTIMATES TO TYPICAL RANDOM ERRORS IN STACK EXIT GAS PARAMETERS

Station	Area Source	Small Point Source	Large Point Source	Total	% Error
104	33	4	0	36	5
109	4	10	714	728*	4
110	25	10	47	82	5
115	1	1	124	127*	16
117	6	9	312	327*	3
123	1	17	52	70	7

Average error = 7; average significant error = 8.

*Used to calculate average significant error.

Table 39

SUMMARY 1: SIGNIFICANT GROUND-LEVEL CONCENTRATION AVERAGE ERROR CAUSED BY TYPICAL INPUT PARAMETER ERROR

Parameter	Error (%)
Q_1 = Emission rate	6
Q_2 = Stack exit parameters	8
G_1 = Wind direction	13
G_2 = Wind speed	2
G_3 = Atmospheric stability	11

Table 40

SUMMARY 2: SIGNIFICANT GROUND-LEVEL CONCENTRATION AVERAGE ERROR CAUSED BY WORST-CASE INPUT PARAMETER ERROR

Parameter	Error (%)
Q_1 = Emission rate	19
G_3 = Atmospheric stability	62

and relative orientation of sources. In any case, the analysis does reveal that the accuracy of the SO_2 emission estimation methodology is consistent with accuracies for meteorological inputs, even allowing for reasonable improvements in quantifying the meteorological parameters. Moreover, our test case assumed that the model represented the physics of the atmosphere perfectly. Therefore, our approach was quite conservative.

Our tests also revealed, that, as expected, SO_2 ground-level concentrations are primarily caused by large (1000 tons/year and above) point sources. These are the sources that are being monitored most closely; i.e., hourly process data are being collected. Also, a number of stack measurements were collected to verify emission factors.

B. Area Source Dominated Inventory (CO)

1. Discussion

Much of the discussion for point sources (Section XI.A) applies to area sources also. The sensitivity analysis for meteorological parameters generally applies. The percentage of error in area source CO estimates caused by variations in meteorological parameters (G_1, G_2, and G_3) will be somewhat less than for a point source dominated inventory. This lower percentage of error results from area sources being more uniformly spread out over relatively large areas and, hence, less sensitive to horizontal variations in the meteorological parameters. Also, area source emissions are not as sensitive to plume rise variations resulting from errors in stack characteristics, Q_2. Therefore, air quality estimates should be less sensitive to errors from area sources than to errors from point sources.

2. Sensitivity

During the course of this study, the RAPS inventory was unavailable for use as an input to a comprehensive sensitivity analysis. Nevertheless, we were able to make some estimates based on previous analyses for SO_2, which also treated area sources.

To give some idea of the sensitivity of area dominated sources to emission estimate inaccuracies, we have reduced previous results from Tables 29, 36, and 37. This result appears in Table 41. As shown, even for large errors (coefficients of precision of 0.75 T and 1.5 T), the average observed error in ground-level concentration is between 7 and 29%.

Table 41

AREA SOURCE SENSITIVITY COMPARISON

Station	Ref	σ_e = 0.75 T		σ_e = 1.5 T	
		Value	Error (%)	Value	Error (%)
104	33	31	6	44	33
109	4	4	0	5	25
110	25	26	4	35	40
115	1	2	--	2	--
117	6	7	17	7	17
123	1	1	--	1	--
Average	--	--	7	--	29

3. Adequacy of the CO Inventory

It is tempting to say that errors in the CO inventory should not result in prediction errors in excess of 30%. Based on the number of assumptions in estimating the error's coefficient of precision, this upper bound of 30% is tenuous at best. Nevertheless, it is the best estimate that can be made at this time.

It should also be noted that sensitivity is a function of the air quality model used. For our evaluation, CDM was used. We have assumed that the CDM results are representative of what other models might yield. Also, our sensitivity analysis did not use the CO RAPS inventory, which was not available. Therefore, the actual numbers (7 and 29%) could change somewhat if the real inventory were used.

C. Other Primary Pollutants

1. Total Hydrocarbons

As in the case for CO, the THC inventory is dominated by highway source emissions. However, THC point sources and stationary area sources do contribute more than they do for CO. Nevertheless, the point sources contribute 23.3% of the total THC emissions (compared with 9.7% for CO; see Table 25).

Since we have estimated comparable accuracies for both CO and THC (see Table 25), it would appear that that air quality prediction errors caused by errors in the THC emissions inventory should be about the same for both pollutants--7 to 30%.

2. Nitrogen Oxides

The NO_x inventory is dominated by point source emissions, although to a lesser extent than point source emissions dominated the SO_2 inventory. As discussed in Section V.B, the NO_x estimates are not as accurate as the SO_2 estimates. Furthermore, the point source data may have considerable bias--estimated as 20% (see subsection V.B). Neglecting this bias, we estimate that random errors in the NO_x emission inventory could typically produce errors in predicted ambient NO_x concentrations comparable to the worst case SO_2 estimates, perhaps somewhat less than average 19% shown in Table 37.

3. Particulates

The TSP inventory consists primarily of fugitive dust sources. This inventory relies on a totally different methodology than other sources. The TSP inventory is also much more cumbersome to verify. Only limited quantities of field test data exist. These are not adequate to assess fully the bias and coefficient of precision of the emission estimates. This is a current research area that may produce results that can be used to assess the accuracy of the RAPS data. Because of these several factors, we have not included an estimate on TSP emission inventory inaccuracies. More work is needed on particle size distribution, and more effort must be expended in collecting validation data.

D. Photochemical Model Implications

Hydrocarbons (HC) and nitrogen oxides (NO_x) are the two primary pollutants of interest in the context of photochemical oxidants. Although estimates of pollutant emissions contain inaccuracies, it is worthwhile to have an estimate of the magnitude of the errors that might be encountered when computing secondary pollutants such as O_3 and NO_2. This problem can be treated within the framework of sensitivity analysis since some kind of transfer function linking secondary and primary pollutants must be postulated.

Let S denote the concentration of the secondary pollutant--i.e., O_3 or NO_2-- and let Q_{HC} and Q_{NO_x} denote the emissions of HC and NO_x. Then, the transfer function has the form

$$S = f(x, y, z, t, Q_{HC}, Q_{NO_x}, G) \tag{30}$$

where x, y, and z denote the spatial coordinates, t denotes the time coordinates, and G denotes generically the weather conditions. The function f may be as simple as the linear rollback equation, or as complicated as a nonlinear chemical diffusion model.

Estimates of pollutant emissions are generally available as aggregated tonnages over a large area, e.g., a metropolitan area. One can postulate a range of error for the aggregated estimate, e.g., ±25%, and attempt to estimate the effect of this error on S. In this case localized effects are ignored and only the chemistry of HC and NO_x remains as the major factor relating emissions and secondary pollutants.

For ozone, an upper bound on the magnitude of the change in concenmay be obtained by a simple proportional model:

$$\Delta S \propto \Delta Q \tag{31}$$

This applies only if ΔQ_{HC} and ΔQ_{NO_x} are relatively small (less than 20%) and their respective signs are the same. If the signs are different--e.g., if E_{HC} is low and E_{NO_x} is high--then Eq. (31) can yield very misleading results for ΔO_3 because of the nonlinearity of the chemical interaction between HC and NO_x.

Equation (31) also applies to NO_2 only in the case of ΔQ_{NO_2} and ΔQ_{HC} have the same sign and roughly the same magnitude. If the size of the error for NO_2 emissions differs greatly from the error of the HC emissions, then Eq. (31) will yield a low value for the impact of the error on NO_2 levels. For example, if ΔQ_{HC} = -15% and ΔQ_{NO_x} = -2%, then Eq. (31) would yield an optimistic (low) value for ΔNO_2.

In summary, errors in aggregated areawide emissions can be used to provide pessimistic (large) upper bounds for O_3 uncertainties and optimistic (small) lower bounds for NO_2 inaccuracies. This can be done only when certain conditions associated with the size and sign of the emissions estimates are satisfied. Highly inaccurate error bounds will be obtained when the errors in HC and NO_x emissions have different signs or their respective magnitudes are far apart, or both. For the RAPS inventory, we cannot be sure whether the signs are typically different or the same. One complication is that HC emissions are dominated by highway sources and NO_x is dominated by large point sources. Further field tests, as described earlier, would alleviate this uncertainty.

E. Other Inventory Factors

Previous studies have addressed such issues as grid size (for area source), resolution of point source coordinates, and source heights (see Section II). The resolution of point source coordinates is generally accepted to be about 10 m. The rationale was described in a previous SRI report (Littman et al., 1974). In general, Rockwell International has endeavored to use the 10-m criteria in their compilation.

1. Source Heights

Some discussion on source heights appears in the background literature (see Section II). Earlier, in Section XI.A, we have shown the effect of inaccuracies of source height estimates (including plume rise calculations) for point sources. For the other dominant inventory (highway sources), the emission heights are well known.

2. Area Grid Size

The smallest grid in the RAPS system is 1 km by 1 km. A previous sensitivity analysis, described in Section II, indicates that grids larger than 1 mi^2 can lead to significant errors in estimated pollutant concentrations.

In reality, the required grid size is a function of: (1) the spatial variability of emissions, and (2) the ability of the air quality model to handle the resulting grid matrix.

For the problem of handling the grid matrix, with the advent of more efficient computers and more advanced models, the 1-km grid will in the future be larger than desired. At present, it is consistent with the current state of the art.

For economy and efficiency, the 1-km grids are convenient now because they are consistent and compatible with the census data. Therefore, 1-km grids appear to be a reasonable compromise in satisfying RAPS requirements. Should smaller grid sizes be required at some future date, new algorithms could be used to refine the spatial resolution.

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