A MATHEMATICAL PROCEDURE FOR AIR MONITORING INSTRUMENTATION LOCATION

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Thomas Davis Lee

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Approved:

R. J. Graves, Co-Chairman

L. F. McGinnis, Co-Chairman

P. S. Jones

Date approved by Chairman 6/6/77

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SUMMARY

The attainment and maintenance of air quality standards is a complicated process. A crucial element in this process is the measurement of ambient air quality. The configuration of an air monitoring network and the sampling frequencies employed must satisfy the objectives of the network, meet the location criteria, and consider the factors influencing location determination. Because of the complexity of these often conflictive considerations and because there is no standard procedure, the network design process is normally very subjective.

This paper develops a mathematical procedure for selecting optimum monitoring locations and sampling frequencies. The procedure consists of three phases: (1) atmospheric simulation modeling, (2) statistical modeling, and (3) mathematical modeling. It employs data analysis and diffusion modeling currently required by EPA and resolves the conflicting objectives of violation detection and population protection by a sequential reduction of the feasible set. Methods are included for the following:

(1) Identifying and evaluating integer solutions,

(2) Identifying alternate optimal or suboptimal network configurations,

(3) Evaluating the trade-offs between detection

and protection capabilities,

(4) Investigating the effect of allocating additional monitoring resources,

(5) Determining new network configurations with increased resources.

The procedure is successfully applied to the particulate monitoring network of Fulton County, Georgia with significant improvements over the present system in both violation detection and population protection capabilities.

CHAPTER I

INTRODUCTION

Background

During the years since the passage of the Clean Air Act of 1970, much progress has been made toward a national commitment to clean air. This progress is primarily the result of the diligent efforts of government agencies at three levels, federal, state, and local, for the attainment and maintenance of national ambient air quality standards. At the federal level the Environmental Protection Agency (EPA) has the overall responsibility of providing the guidelines and technical leadership necessary to achieve the standards, of assuring reasonable progress toward the attainment of the standards, and of insuring the maintenance of the standards after attainment. Each state has the responsibility of establishing implementation plans for the attainment and maintenance of air quality standards within its boundaries. Some of the responsibility of implementation has been delegated to local agencies.

The attainment of air quality standards is a complicated process and involves many varied and often conflicting considerations. The quest for attainment involves assuring compliance of each existing or potential source of air pollution through the cataloging of these sources and their emissions (Emissions Inventory), the issuance of operating permits to existing and new sources (Permit System), the determination of violators (Field Inspection), and the use of legal action against violators (Field Enforcement), which sometimes involves extended time tables of compliance (Compliance Scheduling). All of these actions are aimed at the sources of pollution with the purpose of producing ambient air of the required quality, and, indeed, this is the only practical method. But the net result of these efforts upon the ambient air must be measured to ensure that the desired quality does in fact exist. This is the function of Air Monitoring and is conducted by all air pollution control agencies.

Air monitoring data is the most accurate and only tangible indicator to the control agencies of their advancement toward their goals, i.e. the attainment and maintenance of air quality standards. If air monitoring data is this important, then it is apparent that the configuration of the air monitoring network is all important to the production of useful air quality data. Yet the Environmental Protection Agency, in fulfilling its responsibility under the Clean Air Act, has established only subjective and often conflicting guidelines for the design of an optimum air monitoring network. State and local agencies must weigh subjectively such location criteria as pollutant concentration, source location, meterological conditions, population density, growth projections, and geographical coverage and establish their individual networks. In addition, they must resolve the question of sampling frequency. This question arises from the decision of choosing continuous or intermittent samples which must be taken. The result of this subjective network design procedure is a wide variation in the types of networks constructed and extreme difficulty in assessing from area to area the quality of the networks and progress toward clean air goals.

Problem Statement

Given the conditions just described, the existence of a significant problem in the field of air monitoring is apparent. Although air monitoring data is the only tangible evidence of the attainment and maintenance of air quality standards, there exist only subjective and often conflicting guidelines for designing the air monitoring network which provides this data. A standard methodology is needed for locating air monitoring instrumentation, yet none exists.

Purpose of the Research

Therefore, a significant contribution to the field of air pollution in general and to air monitoring in particular would be the development of a mathematical procedure for determining the optimum network configuration for air monitoring instrumentation over a planning horizon. The purpose of this research is to develop such a procedure.

If this procedure is to be useful and attractive, it must address all or most of the location guidelines, and it should be based upon or incorporate related methods currently used by air pollution agencies. Two of these methods are in the field of air pollution modeling. Atmospheric simulation modeling involves the prediction of air pollutant concentrations over a geographical area. Statistical modeling involves the prediction of air pollutant concentrations with time.

The procedure developed will incorporate both atmospheric simulation modeling and statistical modeling with the intent of providing sufficient data for a mathematical programming formulation and thus a system of selecting optimum air monitoring instrumentation locations and optimum sampling frequencies.

So that the procedure will be realistic, it will be developed for a specific area, Fulton County, Georgia, for which the vast amount of needed data is available.

CHAPTER II

LITERATURE SURVEY

Three aspects of the proposed procedure require a search of the literature to determine the state of the art. These aspects are air monitoring network design, atmospheric simulation modeling, and statistical modeling and analysis of air pollutants. This chapter will cite and analyze research in these areas and will indicate any usefulness for the proposed procedure.

Air Monitoring Network Design

Most of the research in air monitoring network design has been done by federal, state, and local pollution control agencies. It is one of their primary concerns but has failed to attract much interest elsewhere. Most of the results of that research are published in the form of guideline documents by the Environmental Protection Agency (2), (12), (13), (16), (17), (21).

The first consideration in the establishment of an air monitoring network is a determination of its objectives. The basic, fundamental goal of ambient air quality monitoring is the protection of health and welfare under the Clean Air Act (16). Because this is too general to be of specific help, more definitive objectives have been stated as EPA regulations and in EPA guideline documents. These objectives are, however, still rooted in the basic purpose of the law (16). General monitoring objectives that are specified in several EPA guideline documents (13), (16), (17), (21), (24) are the following:

(1) Ascertain attainment and maintenance of National Ambient Air Quality Standards.

(2) Provide data for emergency episode prevention.

(3) Provide data for air quality planning efforts including emission control regulations.

(4) Monitor time trends and patterns.

(5) Provide data for research.

(6) Provide data to support enforcement actions.

(7) Monitor source compliance with regulations.

(8) Determine impact of specific proposed or constructed facilities or source concentrations.

The first five of these objectives are normally intended to be met by basic, fixed networks; the others are relevant to source-oriented networks (16). Basic, fixed networks are deployed over a significant geographical area and are intended to provide consistent, ongoing data over a period of many years. (Here fixed does not preclude periodic evaluation and reallocation but is to be distinquished from mobile or portable.) Source-oriented networks are developed for specific short-term purposes and are more intensive in both time and space. They are not intended to measure overall air quality. Because of this, selecting monitoring locations in a source-oriented network is usually a clear-cut procedure. Designing a basic, fixed, ongoing network, however, is much more difficult.

The development of a permanent air quality monitoring network includes determining the number and location of sampling sites, selecting appropriate instrumentation, determining the frequency of sampling, and following established instrument siting criteria (16), (21). Historically, most attention has been given to selecting appropriate instrumentation and developing instrument siting criteria. The Environmental Protection Agency has established reference methods for the determination of each criteria pollutant and tests all instrumentation submitted to determine equivalency. The specifications that must be met by each type of instrumentation are extensive. This and the fact that the EPA must approve all instrument purchases by agencies receiving grant money (virtually all monitoring agencies) makes the instrument selection process easier. Specific instrument siting criteria have also been established by the EPA. Here instrument siting involves the physical placement of a monitor after a location has been chosen. This criteria includes height from the ground, distance from the street, distance from the edge of buildings, heights from the tops of buildings, etc. It allows enough latitude for the realistic placement of monitors and, whether good or bad, is a standard procedure. Several EPA guideline documents address instrument selection and physical instrument siting (12), (13), (16), (17), (21). Determining the number and location of sampling sites and selecting the sampling frequencies are the elements of the network design process that have not been treated adequately, although at first this would not appear to be true.

The configuration of an air quality monitoring network involves two distinct elements: the number of sampling sites of various types and their geographical location. Historically, networks were sized directly or indirectly in relation to the available resources, and the sites were distributed with as much consideration as possible of sources, meteorology, topography, etc. (16), (21). The Environmental Protection Agency Regulations (40 CFR 51.17), in detailing the requirements of State Implementation Plans, specify a minimum number of monitoring sites and a minimum sampling frequency in each Air Quality Control Region as a function of population and the priority classification assigned to it for each criteria pollutant. Here, priority classes are based on pollutant concentration estimates. Table 1 lists the criteria pollutants and the concentration ranges for each priority class. Table 2 contains the required minimum number of sites and sampling frequency as well as the measurement method. This method of determining minimum sampling requirements has serious shortcomings. First, the air quality data that was used for determining priority classification in many instances was very limited and very inaccurate. In some cases it was based on surveys only three months in duration. Yet, that original priority classification is very difficult to change even with thorough and more accurate data. Second, although population may be a meaningful index for determining sampling requirements, it is very unlikely that the correlation between population and factors affecting air quality is consistent from region to region. However, in the years since minimum networks were established, they have been expanded and modified in the light of increasing knowledge, experience and funding (16), (21).

Recently, the emphasis in air monitoring has shifted from the determination of air quality to the attainment and maintenance of air quality standards (16), (17), (21). In concert with this shift in emphasis has been a change in the manner of designing monitoring networks.

Table 1. Criteria for Classification of Air Quality Control Regions

Concentrations in micrograms per cubic meter (ppm in parentheses)

Pollutant	Priority I	Priority II	Priority III
Sulfur Oxides			
annual arithmetic mean	>100 (.04)	60-100 (.02-.04)	< 60 (.02)
24-hour maximum	>455 (.17)	260-455 (.10-17)	< 260 (.10)
3-hour maximum		>1300 (.50)	<1300 (.50)
Particulate matter			
annual geometric mean	> 95	60-95	< 60
24-hour maximum	>325	150-325	< 150
Carbon monoxide			
8-hour maximum	≥ 14[a] (12)		< 14[a] (12)
1-hour maximum	≥ 55[a] (48)		< 55[a] (48)
Nitrogen dioxide			
annual arithmetic mean	≥110 (.06)		< 110 (.06)
Photochemical oxidants			
1-hour maximum	≥195 (.10)		< 195 (.10)

[a] Concentration in milligrams per cubic meter.

Table 2. Recommended Number of Air Quality Monitoring Sites

Classification of region	Pollutant	Measurement method[i]	Minimum frequency of sampling	Region population	Minimum number of air quality monitoring sites[h]
I	Suspended particulates	High volume sampler	One 24-hour sample every 6 days[a]	Less than 100,000 100,000-1,000,000 1,000,001-5,000,000 Above 5,000,000	4 4+0.6 per 100,000 population[c] 7.5+0.25 per 100,000 population[c] 12+0.16 per 100,000 population[c]
		Tape sampler	One sample every 2 hours		One per 250,000 population[c] up to eight sites.
	Sulfur dioxide	Pararosaniline or equivalent[d]	One 24-hour sample every 6 days (gas bubbler)[a]	Less than 100,000 100,000-1,000,000 1,000,001-5,000,000 Above 5,000,000	3 2.5+0.5 per 100,000 population[c] 6+0.15 per 100,000 population[c] 11+0.05 per 100,000 population[c]
			Continuous	Less than 100,000 100,000-5,000,000 Above 5,000,000	1 1+0.15 per 100,000 population[c] 6+0.05 per 100,000 population[c]
	Carbon monoxide	Nondispersive infrared or equivalent[e]	Continuous	Less than 100,000 100,000-5,000,000 Above 5,000,000	1 1+0.15 per 100,000 population[c] 6+0.05 per 100,000 population[c]
	Photochemical oxidants	Gas phase chemilumi-nesence or equivalent[f]	Continuous	Less than 100,000 100,000-5,000,000 Above 5,000,000	1 1+0.15 per 100,000 population[c] 6+0.05 per 100,000 population[c]
	Nitrogen dioxide	24-hour sampling method (Jacobs-Hochheiser method)	One 24-hour sample every 14 days (gas bubbler)[b]	Less than 100,000 100,000-1,000,000 Above 1,000,000	3 4+0.6 per 100,000 population[c] 10
II	Suspended particulates	High volume sampler	One 24-hour sample every 6 days[a]		3
		Tape sampler	One sample every 2 hours		1
	Sulfur dioxide	Pararosaniline or equivalent[d]	One 24-hour sample every 6 days (gas bubbler)[a]		3
			Continuous		1
III[g]	Suspended particulates	High volume sampler	One 24-hour sample every 6 days[a]		1
	Sulfur dioxide	Pararosaniline or equivalent[d]	One 24-hour sample every 6 days (gas bubbler)[a]		1

[a]Equivalent to 61 random samples per year.

[b]Equivalent to 26 random samples per year.

[c]Total population of a region. When required number of samplers includes a fraction, round-off to nearest whole number.

[d]Equivalent methods are (1) Gas Chromatographic Separation—Flame Photometric Detection (provided Teflon is used throughout the instrument system in parts exposed to the air stream), (2) Flame Photometric Detection (provided interfering sulfur compounds present in significant quantities are removed), (3) Coulometric Detection (provided oxidizing and reducing interferences such as O_3, NO_2, and H_2S are removed), and (4) the automated Pararosaniline Procedure.

Whereas, initially, the size of monitoring networks was determined by resource limitations, now the aggregate size of the monitoring effort will be determined as a result of meeting various specific needs, and resource concerns will affect primarily the length of time required for the network to evolve into its ultimate configuration (16), (21). However, one guideline document (16) states:

> . . . recognizing that, for at least the next several years, resource availability will continue to operate as a constraint, a reallocation of network facilities may be more feasible than an increase in network size.

The specific needs of a monitoring network are based upon the objectives of air monitoring networks previously cited and are discussed in several EPA Guideline Documents (2), (13), (16), (17), (21) as criteria for locating the sampling sites. The general criteria stated in one guideline (17) are the following:

(a) Monitoring stations must be pollution oriented;
(b) Monitoring stations must be population oriented;
(c) Monitoring stations must be source oriented;
(d) Monitoring stations must provide areawide representation of air quality.

Other guidelines (2), (16), (21) state more specifically that monitoring must be performed in the following areas:

(1) Areas where concentrations are currently highest;

(2) Areas projected to have highest concentrations;

(3) Areas which are expected to have the most rapid growth;

(4) Areas which have the highest population density and/or total population;

(5) Clean areas that can be used to estimate background concentrations.

In following these location criteria, one must also consider the factors influencing the determination of the locations. These are meteorology and climatology, source location, source strength, and topography (13), (16), (17), (21). In addition, the economic decision of whether to place more than one type of monitoring device (i.e. for different pollutants) at the same location must be considered. One guideline (16) in clarification of this question states that it is important initially to design a separate network for each pollutant and only then to consider combining sites. However, Hickey et al. (28) have determined that the costs of an air quality monitoring system can be reduced by limiting the number of sites to which monitors are distributed and by altering the method of data reduction and handling. Hence, it is possible to reduce operating costs through location decisions, though this is a less important criterion than others.

All of this leads one guideline document (17) to say:

> Therefore, the selection of the number, location and type of sampling stations within a AQCR is a

> complex problem without a purely objective solution. . . . The network chosen will be the result of subjective judgments, based upon available evidence and the experience of the decision team.

This seems like an accurate assessment, and it is not surprising that monitoring networks such as those in New York (17), New Jersey (62), and Los Angeles (12) bear little resemblance to each other. The need to quantify some of this subjectivity and establish a standard procedure for locating air monitors in a network is apparent.

Atmospheric Simulation Modeling

In contrast to air monitoring network design, air pollution modeling has enjoyed the interest of many researchers outside of the air pollution agencies and has benefited accordingly. This outside interest has probably resulted from the similarity of air pollution modeling to other types of modeling. However, praise should be given to the Environmental Protection Agency not only for contributing significantly to the research in this area but also for documenting the usefulness of other models, contracting the development of models, and issuing guidelines which recommend the use of certain models and exemplify that usage.

Atmospheric simulation modeling is used most often in air quality planning efforts. An atmospheric simulation model is based upon quantitative descriptions of the transport and dispersion of pollutants in the atmosphere and is used to establish the relationship between air pollutant emissions and ambient air concentrations. Once this relationship has been established, predictions of future air quality can be made with different planning and control strategies, and the effectiveness of these strategies can be assessed (2), (15), (22). (Burton and Sanjour (8) and Pechan, Burton, and Sanjour (50) add an interesting and useful tool to this assessment in the form of an integer programming technique for evaluating the cost of different strategies.)

There are many different kinds of atmospheric simulation or dispersion models, varying in complexity and utility, but, basically, three general types can be identified (15):

(1) Box models

(2) Gaussian plume models

(3) Numerical simulation models.

Each type of model is significantly different from the others in approach, level of sophistication, and results. Consequently, each should be used for different purposes.

The box model is the least sophisticated type of model and provides the least detail of air quality information. It considers only total area-wide emissions and uses only general meteorological data, if any. Concentration estimates are either area wide or site specific. Only the impact of total pollutant emissions on air quality can be determined; neither the spatial distribution of emissions nor that for air quality levels can be determined. Examples of this type of model are the Rollback Model, the Appendix J Model, the Miller-Holzworth Model, and the Hanna-Gifford Model (2), (15), (22). These models require only hand calculations.

Gaussian plume models are the next step upward in terms of level of sophistication and can provide very detailed air quality information. Models of this type have been in use for a considerable period of time. Turner (63) gives a brief history of their development and references for further details. These models consider detailed point/line source and area source emissions and meteorological data. Because concentration estimates are produced for any site, these models have considerable utility in air quality planning efforts. Examples of this type of model are the Air Quality Display Model, the Climatological Display Model, the Sampled Chronological Imput Model, and the APRAC-1A Model (2), (15), (22). Because these models require a great deal of data and a high speed digital computer, they are costly and time consuming. Also, the increased level of sophistication provides the opportunity for more errors.

Numerical simulation models are the most sophisticated of dispersion models but are still in a relatively formative stage. They attempt to provide pollutant concentrations on a small physical scale in very detailed two and three dimensional patterns. For this reason, these models are most applicable to determining the localized impact of individual sources on air quality. Because they require a great deal of computer time, these models are expensive even on this smaller scale, but, because they are operationally more flexible than the gaussian models, they offer a potentially more accurate simulation method (15).

All of the models just discussed have significant weaknesses and inaccuracies. Several researchers address these. Hameed (26) compares several diffusions models and concludes that the simple ones are inconsistent (i.e. no consistent error between predicted concentrations and observed air quality) and the more complex ones are usually in error by about a factor of two. He points out the need for better models. Cleary et al. (10) attempt to model particulate diffusion with differential equations. These equations describe the effect of gravity fall and earth boundary conditions, but do not constitute a completely useful model. Horie and Fan (32) also use differential equations and mechanical engineering principles to predict short-term pollutant levels. Lamb and Seinfield (37) use Eulerian and Lagrangian models, include nonlinear chemical reactions, and simulate photochemical smog in a very promising simulation effort. One model that has been developed, although not perfected, the SAI Photochemical Model, includes atmospheric chemical reactions (2), (22). Peterson (52) uses eigenvectors of meteorological data to predict sulfur dioxide levels in broad city-wide patterns with some success. He points out that diffusion models need localized meteorological data to achieve accuracy. Knox and Lange (35) discuss the frequency distributions of pollutants from point and area sources that should be more accurately modeled. The interest of these researchers, although it has not provided better models yet, does provide hope for better models in the future.

Table 3 lists the more commonly used and accepted models and the characteristics of each (2). Primarily because of its reliability and the detail of its concentration predictions, a gaussian type atmospheric simulation model such as AQDM offers the best method of predicting the spatial variation of pollutants but is applicable to particulates and sulfur dioxide only and only for annual average concentrations. However, this model is currently used by most air pollution agencies; indeed, EPA requires its use. Consequently, it is the likely candidate for inclusion in the proposed mathematical procedure.

Statistical Modeling and Analysis

Only during the past ten to fifteen years has there been significant efforts in statistical modeling and

Table 3. Summary of Simulation Model Characteristics

Model Name	Pollutant Specification	Averaging Time Specification	Emission Data	Meteorological Data	Concentration Estimates	Ease of Use	Availability	Reliability	Applicability to AQAS
Rollback	Any	Any	1	1	3	1	1	3	3
Appendix J	O_x	1 hr	1	1	3	1	1	3	3
Miller-Holzworth	SO_2,TSP	1 hr, Annual	1	3	3	1	1	1	3
Hanna-Gifford	SO_2,TSP CO	Annual	1	2	3	1	1	1	3
Hanna-Gifford	SO_2,TSP	1-24 hr	2	5	2	2	1	1	2
w/PS[a] model	SO_2,TSP	1-24 hr	3	5	1	2	2	1	1
w/HIWAY	CO	1-24 hr	3	5	1	2	2	1	1
AQDM, CDM	SO_2,TSP	Annual	3	4	1	3	2	1	1
SCIM,[b] RAM[b]	SO_2,TSP	1-24 hr	3	5	1	3	3	2	1
APRAC-1A	CO	1-24 hr	3	5	1	3	2	2	1
SAI[b]	CO,NO_2,O_x	1-10 hr	2	5	2	3	3	2	2

[a]Point Source

[b]These models are currently in a developmental and debugging phase; they are not available for general distribution as computer programs.

Key to Table

A. Pollutant Specification
- Any pollutant
- Specific Pollutants (SO_2, TSP, CO, O_x, NO_2)

B. Averaging-time Specification
- Any averaging-time
- Annual Average
- 1 to 24 hour Average

C. Emission Data
1. Area-wide Emissions Total
2. Total emission distributed as finite area sources
3. Detailed point, line, and area sources

D. Meteorological Data
1. None
2. Average wind speed
3. Average wind speed and mixing height
4. Frequency distribution of wind direction, wind speed, stability, and mixing height
5. Hourly variations of wind direction, wind speed, stability, and mixing height

E. Concentration Estimates
1. Estimates at any specified point
2. One estimate for each area source grid
3. One estimate applicable to entire AQMA

F. Ease of Use
1. Slide-rule
2. Small computer effort
3. Major computer effort

G. Availability
1. Open literature
2. National Technical Information Service
3. EPA, upon request

H. Reliability
1. Can be verified and calibrated
2. Verification is incomplete, possibility of calibration is uncertain
3. Questionable; acceptable for crude estimates only

I. Applicability to AQAS
1. Can distinguish between specific source and land use type
2. Can distinguish between land use types only
3. Considers no distinction between sources or land uses

analysis of ambient air pollutant concentrations. This was primarily because of the absence, until recently, of sufficient and accurate data to permit this analysis. By far the greatest effort and contribution in this regard has been made by Ralph I. Larsen as an employee of federal air pollution research agencies. His analysis and modeling also precipitated a number of reports either supporting or criticizing his work.

The first article containing Larsen's model was co-authored by Charles E. Zimmer, another major contributor in this area, and presented in the December, 1965 Journal of the Air Pollution Control Association (65). In a 1969 issue (39) of that journal a refined version of Larsen's model was published, and in 1971 (41), the Environmental Protection Agency adopted the model and issued it in document form for use by air pollution agencies. Larsen's model was based on an empirical analysis of seven years of ambient air data from eight cities in the U. S. The general model he developed has the following characteristics (39), (41):

1. Pollutant concentrations are lognormally distributed for all averaging times.
2. Median concentrations are proportional to averaging time raised to an exponent.
3. Maximum concentrations are approximately inversely proportional to averaging time raised to an exponent.

From these characteristics, Larsen developed equations for calculating various parameters at various averaging times. These equations can be used not only for reducing real data and comparing it with air quality standards but also for predicting pollutant concentrations. Thus the model can be used for interpretation, comparison, and prediction. In a 1967 publication of the Journal of the Air Pollution Control Association, Larsen (38) included in this basic model equations for predicting the frequency of occurrence of air pollutant dosages of various intensities. This part of the model was not as accurate or useful and was dropped in later versions. In three later articles, Larsen (40), (43), (44) presented "An Air Quality Data Analysis System for Interrelating Effects, Standards, and Needed Source Reductions" which was based on his model.

After the adoption of Larsen's model by the EPA, a number of articles were written concerning it. Bernarie (7) gave evidence supporting the validity of the lognormal distribution for pollutant concentrations. Singpurwalla (60) gave a theoretical proof of Larsen's empirical findings about maximum concentrations by investigating extreme values from a lognormal law. Kahn (34) presented a heuristic justification of the lognormal distribution of pollutant concentrations. However, not all of the articles were supportive. Patel (49) pointed out what he considered were two basic errors: (1) The implicit assumption of independence between concentrations observed at different times and (2) the interchange of exponentiation and expectation in deriving the equation for calculating the expected maximum concentration. He illustrated a substantial departure from independence in some of the data and showed that the interchange mentioned above produces less than maximum values. Larsen (42), in response, acknowledged some possible errors but defended his model on the basis that it works well with real data and that its usual applications (in planning) allow a margin of error. Naustadter and Sidik (48) supported Larsen's model and pointed out errors in Patel's calculations of independence. Their own calculations reflected a small positive correlation in continuous data but not in intermittent data. They also indicated that the error involved in interchanging exponentiation and expectation is small. Marcus (45) suggested that Larsen reached some of his empirical results because the data he analyzed was not adjusted for trends. The result of this controversy surrounding the model can be seen in later EPA guideline documents (2), (18) which recommend the model but caution its use.

Other attempts or suggestions have been made regarding the modeling of ambient air pollutant concentrations. Patel (49), in criticizing Larsen's model, suggested using a more complex autoregressive normal stochastic process to better describe ambient air concentrations. Marcus (45) concurred and presented such a model but lacked the facilities for doing the analysis. Shoji and Tsukatani (59) offered a model based upon the spectral density function of air pollutant concentrations which is approximated by the Markovian spectrum. Wilkins (64) devised a system of equations for describing data from a monitoring network in isopleth form on a TV screen for analysis and prediction. None of these models have been developed to a useful stage (especially for air pollution agencies) and are certainly not as accepted and tested as Larsen's. They do however provide promise of better models in the future.

A difficulty arises when making inferences about certain parameters of air pollutant concentrations, such as means, medians, and maxima, for which ambient air standards have been established. The confidence intervals which can be established around these values are a function of sample size. Therefore, an optimum sampling frequency must be selected for each site in a monitoring network.

Several researchers have addressed this frequency selection problem. Saltzman (57) presented three charts for determining confidence limits, per cent exceeding certain values, and sample size, but the charts did not prove very useful in practice. In a later article (58) he presented a complicated theory relating sampling size to biological effects in the body and suggested certain relationships. W. F. Hunt (33) developed a more useful set of equations for calculating confidence intervals about the annual mean. The equations are a function of the frequency of sampling, the standard deviations of the logarithms of the air pollutant measurements, and the required confidence levels. Thus, with an estimate of the standard deviation, the precision of a sampling plan can be determined for any level of confidence or period of time. Phinney and Newman (53) have demonstrated the use of these equations on particulate data in Indianapolis. Hunt's method has been recommended by the EPA (2). Hale (25) developed a different equation for determining the sampling frequency required to obtain the desired confidence interval about the mean. Kretzschmar (36) developed a method of constructing charts (and presented a set) for determining confidence intervals.

None of these methods, including Hunt's, is used very often by air pollution agencies, because the EPA has established sampling requirements for each pollutant. For intermittent sampling, this is a choice of every third day or every sixth day sampling. Neustadter and Sidik (48) have questioned these sampling frequencies and have shown with a Monte Carlo analysis that neither is adequate for determining the second highest pollution level within acceptable error bounds. (Some national standards are "not to be exceeded more than once per year".) However, there is some question as to the validity of their analysis, because they assumed an infinite population size and thus had large error bounds even with continuous sampling. Currently, for reasons of economy, most pollution agencies take samples every sixth day. The EPA is considering a blanket decision of requiring every third day sampling. It would seem much more reasonable to make a case by case decision. A mathematical procedure for locating air monitoring instrumentation should address the problem of sampling frequency selection.

CHAPTER III

FORMULATION OF THE PROCEDURE

A major concern of air monitoring efforts is designing monitoring networks, and, of those networks, the basic fixed network is the most difficult to design. The configuration of the network and the sampling frequency employed at each location must satisfy the objectives of the network, meet the location criteria, and consider the factors influencing location determination. Because of the complexity of these considerations and because there is no standard procedure, the network design process is normally very subjective. If all or most of these complex considerations could be adequately treated mathematically, this subjectivity could be eliminated or greatly reduced. This chapter presents three separate, although interrelated, phases which formulate a mathematical procedure for addressing the considerations involved in air monitoring network design. These three phases are atmospheric simulation modeling, statistical modeling, and mathematical modeling (math programming).

Atmospheric Simulation Modeling

Atmospheric simulation modeling is a valuable and appropriate tool to use in a standard procedure not only because it is widely used by air pollution control agencies, but also because it addresses explicitly the factors influencing location determination: meteorology and climatology, source location, source strength, and topography. By using atmospheric simulation modeling first, the procedure begins where pollution begins, at the sources. The Air Quality Display Model is the most widely used and tested atmospheric simulation model, and thus the only one presently acceptable for inclusion in a standard procedure. As other models are fully developed, they can be included in the procedure, and thus it can be expanded to consider more pollutant types.

The Air Quality Display Model is based upon a diffusion model developed by Martin and Tikvart in 1968. It assumes the following:

(1) A Gaussian distribution, in both the vertical and horizontal planes, of the plume spread from a source (See Figure 1.).

(2) No gravity fallout of the effluent.

(3) No reduction of the effluent by chemical reaction.

(4) Total reflection of the plume at the earth's surface.

Basic imputs to the model are a comprehensive emissions inventory, including both point and area sources, and meteorological data as a joint frequency distribution of wind speed (6 classes), wind direction (16 cardinal points), and stability class (Turner's (63) classes 1-6) along with an average annual mixing height. The model determines the impact of all sources at a given receptor, for a given set of meteorological conditions. It then weights this impact by the frequency with which that particular set of meteorological conditions occurs and sums over all meteorological conditions to produce annual average concentrations of sulfur dioxide and total suspended particulate.

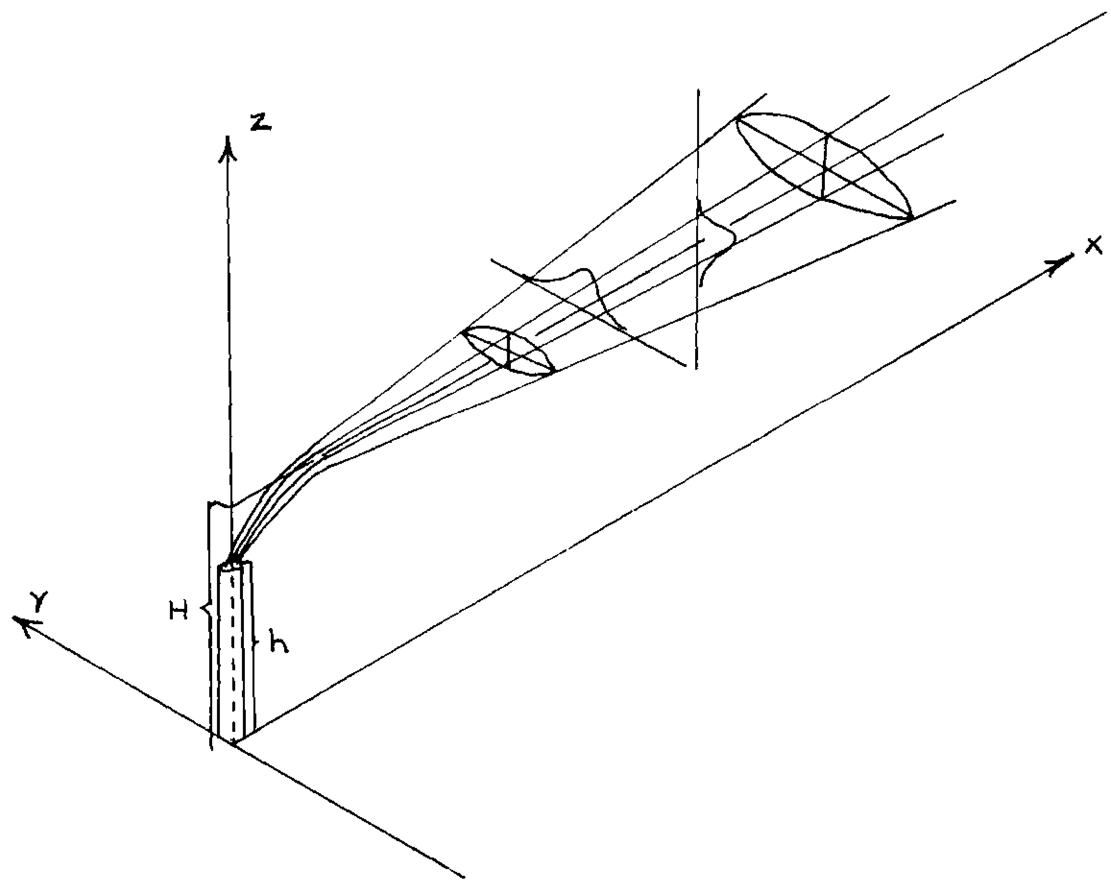


Figure 1. Coordinate System Showing Gaussian Distribution in the Horizontal and Vertical.

The basic equation for determining these average concentrations $\overline{X}$ is:

$$\overline{X} = \sum_{\theta}\sum_{S}\sum_{N}\left\{\frac{2\ Q\ f(\theta,S,N)}{\sqrt{2\pi}\ \sigma_{zs}\ u_N\ (2\pi x/16)}\ \exp\left[-\frac{1}{2}\left(\frac{H}{\sigma_{zs}}\right)^2\right]\right\}$$

where Q = emission rate,

$f(\theta,S,N)$ = frequency during the period of interest for wind direction interval θ, stability class S, and wind speed class N,

$_{zs}$ = vertical dispersion parameter at downwind distance x for stability condition S,

u_N = representative wind speed for class N,

H = effective stack height for wind speed u.

For the development of this equation and a detailed description of the Air Quality Display Model see reference (3). The model is calibrated with existing air quality data using regression analysis techniques.

The model considers explicitly meteorology and climatology, source location, and source strength. It does not consider topography and, therefore, introduces more errors. But the calibration method can reduce the errors to an acceptable level and produce estimates of annual average concentrations at any location. These can be used as a basis for addressing network objectives and considering location criteria.

Statistical Modeling

Annual average concentrations alone are insufficient for adequately addressing network objectives and location criteria. If monitoring stations are to be pollution oriented to provide for the attainment and maintenance of air quality standards, then concentration estimates for other averaging times are needed, and the variability of the concentrations must be considered. Primarily because of the work of Larsen and the interest he initiated this information can be generated statistically.

It is now widely accepted that pollutant concentrations in the ambient air are lognormally distributed with time. Let:

$X = \{x_i\}$ = the set of pollutant measurements,

$Y = \{y_i\}$ = the logarithmic transformation of the measurement values,

N = the population size,

and n = the sample size.

Then the basic equations of a lognormal distribution are the following:

$$y = \frac{\sum_1^N y_i}{N} = \frac{\sum_1^N \ln x_i}{N}$$ = the population arithmetic mean of the logarithms

$$\sigma_y = \sqrt{\frac{\sum_1^N (\mu_y - y_i)^2}{N}}$$ = the population standard deviation of the logarithms

$$m_y = \frac{\sum_1^n y_i}{n} = \frac{\sum_1^n \ln x_i}{n}$$ = the sample arithmetic mean of the logarithms

$$s_y = \sqrt{\frac{\sum_1^n (m_y - y_i)^2}{n-1}}$$ = the sample standard deviation of the logarithms

$$\mu_{gx} = e^{\mu_y}$$ = the population geometric mean of the measurements

$$\sigma_{gx} = e^{\sigma_y}$$ = the population geometric standard deviation

$$m_{gx} = e^{m_y}$$ = the sample geometric mean

$$s_{gx} = e^{s_y}$$ = the sample geometric standard deviation

$$m = \frac{\sum_1^n x_i}{n}$$ = the sample arithmetic mean.

The relationship between the sample arithmetic mean, the sample geometric mean, and the sample geometric standard deviation is expressed as

$$m_g = me^{-\frac{1}{2} \ln^2 s_g}.$$

Thus, with the annual average concentrations predicted by the appropriate diffusion model and estimates of the geometric standard deviations based upon existing air monitoring data, the sample geometric mean can be calculated.

Larsen (41) developed the following empirical equations for calculating the geometric mean and geometric standard deviation for different averaging times:

$$m_{gb} = m\left(\frac{m_{ga}}{m}\right)^{v}$$

$$s_{gb} = s_{ga}^{\;v^{\frac{1}{2}}}$$

$$v = \frac{\ln\,(t_{tot} \,/\, t_b)}{\ln\,(t_{tot} \,/\, t_a)}$$

where a = one averaging time,

b = another averaging time,

t = averaging time,

and t_{tot} = total averaging time, usually 1 year.

The information which can be generated from these equations is still not in a completely usable form. What is needed is a single value that incorporates both the magnitude and variability of the concentrations and their relationship to the ambient air quality standards. Such a value is the probability of exceeding an ambient air quality standard, and it can be calculated from the parameters already generated. The probability density function of a lognormal distribution is

$$f_{c/t}(C/T=t) = \frac{1}{\sqrt{2\pi}\,\sigma_{yt}\ c} \exp\left[\frac{-(\ln C - \mu_{yt})^2}{2\sigma_{yt}^2}\right] , \quad C > 0$$

$$= 0 \text{ , otherwise,}$$

where T denotes the various averaging times. Thus, the probability of exceeding an ambient air quality standard S is

$$P\ (c > S/T=t) = P\ (\ln C > \ln S/T=t)$$

$$= P\ \left(\frac{\ln c - \mu_{yt}}{\sigma_{yt}} > \frac{\ln S - \mu_{yt}}{\sigma_{yt}} / \ T=t\right)$$

$$= P\ \left(\ Z > \frac{\ln S - \mu_{yt}}{\sigma_{yt}} / \ T=t\right)$$

for T less than one year (i.e. for ambient air quality standards for averaging times of less than one year). For T equal to one year (i.e. yearly standards) a modification must be made.

The annual standard for particulates is expressed as a geometric mean. The mean of a normal distribution is normally distributed with standard deviation $\sigma / \sqrt{N}$ (30). Since the log of the geometric mean is the mean μ_g of a normal distribution with standard deviation σ_y, then the log of the geometric mean is normally distributed with mean μ_y and standard deviation $\sigma_y/$ N. Therefore, the probability of the annual geometric mean μ_g exceeding the geometric mean standard S_g is

$$P\ (\mu_g > S_g) = P\ (\ln \mu_g > \ln S_g)$$

$$= P\ \left(\frac{\ln \mu_g - \mu_y}{\sigma_y/\sqrt{N}} > \frac{\ln S_g - \mu_y}{\sigma_y/\sqrt{N}}\right)$$

$$= P\ \left(Z > \frac{\ln S_g - \mu_y}{\sigma_y/\sqrt{N}}\right).$$

This method of calculation must again be modified to accommodate the annual standard for sulfur dioxide which is expressed as an arithmetic mean. The modification is accomplished by using the relationship between the means previously expressed. The probability of the annual arithmetic mean m exceeding the annual arithmetic standard S_a is

$$P\ (m > S_a) = P\ (me^{-\frac{1}{2}\ln^2 sg} > S_a e^{-\frac{1}{2}\ln^2 sg})$$

$$= P\ (m_g > S_a e^{-\frac{1}{2}\ln^2 sg})$$

$$= P\ \left(\frac{\ln m_g - \mu_y}{\sigma_y/\sqrt{N}} > \frac{\ln (S_a e^{-\frac{1}{2}\ln^2 sg}) - \mu_y}{\sigma_y/\sqrt{N}}\right)$$

$$= P\left(Z > \frac{\ln\left(S_a e^{-\frac{1}{2}\ln^2 sg}\right) - \mu_y}{\sigma_y / \sqrt{N}}\right)$$

Since in actual calculations the population parameters will be replaced by the sample estimates, both of the probabilities of exceeding annual standards are dependent upon the sample size. As the sample size is changed the calculated probability changes, because in effect the knowledge about the distribution changes. Therefore, if the original probability is less than one half, increasing the sampling frequency will decrease the probability, if the original probability is greater than one half, increasing the sampling frequency will increase the probability.

Thus, it is possible to generate for each prospective location the probability of exceeding each of the ambient air quality standards and, by varying inputs to the simulation model, to identify areas where concentrations are currently highest, areas projected to have highest concentrations in the future, and areas which will be affected by rapid growth. These are some of the location criteria discussed in CHAPTER II.

When the overall objective of air monitoring is considered, i.e. the protection of health and welfare, and when the general monitoring objectives of a fixed network are also considered, it appears that the problem of air monitoring is one of detection. Therefore, it would be advantageous to translate the probabilities of exceeding standards into the probabilities of detecting violations of the standards. This would also make it possible to incorporate into a single value the question of sampling frequency, because the probabilities of detection would be dependent upon the sampling frequency employed as well as the probability of exceeding a standard.

The taking of ambient air samples for various averaging times can be considered a Bernouilli process since the trials are assumed independent, there are only two possible outcomes for each trial, and the probabilities remain the same throughout the trials. Here the probabilities are those of exceeding a standard for a certain averaging time and, because of their method of calculation, can be assumed unchanging for averaging times of less than one year. Let the random variable X denote the number of successes (i.e. detections of a violation of a standard). Then X has a binomial distribution given by

$$p(x) = \binom{n}{x} p^x (1-p)^{n-x}, \quad x=0,1,2,\ldots,n$$
$$= 0 \quad , \text{ otherwise },$$

where n = the number of trials or samples,

p = the probability of exceeding a standard,

x = the number of successes or detections,

and $p(x)$ = the probability of x successes in n trials.

National ambient air quality standards for averaging times of less than one year are not to be exceeded more than once per year; Fulton County standards are not to be exceeded. Therefore, in the binomial setting the probability of a detection is $P(x \geq 2)$ for national standards and $P(x \geq 1)$ for Fulton County standards where

$$P\ (x \geq 2) = 1 - p\ (0) - p\ (1)$$

and $$P\ (x \geq 1) = 1 - p\ (0).$$

By using different values of n corresponding to different sample sizes, a probability can be generated for each sampling frequency.

The probability of detecting a violation of an annual ambient air quality standard can also be calculated using the binomial distribution. Because of clearly observable trends in yearly averages, estimates of annual means must be based upon one year of data only. Therefore, in the binomial setting, the probability of detection is $P(x=1)$ and n, the number of samples, is equal to one. Thus,

$$\begin{aligned} P\ (x=1) &= p(1) = \binom{1}{1}\ p^1\ (1-p)^{1-1} \\ &= p. \end{aligned}$$

This means that the probability of detection of the violation of an annual air quality standard is equal to the probability of exceeding that standard. Since the probability of exceeding the annual standard varies with the number of samples, a probability of detection can again be generated for each sampling frequency.

Thus, by modeling statistically the annual average concentrations produced by the atmospheric simulation model, a single value has been developed which can be used to evaluate the attainment of certain air monitoring objectives and to measure how well certain location criteria are met at each potential sampling location and for each sampling frequency employed. These objectives and location criteria are those associated with pollutant concentrations. Still to be addressed are those associated with population dosage.

Mathematical Modeling

Now that a means of evaluating potential air monitoring sites has been developed, a procedure is needed for selecting the optimum number of sites, the location of each site, and the sampling frequency to be employed at each site. This problem falls into the class of facilities location problems which have been widely studied in recent years. Considering the type of data available from the simulation and statistical modeling, a discrete space model can be developed with n discrete, potential sampling locations.

Associated with each pollutant type there are a varying number of ambient air quality standards. For each of these air quality standards, a probability of exceeding the standard can be generated for each predicted concentration. Also, for each pollutant type there are either one or two types of measuring devices or monitors; these types are continuous and intermittent. For each type of intermittent measuring device, there are at least two different sampling frequencies which can be employed. Since, for each sampling frequency, a different probability can be generated, each intermittent monitor operating at a particular sampling frequency can be considered as a different type of measuring device. Therefore, the types of measuring devices which may be associated with each pollutant type are continuous, intermittent with sampling frequency A, intermittent with sampling frequency B, etc. Let

l = the number of ambient air quality standards

and m = the types of measuring devices.

Then there are l times m probabilities of detection which can be generated at each potential sampling location. Since there are n potential sampling locations, there are lmn probabilities associated with each pollutant type. If these probabilities are summed for each network configuration (i.e. number of monitors and location) and associated sampling frequencies, that summation can be used to evaluate each network configuration. Consequently, a valid objective function for a mathematical programming formulation is

$$\text{Maximize} \sum_{i=1}^{l} \sum_{j=1}^{m} \sum_{k=1}^{n} p_{ijk}\, x_{ijk}$$

where p_{ijk} is the probability of detection of a violation of ambient air quality standard i with monitor type j at location n and x_{ijk} represents the location vector $\bar{x}$. The value of x_{ijk} can be either one or zero only. If x_{ijk} equals one, then instrument device j will be placed at location k to detect a violation of standard i. The objective function just formulated is linear.

The constraints which must be satisfied by an optimum air monitoring network must now be formulated. A major constraint is the number of measuring devices which are being placed. A lower bound is the number currently available. A constraint of this type is associated with each type of measuring device. However, since only the total number of intermittent measuring devices is known, and each device can be used for any desired sampling frequency, only one constraint can be formulated for intermittent type measuring devices. Therefore, there will be only two constraints dealing with the number of measuring devices to be used: one associated with continuous monitors and one associated with intermittent monitors. These can be formulated as

$$\sum_{i=1}^{l} \sum_{k=1}^{n} x_{i1k} \leq b_1$$

$$\sum_{i=1}^{l} \sum_{j=2}^{m} \sum_{k=1}^{n} x_{ijk} \leq b_2 \qquad (1)$$

where b_1 is the number of continuous monitors and b_2 is the number of intermittent monitors. Another constraint is that only one type of measuring device operating at one sampling frequency should be located at a particular sampling location. This constraint can be formulated as

$$\sum_{i=1}^{l} \sum_{j=1}^{m} x_{ijk} \leq 1, \forall k. \qquad (2)$$

The final constraint necessary for a linear programming formulation deals with the proximity of monitors to each other. For large metropolitan areas a fine resolution of geographic variation of pollutant concentrations is needed in certain sections. But when placing monitors in these sections, it is necessary to insure that they are not clustered, because the probabilities associated with each grid of this fine resolution are usually not independent. Therefore, by formulating a constraint which limits the distance between monitors, it is possible to take advantage of the finer resolution of pollutant concentrations without sacrificing the independence of the probabilities. This constraint also prevents monitors from being clustered around strong point sources and addresses the location criteria of providing adequate geographic coverage. It can be formulated best in a general form (and later via the computer) by noting that the area for consideration should be covered by a rectangular matrix of locations with dimensions n_1 by n_2 as in Figure 2.

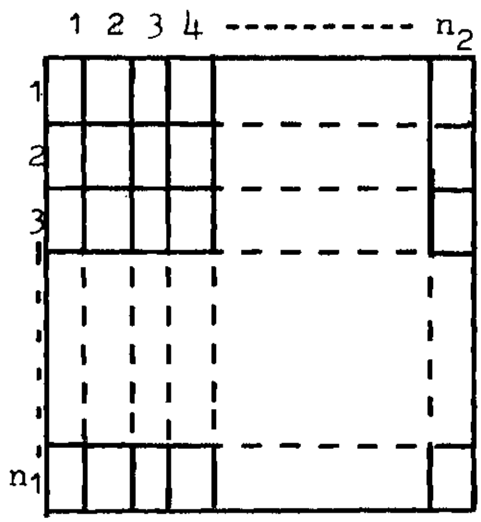


Figure 2. Rectangular Grid-covering

Then the general monitor displacement constraint can be formulated as

$$\sum_{i=1}^{l} \sum_{j=1}^{m} \sum_{k \in I(p,q)} x_{ijk} \leq 1 \ , \quad \begin{array}{l} p = 1,2,\ldots,n_1-s+1, \\ q = 1,2,\ldots,n_2-s+1, \end{array} \qquad (3)$$

where s is the side length in grids over which the constraint applies and

$$I\ (p,q) = \left\{ K : K = (p+s_1-2)n_2+(q+s_2-1),\ s_2=1,2,\ldots,s;\ s_1=1,2,\ldots,s \right\}$$

Note that constraint (2) is subserved by constraint (3) and therefore can be dropped from the general formulation.

The general linear programming formulation is the following:

$$\text{Maximize } Z = \sum_{i=1}^{l} \sum_{j=1}^{m} \sum_{k=1}^{n} p_{ijk}\, x_{ijk}$$

$$\text{Subject to } \sum_{i=1}^{l} \sum_{k=1}^{n} x_{i1k} \leq b_1$$

$$\sum_{i=1}^{l} \sum_{j=2}^{m} \sum_{k=1}^{n} x_{ijk} \leq b_2 \qquad (1)$$

$$\sum_{i=1}^{l} \sum_{j=1}^{m} \sum_{k\in I(p,q)} x_{ijk} \leq 1, \quad p = 1,2,\ldots,n_1-s+1, \quad q = 1,2,\ldots,n_2-s+1 \qquad (3)$$

$$x_{ijk} \geq 0$$

As an example of the constraint matrix formulation consider the area formed by $n_1 = 3$ and $n_2 = 4$ with the grids numbered as in Figure 3.

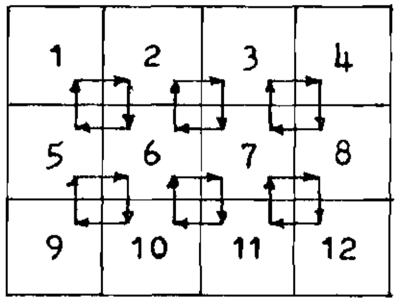


Figure 3. Example Grid-covering

Let $l = 1$ and $m = 3$. Since $n = 12$, the total number of probabilities is $(l)(m)(n) = 36$. Let $s = 2$; this means that only one monitor can be placed in each four square grid area. Constraint (3) becomes

$$\sum_{i=1}^{1} \sum_{j=1}^{3} \sum_{k\ I(p,q)} x_{ijk} \leq 1 \ , \ p = 1,2 \ , \ q = 1,2,3$$

and $I\ (p,q) = \{ K : K = (p + s_1 - 2)4 + (q + s_2 - 1),\ s_2 = 1,2;\ s_1 = 1,2 \}$.

Note that $I\ (1,1) = \{1,2,5,6\}$,

$I\ (1,2) = \{2,3,6,7\}$, etc.

These sets are shown in Figure 3. There will be

$$(n_1 - 2 + 1)\ (n_2 - 2 + 1) = 6$$

The complete constraint matrix is shown in Figure 4.

Because of the large number of locations and the relatively small number of monitors which will usually be considered in the network design process, it is very likely there will be alternate optimal or slightly suboptimal solutions (i.e. network configurations) to the linear programming problem just formulated.

i	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
X j	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	
k	1	1	1	2	2	2	3	3	3	4	4	4	5	5	5	6	6	6	7	7	7	8	8	8	9	9	9	10	10	10	11	11	11	12	12	12	
(1)	1			1			1			1			1			1			1			1			1			1			1			1			$\leq b_1$
		1	1		1	1		1	1		1	1		1	1		1	1		1	1		1	1		1	1		1	1		1	1		1	1	$\leq b_2$
(3)	1	1	1	1	1	1							1	1	1	1	1	1																			≤ 1
				1	1	1	1	1	1							1	1	1	1	1	1																≤ 1
							1	1	1	1	1	1							1	1	1	1	1	1													≤ 1
													1	1	1	1	1	1							1	1	1	1	1	1							≤ 1
																1	1	1	1	1	1							1	1	1	1	1	1				≤ 1
																			1	1	1	1	1	1							1	1	1	1	1	1	≤ 1

Figure 4. Example Constraint Matrix

In keeping with EPA guidelines, which state that the first consideration should be pollutant concentrations and the second population dosage, the procedure thus far has addressed the air monitoring objectives and location criteria associated with pollutant concentrations while also considering the factors influencing location determination. Since the prospect of alternate optimal solutions to the linear programming problem suggests the inclusion of other considerations, now is the time to address the objectives and location criteria associated with population dosage.

The geographic variation of the population affected by pollutant concentrations for averaging times of one day or longer is fairly well represented by the standard population density. For averaging times of eight hours or less, consideration should also be given to employment density and shopping density, because the inclusion of these densities represents more accurately the geographic variation of the population that will be affected by these shorter term concentrations. When devising these densities for shorter term effects, proper adjustments must be made in the standard population density. A population density can be developed for each potential sampling location for each averaging time associated with an ambient air quality standard. To place this in the same format as the probabilities of detection, a population density can be generated to correspond to each probability of detection which is generated, although there will not be as much variation in the population densities (i.e. The population density associated with several different averaging times may be the same.). The summation of these population densities can be used for judging alternative network configurations.

Now to follow the same formulation scheme used in developing the previous linear programming problem, these population densities can be combined with the location vector $\bar{x}$ in an objective function as in the following:

$$\text{Maximize } Y = \sum_{i=1}^{l} \sum_{j=1}^{m} \sum_{k=1}^{n} q_{ijk} \, x_{ijk}$$

where q_{ijk} is the population density that will be protected by the detection of a violation of standard i with monitor type j at location k. This objective function will be subject to the same constraints as the first LP problem and one additional constraint. This additional constraint is the objective function of that first LP problem, and its inclusion assures that only optimal solutions to the first problem will be considered as optimal solutions to the second problem. The final formulation of the second linear programming problem is the following:

$$\text{Maximize } Y = \sum_{i=1}^{l} \sum_{j=1}^{m} \sum_{k=1}^{n} q_{ijk}\, x_{ijk}$$

$$\text{Subject to} \quad \sum_{i=1}^{l} \sum_{j=1}^{m} \sum_{k=1}^{n} p_{ijk}\, x_{ijk} = Z^{*}$$

$$\sum_{i=1}^{l} \sum_{k=1}^{n} x_{i1k} \leq b_1$$

$$\sum_{i=1}^{l} \sum_{j=2}^{m} \sum_{k=1}^{n} x_{ijk} \leq b_2$$

$$\sum_{i=1}^{l} \sum_{j=1}^{m} \sum_{k\in I(p,q)} x_{ijk} \leq 1 \;, \quad p=1,2,\ldots,n_1-s+1, \; q=1,2,\ldots,n_2-s+1$$

$$x_{ijk} \geq 0$$

where Z^* is the optimum objective function value of the first LP problem.

It is still possible that there will be alternate optimal solutions to this second LP problem. If there are, the set of optimal solutions can further be reduced by cost and siting considerations such as ease of placement, ease of access, and security. Consideration can also be given to combining monitoring sites which measure different pollutants into one site so long as the optimum design of each monitoring network is not violated. Until now, no consideration has been given to combining sites. This is in accordance with EPA quidelines which state that a monitoring network for each pollutant should be developed individually and only then consideration given to combining sites within the networks.

In summary, this phase (math programming) of the procedure selects the optimum network configuration and sampling frequencies by a sequential reduction of the feasible region. The first step of the sequence reduces the feasible region according to monitoring objectives and location criteria associated with pollutant concentrations. The second step of the sequence reduces the feasible region according to monitoring objectives and location criteria associated with population dosage. The third and final step of the sequence reduces the feasible region according to siting and cost considerations and in addition allows for an element of variation which helps to achieve reality in the location procedure.

CHAPTER IV

APPLICATION OF THE PROCEDURE

A mathematical procedure has been formulated for air monitoring instrumentation location and sampling frequency selection. The procedure consists of three phases, each of which uses a modeling technique to refine existing information about emissions and air quality and to make predictions so that the many varied and often conflicting criteria for air monitoring network design can be considered mathematically. The first phase of the procedure, atmospheric simulation modeling, considers the factors influencing location determination and provides input to the second phase of the procedure, statistical modeling of pollutant concentrations. This second phase addresses the air monitoring objectives and location criteria associated with pollutant concentrations and provides input into the third phase of the procedure, mathematical modeling or programming. This final phase addresses not only monitoring objectives and location criteria associated with pollutant concentrations and population dosage but also cost and siting considerations and culminates in the selection of the optimum monitoring locations and sampling frequencies to be employed. Thus the procedure insures that air monitoring objectives are satisfied, location criteria are met, and factors influencing location determination are considered and, therefore, successfully treats mathematically what previously has been a very subjective network design process.

This chapter presents an application of the mathematical procedure to the network design process in Fulton County, Georgia to illustrate its use and test its performance. The application will concern the design of a particulate monitoring network and a sulfur dioxide monitoring network only.

Predicting Concentrations with the Atmospheric Simulation Model

The Air Quality Display Model (AQDM) (3) has been cited as the most accurate and reliable for predicting the geographical variation of annual average concentrations of particulate and sulfur dioxide. Therefore it was used in the Fulton County test case.

Before a discussion of the input data is begun, it is necessary to describe the co-ordinate system which will be used throughout the application process. The most convenient and widely used system for air pollution activities is the Universal Transverse Mercator (UTM) system which is discussed in reference (3). The UTM coordinate system is used to construct a grid system which covers the area of interest. Figure 5 shows the UTM coordinate system and Fulton County's

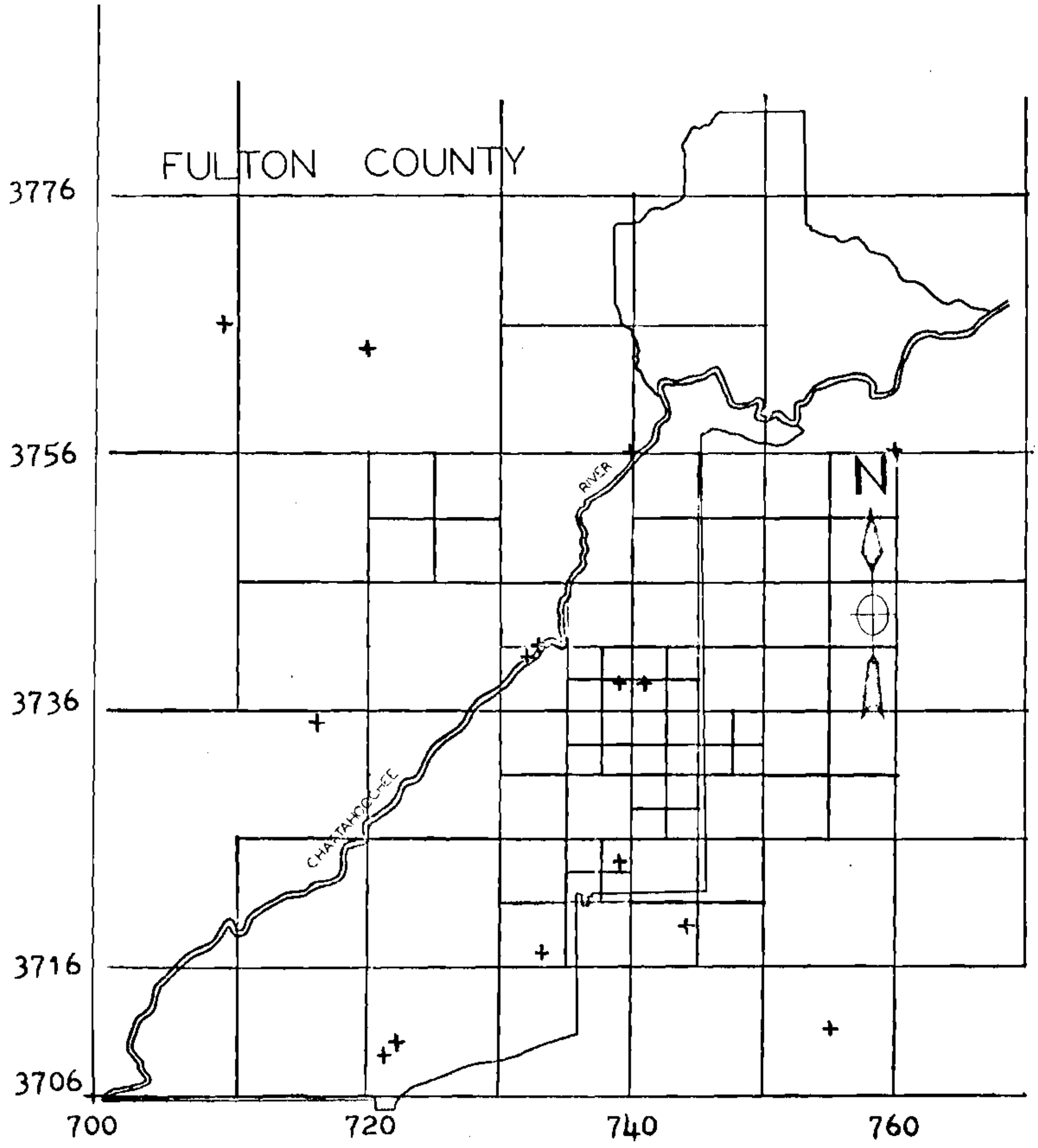


Figure 5. Area Sources and Significant Point Sources

jurisdictional boundaries. The location of all point sources, area sources, air monitoring network sites, and receptors (the points at which pollutant concentrations are predicted) will be specified in UTM coordinates.

The required input data includes:

(1) Point source emissions data,

(2) Area source emissions data,

(3) Meteorological data,

(4) Air quality data.

The development of this data and the use of this model is very expensive and time-consuming, but the fact that the Environmental Protection Agency requires the use of this model in all air quality control regions for planning and for attainment and maintenance considerations means that, with only a small additional effort, the application of this model necessary for inclusion in the mathematical location decision procedure can be achieved.

The point source emissions data necessary for input to the AQDM can usually be obtained from EPA. In the Fulton County test case, this data was updated with more recent data and estimates obtained from both the Fulton County Air Pollution Control Program and the State of Georgia Environmental Protection Division (EPD). Although monitors will be placed only within the jurisdictional limits of Fulton County, pollution sources outside of its jurisdictional limits must be included in the model because of their impact upon the air quality inside of the county. Figure 5 shows the geographical location of the most significant of these point sources.

Area source emissions data is much more difficult to obtain than point source emissions data. Area source emissions are those which cannot be pinpointed to individual point sources or which result from so many point sources that they cannot be identified individually. Emissions of this type include fugitive dust from paved and unpaved roads, emissions from home, office, and industrial heating, automobile emissions, aircraft emissions, and many others. The density of these emissions must be described geographically over the region of interest. The usual method is to obtain estimates of the total emissions of each type of area source for the entire region and then to allocate these estimates to subregion areas using the appropriate allocation parameter, i.e. population, employment, transportation, etc. This results in several allocations with different spatial resolutions. A process called mastergridding is used to combine all of these into one set of area sources. Several EPA quidelines (2), (19), (20), (23) discuss and illustrate this allocation procedure. There are many inherent inaccuracies associated with this laborious procedure and these result in inaccurate emissions data which causes difficulties later in the atmospheric simulation modeling. One of the major inaccuracies, estimating amounts of resuspended particulate matter, is discussed in reference (55). For the Fulton County example case, the area source emissions data was obtained from a very comprehensive report by PEDCO-Environmental Specialists, Inc. (5) which was prepared under EPA contract using EPA methods. The most significant area source emissions indicated by this report were investigated for accuracy and compared to existing Fulton County data. Corrections were made where they were warranted. Figure 5 shows the area source representation in the UTM coordinate system.

The meteorological data required by the AQDM must be in the form of a joint frequency distribution of wind speed (6 classes), wind direction (16 cardinal points), and stability class (Turner's classes 1-6). This information was obtained for Fulton County from the National Climate Center (NCC) in Ashville, North Carolina via the Georgia EPD. The required annual average ambient temperature and pressure were also obtained from the NCC, and the annual average mixing height was obtained from references (46) and (47).

Ambient air quality data is necessary for correlating predicted pollutant concentrations with observed air quality. Because of inaccuracies in the prediction process, predictions are meaningless until an acceptable correlation is achieved. For the example application, existing air quality data was obtained from the Fulton County Air Surveillance

Network and supplemented with data from the Georgia EPD network sites near Fulton County. Table 1 of the Appendix lists the network sites and the observed air quality values. Figure 6 shows the geographical location of the monitoring sites listed in Table 1.

To achieve a proper correlation between predicted pollutant concentrations and observed air quality, it is mandatory that point source data, area source data, meteorological data, and air quality data cover the same period of time. For the Fulton County application this was the calender year 1975. Once an acceptable correlation has been achieved, pollutant concentrations are predicted for future years. At this time any knows changes in emissions, including addition or deletion of sources, should be input to the model. Meteorological data too must be changed. Rubin (56) suggests using either the historical one year data which produces the worst concentrations or a long-term average stability wind rose for predicting future concentrations. In this application a five-year stability wind rose was used to predict concentrations for 1976.

A somewhat modified version of the Air Quality Display Model was obtained from the Georgia EPD, adapted to the Fulton County IBM Systems 370 computer, and verified and validated using the test city data specified in reference (3). Because of the very large number of calculations performed, the AQDM proved to be very time consuming on the

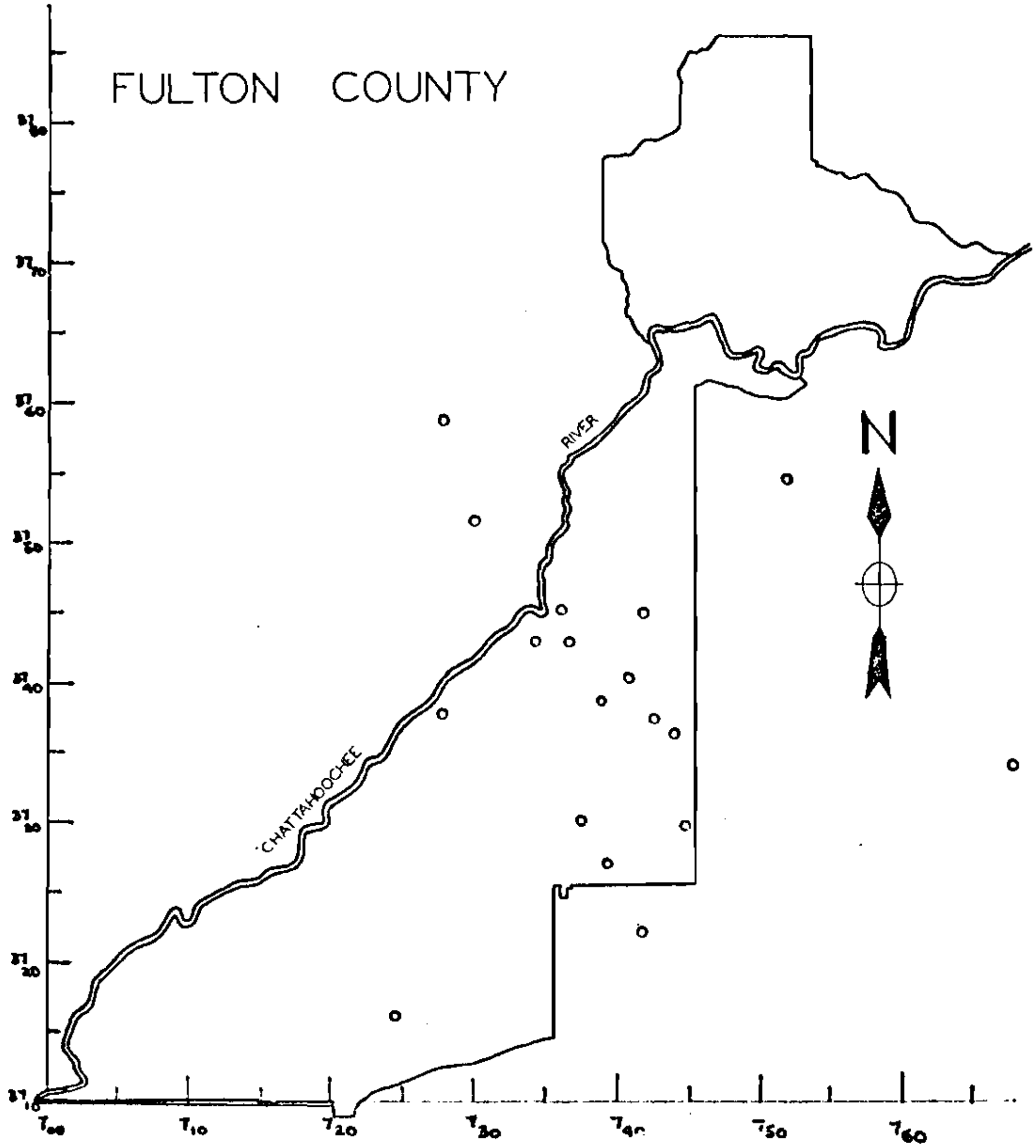


Figure 6. Air Monitoring Sites Used in the Diffusion Model

computer. In fact, to segregate the time requirements into acceptable increments, Fulton County had to be broken down into several smaller regions and the model applied to each. The resulting receptor grid system is shown in Figure 7. Note that in the northern and southern ends of the county the grid resolution is not as fine as in the central region. This variation in resolution was used because the variation in pollutant concentrations is not expected to be as great in the less developed northern and southern regions of the county as it is in the highly developed central region (Atlanta) where most of the emission sources are concentrated. Also, note that receptor locations are the centroids of the individual grids.

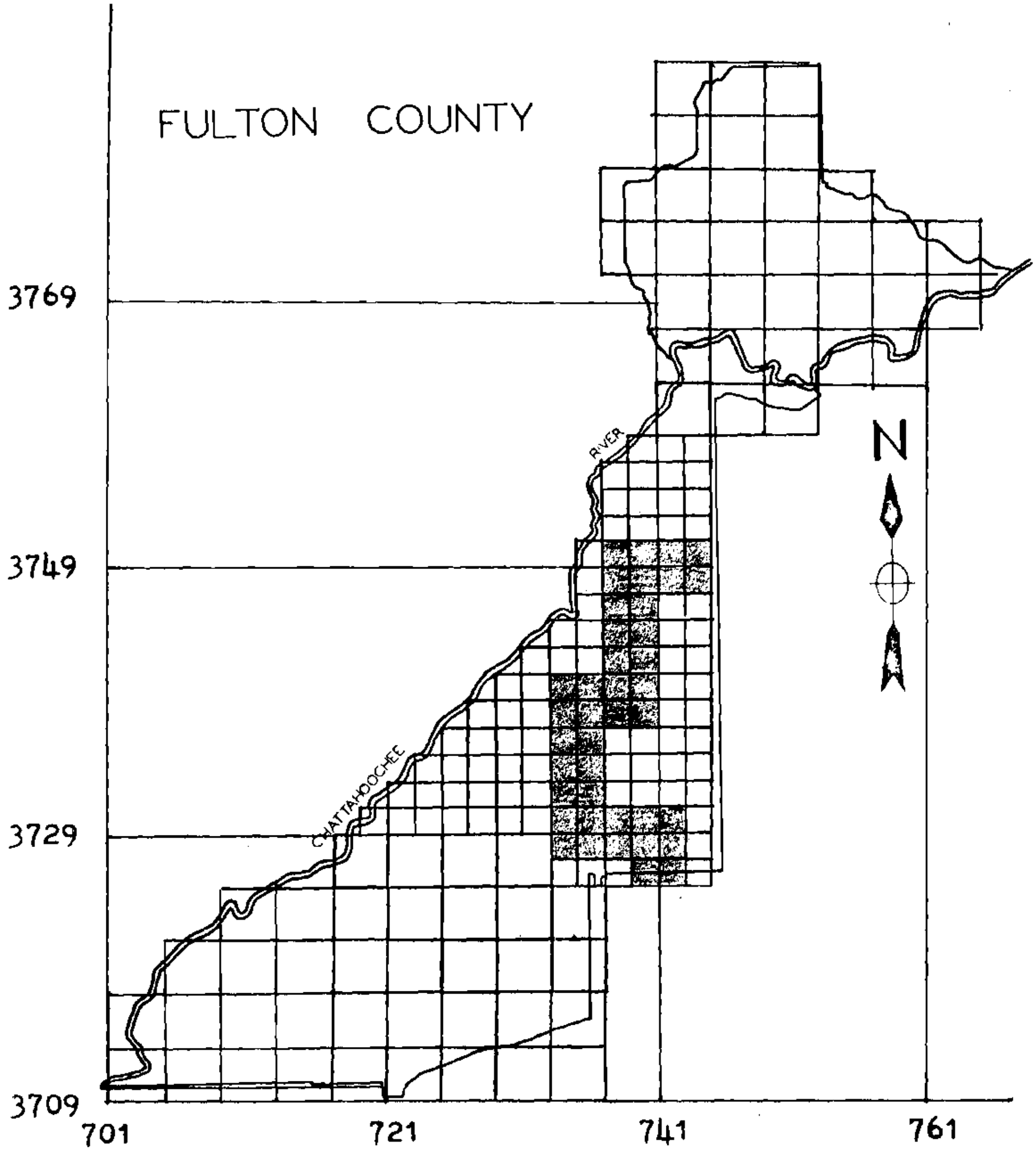
Obtaining an acceptable correlation between predicted pollutant concentrations and observed air quality is a very difficult process. There are many sources of errors in both the input data and the model procedure which cause this difficulty. Some of the most frequently occurring reasons for poor correlation are the following:

(1) Inadequate or inaccurate emissions data.

(2) Unrepresentative air quality data.

(3) Complex topography and/or meteorology not accounted for in the model.

(4) Incomplete description of source variation (the model cannot account for diurnal or seasonal variation).



*Modeled correlation changes in center of gray area; actual line of change is not known.

Figure 7. Receptor Grid System Used in the Diffusion Model

(5) Atmospheric processes not accounted for in the model.

(6) Imperfect modeling of area sources.

For a discussion of these problems see references (2) and (3). An acceptable correlation for particulate concentrations was obtained for the Fulton County test case only after several thorough examinations and adjustments of the input data. Due to inaccuracies in the input data and the model procedure, predicted pollutant concentrations in the central county region (Atlanta) were very close to observed concentrations, while predicted concentrations in the surrounding area were approximately one-half of observed concentrations. This does not mean that the model performs better in the central business district but rather that in the area source allocation procedure too much emissions were allocated to that area and too little to the surrounding area. Therefore, the county was separated into two areas and two different, acceptable correlations were obtained: one for the central business district and one for the surrounding area. Unfortunately this produces and ill-defined or gray area surrounding the central business district, because the exact place where the correlations change cannot be definitely pinpointed with existing air quality data. This gray area is shown in Figure 7. More air quality data, better emissions allocation procedures, better modeling procedures, or all three are needed to resolve this problem.

Just prior to this modeling and analysis, the EPA and Fulton County judged that, due to problems in the sampling procedure, all data from intermittent monitoring sites for sulfur dioxide was invalid. This left only three continuous monitoring sites which could be used in the correlation procedure for sulfur dioxide. Although an acceptable correlation was obtained with these remaining sites, the predicted annual average concentrations of sulfur dioxide are not as reliable.

From the correlation data, the model develops equations for adjusting predicted concentrations. These equations were developed for Fulton County from 1975 data, and then, after proper changes were made in the input data (i.e. changes in meteorological data, point source data, area source data) to simulate calender year 1976, they were used to predict the geographical variation of annual average concentrations of particulates and sulfur dioxide for that year. These predicted concentrations are listed in Table 2 of the Appendix.

Generating Probabilities with the Statistical Model

Although the Air Quality Display Model contains a statistical segment based on Larsen's model, it is neither sufficient nor acceptable for the required statistical modeling and analysis. Therefore, a computer code was written for use on Fulton County's IBM System 370 computer to implement the statistical procedure developed in Chapter III. After verification and validation, this code was used to model the time variation of ambient air pollutant concentrations and to calculate pollutant concentrations for the averaging times of air quality standards, the probabilities of violating these standards, and the probabilities of detecting these violations with different monitoring devices and sampling frequencies. It was also used to generate, based on these probabilities and the linear programming problem formulation, input data for the linear programming solution procedure of the third phase.

The required input data for this statistical model consists of the predicted pollutant concentrations of the atmospheric simulation model and a corresponding estimate of the geometric standard deviation of these concentrations for each receptor location. The success of the procedure in determining the optimum monitoring locations and sampling frequencies depends upon the accuracy of the input data in this phase. Because it was successfully correlated with existing air quality data, pollutant concentration data generated with the Air Quality Display Model is sufficiently accurate (although there is certainly room for improvement). However, there is no readily available, accurate method for generating estimates of the geometric standard deviations at receptor locations. Because obtaining these estimates would necessarily involve calculating day to day variations in pollutant concentrations in addition to annual averages, any accurate estimation procedure would involve a model more sophisticated than the AQDM. The only other alternative is sampling the ambient air at every receptor location to obtain estimates; this is impossible. Recognizing these problems, a method was developed which takes advantage of estimates of the geometric standard deviation (GSD) which exist for each site in the current air monitoring network in Fulton County. This method consists of a simple linear geographical interpolation of GSD's between monitoring sites. While this procedure admits to the existence of no larger GSD than the highest measured in the monitoring network, and this may be unlikely, no evidence exists to indicate which receptor locations may have larger GSD's. This estimation procedure is given some validity by the dispersion of the existing network sites (i.e. a concentration of sites where emissions are highest and variation is probably greatest, and some estimates in lesser impacted areas). Regardless, the fact is no better method exists. Estimates of the GSD's, resulting from this method for particulates and sulfur dioxide at each receptor location, are listed in Table 2 of the Appendix.

Also required for input to the statistical model are the applicable ambient air quality standards and the associated averaging times of these standards. Since in every case Fulton County air quality standards are as stringent or more stringent than national or state air quality standards, they were input as the standards not to be exceeded for the calculation of the probabilities of violation. Table 4 lists the Fulton County ambient air quality standards and associated averaging times for total suspended particulates (TSP) and sulfur dioxide (SO_2).

Table 4. Fulton County Ambient Air Quality Standards

Pollutant	Averaging Time	Standard (μ_g/m^3)
TSP	24 Hrs.	150
	1 Yr.	60(m_g)
SO_2	1 Hr.	715
	24 Hrs.	229
	1 Yr.	43(m)

First, the statistical model uses the equations of Larsen (41) to calculate the predicted pollutant concentrations and corresponding geometric standard deviations for each averaging time for particulates and sulfur dioxide. Next it uses the probability equations developed in Chapter III to calculate the probability of exceeding each standard at each receptor location given the predicted concentration and geometric standard deviation for that averaging time and that receptor. Since Fulton County standards are not to be exceeded, the probability of exceeding a standard is the probability of violating a standard. Table 2 of the Appendix lists the calculated averaging time parameters and associated probabilities for each TSP and SO_2 standards.

The final input to the statistical model is the sampling frequencies which can be employed to detect violations of each standard. Both continuous and intermittent monitors can be included merely by specifying the sampling frequency. A sampling frequency of 330 days per year (considering historical per cent downtime) represents continuous monitors. Any smaller sampling frequency represents intermittent monitors operating at that frequency. For particulates there is only one type of monitor. It could be operated (in the Fulton County example) at a sampling frequency of either 60 days per year or 120 days per year. For sulfur dioxide there are two types of monitors: (1) continuous and (2) intermittent. The intermittent monitors can be operated at a sampling frequency of either 60 or 120 days per year. Therefore, for particulates, there are two sampling frequencies which can be employed for detecting a violation of either the 24-hour or annual standard; while, for sulfur dioxide, there are three sampling frequencies which can be employed for detecting a violation of either the 24-hour or annual standard. Since intermittent monitors collect 24-hour samples only, they cannot be used to detect a violation of a standard with an averaging time of less than 24 hours. Consequently, there is only one sampling frequency (i.e. continuous) which can be used for detecting a violation of the one hour sulfur dioxide standard.

The statistical model uses the Binomial equations of CHAPTER III to calculate a probability of detection of a violation of each standard for each sampling frequency which can be employed. This means that there are a total of four probabilities associated with particulates, two for each standard, and seven probabilities associated with sulfur dioxide, one for the one hour standard and three for each of the other two standards. Table 2 of the Appendix lists the calculated probabilities, associated with each sampling frequency, of detecting a violation of each TSP and SO_2 standard for each receptor location in the Fulton County example case.

The computer coded statistical model also sets up the objective function values (i.e. detection probabilities) and generates the constraint matrix of the linear programming problem, using the methods of CHAPTER III, in the proper format for input to the computer solution procedure used in the third phase.

Sequential Reduction of the Feasible Region with the Linear Programming Model

In the linear programming formulation of CHAPTER IV, for the Fulton County example, $l = 2$ and $m = 2$ for particulates and $l = 2$ and $m = 3$ for sulfur dioxide, where l is the number of standards and m is the number of sampling frequencies. Since for every positive probability of violating a standard there will be a positive probability of detecting a violation, the number of probabilities in the largest set of probabilities associated with a standard for a pollutant, out of all of the sets associated with the standards for that pollutant, is the number of receptor locations or sites which will be considered for monitor placement. Receptor locations with probabilities of zero will not be considered. Therefore, from the output of the statistical model, $k = 122$ for particulates and $k = 10$ for sulfur dioxide. The consequences of the small number of sites to be considered for sulfur dioxide monitor placement will be discussed fully in subsequent chapters. The immediate consequence is that the problem is simplified and the location procedure need not be used for designing the sulfur dioxide network. Therefore the procedure will be carried out for total suspended particulates only. The resulting matrix of potential locations for particulate monitor placement is shown in Figure 8.

In considering the grid resolution used in the atmospheric simulation model and the recommended distance between monitors specified in reference (16), it is concluded that for this example s should equal two. This value of s will also be used in the sections of larger grids because of

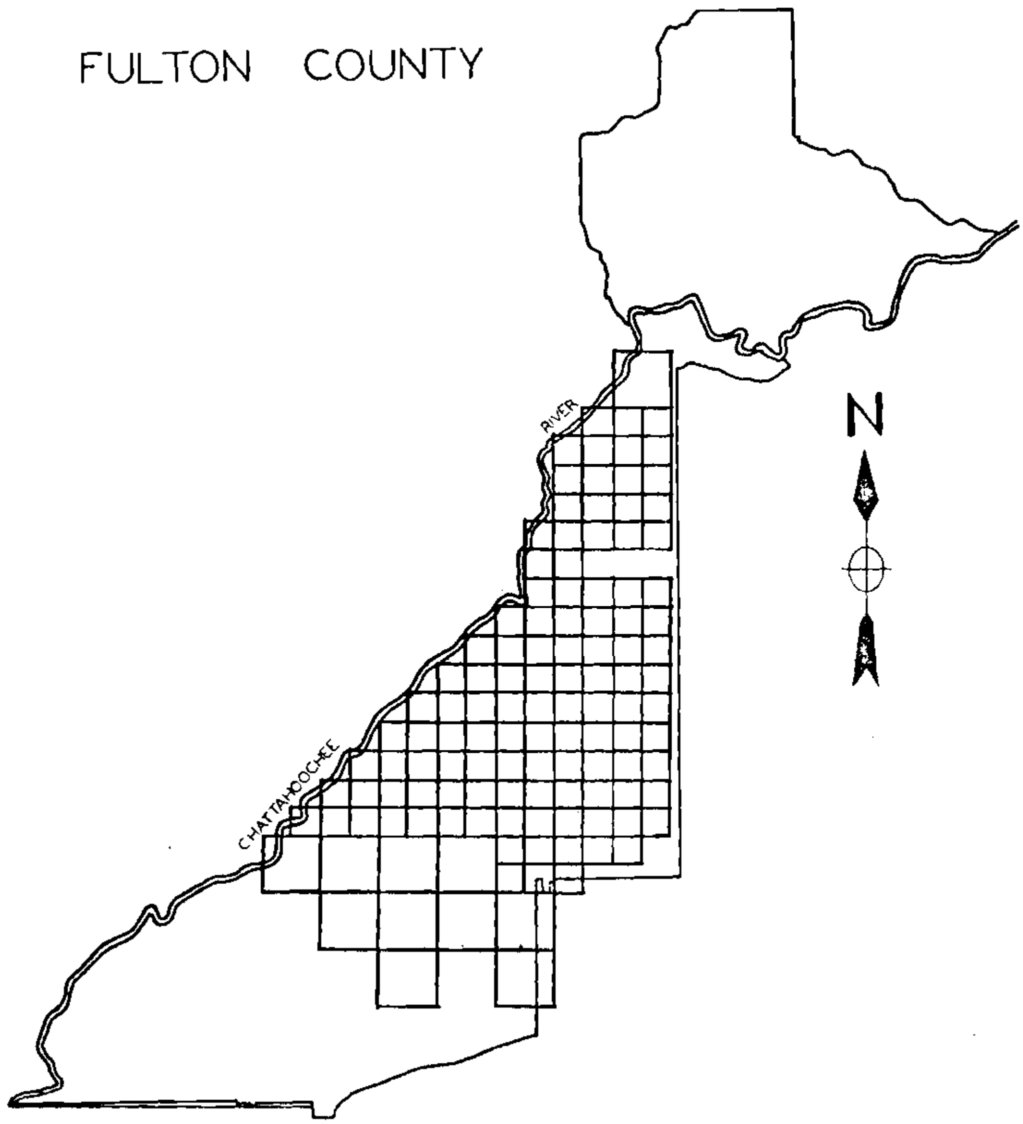


Figure 8. Potential Locations for Particulate Monitor Placement

the limited number of sources and the limited variation of concentrations in those areas.

The linear programming formulation for particulates in the Fulton County example then becomes the following:

$$\text{Maximize} \quad \sum_{i=1}^{2} \sum_{j=1}^{2} \sum_{k=1}^{122} p_{ijk}\, x_{ijk}$$

$$\text{Subject to} \quad \sum_{i=1}^{2} \sum_{j=1}^{2} \sum_{k=1}^{122} x_{ijk} \le b$$

$$\sum_{i=1}^{2} \sum_{j=1}^{2} \sum_{K \in I(p,q)} x_{ijk} \le 1 \; , \quad p = 1,2,\ldots,n_1-s+1, \quad q = 1,2,\ldots,n_2-s+1$$

$$x_{ijk} \ge 0$$

where b is the number of particulate monitors and

$$I(p,q) = \left\{k;\ k=(p+s_1-2)n_2+(q+s_2-1), s_2=1,2 \ ;\ s_1=1,2\right\}.$$

In Fulton County the number of monitors currently available for placement is thirteen and therefore b = 13 initially, but the value of b will be varied to determine the effect of expanding the network.

The constraint matrix was generated by the computer program used in the statistical modeling. It was necessary to limit the rectangular grid-covering area described in CHAPTER III to include only the portion of receptor locations composed of grids two kilometers square (n_1 = 15 and n_2 = 13).

The four kilometer square grids and some two kilometer square grids were excluded. These grids outside the rectangular covering area were then added to the constraint matrix. All of the grid squares in this covering not included in Fulton County are given zero probabilities. The sets of probabilities of size 122 for some sampling frequencies and standards also contain some zero probabilities. Therefore, the constraint matrix and the objective function were reduced to include only x_{ijk} variables which have positive probabilities. This reduced matrix and the objective function probabilities were output from the statistical model computer program in the format necessary for input to the linear programming solution procedure used in this phase.

This linear programming solution procedure consists of a computer coded package called Subroutines for Experimental Optimization (SEXOP) (4) which was obtained from the Massachusetts Institute of Technology via Georgia Tech. It is composed of 24 subroutines which, in addition to solving large linear programming problems (specific dimensions must be input) and allowing for the addition of columns to the problem, will also permit changing of the right hand side and the objective function and will perform a parametric analysis on each.

In the second LP problem formulation the objective function of the first LP must be added as a constraint (row).

Since the SEXOP procedure allows only the addition of columns, the first LP problem was transformed into its dual to take advantage of this SEXOP feature in solving the second problem. If the reduced constraint matrix is designated A, the right hand side B, and the objective function coefficients P, the first problem becomes the following:

$$\begin{array}{ll} \text{Maximize} & Px \\ \text{Subject to} & Ax \leq B \\ & x \geq 0 \end{array}$$

The dual of this problem is then:

$$\begin{array}{ll} \text{Minimize} & wB \\ \text{Subject to} & -wA \leq -P \\ & w \geq 0 \end{array}$$

The population densities needed for the second LP problem were calculated from the Atlanta Regional Commission (54) population estimates for 1976. Since only the particulate network is being designed and there are no standards with averaging times of less than 24 hours for particulates, it was not necessary to consider employment density and shopping density in determining the population densities subjected to the particulate concentrations. If the population densities are designated D, the second LP problem becomes the following:

$$\begin{aligned} &\text{Maximize} && Dx \\ &\text{Subject to} && -Px \leq -Z^{*} \\ &&& Ax \leq B \\ &&& x \geq 0 \end{aligned}$$

The dual of this problem is the following:

$$\begin{aligned} &\text{Minimize} && -w_1 Z^{*} + w_2 B \\ &\text{Subject to} && w_1 P - w_2 A \leq -D \\ &&& w_1 \geq 0 \quad w_2 \geq 0 \end{aligned}$$

Since SEXOP is only a package of subroutines, a control program was written to use the needed subroutines in proper order. This control program reads in the data for the first LP dual problem, calls the appropriate subroutines to solve the problem using the primal simplex procedure, reads the population densities for the second LP dual problem, reoptimizes, adds the objective function of the first LP as a column, and reoptimizes using the primal simplex method. This procedure was followed not only to determine the maximum values of the objective functions for the existing number of monitors but also to determine the curve representing the maximums that can be attained with any number that can be placed in the area. These curves can be viewed as system effectiveness curves.

This math programming solution procedure accomplished a two step sequential reduction of the feasible region. The next chapter discusses the results of this procedure and the third reduction described in CHAPTER III. It also discusses the system effectiveness curves that were generated by this procedure and the optimum monitoring networks that can be designed for Fulton County.

CHAPTER V

MODIFICATIONS AND RESULTS

There are two problems associated with the identification of the optimum network sites from the results of the solution procedure used in CHAPTER IV. The first problem, the probable existence of alternate optimal sites and therefore network configurations, has been partially addressed by the inclusion of population dosage considerations in the second LP problem formulation. Also the existence of alternate optimal sites has been cited as beneficial from the point of view of actual siting of the monitors. (If a selected grid area is unacceptable, alternate sites or configurations could be examined.) However, the identification of these alternate optimal sites or network configurations is very difficult, and, even when identified, an examination process would have to be developed to evaluate all of the alternatives (which could be numerous). The second problem is that integer solutions cannot be assured to either LP problem. This is true because neither matrix of coefficients is totally unimodular; the constraint matrix contains many odd cycles. Thus, the optimal solution to the problem set may not be in a totally usable form. A procedure is needed to resolve non-integer solutions should they appear. Hopefully, an optimal integer solution can be identified from the (hypothetical) alternative solutions. However, if one cannot be identified, a suboptimal, integer solution must be selected. This chapter discusses how these problems can be resolved in selecting the best particulate monitoring network for Fulton County, both with existing resources and with additional resources.

Fulton County's current resources for particulate monitoring consist of 13 intermittent monitors. The network configuration of the linear programming solution to the first problem with b = 13 is shown in Figure 9. As anticipated, an integer solution was not achieved. When the second problem was solved using the constraint

$$\sum_{i} \sum_{j} \sum_{k} p_{ijk} x_{ijk} = Z^*,$$

where Z^* is the optimum objective function value of the first problem (Z^* = the detection capability), no change in configuration occurred. Yet the corresponding objective function value of the second problem Y^* (Y^* = the protection capability), was only 60 percent of the maximum achievable without the above constraint. Since the detection probabilities are not absolutely accurate, it seems necessary to investigate the effect on the solution configuration of a tradeoff between protection capability and detection capability. Therefore, the above constraint was modified to

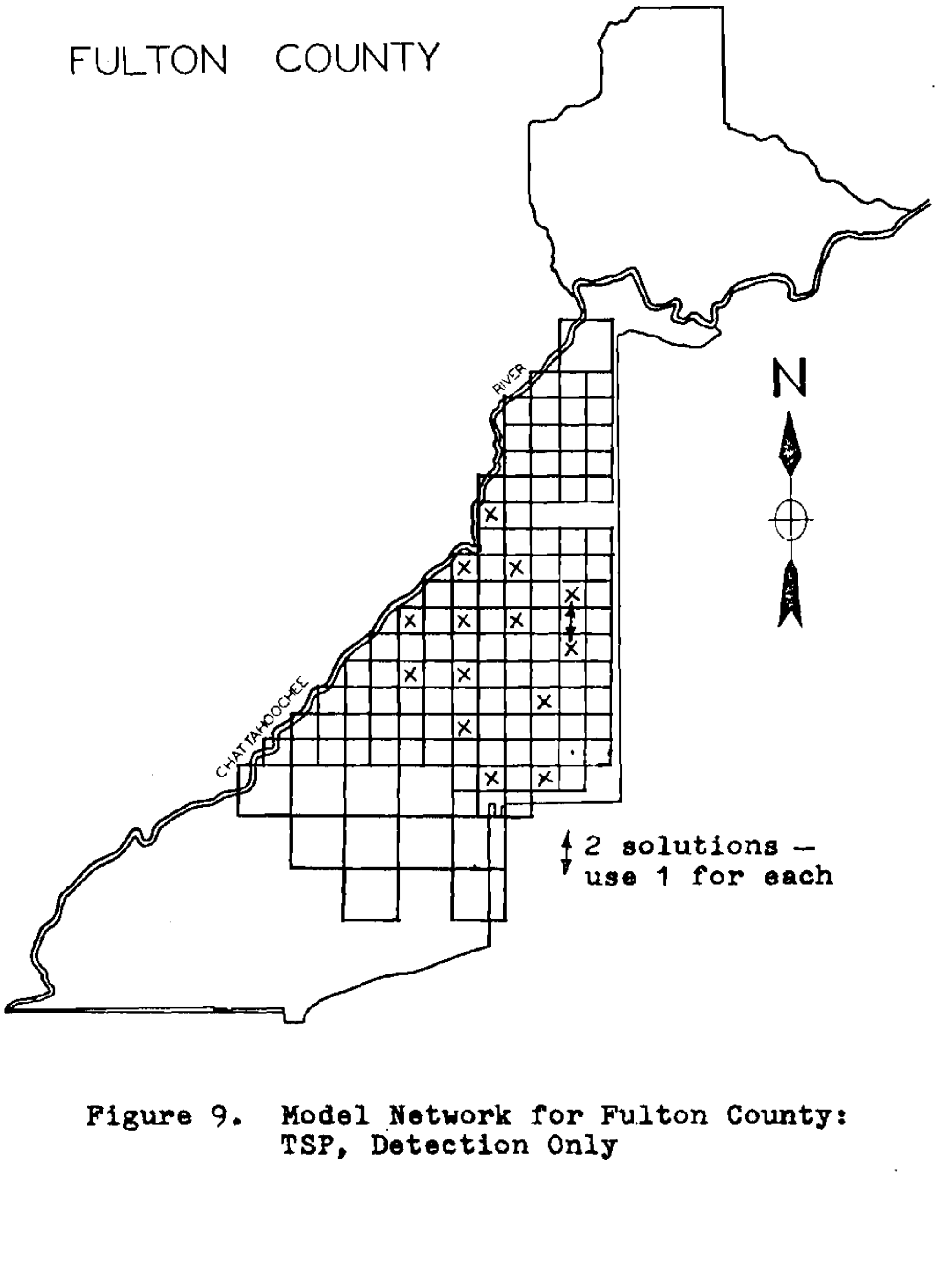


Figure 9. Model Network for Fulton County: TSP, Detection Only

the following:

$$\sum_i \sum_j \sum_k p_{ijk} \, x_{ijk} \geq Z^* (1 - \epsilon)$$

For $1 \geq \epsilon \geq 0$, the detection capability of the solution to the protection problem will be within 100ϵ percent of its optimal value. The protection problem was then solved with increasing values of ϵ. Table 5 shows the detection capabilities and protection capabilities for these values of ϵ. The table shows that a five percent decrease in the detection capability yields a protection capability of 84 percent of its maximum, a ten percent decrease yields a protection capability of 91 percent; and a twenty percent decrease yields a protection capability of 99 percent.

Table 5. Summary of Monitor Location Results: 13 Monitors

ϵ	0.00	0.05	0.10	0.20	1.00
Detection Capability	10.783	(1)10.324 (2)10.208	(1) 9.882 (2) 9.605	8.626	4.415
Protection Capability	63.455	(1)88.522 (2)90.432	(1)95.346 (2)99.156	106.469	107.320

When evaluating trade-offs such as these, it must be remembered that the primary objective of an air monitoring network is detection. Therefore, the 95 percent detection capability, 84 percent protection capability solution was chosen as the best for Fulton County. The five percent decrease in detection is well within the error limits of the detection probabilities and the increase in protection capability achieved is significant. Further reductions in detection capability do not yield significant increases in protection capability. This solution configuration is shown in Figure 10. The configuration for the 90 percent, 91 percent solution is shown in Figure 11. Again integer solutions were not achieved. However, the configurations are such that only two possible integer solutions can be identified. An evaluation of these two integer solutions reveals that one has superior detection capability, while the other has superior protection capability. These values are also shown in Table 5. To be consistent with monitoring objectives the solution with 96 percent detection capability and 83 percent protection capability should be chosen as optimal for Fulton County.

The current particulate monitoring network in Fulton County operates on a six day sampling schedule. At this frequency, it has a detection capability of 5.87 and a protection capability of 77.84. If the sampling frequency were increased to a three day schedule to match that of the

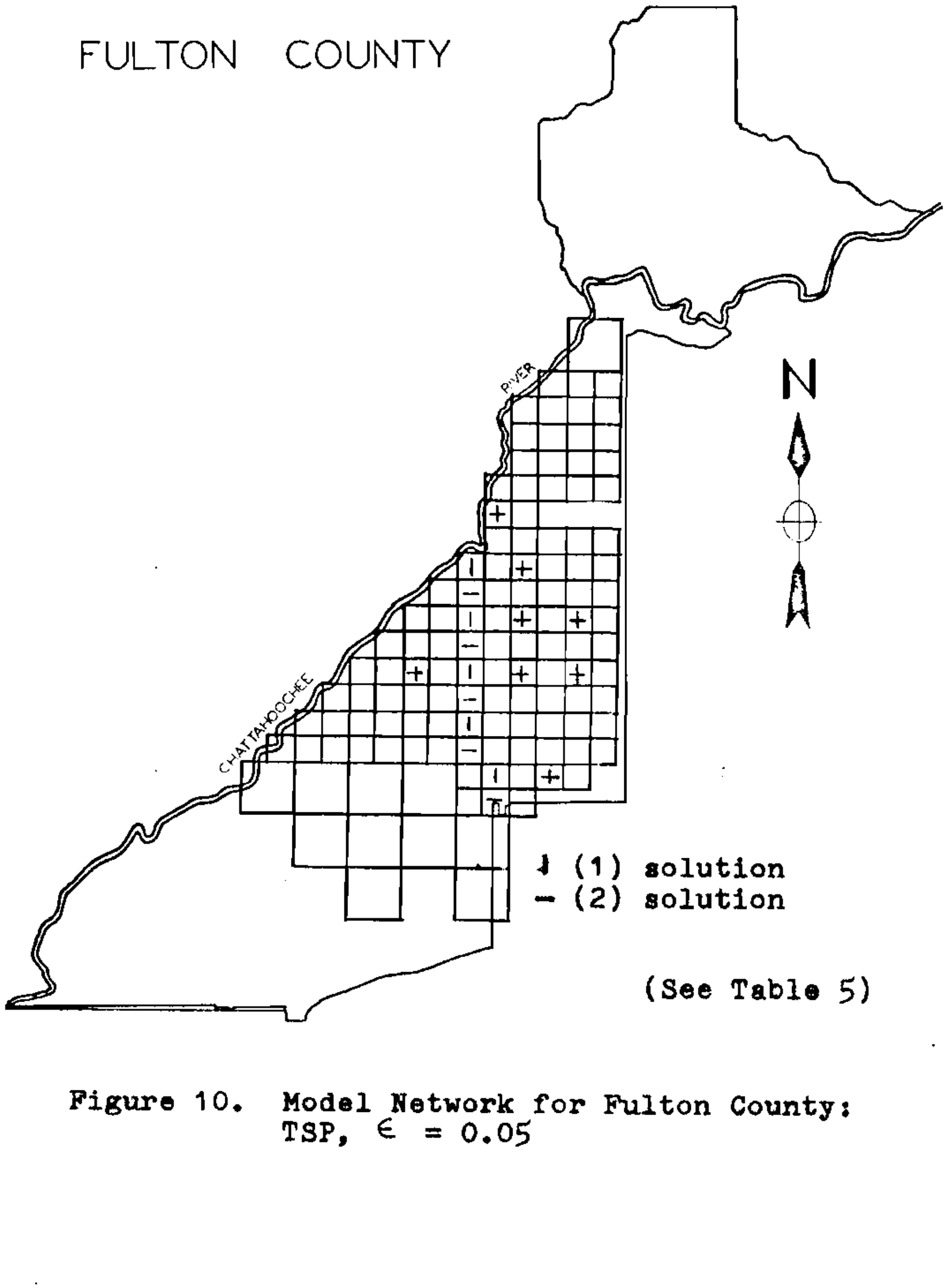


Figure 10. Model Network for Fulton County: TSP, $\epsilon = 0.05$

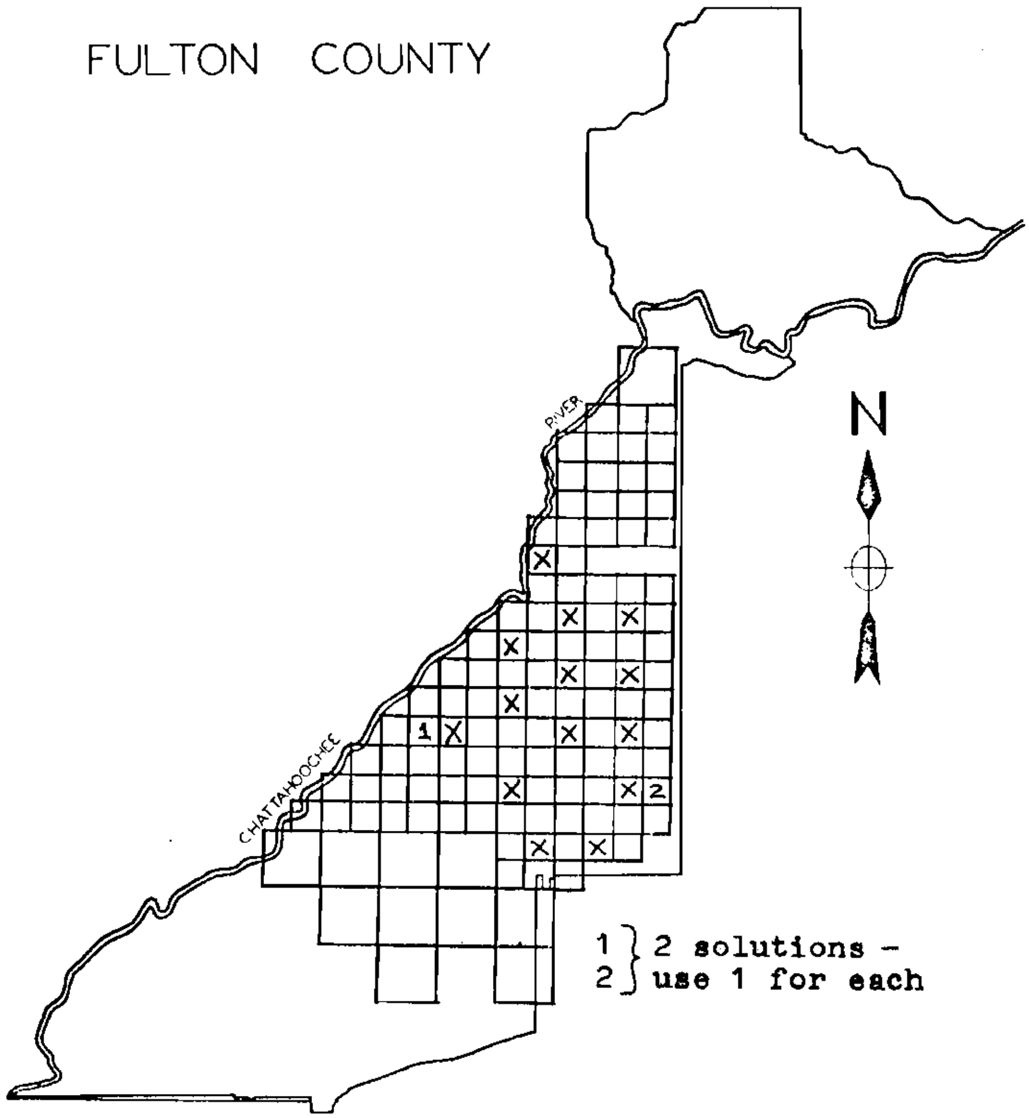


Figure 11. Model Network for Fulton County: TSP, ϵ = 0.10

chosen model solution, the detection capability would be increased to 7.649. (These values are actually biased because the current configuration violates a monitor proximity constraint. This means that one monitor, according to the model formulation, is being wasted. However, this monitor was not excluded from the capability calculations.) The model solution cited as optimal for Fulton County would operate with a three day sampling frequency and would increase the detection capability 76 percent over the current network with six day sampling and 35 percent over the maximum achievable with a three day sampling frequency. This improvement in detection capability is dramatic. The improvement in protection capability of 14 percent is less dramatic. However, it is still significant considering the fact that it is easier to identify population densities than pollutant densities in the network design process. A comparison of the current network configuration and the optimal model configuration is shown in Figure 12.

As indicated previously, the selected model network according to the solution results, would operate with a three day sampling frequency. However, when the detection probabilities with a six day and a three day sampling frequency are compared, as in Table 6, it is evident that at least one and possibly more of the monitoring sites could be operated on a six day sampling frequency with very little decrease in the overall detection capability. In actual situations the

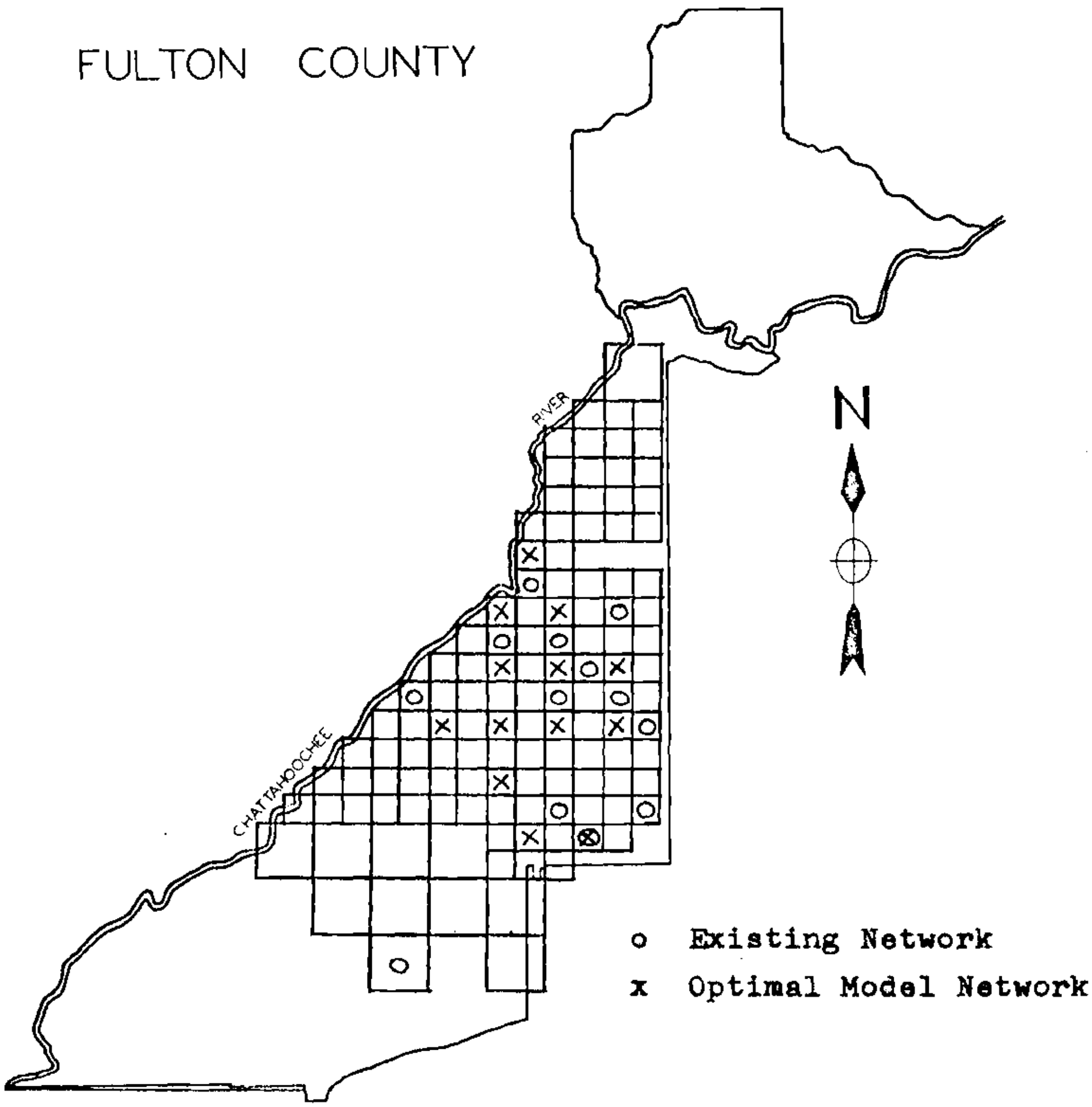


Figure 12. Comparison of Existing TSP Network in Fulton County and Best Model Network

sampling frequency decision must consider cost factors. The present formulation does not consider costs. Therefore, although one announced intent of this procedure was to make the sampling frequency decision-and it does indicate the best frequency given the model criteria-it cannot, except in certain clear cases such as the one in Table 6, actually evaluate the tradeoffs involved in the decision. Although cost is a less important criterion than detection and protection, a cost model should be developed.

Table 6. Detection Capabilities at Various Sampling Frequencies

Location	Detection Probability	
	Three-day	Six-day
146	.912	.703
153	.812	.648
155	.978	.851
168	.842	.742
172	.731	.481
185	.664	.420
187	.842	.655
189	.464	.268
191	.483	.281
210	.812	.566
234	.857	.621
236	.927	.729
346	*1.000	*.994

* Six-day sampling could be used.

It is possible that one or more of the grids in the optimum model network will fail to provide a suitable site for physically placing the monitors. Should this occur, one or more alternates must be selected. These alternates can easily be identified by giving the unacceptable grids zero detection probabilities and population densities in the input data and resolving the LP problems. If there are alternate optimal configurations, this will guarantee their selection. If there are no alternate optimal configurations, the best suboptimal configuration will be selected. This method avoids identifying any alternate optimal configurations unless they are needed.

When a new solution is achieved, the resulting network configuration may be changed completely. (Therefore it is not reasonable to merely select alternates for the unacceptable sites using only judgment.) This procedure was tested on the chosen model network by arbitraily declaring two sites unacceptable. The resulting configuration and network capabilities are shown in Figure 13.

The previous discussion has dealt with designing the optimal network configuration using the monitoring resources currently available. Of equal interest is the result of allocating additional resources to the monitoring effort. To investigate this effect in Fulton County, the detection and protection capabilities were determined from the solution procedure for recources from zero to the maximum that can be placed in the county given the model constraints.

Plots were made of these capabilities for various values of ϵ. These plots are shown in Figures 14 and 15.

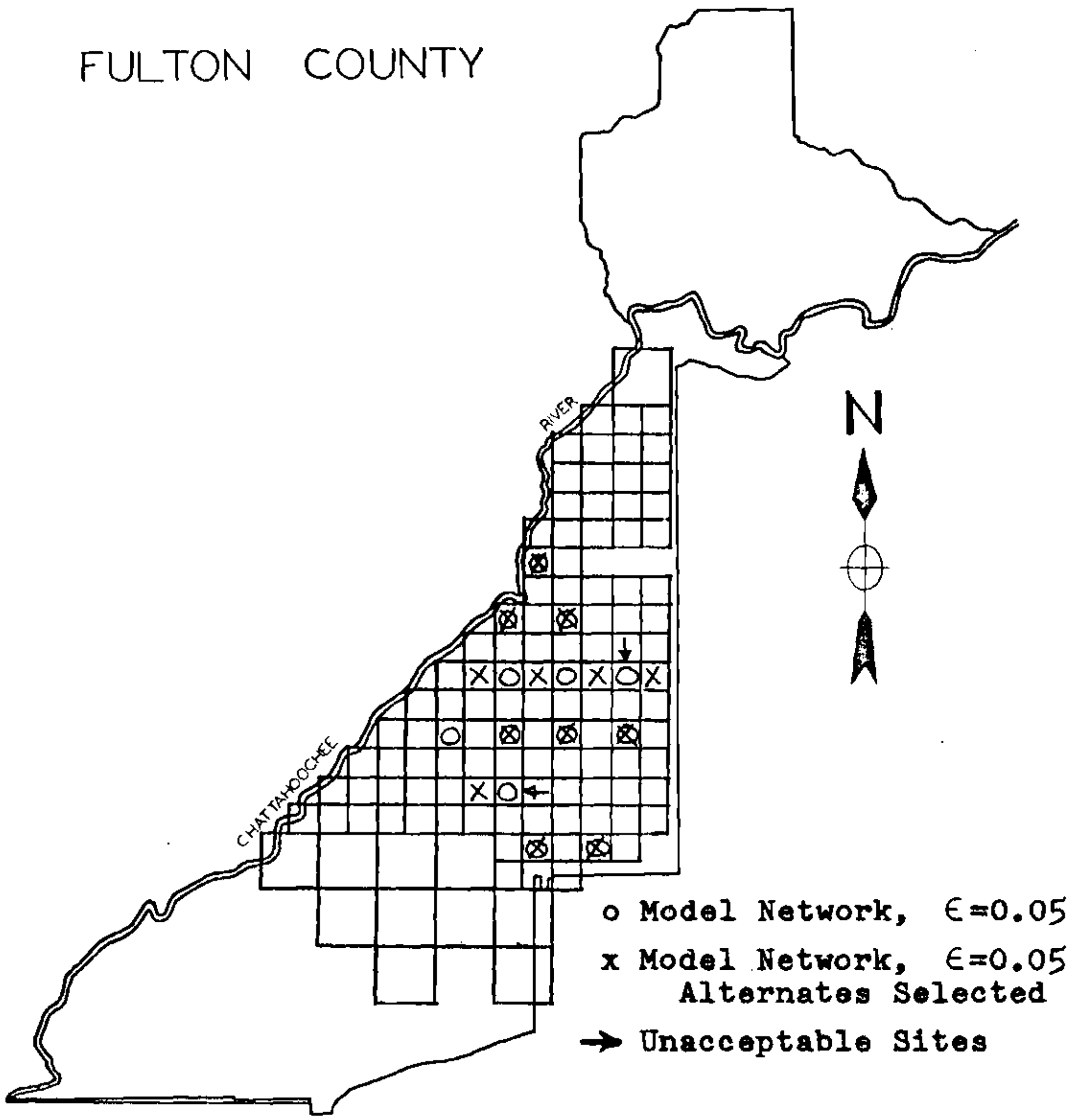
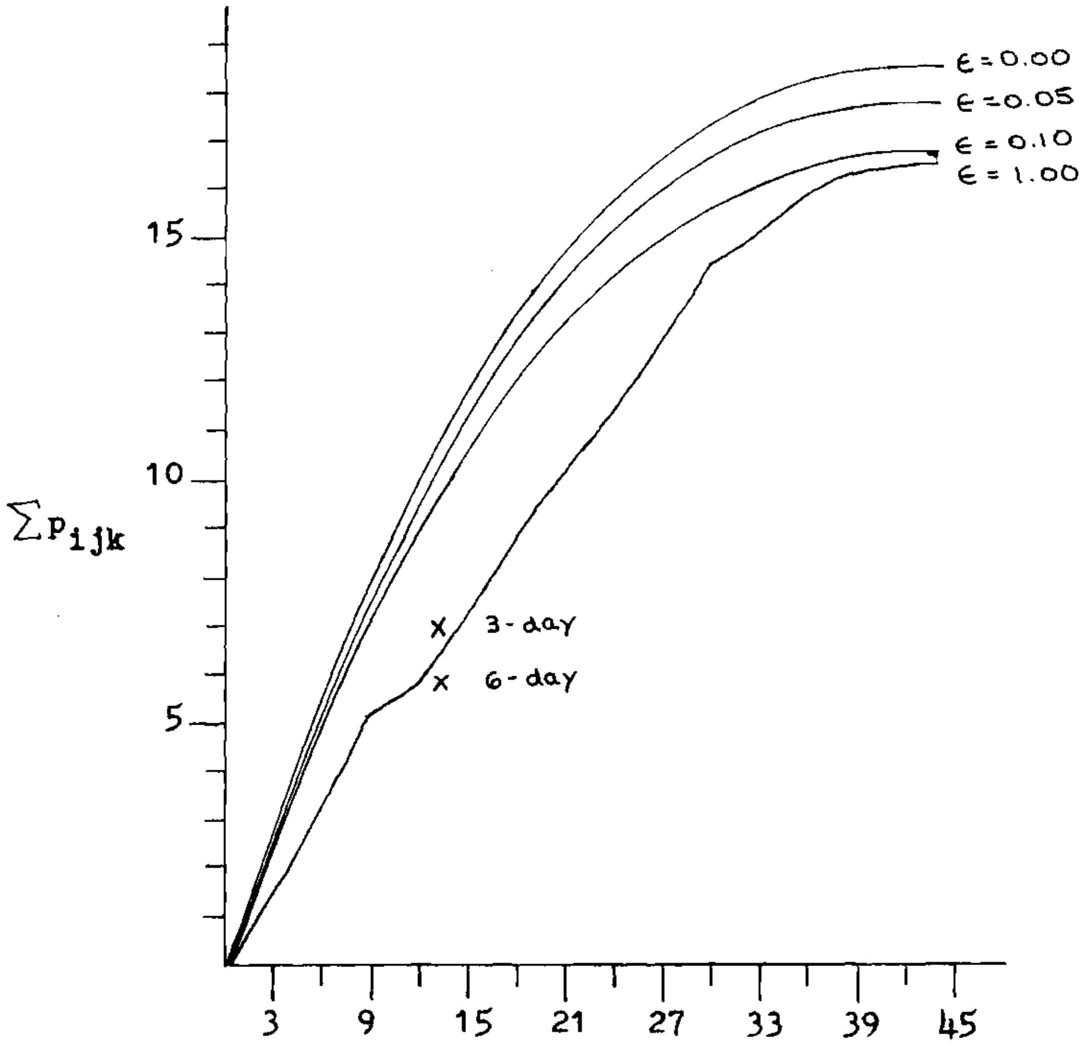


Figure 13. Model Network for Fulton County: TSP, Alternate Configuration with Two Sites Unacceptable

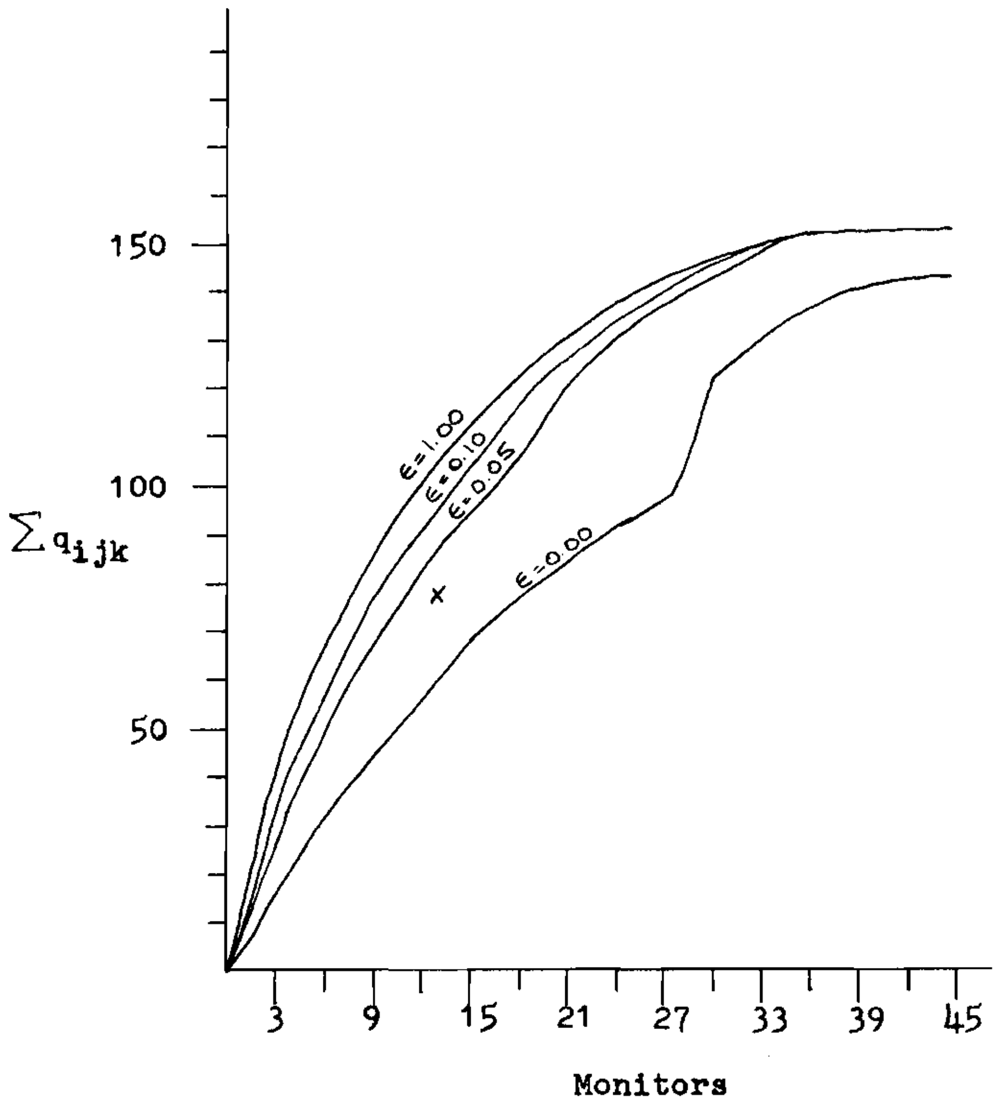
From these plots it is clear that the marginal value of the monitors begins to drop off rapidly as the number of monitors increases beyond fifty percent of the maximum. This maximum is actually 38. Therefore, significant improvement in the particulate monitoring network can be achieved by adding monitors to the system up to approximately 21. Twenty-one monitors obtain 80 percent of the maximum achievable detection capability and 81 percent of the maximum protection capability. Figure 16 shows the tradeoff between detection and protection capabilities for any number of monitors and any value of ϵ. The curves in Figures 14, 15, and 16 are system effectiveness curves. They allow not only the determination of the optimal monitoring network for a given number of monitors but also for any increased number of monitors up to the total system optimum. By using these curves (and the corresponding model results) and the methods for resolving non-integrality and identifying alternates developed in this chapter, the best particulate monitoring system can be identified for Fulton County, both now and in the future.

As indicated in CHAPTER IV, the application of the procedure to the sulfur dioxide monitoring network was discontinued after the results of the second phase were obtained. Only a few of the detection probabilities had positive values. There were not enough to warrant the application of phase three of the procedure. In selecting



x Present Network

Figure 14. Detection Capability Versus Number of Monitors



x Present Network

Figure 15. Protection Capability Versus Number of Monitors

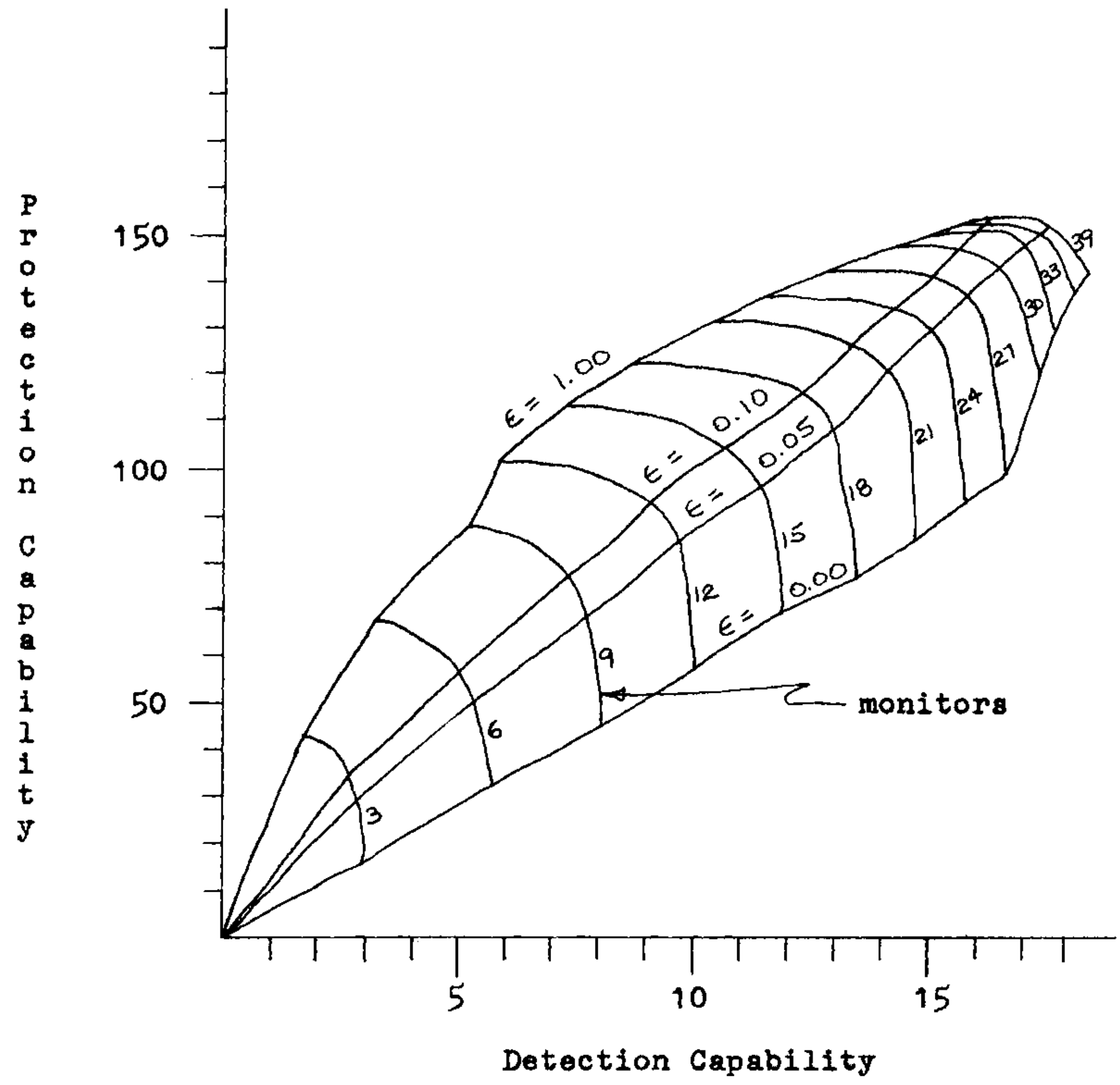


Figure 16. Trade-offs Between Protection and Detection Capabilities

the best sites for the monitors, it is only necessary to consider the small number of detection probabilities and their associated population densities and choose those with the highest values, while considering monitor displacement criteria. The tradeoffs involved can be effectively considered without the aid of linear programming. Figure 17 shows the SO_2 model network which results from such an analysis. The network consists of only three monitors. Fulton County currently has three continuous SO_2 monitors and six intermittent monitors. Therefore, the current resources exceed the requirements. However, recall that only three monitoring sites had produced usable historical monitoring data; all data from intermittent monitors was declared inaccurate by the EPA and Fulton County. Thus, the correlations of the diffusion model and the resulting predictions of SO_2 concentrations were based on insufficient data. Before the results of the application of this procedure to the SO_2 monitoring network can be accepted, a larger data base must be developed.

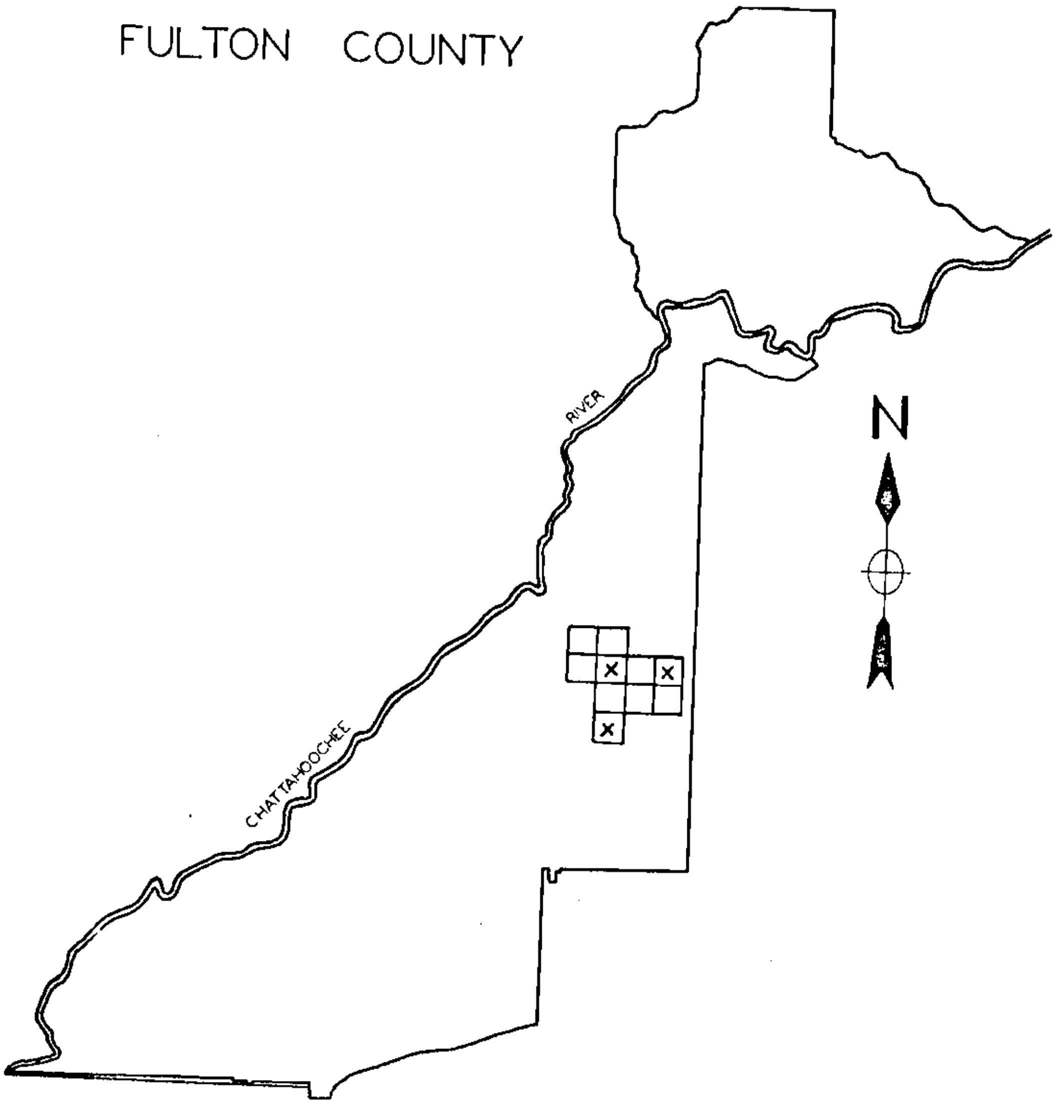


Figure 17. Model Network for Fulton County: SO_2

CHAPTER VI

CONCLUSIONS AND RECOMMENDATIONS

A mathematical procedure for air monitoring instrumentation location and sampling frequency selection has been developed. The need for such a procedure arises from the necessity of developing air monitoring networks in the quest for clean air and the lack of a structured, objective method of satisfying monitoring objectives, meeting location criteria, and considering the factors influencing location determination.

The procedure which has been developed incorporates atmospheric simulation modeling and statistical modeling currently used by air pollution agencies and, by further developing the statistical modeling, provides sufficient data for a mathematical programming formulation and thus a means of selecting instrumentation locations. It has been successfully applied to the particulate monitoring network of Fulton County, Georgia with significant increases over the present system in both violation detection and population protection capabilities. In addition, it generates valuable information for evaluating the potential benefits of allocating more sources to the monitoring effort and for determining new network configurations with increased resources.

Because the methodology employed is quite general, the procedure can be easily adopted, understood, and implemented in other air quality regions. However, the procedure is not without shortcomings, and these have led to certain conclusions regarding its usage and recommendations for further development.

The data base required by the procedure is extensive. However, the data preparation effort is reduced considerably by the use of data whose development is currently required by EPA. At least in metropolitan areas the data base should be readily available. One type of data not readily available is estimates of the geometric standard deviations of the pollutant concentrations at each receptor of the network grid. These are available only at current monitoring sites and in Fulton County were obtained for other sites by interpolation. A procedure for generating or more accurately estimating these values is needed. Since the location procedure is dynamic and should be applied at specific time intervals to reassess the network design, the data base will be constantly enlarged and initial inadequacies in this and other data can be overcome in subsequent years.

The atmospheric simulation model used in the procedure could only predict concentration of particulates and sulfur dioxide and these with limited success due to inadequacies and inaccuracies in both the model and the input data. Better methods are needed in developing input data particularly area source emissions. Since the procedure is highly dependent on the integrity of the simulation model, improvements in the model structure would achieve more confidence in the results of the procedure. Models which predict concentrations of other pollutants such as carbon monoxide can be incorporated into the procedure when these models become more reliable and as more input data is developed. Modification of the mathematical model to address any specific location or displacement criteria peculiar to another pollutant should be achievable.

Primarily because of the atmospheric simulation model, the procedure is expensive in terms of computer resources. However, simulation modeling is currently required by EPA in metropolitan areas, and thus the added costs of the procedure are only those of the statistical modeling and the mathematical solution procedure which are not excessive.

A stated objective of the development of the location procedure was the selection of the optimum sampling frequency at each selected monitor location. The procedure does in fact indicate the optimum sampling frequency according to the stated criteria and provides information for determining the capabilities of the system at other sampling frequencies. However, except in certain obvious cases, it does not allow a true evaluation of the trade-offs between sampling frequencies, because it does not explicitly consider the associated monetary costs involved in the tradeoffs.

Therefore, an extension of the procedure to further address the selection of optimum sampling frequencies is needed.

Although it was possible to identify optimum location configurations from the results of the mathematical solution procedure, significant improvements could be made in this area. Methods were developed for identifying integer solutions from the fractional solutions obtained and for identifying alternate sites. These additional methods were needed because the solution procedure chosen was not really suited to the problem as formulated. Linear programming was chosen as the solution procedure because of the size of the problem (and potential problems) and the fact that no better procedure exists for the special structure of this problem. (At least the author is unaware of its existence.)

The size of the problem can actually be reduced by further considerations. For a given standard, at any site, the constraint vectors for all sampling frequencies are identical. Since only one frequency can be selected, only the one yielding the largest detection probability need be considered. If more than one standard is considered, the constraint vectors for continuous monitors would be identical, as would the constraint vectors for intermittent monitors. Therefore, at a given site for a particular monitor type, only the standard with the highest probability of detection need be considered. These observations reduce the number of location variables from lmn to 2n. This reduction was actually made by the linear programming procedure. However, in the interest of considering a smaller problem, the reduction could be made by the statistical model when the input data for the solution procedure is generated.

The smaller problem is seen to be a set-packing problem (45,47) with two additional generalized upper bound constraints. The set-packing problem is a integer programming problem; however, there is still no known procedure for solving it with additional constraints. Therefore, for future procedure improvements, the major effort should perhaps be concentrated toward the development of better solution procedures.

In summary, a procedure for air monitoring instrumentation location and sampling frequency selection has been developed to treat mathematically what has previously been a very subjective process. Through application to real world data, it has been shown to give significantly improved solutions to existing monitoring networks. Although this procedure is not the final word in solving the location problem, it hopefully represents a substantial step toward that end.

APPENDIX

Table 1. Monitoring Sites Used in the Diffusion Model

UTM Coordinates		Annual Mean ($\mu g/m^3$)	
Easting	Northing	TSP	SO_2
Fulton County Sites			
737	3730	47	
742	3738	58	38
745	3730	49	24
742	3745	43	
741	3741	60	
728	3738	50	
734	3743	60	
737	3743		30
744	3737	59	
739	3739	50	
736	3745	68	
725	3716	36	
Georgia EPD Sites			
740	3742	70	
752	3755	56	
742	3722	62	
728	3759	50	
730	3752	50	

Table 2. STATISTICAL DATA FOR SELECTED RECEPTORS

ANNUAL PARTICULATES

AVERAGING TIME 24.HOURS STANDARD 150.MICROGRAMS / CUBIC METER

RECEPTOR LOCATION		EXPECTED ARITHMETIC MEAN	EXPECTED GEOMETRIC MEAN	GEOMETRIC STANDARD DEVIATION	EXPECTED MAXIMUM CONCENTRATION	PROBABILITY OF EXCEEDING STANDARD	PROBABILITY OF DETECTION OF A VIOLATION SAMPLING FREQUENCY--DAYS PER YEAR 61	122	365
704.	3710.	41.	38.	1.50	125.	0.0	0.0	0.0	NA
708.	3710.	42.	39.	1.50	127.	0.0	0.0	0.0	NA
708.	3714.	42.	39.	1.50	129.	0.0	0.0	0.0	NA
708.	3718.	43.	40.	1.50	131.	0.0	0.0	0.0	NA
712.	3710.	42.	39.	1.50	129.	0.0	0.0	0.0	NA
712.	3714.	43.	40.	1.50	131.	0.0	0.0	0.0	NA
712.	3718.	44.	41.	1.50	134.	0.0	0.0	0.0	NA
712.	3722.	45.	42.	1.50	137.	0.0	0.0	0.0	NA
716.	3710.	43.	40.	1.50	131.	0.0	0.0	0.0	NA
716.	3714.	44.	41.	1.50	133.	0.0	0.0	0.0	NA
716.	3718.	45.	42.	1.50	139.	0.0	0.0	0.0	NA
716.	3722.	45.	43.	1.50	140.	0.0	0.0	0.0	NA
716.	3726.	47.	43.	1.50	143.	0.0	0.0	0.0	NA
720.	3710.	43.	40.	1.50	131.	0.0	0.0	0.0	NA
720.	3714.	47.	44.	1.50	144.	0.0	0.0	0.0	NA
720.	3718.	47.	43.	1.50	141.	0.0	0.0	0.0	NA
720.	3722.	48.	44.	1.50	146.	0.0	0.0	0.0	NA
720.	3726.	50.	46.	1.50	151.	0.002	0.104	0.197	NA
724.	3710.	44.	40.	1.50	133.	0.0	0.0	0.0	NA
724.	3714.	47.	43.	1.50	141.	0.0	0.0	0.0	NA
724.	3718.	48.	44.	1.50	144.	0.0	0.0	0.0	NA
724.	3722.	50.	46.	1.50	151.	0.002	0.104	0.197	NA
724.	3726.	52.	48.	1.50	157.	0.002	0.136	0.254	NA
728.	3714.	45.	42.	1.50	137.	0.0	0.0	0.0	NA
728.	3718.	48.	45.	1.50	147.	0.001	0.082	0.157	NA
728.	3722.	52.	47.	1.50	156.	0.002	0.131	0.245	NA
728.	3726.	55.	50.	1.50	166.	0.004	0.202	0.364	NA
732.	3718.	48.	44.	1.50	146.	0.0	0.0	0.0	NA
732.	3722.	54.	50.	1.50	164.	0.003	0.193	0.332	NA
732.	3726.	58.	53.	1.50	176.	0.006	0.286	0.490	NA
734.	3718.	49.	45.	1.50	149.	0.002	0.088	0.167	NA
734.	3722.	54.	50.	1.50	164.	0.003	0.183	0.332	NA
734.	3726.	58.	53.	1.53	184.	0.007	0.353	0.591	NA
734.	3728.	62.	57.	1.53	198.	0.011	0.500	0.750	NA
736.	3726.	60.	54.	1.56	200.	0.011	0.491	0.741	NA
736.	3728.	64.	58.	1.56	213.	0.016	0.621	0.857	NA
738.	3726.	61.	55.	1.60	217.	0.016	0.621	0.857	NA
738.	3728.	66.	59.	1.60	236.	0.024	0.778	0.951	NA
740.	3728.	64.	58.	1.60	229.	0.021	0.729	0.927	NA
742.	3728.	46.	41.	1.56	153.	0.002	0.110	0.207	NA
744.	3728.	47.	43.	1.52	145.	0.0	0.0	0.0	NA
720.	3730.	51.	47.	1.50	156.	0.002	0.131	0.245	NA
722.	3730.	53.	48.	1.50	160.	0.003	0.152	0.281	NA

Table 2. (con't.) STATISTICAL DATA FOR SELECTED RECEPTORS

ANNUAL PARTICULATES

AVERAGING TIME 24.HOURS STANDARD 150.MICROGRAMS / CUBIC METER

RECEPTOR LOCATION		EXPECTED ARITHMETIC MEAN	EXPECTED GEOMETRIC MEAN	GEOMETRIC STANDARD DEVIATION	EXPECTED MAXIMUM CONCENTRATION	PROBABILITY OF EXCEEDING STANDARD	PROBABILITY OF DETECTION OF A VIOLATION SAMPLING FREQUENCY--DAYS PER YEAR 61	122	365
722.	3738.	53.	49.	1.50	151.	0.003	0.157	0.290	NA
724.	3730.	54.	50.	1.50	164.	0.003	0.193	0.332	NA
724.	3732.	54.	50.	1.50	165.	0.004	0.193	0.348	NA
724.	3734.	54.	50.	1.50	165.	0.004	0.193	0.348	NA
726.	3730.	55.	51.	1.50	167.	0.004	0.207	0.372	NA
726.	3732.	56.	51.	1.50	168.	0.004	0.217	0.387	NA
726.	3734.	56.	51.	1.50	169.	0.004	0.221	0.400	NA
726.	3736.	56.	52.	1.50	170.	0.004	0.221	0.400	NA
728.	3730.	58.	53.	1.50	175.	0.005	0.272	0.471	NA
728.	3732.	57.	52.	1.50	172.	0.005	0.254	0.444	NA
728.	3734.	59.	54.	1.50	179.	0.006	0.316	0.532	NA
728.	3736.	59.	55.	1.50	180.	0.006	0.324	0.543	NA
728.	3738.	58.	53.	1.50	176.	0.005	0.291	0.493	NA
730.	3730.	60.	55.	1.50	182.	0.007	0.353	0.581	NA
730.	3732.	60.	56.	1.50	183.	0.007	0.353	0.581	NA
730.	3734.	62.	57.	1.50	187.	0.008	0.402	0.643	NA
730.	3736.	62.	57.	1.50	189.	0.009	0.420	0.664	NA
730.	3738.	62.	57.	1.50	187.	0.008	0.402	0.643	NA
732.	3730.	62.	57.	1.51	190.	0.009	0.427	0.672	NA
732.	3732.	61.	56.	1.51	190.	0.009	0.420	0.664	NA
732.	3734.	64.	59.	1.51	198.	0.012	0.518	0.768	NA
732.	3736.	65.	60.	1.50	196.	0.012	0.509	0.759	NA
732.	3738.	63.	58.	1.50	192.	0.010	0.465	0.714	NA
734.	3730.	64.	58.	1.52	199.	0.012	0.518	0.768	NA
734.	3732.	65.	59.	1.52	203.	0.014	0.566	0.812	NA
734.	3734.	65.	60.	1.52	207.	0.015	0.602	0.842	NA
734.	3736.	67.	61.	1.51	206.	0.015	0.602	0.842	NA
734.	3738.	67.	62.	1.51	208.	0.016	0.631	0.864	NA
736.	3730.	48.	44.	1.53	152.	0.002	0.110	0.207	NA
736.	3732.	49.	45.	1.53	156.	0.002	0.131	0.245	NA
736.	3734.	51.	46.	1.52	159.	0.003	0.147	0.272	NA
736.	3736.	52.	48.	1.52	163.	0.003	0.173	0.315	NA
736.	3738.	53.	48.	1.52	166.	0.004	0.193	0.348	NA
738.	3730.	48.	44.	1.53	154.	0.002	0.120	0.226	NA
738.	3732.	50.	45.	1.53	159.	0.003	0.147	0.272	NA
738.	3734.	54.	50.	1.52	170.	0.004	0.231	0.409	NA
738.	3736.	56.	51.	1.52	175.	0.005	0.268	0.464	NA
738.	3738.	56.	52.	1.52	177.	0.005	0.281	0.483	NA
740.	3730.	53.	49.	1.53	170.	0.004	0.217	0.387	NA
740.	3732.	55.	51.	1.52	174.	0.005	0.259	0.451	NA
740.	3734.	62.	57.	1.51	191.	0.009	0.438	0.684	NA
740.	3736.	60.	56.	1.50	183.	0.007	0.360	0.591	NA
740.	3738.	64.	58.	1.50	193.	0.010	0.465	0.714	NA

Table 2. (cont.) STATISTICAL DATA FOR SELECTED RECEPTORS

ANNUAL PARTICULATES

AVERAGING TIME 24.HOURS STANDARD 150.MICROGRAMS / CUBIC METER

RECEPTOR LOCATION		EXPECTED ARITHMETIC MEAN	EXPECTED GEOMETRIC MEAN	GEOMETRIC STANDARD DEVIATION	EXPECTED MAXIMUM CONCENTRATION	PROBABILITY OF EXCEEDING STANDARD	PROBABILITY OF DETECTION OF A VIOLATION SAMPLING FREQUENCY--DAYS PER YEAR 61	122	365
742.	3730.	50.	46.	1.52	157.	0.002	0.136	0.254	NA
742.	3732.	55.	51.	1.50	159.	0.004	0.217	0.387	NA
742.	3734.	58.	54.	1.49	173.	0.005	0.250	0.451	NA
742.	3736.	59.	55.	1.48	174.	0.005	0.281	0.493	NA
742.	3738.	60.	55.	1.54	196.	0.010	0.465	0.714	NA
744.	3730.	50.	46.	1.52	159.	0.003	0.142	0.263	NA
744.	3732.	53.	49.	1.50	162.	0.003	0.167	0.307	NA
744.	3734.	56.	52.	1.49	167.	0.004	0.207	0.372	NA
744.	3736.	57.	53.	1.48	167.	0.004	0.212	0.379	NA
744.	3738.	58.	54.	1.48	171.	0.005	0.254	0.444	NA
730.	3740.	62.	57.	1.50	198.	0.009	0.413	0.656	NA
732.	3740.	64.	59.	1.50	194.	0.011	0.481	0.731	NA
732.	3742.	62.	57.	1.50	199.	0.009	0.420	0.664	NA
734.	3740.	67.	62.	1.50	204.	0.015	0.602	0.842	NA
734.	3742.	67.	62.	1.50	204.	0.015	0.592	0.834	NA
734.	3744.	66.	61.	1.50	202.	0.014	0.566	0.812	NA
736.	3740.	72.	64.	1.59	252.	0.034	0.882	0.986	NA
736.	3742.	70.	61.	1.66	272.	0.039	0.913	0.992	NA
736.	3744.	69.	59.	1.73	296.	0.045	0.938	0.996	NA
736.	3746.	65.	56.	1.71	273.	0.034	0.882	0.986	NA
736.	3748.	61.	54.	1.64	232.	0.020	0.703	0.912	NA
738.	3740.	76.	69.	1.54	245.	0.037	0.898	0.990	NA
738.	3742.	76.	69.	1.54	245.	0.036	0.892	0.988	NA
738.	3744.	68.	61.	1.62	251.	0.031	0.851	0.979	NA
738.	3746.	65.	58.	1.62	240.	0.025	0.787	0.954	NA
738.	3748.	62.	56.	1.56	206.	0.013	0.555	0.802	NA
740.	3740.	66.	59.	1.60	235.	0.024	0.770	0.947	NA
740.	3742.	59.	54.	1.57	202.	0.011	0.500	0.750	NA
740.	3744.	52.	47.	1.58	180.	0.006	0.294	0.502	NA
740.	3746.	48.	43.	1.56	160.	0.003	0.152	0.281	NA
740.	3748.	45.	41.	1.53	143.	0.0	0.0	0.0	NA
742.	3740.	61.	56.	1.54	198.	0.011	0.481	0.731	NA
742.	3742.	60.	55.	1.54	195.	0.010	0.465	0.714	NA
742.	3744.	51.	47.	1.54	167.	0.004	0.197	0.356	NA
742.	3746.	47.	43.	1.54	153.	0.002	0.115	0.217	NA
742.	3748.	44.	40.	1.52	137.	0.0	0.0	0.0	NA
744.	3740.	57.	53.	1.52	180.	0.006	0.316	0.532	NA
744.	3742.	54.	50.	1.52	170.	0.004	0.231	0.409	NA
744.	3744.	52.	47.	1.52	162.	0.003	0.167	0.307	NA
744.	3746.	48.	44.	1.52	152.	0.002	0.110	0.207	NA
744.	3748.	45.	41.	1.50	135.	0.0	0.0	0.0	NA
736.	3750.	59.	55.	1.50	180.	0.006	0.324	0.543	NA
738.	3750.	60.	55.	1.50	192.	0.007	0.345	0.570	NA

Table 2. (cont.) STATISTICAL DATA FOR SELECTED RECEPTORS

ANNUAL PARTICULATES

AVERAGING TIME 24.HOURS STANDARD 150.MICROGRAMS / CUBIC METER

RECEPTOR LOCATION		EXPECTED ARITHMETIC MEAN	EXPECTED GEOMETRIC MEAN	GEOMETRIC STANDARD DEVIATION	EXPECTED MAXIMUM CONCENTRATION	PROBABILITY OF EXCEEDING STANDARD	PROBABILITY OF DETECTION OF A VIOLATION SAMPLING FREQUENCY--DAYS PER YEAR 61	122	365
738.	3752.	57.	52.	1.50	173.	0.005	0.254	0.444	NA
738.	3754.	56.	52.	1.50	170.	0.004	0.231	0.409	NA
738.	3756.	54.	49.	1.50	163.	0.003	0.178	0.324	NA
738.	3758.	51.	47.	1.50	154.	0.002	0.120	0.226	NA
740.	3750.	61.	56.	1.50	185.	0.008	0.390	0.615	NA
740.	3752.	58.	53.	1.50	175.	0.005	0.291	0.493	NA
740.	3754.	56.	52.	1.50	170.	0.004	0.236	0.416	NA
740.	3756.	55.	51.	1.50	167.	0.004	0.207	0.372	NA
740.	3758.	52.	49.	1.50	157.	0.003	0.142	0.263	NA
742.	3750.	60.	55.	1.50	182.	0.007	0.353	0.581	NA
742.	3752.	57.	52.	1.50	172.	0.005	0.250	0.437	NA
742.	3754.	56.	52.	1.50	170.	0.004	0.231	0.409	NA
742.	3756.	55.	50.	1.50	166.	0.004	0.197	0.356	NA
742.	3758.	52.	48.	1.50	157.	0.002	0.131	0.245	NA
744.	3750.	61.	56.	1.50	184.	0.008	0.390	0.615	NA
744.	3752.	58.	53.	1.50	175.	0.005	0.291	0.493	NA
744.	3754.	56.	52.	1.50	171.	0.005	0.241	0.423	NA
744.	3756.	55.	50.	1.50	166.	0.004	0.202	0.364	NA
744.	3758.	52.	48.	1.50	157.	0.002	0.136	0.254	NA
740.	3760.	50.	46.	1.50	153.	0.002	0.110	0.207	NA
740.	3764.	47.	43.	1.50	143.	0.0	0.0	0.0	NA
740.	3768.	45.	41.	1.50	135.	0.0	0.0	0.0	NA
740.	3772.	43.	40.	1.50	130.	0.0	0.0	0.0	NA
740.	3776.	41.	38.	1.50	125.	0.0	0.0	0.0	NA
744.	3760.	50.	46.	1.50	152.	0.002	0.104	0.197	NA
744.	3764.	46.	43.	1.50	141.	0.0	0.0	0.0	NA
744.	3768.	44.	41.	1.50	134.	0.0	0.0	0.0	NA
744.	3772.	43.	40.	1.50	131.	0.0	0.0	0.0	NA
744.	3776.	41.	38.	1.50	126.	0.0	0.0	0.0	NA
748.	3764.	46.	42.	1.50	140.	0.0	0.0	0.0	NA
748.	3768.	44.	41.	1.50	133.	0.0	0.0	0.0	NA
748.	3772.	43.	39.	1.50	130.	0.0	0.0	0.0	NA
748.	3776.	42.	38.	1.50	126.	0.0	0.0	0.0	NA
752.	3768.	44.	40.	1.50	133.	0.0	0.0	0.0	NA
752.	3772.	42.	38.	1.50	129.	0.0	0.0	0.0	NA
752.	3776.	41.	38.	1.50	125.	0.0	0.0	0.0	NA
756.	3768.	43.	40.	1.50	132.	0.0	0.0	0.0	NA
756.	3772.	42.	39.	1.50	128.	0.0	0.0	0.0	NA

Table 2. (cont.) STATISTICAL DATA FOR SELECTED RECEPTORS

ANNUAL PARTICULATES

AVERAGING TIME 8760.HOURS STANDARD 60.MICROGRAMS / CUBIC METER

RECEPTOR LOCATION		EXPECTED ARITHMETIC MEAN	EXPECTED GEOMETRIC MEAN	GEOMETRIC STANDARD DEVIATION	EXPECTED MAXIMUM CONCENTRATION	PROBABILITY OF EXCEEDING STANDARD	PROBABILITY OF DETECTION OF A VIOLATION SAMPLING FREQUENCY--DAYS PER YEAR 61	122	365
704.	3710.	41.	41.	1.00	41.	0.0	0.0	0.0	NA
708.	3710.	42.	42.	1.00	42.	0.0	0.0	0.0	NA
708.	3714.	42.	42.	1.00	42.	0.0	0.0	0.0	NA
708.	3718.	43.	43.	1.00	43.	0.0	0.0	0.0	NA
712.	3710.	42.	42.	1.00	42.	0.0	0.0	0.0	NA
712.	3714.	43.	43.	1.00	43.	0.0	0.0	0.0	NA
712.	3718.	44.	44.	1.00	44.	0.0	0.0	0.0	NA
712.	3722.	45.	45.	1.00	45.	0.0	0.0	0.0	NA
715.	3710.	43.	43.	1.00	43.	0.0	0.0	0.0	NA
715.	3714.	44.	44.	1.00	44.	0.0	0.0	0.0	NA
715.	3718.	45.	45.	1.00	45.	0.0	0.0	0.0	NA
715.	3722.	46.	46.	1.00	46.	0.0	0.0	0.0	NA
715.	3726.	47.	47.	1.00	47.	0.0	0.0	0.0	NA
720.	3710.	43.	43.	1.00	43.	0.0	0.0	0.0	NA
720.	3714.	47.	47.	1.00	47.	0.0	0.0	0.0	NA
720.	3718.	47.	47.	1.00	47.	0.0	0.0	0.0	NA
720.	3722.	48.	48.	1.00	49.	0.0	0.0	0.0	NA
720.	3726.	50.	50.	1.00	50.	0.0	0.0	0.0	NA
724.	3710.	44.	44.	1.00	44.	0.0	0.0	0.0	NA
724.	3714.	47.	47.	1.00	47.	0.0	0.0	0.0	NA
724.	3718.	48.	48.	1.00	49.	0.0	0.0	0.0	NA
724.	3722.	50.	50.	1.00	50.	0.0	0.0	0.0	NA
724.	3726.	52.	52.	1.00	52.	0.0	0.0	0.0	NA
728.	3714.	45.	45.	1.00	45.	0.0	0.0	0.0	NA
728.	3718.	48.	48.	1.00	48.	0.0	0.0	0.0	NA
728.	3722.	52.	52.	1.00	52.	0.0	0.0	0.0	NA
728.	3726.	55.	55.	1.00	55.	0.0	0.0	0.0	NA
732.	3718.	48.	48.	1.00	48.	0.0	0.0	0.0	NA
732.	3722.	54.	54.	1.00	54.	0.0	0.0	0.0	NA
732.	3726.	58.	59.	1.00	59.	0.013	0.012	0.0	NA
735.	3718.	49.	49.	1.00	49.	0.0	0.0	0.0	NA
735.	3722.	54.	54.	1.00	54.	0.0	0.0	0.0	NA
734.	3726.	58.	58.	1.00	59.	0.009	0.009	0.0	NA
734.	3730.	62.	62.	1.00	62.	0.149	0.149	0.069	NA
735.	3726.	60.	60.	1.00	60.	0.034	0.033	0.005	NA
735.	3730.	64.	64.	1.00	64.	0.242	0.239	0.159	NA
738.	3726.	61.	61.	1.00	61.	0.061	0.059	0.014	NA
738.	3730.	66.	66.	1.00	66.	0.421	0.417	0.386	NA
740.	3730.	64.	64.	1.00	64.	0.255	0.251	0.171	NA
742.	3730.	46.	46.	1.00	46.	0.0	0.0	0.0	NA
744.	3730.	47.	47.	1.00	47.	0.0	0.0	0.0	NA
720.	3730.	51.	51.	1.00	51.	0.0	0.0	0.0	NA
722.	3730.	53.	53.	1.00	53.	0.0	0.0	0.0	NA

Table 2. (cont.)

STATISTICAL DATA FOR SELECTED RECEPTORS

ANNUAL PARTICULATES

AVERAGING TIME 8760.HOURS STANDARD 60.MICROGRAMS / CUBIC METER

RECEPTOR LOCATION		EXPECTED ARITHMETIC MEAN	EXPECTED GEOMETRIC MEAN	GEOMETRIC STANDARD DEVIATION	EXPECTED MAXIMUM CONCENTRATION	PROBABILITY OF EXCEEDING STANDARD	PROBABILITY OF DETECTION OF A VIOLATION SAMPLING FREQUENCY--DAYS PER YEAR 61	122	365
722.	3732.	53.	53.	1.00	53.	0.0	0.0	0.0	NA
724.	3730.	54.	54.	1.00	54.	0.0	0.0	0.0	NA
724.	3732.	54.	54.	1.00	54.	0.0	0.0	0.0	NA
724.	3736.	54.	54.	1.00	54.	0.0	0.0	0.0	NA
726.	3730.	55.	55.	1.00	55.	0.0	0.0	0.0	NA
726.	3732.	56.	56.	1.00	56.	0.0	0.0	0.0	NA
726.	3734.	56.	56.	1.00	56.	0.002	0.002	0.0	NA
726.	3736.	56.	56.	1.00	56.	0.002	0.002	0.0	NA
728.	3730.	58.	58.	1.00	58.	0.009	0.009	0.0	NA
728.	3732.	57.	57.	1.00	57.	0.005	0.005	0.0	NA
728.	3734.	59.	59.	1.00	59.	0.029	0.028	0.004	NA
728.	3736.	59.	59.	1.00	59.	0.036	0.034	0.005	NA
728.	3738.	58.	58.	1.00	58.	0.012	0.011	0.0	NA
730.	3730.	60.	59.	1.00	60.	0.062	0.059	0.014	NA
730.	3732.	60.	60.	1.00	60.	0.069	0.068	0.017	NA
730.	3734.	62.	62.	1.00	62.	0.154	0.154	0.074	NA
730.	3736.	62.	62.	1.00	62.	0.199	0.195	0.111	NA
730.	3738.	62.	62.	1.00	62.	0.142	0.140	0.063	NA
732.	3730.	62.	62.	1.00	62.	0.136	0.134	0.058	NA
732.	3732.	61.	61.	1.00	61.	0.127	0.125	0.052	NA
732.	3734.	64.	64.	1.00	64.	0.378	0.375	0.326	NA
732.	3736.	65.	65.	1.00	65.	0.440	0.440	0.417	NA
732.	3738.	63.	63.	1.00	63.	0.309	0.309	0.237	NA
734.	3730.	64.	64.	1.00	64.	0.291	0.291	0.215	NA
734.	3732.	65.	65.	1.00	65.	0.421	0.421	0.386	NA
734.	3734.	66.	66.	1.00	66.	0.548	0.548	0.571	NA
734.	3736.	67.	67.	1.00	67.	0.655	0.655	0.716	NA
734.	3738.	67.	67.	1.00	67.	0.726	0.726	0.802	NA
736.	3730.	48.	48.	1.00	48.	0.0	0.0	0.0	NA
736.	3732.	49.	49.	1.00	49.	0.0	0.0	0.0	NA
736.	3734.	51.	51.	1.00	51.	0.0	0.0	0.0	NA
736.	3736.	52.	52.	1.00	52.	0.0	0.0	0.0	NA
736.	3738.	53.	53.	1.00	53.	0.0	0.0	0.0	NA
738.	3730.	48.	48.	1.00	48.	0.0	0.0	0.0	NA
738.	3732.	50.	50.	1.00	50.	0.0	0.0	0.0	NA
738.	3734.	54.	54.	1.00	54.	0.0	0.0	0.0	NA
738.	3736.	56.	56.	1.00	56.	0.002	0.001	0.0	NA
738.	3738.	55.	56.	1.00	55.	0.003	0.002	0.0	NA
740.	3730.	53.	53.	1.00	53.	0.0	0.0	0.0	NA
740.	3732.	55.	55.	1.00	55.	0.0	0.0	0.0	NA
740.	3734.	62.	62.	1.00	62.	0.159	0.156	0.076	NA
740.	3736.	60.	60.	1.00	60.	0.072	0.069	0.018	NA
740.	3738.	64.	63.	1.00	63.	0.316	0.312	0.245	NA

Table 2. (cont.) STATISTICAL DATA FOR SELECTED RECEPTORS

ANNUAL PARTICULATES

AVERAGING TIME 8760.HOURS STANDARD 60.MICROGRAMS / CUBIC METER

RECEPTOR LOCATION		EXPECTED ARITHMETIC MEAN	EXPECTED GEOMETRIC MEAN	GEOMETRIC STANDARD DEVIATION	EXPECTED MAXIMUM CONCENTRATION	PROBABILITY OF EXCEEDING STANDARD	PROBABILITY OF DETECTION OF A VIOLATION SAMPLING FREQUENCY--DAYS PER YEAR 61	122	365
742.	3730.	50.	50.	1.00	50.	0.0	0.0	0.0	NA
742.	3732.	56.	56.	1.00	56.	0.0	0.0	0.0	NA
742.	3734.	58.	58.	1.00	58.	0.014	0.013	0.0	NA
742.	3736.	59.	59.	1.00	59.	0.043	0.042	0.007	NA
742.	3738.	60.	60.	1.00	60.	0.061	0.059	0.014	NA
744.	3730.	50.	50.	1.00	50.	0.0	0.0	0.0	NA
744.	3732.	53.	53.	1.00	53.	0.0	0.0	0.0	NA
744.	3734.	56.	56.	1.00	56.	0.002	0.002	0.0	NA
744.	3736.	57.	57.	1.00	57.	0.006	0.006	0.0	NA
744.	3738.	58.	58.	1.00	58.	0.022	0.021	0.002	NA
730.	3740.	62.	62.	1.00	62.	0.176	0.176	0.093	NA
732.	3740.	64.	64.	1.00	64.	0.375	0.371	0.323	NA
732.	3742.	62.	62.	1.00	62.	0.187	0.184	0.100	NA
734.	3740.	67.	67.	1.00	67.	0.739	0.742	0.821	NA
734.	3742.	67.	67.	1.00	67.	0.712	0.716	0.791	NA
734.	3744.	66.	66.	1.00	66.	0.644	0.649	0.702	NA
736.	3740.	72.	72.	1.00	72.	0.879	0.891	0.952	NA
736.	3742.	70.	70.	1.00	70.	0.625	0.625	0.677	NA
736.	3744.	69.	69.	1.00	69.	0.409	0.405	0.371	NA
736.	3746.	65.	65.	1.00	65.	0.189	0.189	0.106	NA
736.	3748.	61.	61.	1.00	61.	0.054	0.053	0.011	NA
738.	3740.	76.	76.	1.00	76.	0.994	0.994	1.000	NA
738.	3742.	76.	76.	1.00	76.	0.993	0.993	1.000	NA
738.	3744.	68.	68.	1.00	68.	0.587	0.587	0.622	NA
738.	3746.	65.	65.	1.00	65.	0.298	0.295	0.224	NA
738.	3748.	62.	62.	1.00	62.	0.106	0.104	0.037	NA
740.	3740.	66.	66.	1.00	66.	0.397	0.397	0.352	NA
740.	3742.	59.	59.	1.00	59.	0.026	0.026	0.003	NA
740.	3744.	52.	52.	1.00	52.	0.0	0.0	0.0	NA
740.	3746.	48.	48.	1.00	48.	0.0	0.0	0.0	NA
740.	3748.	45.	45.	1.00	45.	0.0	0.0	0.0	NA
742.	3740.	61.	61.	1.00	61.	0.084	0.082	0.024	NA
742.	3742.	60.	60.	1.00	60.	0.055	0.054	0.011	NA
742.	3744.	51.	51.	1.00	51.	0.0	0.0	0.0	NA
742.	3746.	47.	47.	1.00	47.	0.0	0.0	0.0	NA
742.	3748.	44.	44.	1.00	44.	0.0	0.0	0.0	NA
744.	3740.	57.	57.	1.00	57.	0.007	0.007	0.0	NA
744.	3742.	54.	54.	1.00	54.	0.0	0.0	0.0	NA
744.	3744.	52.	52.	1.00	52.	0.0	0.0	0.0	NA
744.	3746.	48.	48.	1.00	48.	0.0	0.0	0.0	NA
744.	3748.	45.	45.	1.00	45.	0.0	0.0	0.0	NA
736.	3750.	59.	59.	1.00	59.	0.034	0.032	0.005	NA
738.	3750.	60.	60.	1.00	60.	0.057	0.055	0.012	NA

Table 2. (cont.) STATISTICAL DATA FOR SELECTED RECEPTORS

ANNUAL PARTICULATES

AVERAGING TIME 8760. HOURS STANDARD 60. MICROGRAMS / CUBIC METER

RECEPTOR LOCATION		EXPECTED ARITHMETIC MEAN	EXPECTED GEOMETRIC MEAN	GEOMETRIC STANDARD DEVIATION	EXPECTED MAXIMUM CONCENTRATION	PROBABILITY OF EXCEEDING STANDARD	PROBABILITY OF DETECTION OF A VIOLATION SAMPLING FREQUENCY--DAYS PER YEAR 61	122	365
738.	3752.	57.	57.	1.00	57.	0.005	0.005	0.0	NA
738.	3754.	55.	56.	1.00	56.	0.002	0.002	0.0	NA
738.	3756.	54.	54.	1.00	54.	0.0	0.0	0.0	NA
738.	3758.	51.	51.	1.00	51.	0.0	0.0	0.0	NA
740.	3750.	61.	61.	1.00	61.	0.097	0.095	0.032	NA
740.	3752.	57.	58.	1.00	58.	0.011	0.010	0.0	NA
740.	3754.	56.	56.	1.00	56.	0.002	0.002	0.0	NA
740.	3756.	55.	55.	1.00	55.	0.0	0.0	0.0	NA
740.	3758.	52.	52.	1.00	52.	0.0	0.0	0.0	NA
742.	3750.	60.	60.	1.00	60.	0.064	0.063	0.015	NA
742.	3752.	57.	57.	1.00	57.	0.004	0.003	0.0	NA
742.	3754.	56.	56.	1.00	56.	0.002	0.002	0.0	NA
742.	3756.	55.	55.	1.00	55.	0.0	0.0	0.0	NA
742.	3758.	52.	52.	1.00	52.	0.0	0.0	0.0	NA
744.	3750.	61.	61.	1.00	61.	0.095	0.093	0.031	NA
744.	3752.	59.	59.	1.00	59.	0.010	0.010	0.0	NA
744.	3754.	56.	56.	1.00	56.	0.003	0.003	0.0	NA
744.	3756.	55.	55.	1.00	55.	0.0	0.0	0.0	NA
744.	3758.	52.	52.	1.00	52.	0.0	0.0	0.0	NA
740.	3760.	50.	50.	1.00	50.	0.0	0.0	0.0	NA
740.	3764.	47.	47.	1.00	47.	0.0	0.0	0.0	NA
740.	3768.	45.	45.	1.00	45.	0.0	0.0	0.0	NA
740.	3772.	43.	43.	1.00	43.	0.0	0.0	0.0	NA
740.	3776.	41.	41.	1.00	41.	0.0	0.0	0.0	NA
744.	3760.	50.	50.	1.00	50.	0.0	0.0	0.0	NA
744.	3764.	46.	46.	1.00	46.	0.0	0.0	0.0	NA
744.	3768.	44.	44.	1.00	44.	0.0	0.0	0.0	NA
744.	3772.	43.	43.	1.00	43.	0.0	0.0	0.0	NA
744.	3776.	41.	41.	1.00	41.	0.0	0.0	0.0	NA
748.	3764.	45.	46.	1.00	46.	0.0	0.0	0.0	NA
748.	3768.	44.	44.	1.00	44.	0.0	0.0	0.0	NA
748.	3772.	43.	43.	1.00	43.	0.0	0.0	0.0	NA
748.	3776.	42.	42.	1.00	42.	0.0	0.0	0.0	NA
752.	3768.	44.	44.	1.00	44.	0.0	0.0	0.0	NA
752.	3772.	42.	42.	1.00	42.	0.0	0.0	0.0	NA
752.	3776.	41.	41.	1.00	41.	0.0	0.0	0.0	NA
756.	3768.	43.	43.	1.00	43.	0.0	0.0	0.0	NA
756.	3772.	42.	42.	1.00	42.	0.0	0.0	0.0	NA

Table 2. (Cont.)

STATISTICAL DATA FOR SELECTED RECEPTORS

ANNUAL SULFUR DIOXIDE **(partial)**

AVERAGING TIME 24.HOURS STANDARD 220.MICROGRAMS / CUBIC METER

RECEPTOR LOCATION		EXPECTED ARITHMETIC MEAN	EXPECTED GEOMETRIC MEAN	GEOMETRIC STANDARD DEVIATION	EXPECTED MAXIMUM CONCENTRATION	PROBABILITY OF EXCEEDING STANDARD	PROBABILITY OF DETECTION OF A VIOLATION SAMPLING FREQUENCY--DAYS PER YEAR 61	122	365
742.	3730.	21.	19.	1.56	72.	0.0	0.0	0.0	0.0
742.	3732.	25.	22.	1.60	89.	0.0	0.0	0.0	0.0
742.	3734.	28.	24.	1.74	124.	0.0	0.0	0.0	0.0
742.	3736.	32.	27.	1.82	155.	0.0	0.0	0.0	0.0
742.	3738.	37.	30.	1.90	197.	0.0	0.0	0.0	0.0
744.	3730.	22.	20.	1.60	79.	0.0	0.0	0.0	0.0
744.	3732.	25.	22.	1.66	99.	0.0	0.0	0.0	0.0
744.	3734.	28.	24.	1.74	124.	0.0	0.0	0.0	0.0
744.	3736.	31.	26.	1.82	151.	0.0	0.0	0.0	0.0
744.	3738.	35.	29.	1.82	169.	0.0	0.0	0.0	0.0
733.	3740.	22.	16.	1.90	109.	0.0	0.0	0.0	0.0
733.	3742.	22.	17.	2.00	132.	0.0	0.0	0.0	0.0
733.	3744.	21.	16.	2.00	126.	0.0	0.0	0.0	0.0
734.	3740.	25.	20.	2.00	151.	0.0	0.0	0.0	0.0
734.	3742.	24.	19.	2.10	163.	0.0	0.0	0.0	0.0
734.	3744.	23.	17.	2.10	152.	0.0	0.0	0.0	0.0
735.	3740.	30.	23.	2.10	190.	0.0	0.0	0.0	0.0
735.	3742.	29.	21.	2.20	216.	0.0	0.0	0.0	0.0
736.	3744.	25.	19.	2.20	183.	0.0	0.0	0.0	0.0
736.	3746.	23.	17.	2.10	152.	0.0	0.0	0.0	0.0
736.	3748.	20.	16.	2.00	120.	0.0	0.0	0.0	0.0
738.	3740.	36.	29.	2.00	219.	0.0	0.0	0.0	0.0
738.	3742.	33.	25.	2.10	225.	0.002	0.088	0.167	0.391
738.	3744.	23.	21.	2.10	180.	0.0	0.0	0.0	0.0
738.	3746.	24.	19.	2.00	145.	0.0	0.0	0.0	0.0
738.	3748.	20.	16.	1.90	108.	0.0	0.0	0.0	0.0
740.	3740.	42.	33.	2.00	252.	0.003	0.147	0.272	0.576
740.	3742.	36.	28.	2.00	216.	0.0	0.0	0.0	0.0
740.	3744.	29.	23.	2.00	175.	0.0	0.0	0.0	0.0
740.	3746.	25.	20.	1.90	135.	0.0	0.0	0.0	0.0
740.	3748.	22.	18.	1.80	103.	0.0	0.0	0.0	0.0
742.	3740.	41.	32.	1.95	231.	0.002	0.104	0.197	0.448
742.	3742.	36.	29.	1.95	206.	0.0	0.0	0.0	0.0
742.	3744.	29.	23.	1.95	165.	0.0	0.0	0.0	0.0
742.	3746.	26.	20.	1.90	130.	0.0	0.0	0.0	0.0
742.	3748.	21.	17.	1.80	97.	0.0	0.0	0.0	0.0
744.	3740.	36.	29.	1.90	191.	0.0	0.0	0.0	0.0
744.	3742.	32.	26.	1.90	171.	0.0	0.0	0.0	0.0
744.	3744.	28.	23.	1.90	149.	0.0	0.0	0.0	0.0
744.	3746.	24.	20.	1.80	114.	0.0	0.0	0.0	0.0
744.	3748.	21.	18.	1.80	109.	0.0	0.0	0.0	0.0
735.	3750.	18.	15.	1.90	97.	0.0	0.0	0.0	0.0
733.	3750.	19.	16.	1.80	90.	0.0	0.0	0.0	0.0

Table 2. (Cont.) STATISTICAL DATA FOR SELECTED RECEPTORS

ANNUAL SULFUR DIOXIDE

AVERAGING TIME 8760. HOURS   STANDARD 43. MICROGRAMS / CUBIC METER

RECEPTOR LOCATION		EXPECTED ARITHMETIC MEAN	EXPECTED GEOMETRIC MEAN	GEOMETRIC STANDARD DEVIATION	EXPECTED MAXIMUM CONCENTRATION	PROBABILITY OF EXCEEDING STANDARD	PROBABILITY OF DETECTION OF A VIOLATION SAMPLING FREQUENCY--DAYS PER YEAR 61	122	365
722.	3732.	13.	13.	1.00	13.	0.0	0.0	0.0	0.0
724.	3730.	14.	14.	1.00	14.	0.0	0.0	0.0	0.0
724.	3732.	14.	14.	1.00	14.	0.0	0.0	0.0	0.0
724.	3734.	15.	15.	1.00	15.	0.0	0.0	0.0	0.0
726.	3730.	15.	15.	1.00	15.	0.0	0.0	0.0	0.0
726.	3732.	15.	15.	1.00	15.	0.0	0.0	0.0	0.0
726.	3734.	16.	16.	1.00	16.	0.0	0.0	0.0	0.0
726.	3736.	16.	16.	1.00	16.	0.0	0.0	0.0	0.0
728.	3730.	16.	16.	1.00	16.	0.0	0.0	0.0	0.0
728.	3732.	16.	16.	1.00	16.	0.0	0.0	0.0	0.0
728.	3734.	17.	17.	1.00	17.	0.0	0.0	0.0	0.0
728.	3736.	18.	18.	1.00	18.	0.0	0.0	0.0	0.0
728.	3738.	18.	18.	1.00	18.	0.0	0.0	0.0	0.0
730.	3730.	17.	17.	1.00	17.	0.0	0.0	0.0	0.0
730.	3732.	18.	18.	1.00	18.	0.0	0.0	0.0	0.0
730.	3734.	19.	19.	1.00	19.	0.0	0.0	0.0	0.0
730.	3736.	20.	20.	1.00	20.	0.0	0.0	0.0	0.0
730.	3738.	20.	20.	1.00	20.	0.0	0.0	0.0	0.0
732.	3730.	18.	18.	1.00	18.	0.0	0.0	0.0	0.0
732.	3732.	19.	19.	1.00	19.	0.0	0.0	0.0	0.0
732.	3734.	21.	21.	1.00	21.	0.0	0.0	0.0	0.0
732.	3736.	22.	22.	1.00	22.	0.0	0.0	0.0	0.0
732.	3738.	22.	22.	1.00	22.	0.0	0.0	0.0	0.0
734.	3730.	20.	20.	1.00	20.	0.0	0.0	0.0	0.0
734.	3732.	21.	21.	1.00	21.	0.0	0.0	0.0	0.0
734.	3734.	22.	22.	1.00	22.	0.0	0.0	0.0	0.0
734.	3736.	24.	24.	1.00	24.	0.0	0.0	0.0	0.0
734.	3738.	25.	25.	1.00	25.	0.0	0.0	0.0	0.0
736.	3730.	20.	20.	1.00	20.	0.0	0.0	0.0	0.0
736.	3732.	22.	22.	1.00	22.	0.0	0.0	0.0	0.0
736.	3734.	23.	23.	1.00	23.	0.0	0.0	0.0	0.0
736.	3736.	26.	26.	1.00	26.	0.0	0.0	0.0	0.0
736.	3738.	28.	28.	1.00	28.	0.0	0.0	0.0	0.0
738.	3730.	20.	20.	1.00	20.	0.0	0.0	0.0	0.0
738.	3732.	21.	21.	1.00	21.	0.0	0.0	0.0	0.0
738.	3734.	25.	25.	1.00	25.	0.0	0.0	0.0	0.0
738.	3736.	28.	28.	1.00	28.	0.0	0.0	0.0	0.0
738.	3738.	30.	30.	1.00	30.	0.0	0.0	0.0	0.0
740.	3730.	21.	21.	1.00	21.	0.0	0.0	0.0	0.0
740.	3732.	23.	23.	1.00	23.	0.0	0.0	0.0	0.0
740.	3734.	31.	31.	1.00	31.	0.0	0.0	0.0	0.0
740.	3736.	34.	34.	1.00	34.	0.003	0.002	0.0	0.0
740.	3738.	39.	39.	1.00	39.	0.108	0.106	0.038	0.002

Table 2. (cont.) STATISTICAL DATA FOR SELECTED RECEPTORS

ANNUAL SULFUR DIOXIDE

AVERAGING TIME 8760.HOURS STANDARD 43.MICROGRAMS / CUBIC METER

RECEPTOR LOCATION		EXPECTED ARITHMETIC MEAN	EXPECTED GEOMETRIC MEAN	GEOMETRIC STANDARD DEVIATION	EXPECTED MAXIMUM CONCENTRATION	PROBABILITY OF EXCEEDING STANDARD	PROBABILITY OF DETECTION OF A VIOLATION SAMPLING FREQUENCY--DAYS PER YEAR 61	122	365
742.	3730.	21.	21.	1.00	21.	0.0	0.0	0.0	0.0
742.	3732.	25.	25.	1.00	25.	0.0	0.0	0.0	0.0
742.	3734.	23.	23.	1.00	23.	0.0	0.0	0.0	0.0
742.	3736.	32.	32.	1.00	32.	0.0	0.0	0.0	0.0
742.	3738.	37.	37.	1.00	37.	0.027	0.027	0.003	0.0
744.	3730.	22.	22.	1.00	22.	0.0	0.0	0.0	0.0
744.	3732.	25.	25.	1.00	25.	0.0	0.0	0.0	0.0
744.	3734.	28.	28.	1.00	28.	0.0	0.0	0.0	0.0
744.	3736.	31.	31.	1.00	31.	0.0	0.0	0.0	0.0
744.	3738.	35.	35.	1.00	35.	0.003	0.003	0.0	0.0
730.	3740.	20.	20.	1.00	20.	0.0	0.0	0.0	0.0
732.	3740.	22.	22.	1.00	22.	0.0	0.0	0.0	0.0
732.	3742.	21.	21.	1.00	21.	0.0	0.0	0.0	0.0
734.	3740.	25.	25.	1.00	25.	0.0	0.0	0.0	0.0
734.	3742.	24.	24.	1.00	24.	0.0	0.0	0.0	0.0
734.	3744.	23.	23.	1.00	23.	0.0	0.0	0.0	0.0
736.	3740.	30.	30.	1.00	30.	0.0	0.0	0.0	0.0
736.	3742.	29.	29.	1.00	29.	0.0	0.0	0.0	0.0
736.	3744.	25.	25.	1.00	25.	0.0	0.0	0.0	0.0
736.	3746.	23.	23.	1.00	23.	0.0	0.0	0.0	0.0
736.	3748.	20.	20.	1.00	20.	0.0	0.0	0.0	0.0
738.	3740.	36.	36.	1.00	36.	0.027	0.027	0.003	0.0
738.	3742.	33.	33.	1.00	33.	0.004	0.004	0.0	0.0
738.	3744.	28.	28.	1.00	28.	0.0	0.0	0.0	0.0
738.	3746.	24.	24.	1.00	24.	0.0	0.0	0.0	0.0
738.	3748.	20.	20.	1.00	20.	0.0	0.0	0.0	0.0
740.	3740.	42.	42.	1.00	42.	0.382	0.382	0.334	0.239
740.	3742.	36.	36.	1.00	36.	0.020	0.019	0.002	0.0
740.	3744.	29.	29.	1.00	29.	0.0	0.0	0.0	0.0
740.	3746.	25.	25.	1.00	25.	0.0	0.0	0.0	0.0
740.	3748.	22.	22.	1.00	22.	0.0	0.0	0.0	0.0
742.	3740.	41.	41.	1.00	41.	0.249	0.245	0.164	0.054
742.	3742.	36.	36.	1.00	36.	0.023	0.022	0.002	0.0
742.	3744.	29.	29.	1.00	29.	0.0	0.0	0.0	0.0
742.	3746.	24.	24.	1.00	24.	0.0	0.0	0.0	0.0
742.	3748.	21.	21.	1.00	21.	0.0	0.0	0.0	0.0
744.	3740.	36.	36.	1.00	36.	0.011	0.010	0.0	0.0
744.	3742.	32.	32.	1.00	32.	0.0	0.0	0.0	0.0
744.	3744.	28.	28.	1.00	28.	0.0	0.0	0.0	0.0
744.	3746.	24.	24.	1.00	24.	0.0	0.0	0.0	0.0
744.	3748.	21.	21.	1.00	21.	0.0	0.0	0.0	0.0
736.	3750.	18.	18.	1.00	18.	0.0	0.0	0.0	0.0
738.	3750.	19.	19.	1.00	19.	0.0	0.0	0.0	0.0

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