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GUIDELINE SERIES

TECHNIQUE FOR SUPPLEMENTARY CONTROL SYSTEM RELIABILITY ANALYSIS AND UPGRADING

U.S. ENVIRONMENTAL PROTECTION AGENCY
Office of Air and Waste Management
Office of Air Quality Planning and Standards
Research Triangle Park, North Carolina 27711

A TECHNIQUE FOR SUPPLEMENTARY CONTROL SYSTEM
RELIABILITY ANALYSIS AND UPGRADING

March 1976

OAQPS No. 1.2-037

Source Receptor Analysis Branch
Monitoring and Data Analysis Division
Office of Air Quality Planning and Standards
Research Triangle Park, N.C.

This document does not constitute a general endorsement of supplementary control systems as a control alternative. It is intended only to assist the SCS user and the responsible control agencies in those limited situations where legislation, EPA or the courts permit its use.

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PREFACE

The purpose of this document is to emphasize the key factors that affect the reliability of a supplementary control system (SCS) and to present an analytical concept applicable to the analysis of SCS reliability. Examples are presented that demonstrate the type of information obtainable through application of the concept.

Except for relatively minor changes, Sections 2, 3 and 4 were extracted from the final report prepared by Environmental Research and Technology, Inc., under EPA Contract No. 68-02-1342. Credit for that report is gratefully extended to Dr. Bruce A. Egan, ER&T project leader under that contract. A follow-on effort by ER&T is underway to supplement this document with a manual that will enable the user to apply the reliability analysis concept presented herein.

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1. SUMMARY

Through a supplementary control system (SCS), stack emissions of pollutants are temporarily curtailed when meteorological conditions are conducive to ground-level concentrations in excess of an ambient air quality standard. This document addresses the reliability of an SCS. Reliability is defined herein as the ability of an SCS to prevent ambient pollutant concentrations from exceeding ambient standards.

The intent of this document is to present the fundamentals of a mathematical concept that can be applied to the reliability analysis and upgrading (improving the reliability) of an SCS. Also presented are hypothetical examples that demonstrate the type of information that can be obtained through application of the concept. Specific procedures for applying the concept will be presented in a user manual to be published about the end of 1976.

The reliability analysis concept, presented in Section 3, requires the analysis of source, meteorological and air quality data collected concurrently during several months or more of SCS operation. Application of the concept, as demonstrated in Section 4, can yield information on (1) the overall reliability of an SCS and (2) the degree to which reliability can be improved by adjusting key system parameters.

In general, the true reliability of an SCS will be known only after a year or more of system operation in conjunction with a well-planned air quality monitoring program. Nevertheless, an assessment of system reliability should be made as early as possible in the development phase of an SCS to pinpoint sources of error and to provide a basis for further development and refinement of the system.

The reader should be aware of related documents concerning SCS. Probably of most interest to anyone concerned with the technical aspects of supplementary control systems will be the "Guidelines for Evaluating Supplementary Control Systems" (EPA, February 1976). That document provides detailed guidance for the design and development of an SCS. "Guidelines for Enforcement and Surveillance of Supplementary Control Systems" (EPA, September 1975) provides guidance to the control agency in the surveillance and enforcement of such systems. "Reviewing New Stationary Sources" (EPA, 1976a) is one of several documents providing basic guidance in pollutant dispersion modeling, which is an essential tool in the development of an SCS. "Guidance for Air Quality Monitoring in the Vicinity of Large Point Sources" (EPA, 1976b) provides information useful for air quality monitor siting in the vicinity of a facility proposing to use SCS.

2. FACTORS AFFECTING RELIABILITY

2.1 Introduction

There are four generalized components of an SCS in which uncertainty can exist. These components are: (1) air quality monitoring; (2) meteorological forecasting; (3) emissions forecasting; and (4) air quality modeling. The meaning of the first three components is self-evident. Air quality modeling implies the algorithms and methodology which are used to relate emission rates, other source data, meteorological inputs and topographic factors to current and future air quality in the vicinity of the source. Components 1, 2, and 4 are considered individually in this section with respect to their (general) effect on overall SCS reliability. Emission forecasting is discussed in Example 6 of Section 4.

2.2 Air Quality Monitoring Reliability and Upgrading

Every Supplementary Control System must have a monitoring network to verify that the required air quality is being maintained through the operation of the SCS. Also, real-time air quality monitoring data must be available as an input to the decisions to curtail emissions. In addition, monitoring data are used during the development phase of the SCS and whenever the forecast models are calibrated and periodically upgraded.

The following sources of uncertainty in a monitoring system will contribute to a degradation of system reliability:

- Instrumentation accuracy limits
- Percentage data capture statistics
- Information transfer errors
- Insufficient and/or inappropriate sampling locations.

Section 2.2.1 provides a brief discussion of the first three items. The last item is addressed in more detail in Section 2.2.2.

2.2.1 Sampling and Information Transfer Errors

Proper choice of SO_2 monitoring instruments depends on many factors. A primary requirement is that the air quality monitors provide continuous SO_2 data. For purposes of evaluating a system for an SCS application, it is also important to consider sensitivity, lag time and response time, interferences, accuracy, calibration drift, and maintenance requirements.

The lag time of a monitoring network is the time between the occurrence of the concentration and the time that this value is displayed for use by SCS personnel. With telemetered data, short term averages (e.g., 2-minute averages or instantaneous concentration values less than 2 minutes old) are usually available for examination before a 1-hour or 3-hour averaging period has transpired. In these cases, the lag time is no constraint on the system. For systems which require analysis of strip charts, manual data handling, or chemical analysis, the lag time between collection and display of the data severely constrains the potential uses of the systems.

The percentage of useful data capture depends upon the combined downtime of the sensors and associated data capture and transmission components. Sensor downtime includes time periods of instrumentation calibration and maintenance as well as identifiable data sets of inaccurate measurements. A well designed system will attempt to minimize these sensor downtime contributions by providing automatic instrument calibration, remote sensing of possible instrument malfunctioning and generally, remote control of the instrumentation. Thus, real-time monitoring and telemetry of information provides mechanisms for substantially enhancing data capture. If the system involves telemetry such as telephone line usage, the percent data capture will depend additionally upon the downtime of this telemetry system and the remote recording devices. If the system requires any real-time data processing, the downtime of the data processing equipment must also be considered.

2.2.2 Example Analysis to Optimize the Siting of Air Quality Monitors

The question of sufficient number and spacing of monitors is difficult to assess in general because every site has peculiar meteorology, terrain, and land use. Monitor locations should, in general, be chosen to monitor the highest concentrations in the vicinity of the source. They should not be significantly influenced by minor local sources.

An analysis methodology designed to assist in determining the best distribution of monitors for SCS applications is presented in

"Guidance for Air Quality Monitoring in the Vicinity of Large Point Sources" (EPA, 1976b). The analysis provides an estimate of the percentage of air quality violations expected to be directly observed by any monitoring network. Through this analysis, the improvement in the monitor network anticipated by the addition of one or more monitors can be assessed and the concomitant improvement in SCS reliability can be weighed against the increased cost and effort. An example application of a similar methodology is discussed in the following paragraphs.

In the example analysis, the emission rate and other source statistics were those of two stacks at an actual source under full load conditions. A dispersion model appropriate for application to the source was then utilized to compute concentration versus downwind distance for each of a wide range of possible stability-wind conditions. A stability-wind rose from a nearby airport was used to determine the frequency of occurrence of each condition.

Given the above data, it was then possible to determine, for each wind direction sector, the downwind distance at which the maximum number of occurrences of concentrations above a specified threshold level can be expected to occur. Such information is presented in Table 2-1, which provides a ranked listing of 25 monitor locations considering all wind directions. The location is defined by an azimuth (wind direction) and a radial distance (distance downwind). The monitors are ranked by the proportion of the time that each

TABLE 2-1

Optimum Monitor Locations Ranked by Expected Frequency of Monitored Values Exceeding the Concentration Threshold

CONCENTRATION THRESHOLD = 0.20 ppm

OPTIMAL MONITORING LOCATIONS

MONITOR #	WIND DIRECTION	DISTANCE DOWNWIND	FREQUENCY	CUMULATIVE FREQUENCY
1	9	2916.83	0.02269	0.02269
2	8	2916.83	0.02065	0.04334
3	11	2916.83	0.01657	0.05991
4	12	2916.83	0.01638	0.07629
5	10	2916.83	0.01554	0.09183
6	7	2916.83	0.01463	0.10646
7	6	2916.83	0.01259	0.11905
8	13	2916.83	0.01207	0.13112
9	2	3218.43	0.01193	0.14305
10	5	2916.83	0.01031	0.15336
11	3	3218.43	0.00948	0.16284
12	14	2916.83	0.00827	0.17111
13	1	3218.43	0.00818	0.17929
14	4	2916.83	0.00694	0.18623
15	15	2916.83	0.00476	0.19099
16	16	2916.83	0.00343	0.19442
17	9	4427.75	0.00258	0.19700
18	8	4427.75	0.00209	0.19909
19	7	4427.75	0.00189	0.20098
20	2	1065.35	0.00174	0.20272
21	10	4427.75	0.00160	0.20432
22	3	1065.35	0.00152	0.20584
23	4	4427.75	0.00134	0.20718
24	1	1065.35	0.00129	0.20847
25	6	4427.75	0.00129	0.20976

Total Frequency of Maximum Concentrations Greater than 0.20 is 0.23290 monitor will observe concentrations above the 0.20 ppm threshold. The improvement in the fraction of observed violations is indicated in the cumulative capture frequency in column 5. For this example, the total percent frequency of occurrence of values above 0.20 ppm is 23.29%. Thus, with 25 receptors 90.06% (20.976/23.29) of all observed concentration values greater than 0.20 ppm would be observed. Clearly, the use of this many monitors would be a very expensive and yet not a foolproof way of assuring that required air quality is being maintained. It is interesting to note that by adding the 17th monitor to a network including the best 16 locations, an order of magnitude less improvement in important data capture is gained than when the second monitor was added to the first.

From the previous example, one can deduce two general results:

1. For any reasonable number of sensors, a relatively high percentage of significant peak values may go unobserved.

2. Using monitoring alone as the only guide to decisions concerning emission curtailments in an SCS could result in a significant number of undetected violations of the short-term standards given that violations are expected to occur.

2.3 Meteorological Forecasting Reliability and Upgrading

2.3.1 Introduction

The purpose of every SCS is to avoid violations of air quality standards by reducing emissions during periods when weather conditions are not conducive to adequate dispersion of the pollutants. Identification of these poor dispersion periods must be accomplished with some advance notice since there exist practical limits to the speed with which emission reduction orders can result in lower emissions from the stack. Furthermore, there is a significant "transport time" before the emissions can travel from the stack to the point of maximum ground-level impact. The requirement for advance warning of impending poor dispersive periods forces the supplementary control system to include some form of meteorological forecasting. Some conditions, such as inversion breakup fumigation, demand advance forecasting. Monitored air quality levels alone would provide no advance warning of such conditions.

The principal role of meteorological forecasting for an SCS is to provide a basis for the appropriate SCS response to anticipated poor dispersion conditions. After the SCS has been operative and meteorological forecasts and observed concentration levels have been recorded, analysis of the data can verify the meteorological conditions which accompany poor air quality, and point to ways of improving the meteorological forecast system.

2.3.2 Criteria for Assessing Meteorological Forecasting Reliability

The following factors are essential to a meteorological forecasting system and provide a framework with which to discuss the reliability of this important SCS component:

- The spatial and temporal scales of the forecasting procedures must be appropriate for the requirements of the SCS.
- The relationship between errors in meteorological parameter forecasts and errors in predicted concentration levels must be understood.
- Verification of all aspects of the meteorological forecasting system must be a part of the SCS.

These criteria are considered in detail below.

Spatial and Temporal Scales of Forecasted Conditions

Meteorological forecasting for the estimation of air quality is categorized by space and time scales. Forecasting for time scales of 24 hours or more requires the prediction of synoptic scale (hundreds to thousands of kilometers) meteorological events.

For example, it entails the prediction of the movement and location of stagnating anticyclones with their associated light winds and poor dispersion characteristics. Short time periods require detailed forecasts on smaller spatial scales. In determining the reliability of meteorological forecasting for an SCS, it is necessary to consider forecasts on temporal scales of 1 to 24-hours and on spatial scales of several thousand square miles to within a few thousand feet of the pollutant source.

The "weather" variables which the meteorologist must forecast are those which influence the dilution capacity of the lower atmosphere. As direct forecasts and measurements of the turbulent components of the wind are frequently unavailable, related parameters become the forecast requirement. These include wind speed and direction, atmospheric stability, cloudiness, precipitation, and mixing depth.

The reliability of any weather forecast is never perfect and in general depends on several diverse and often highly variable factors. A 6-hour forecast of cloud cover is usually more reliable than a 24-hour forecast of the same event. Local effects are important. The onset of a sea breeze circulation in coastal areas can be in opposition to the wind flow normally associated with a weather system where there is no large body of water nearby. Similarly, the diurnal variation in temperature is different in urban areas compared to rural areas.

Meteorological Forecasting Errors vs. Air Quality Forecast Errors

The reliability of a forecast for air quality is a function of the reliability of forecasting the meteorological parameters which dictate the ensuing air quality. First, consider wind speed and direction. For an isolated source unaffected by terrain, the wind direction may be unimportant as possible high pollutant concentrations may occur in any downwind direction from the source. Two examples when wind direction is important are plume downwash, which may occur with strong winds from particular directions, and terrain modified winds which might produce high concentrations at a particular critical location. The predictability of wind direction is generally good, especially with well-defined synoptic systems. The predictability decreases with time and is often lower in areas with complicated terrain features. When an anticyclone is over the station, wind direction can be variable and, hence, difficult to predict.

Wind speed usually is more difficult to forecast. It varies diurnally with high speeds during the day, when there is a transfer of momentum from higher levels to the surface boundary layer, and with low speeds at night. Wind speed depends on the intensity of the pressure gradient, insolation, surface roughness, terrain channeling, and other local factors. The reliability of wind speed forecasts also decreases with length of forecast time.

The stability of the lowest kilometer of the atmosphere broadly describes its turbulent characteristics. An unstable atmosphere is characterized by thermal convection, turbulence, and good mixing. A stable atmosphere is characterized by weak turbulence and poor mixing.

Temperature measurements in the vertical are usually the best indicator of stability. If continuous temperature measurements in the vertical (e.g., on a meteorological tower) are available, then atmospheric stability can be accurately estimated. Temperature typically varies diurnally, with changing air mass and with local effects.

When a vertical temperature profile is unavailable, the prediction of stability is indirect and, hence, less reliable. The stability, however, may be estimated by the prediction of cloud cover, wind speed, type of air mass over the region, ground cover (e.g., snow cover, proximity to large bodies of water) and time of day.

The atmospheric mixing height is defined as the depth of the surface layer of the atmosphere through which complete vertical mixing occurs, and is thereby a function of the vertical temperature structure of the atmospheric boundary layer. Local temperature sounding data provide an excellent basis for the estimation of the mixing height. The predictability of the mixing height depends upon the predictability of such factors as the vertical distribution of temperature in the lowest few kilometers and the presence and height of subsidence inversions associated with synoptic scale anticyclones. The afternoon mixing height is identified by the height of the intersection of the dry adiabatic lapse rate from the surface maximum temperature with the observed or predicted vertical temperature profile. Pollutants trapped in a shallow mixing layer could result in high ground-level concentrations.

The prediction of maximum temperature is routine and generally quite reliable. The reliability of a temperature forecast decreases with time and is affected by cloud cover, wind speed and direction, time of year, and local effects.

The forecasting of meteorological parameters is strongly related to the predictability of synoptic scale weather systems. The prediction of the growth and movement of cyclones and anticyclones is routinely performed by forecasters in the National Weather Service (NWS) and in private industry. At present, forecasts of synoptic scale weather are made in a "man-machine mix" mode. Completely objective numerical forecasts provide guidance to the meteorologist who prepares the "best" forecast.

Even if meteorological forecasts are available from a nearby NWS station, forecasting for a supplementary control system will require additional on-site meteorological information. Pilot balloons, radiosondes, and on-site wind and temperature sensors are important sources of forecast inputs. It is obvious that the mix of

NWS guidance, on-site data collection, and forecasting experience and skill are important for meteorological forecasting reliability. The reliability of these predictions varies with geographical area, temporal length of forecast, and large-scale weather patterns. It is difficult to assess the absolute reliability of these predictions as one must consider the unique meteorological and engineering needs of each proposed SCS. For example, the time requirements necessary to change fuel usage or to reduce fuel load at a power plant will dictate the minimum forecast time scale and, hence, will enter into the assessment of forecast reliability.

To assess the reliability of a forecasting capability in reference to air quality, a basic understanding of the relationship between pollutant emissions, atmospheric dispersion potential, and ambient pollutant concentrations is assumed. This knowledge should be gained by an extensive dispersion analysis and meteorology-air quality monitoring program in which their relationship is modeled and observed over an extended time period. An understanding of the relationship between pollutant emissions, dispersion potential and air quality is a primary prerequisite in any SCS.

Verification of Meteorological Events

During the development of an SCS there should be a continuous review of the forecast accuracy through verification of the predicted meteorological parameters. Verification of these forecast meteorological parameters is relatively simple. Predictions are compared to observations to determine forecast accuracy. The verification program should indicate the average reliability of meteorological forecasts for different time periods and different initial conditions. For example, at a certain pollutant source, plume downwash is expected with northeast winds above a certain wind speed, U_c. When the wind speed exceeds U_c, high ground-level SO_2 concentrations are measured. The verification program must then demonstrate the ability to forecast strong winds from the northeast. If this pollution source were located in the Boston area the relative frequency of northeast winds is low, about 8 percent; and, hence, the predictability of this wind direction may be lower than the predictability of more frequent wind directions. However, if this meteorological event is the only weather condition with a high pollution potential, then the verification program must emphasize the predictability of strong northeast winds. Accurate prediction of other wind directions may be unimportant. Forecasting light northeast winds may be very difficult but is also unimportant as related to air quality prediction since downwash or other situations conducive to air quality problems do not occur.

The air quality-meteorology relationship, specific to the locale under consideration, must guide the verification program and must also guide the assessment of forecasting reliability.

The verification program should thereby emphasize the predictability of those meteorological conditions that produce the highest air pollution potential. It is important to ascertain the reliability of those predictions - especially the probability of occurrence of adverse meteorological conditions that were not predicted.

NWS and U.S. Air Force aviation forecasters routinely predict winds, sky cover, visibility, precipitation, and temperature for a 24-hour period at a specific location. If verification statistics for several years are available for the location in question, the predictability of the meteorological parameters important to air quality can be assessed. (Verification statistics are indicative of the relative reliability of forecasts at a particular locale.)

2.4 Air Quality Modeling Reliability and Upgrading

Several types of air quality models have been developed to predict ambient pollution levels resulting from pollutant emission sources. These models fall into two general categories: (1) deterministic-atmospheric dispersion models which calculate concentrations based upon physical relations between emission and meteorological parameters and effluent plume dispersion; and (2) statistical or empirical models based upon the determination of statistical relations between emission rates, meteorological conditions, etc., and air quality levels. Models based upon multiple applications of a Gaussian plume equation to calculate the pollutant concentration at a receptor or models based upon the numerical solution of a conservation of pollutant mass equation are of the former type and will be primarily addressed in this section.

The reliability of a model is defined by its ability to predict ambient pollutant concentrations based upon given meteorological conditions and emission parameters. The best method for the evaluation of prediction model accuracy is thorough analysis of the accuracy resulting from a large data set of predictions with the model. With a sufficiently large data set, the model reliability can be assessed over all weather conditions and observed emission rates. Such an evaluation procedure results in three benefits: (1) the model is immediately useful for operational application; (2) the expected accuracy of short-term forecasts can be evaluated; and (3) threshold pollutant concentrations for the reliable operation of an SCS can be determined.

To assess the reliability of an atmospheric dispersion model for a particular locale, i.e., an isolated SCS, a basic understanding of the relationship between meteorology, emissions, and pollutant concentrations must be established. This can be determined through a joint meteorology-air quality monitoring program and a model validation program.

Of interest to the maintenance of air quality standards is an indication of the maximum "underprediction" observed during the time the verification program has been in operation. For example, a predicted 24-hour SO_2 average of 0.05 ppm in comparison to an actual observation of 0.10 ppm represents a marked underprediction and certainly should be accounted for in the design of the SCS.

For some applications a comprehensive verification program may be unnecessary. If it has been determined that high pollutant concentrations rarely occur or occur only under certain well defined weather conditions, then the model validation study need only concentrate on the occurrence of those particular adverse weather conditions and source emissions which cause high pollutant concentrations. The model reliability, then, must most carefully be established for the emissions and meteorology that will produce concentrations above a specific threshold level. Because of the differences in the characteristics of the models it is difficult to establish general analysis criteria applicable to all model types. Therefore, each type of model is considered individually below.

Gaussian Plume Models

The empirical plume equation most frequently used to estimate the down-wind dispersion of a pollutant from an elevated continuous point source is the bi-normal Gaussian plume equation:

$$C = \frac{Q}{2\pi u\sigma_y\sigma_z} \exp\left(-\frac{y^2}{2\sigma_y^2}\right) \left[\exp - \frac{(z-h)^2}{2\sigma_z^2} + \exp - \frac{(z+h)^2}{2\sigma_z^2}\right]$$

where C is the pollutant concentration at height, z

Q is the source strength;

u is the mean horizontal wind speed;

σ_y, σ_z are the standard deviations of the distributions of concentrations in the y (cross-wind) and z (vertical) directions, and are functions of downwind distance, x, atmospheric stability, and averaging time; and

h is the effective source height.

The Gaussian form of a plume equation is convenient because of its simple analytical form. The Gaussian dispersion equation and its application to various source configurations is discussed in "Reviewing New Stationary Sources" (EPA, 1976a).

The causes of errors in point source model calculations may be broadly grouped into three categories: inaccuracies in the representation of the atmospheric transport and dispersion process by the model, errors in the emissions data and errors in estimating meteorological parameters.

Gaussian point source models also generally assume that wind speed and direction are constant throughout the area. Model calculations are particularly sensitive to errors in wind direction as non-centerline pollutant concentrations decrease exponentially away from the centerline. Wind direction persistence information is especially important for estimating concentrations over time periods of a few hours.

The effective height (h) of a stack, which determines the centerline height in the Gaussian plume model, is computed as the sum of the physical stack height and the plume rise due to the vertical momentum and buoyancy of the effluent. Plume rise is related to the dimensions of the stack, effluent characteristics such as temperature and heat flux, the wind speed above the stack, and atmospheric stability. Uncertainties in these parameters will affect the plume rise calculation. Several formulae (see Briggs 1969 for a review) have been developed to describe plume rise. Deciding which equation is applicable to a particular source is difficult and, at best, uncertainty by a factor of two in estimates of the plume rise is likely on any one occasion.

If a stack is located on a building and its efflux velocity is low or if the stack is not tall enough with respect to nearby buildings, plume downwash could occur, resulting in high ground-level pollutant concentrations. The following parameters are important for aerodynamic downwash: the strength of the undisturbed wind, stack height, effluent exit velocity and buoyancy, and the dimensions and spacing of local obstructions to the wind. These parameters will determine the likelihood of downwash. In turn, their reliability will affect the reliability of the pollutant concentration calculation.

To eliminate some of the uncertainties of the Gaussian plume model a comprehensive model validation program should be instituted for the point source of interest. The primary objective of the validation effort is to assure that the model adequately predicts concentrations over the time and space scales of interest and over the range of expected source emissions.

Model validation implies a detailed investigation of the model results and a comparison of those results with measured values in order to identify and evaluate discrepancies. If the model results compare well with the observed data, the model may be used without modification. On the other hand, if systematic discrepancies are found, the investigation may suggest alterations of model parameters or of the model mechanics which would improve the representativeness of the model.

The procedures for validating models will differ somewhat from application to application depending upon the nature and purpose of the study and depending upon the quality of the available data. Ideally, validation should consider individual weather conditions or emission rates depending on the length of the data base. For example, the error for stable atmospheric stability may be greater than for neutral stability. Winter emission rates associated with space heating needs may be positively correlated with cool northerly winds. Neglect of this mechanism often causes models to overpredict pollutant concentrations during other weather conditions. The validation procedure will normally require a thorough study of the implications of model assumptions and the performance of "sensitivity" studies for various input parameters.

Numerical Simulation Models (Conservation of Mass Models)

Gaussian-type models tend to ignore spatial and temporal variations in meteorological conditions by assuming that wind speed, wind direction, and dispersion parameters are uniform in both the vertical and horizontal directions. Large spatial and time variations, however, are generally found in nature and especially in areas with irregular terrain. Numerical dispersion models which attempt to simulate air pollution phenomena associated with vertical and horizontal variations in meteorological parameters are being developed.

The numerical advection - diffusion models are based on solutions to a conservation of mass equation for a trace material in a continuum fluid. The tracer equation may be written

$$\frac{\partial C}{\partial t} = \nabla \cdot (UC) + \nabla \cdot K \nabla C + Q$$

where

C is the concentration

U and K are wind velocity and turbulent diffusivity generally varying with space and time, and

Q is the emission rate per unit volume.

For general wind and diffusivity fields the continuum equation must be solved numerically by finite difference techniques.

In general, the sources of error in a numerical dispersion model are four: (1) emissions data; (2) specification of the wind field; (3) specification of the turbulent diffusivities; and (4) errors resulting from the numerical approximations.

Statistical Air Quality Prediction Models

If an adequate historical data bank of pollutant concentrations and meteorological observations is available for a region, it is possible to construct a statistical model relating observed concentrations to various meteorological parameters. Because statistical models do not consider changes in emission parameters, they are only useful for the prediction of concentrations for short time periods. For short period predictions as is necessary for an SCS, such models, developed from a sufficient data base, can provide the necessary predictions with a minimum of computation.

In common with Gaussian plume models, statistical models rely upon meteorological forecasts for short period predictions. The accuracy of all types of models depends upon the accuracy of the meteorological forecasts.

3. RELIABILITY ANALYSIS CONCEPT

3.1 Introduction

This section presents a mathematical concept that involves the analysis of source, meteorological and air quality data collected concurrently during an extended period of SCS operation. The analysis is designed to yield information on overall system reliability. It also provides information useful in system "upgrading" (improving system reliability).

Section 3.2 describes the probability theory underlying the analysis concept. Section 3.3 describes the concept and Section 3.4 presents examples of its application.

3.2 Relevant Probability Theory

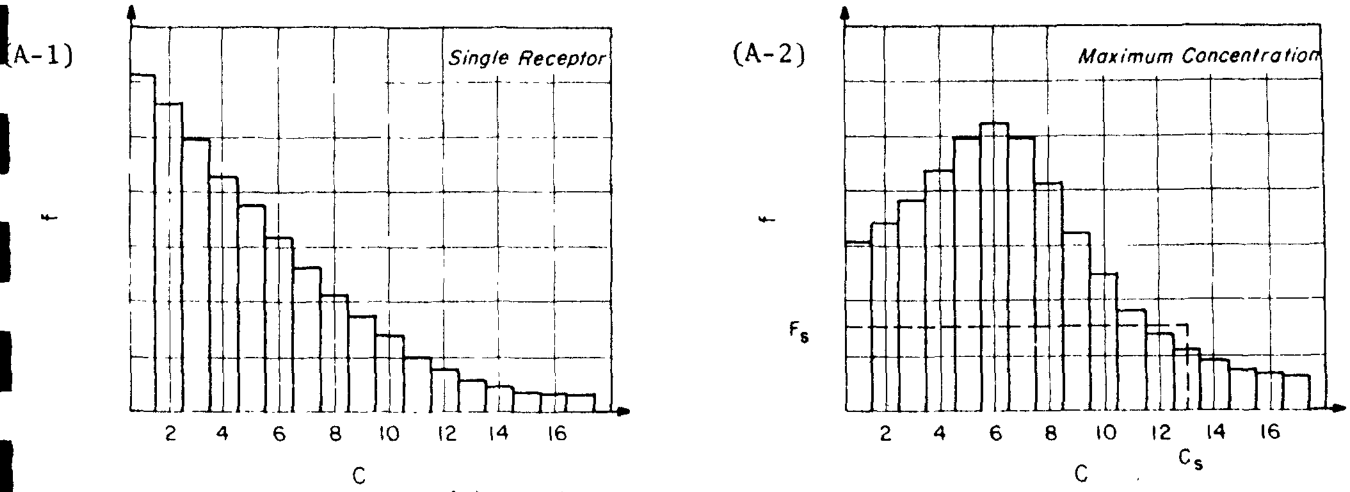
Throughout this document the concept of a frequency distribution is used. A frequency distribution is a representation of the fraction of the time a variable quantity assumes each of the possible values in its range. A frequency distribution of ground level concentrations downwind of a source provides much information about the characteristics of the source emissions.

The analysis model presented in this section is based upon studies of the frequency distributions of air quality levels from point sources whose contributions dominate the concentration fields. Figure 3-1A illustrates two typical concentration distributions.

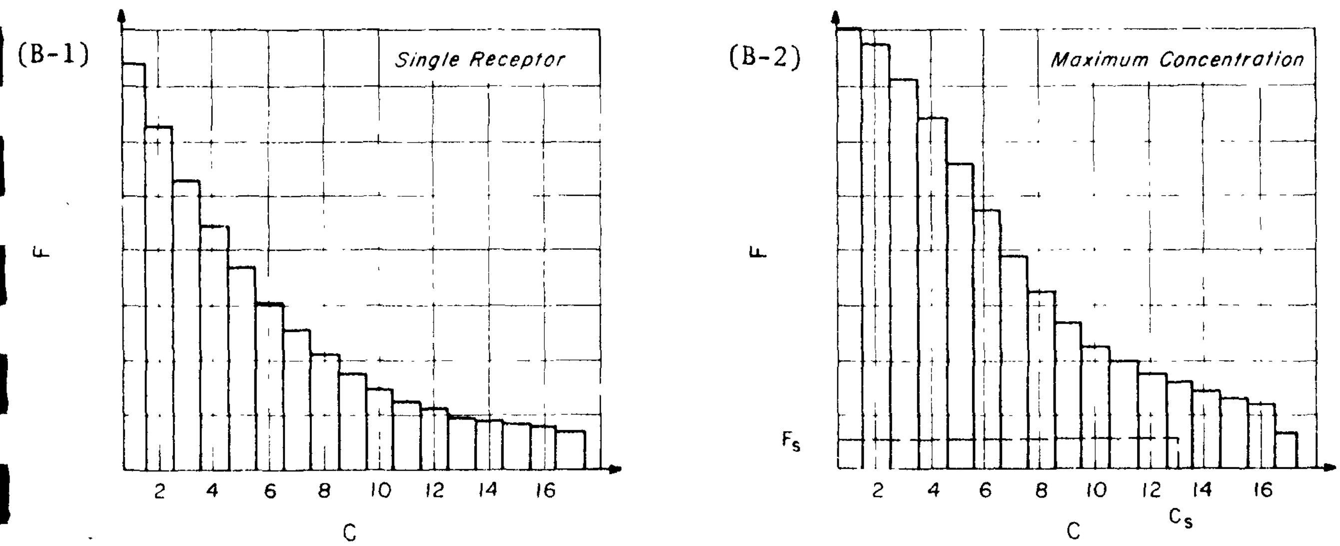
The first would be the case of a single receptor where the wind is often blowing in a direction other than from source to receptor so concentrations are most often near zero. The second is representative of a distribution of highest concentrations at any one of a network of receptors around a source. In the latter case, maximum concentrations near zero are less likely.

The value C_s has been designated on the abscissa of the maximum concentration graph to indicate the value of some air quality standard. The sum of the frequencies of occurrence of all concentration categories greater than C_s is the fraction of the time the air quality standard is expected to be exceeded. The value F_s on the ordinate of each graph has been designated to indicate the permissible frequency of concentration values exceeding C_s. To satisfy the air quality standard the sum of the frequencies for values of concentration to the right of C_s must be less than F_s.

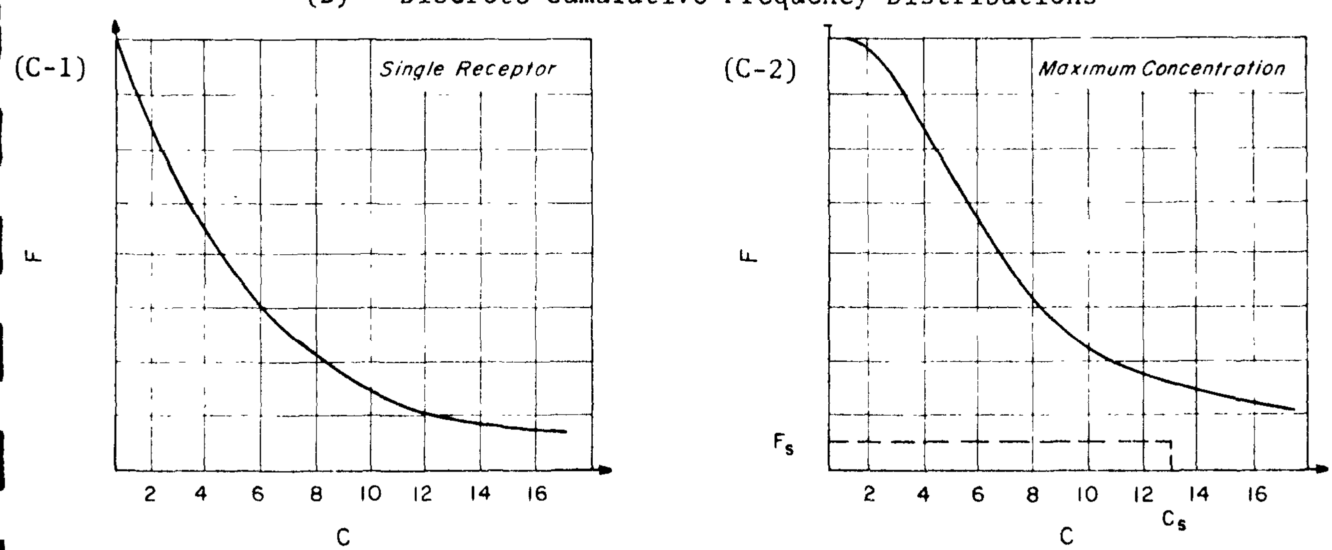
Thus, from a compliance view point, a more useful distribution is the cumulative frequency distribution associated with each of the frequency distributions discussed above. In this case, the sum of the frequencies of all values greater than the abscissa value is plotted as the ordinate. Figure 3-1B illustrates the cumulative frequency distributions associated with the distributions of Figure 3-1A. The sum over the frequency distribution of occurrence for concentrations greater than C_s can now be read directly from the ordinate of the graph.



(A) Discrete Frequency Distributions



(B) Discrete Cumulative Frequency Distributions



(C) Continuous Cumulative Frequency Distributions

Figure 3-1 Representative Frequency Distributions for Ambient Concentrations from a Point Source. (Graphs A-1, B-1 and C-1 apply to a single receptor; Graphs A-2, B-2 and C-2 apply to the maximum concentrations from a network of receptors.)

Since the range of concentration values is continuous, the step function presentation of the cumulative frequency distribution can be replaced by a smooth function as illustrated in Figure 3-1C. Using the graphs of Figure 3-1C, it can be simply stated that the goal of any control procedure is to reduce the locus of F at the abscissa value C_s below the dashed line representing F_s. When it is obvious which frequency distribution of the three presented in Figure 3-1 is being discussed, the term distribution will be used for convenience in this document.

The cumulative frequency distribution can be used to illustrate the effects of any control procedure. Figure 3-2A represents a hypothetical distribution of maximum ground level concentrations. Since the locus of F is above the dashed line at $C = C_s$, the source is exceeding the standard. Assume the graph of F represents the uncontrolled conditions. Direct application of a constant emission control which reduces emissions uniformly by 50% (say, changing from 2% to 1% sulfur fuel or installing 50% efficient removal devices) would move every value of F from the abscissa value C to the abscissa value C/2 to yield the graph illustrated in Figure 3-2B. The graph of F has been reduced, as required, below F_s to satisfy the air quality requirements.

An alternative to a constant emission control system such as discussed above would be an SCS capable of changing the tail of the graph to F to reduce F* to values below F_s for $C \geq C_s$. Figure 3-2C represents some emission reduction $\beta(C)$ which reduces emissions by exactly the amount required to achieve the standard all the time. In practice, no system will be so reliable. It is more likely that some fraction of the attempts to eliminate concentrations greater than C_s will be unsuccessful.

Figure 3-2D represents a more realistic frequency distribution that may result from the operation of an SCS. The curve of F* is not different from the curve of F at the low concentration end of the graph. This is in contrast to the constant emission reduction case of Figure 3-2B where all concentrations are reduced. The tail of the F* curve of Figure 3-2D is below the dashed line for values of $C > C_s$ as required. The values of $C > C_s$ would be the result of uncertainty (errors) in the operation of the SCS, but their frequency is low enough such that the air quality standard is attained.

The SCS reliability analysis procedures discussed below are based upon consideration of modifications to the frequency distributions discussed in this section.

3.3 Reliability Analysis

3.3.1 The Basic Concept

In the following analysis it is assumed that a reliable monitoring system exists and that attainment of all air quality standards is assured if each component of the SCS were without error. The main assumptions of the analysis scheme are the following:

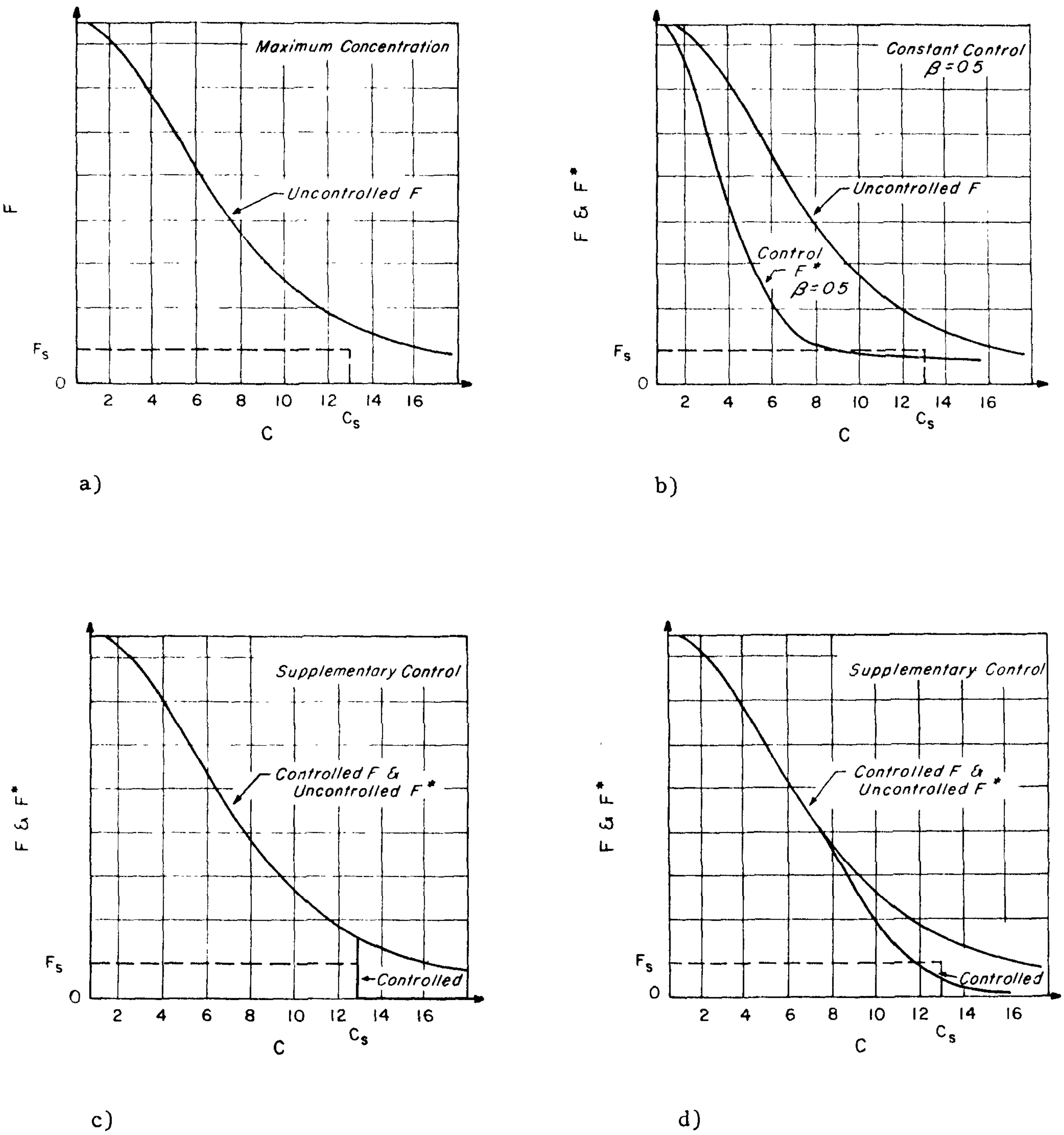


Figure 3-2 Representative Cumulative Frequency Distributions for Maximum Concentrations under Conditions of a) no emission controls, b) absolutely reliable constant emission controls, c) absolutely reliable supplementary emission controls, d) realistic supplementary emission controls.

- A single source of SO_2 is responsible for observed concentration levels;
- Without an SCS, emissions are independent of meteorological conditions;
- With an SCS, emissions are controlled according to rules which depend on predicted meteorological conditions;
- Error in air quality prediction (as defined later) is independent of meteorological conditions. (Section 4.3 discusses how this assumption can be relaxed.)

Consider the following definitions relevant to understanding the model:

$c(x,t)$: concentration at time t and location x

$C(t)$: $\max c(\underline{x},t)$; *maximum concentration over all* x locations at time t

$\underline{x}$: downwind location of $C(t)$

C_s: air quality standard

$Q(t)$: emission rate without SCS

$M(t)$: meteorological function relating the maximum concentration $C(t)$ to source emission rate $Q(t)$ and which will include the effects of stack height, wind conditions, mixing depths or any other pertinent meteorological inputs

$R(t)$: The error ratio of concentration prediction defined as follows:

With or without an operating SCS, the observed maximum concentration C_o is related to the actual emission rate Q through the meteorological function M as follows:

$C_o = Q \cdot M$ at time t

With an operating SCS, the corresponding maximum predicted concentration is related to the actual emission rate Q and the meteorological function M (defined above) through the Error Ratio R as follows:

$C_p = Q \cdot M \cdot R$ at time t

From the above, the error ratio can be defined as

$$R = C_p/C_o \ .$$

The observed maximum concentration under SCS control is given by $C_c = Q_c \cdot M$ where Q_c is the SCS controlled emission rate determined from the forecast concentration C_p.

The value of Q_c depends on the SCS control strategy being used. Two examples of possible control strategies are:

(1) Fuel Switching

$$Q_c = \begin{cases} Q & \text{if } C_p \leq \gamma \\ \beta Q & \text{if } C_p > \gamma \end{cases} \qquad \text{(Strategy 1)}$$

where β is a constant (less than one) which depends on the nature of the fuels. A switch from 2% sulfur fuel to 0.5% sulfur fuel means $\beta = 0.25$. The threshold parameter γ is a function of the air quality levels attempted to be maintained.

(2) Process Curtailment

$$Q_c = \begin{cases} Q & \text{if } C_p \leq \gamma \\ \gamma/C_p \cdot Q & \text{if } C_p > \gamma \end{cases} \qquad \text{(Strategy 2)}$$

In general, the threshold γ is set below standards to provide a margin of safety.

The functions Q, M, and R require more careful description. Q(t) can be a well defined quantity if emission monitors are used or if emission rate is simply related to the production rate. If the plant emissions are not monitored some engineering estimates of the frequency distribution of Q can often be made from production or process control information.

The function M(t) can be determined in various ways. For an operation with an extended historical air quality monitoring record, M(t) could be estimated from the ratios of measured maximum concentrations $C_o(t)$ and known emission rates Q(t). Where a shorter monitoring record exists with an extended meteorological data bank, M could be the output of a statistical model; e.g., $M = a_1m_1 + a_2m_2 + \text{--} + a_nm_n$ where m_1, m_2, -- m_n are meteorological parameters such as stability or air mass characteristics and a_1, a_2, ---a_n are regression coefficients determined from the available air quality data. By knowing the distributions of the m_i's, the statistical data of the shorter monitoring period can be combined with the longer period meteorological distributions. This is frequently the case since meteorological data has been collected at many locations by the National Weather Service for periods up to a century. Finally, where little site monitoring data exists, outputs from air pollution dispersion models can be used in conjunction with the meteorological data to construct M.

The function R(t) may be determined from historical real-time monitoring and forecasting data. Since the function R will depend upon the unique forecasting difficulties for each SCS scheme, initial estimates of R must be made during the design and initial testing of the SCS. The upgrading of an SCS as time proceeds will involve periodic re-evaluations of this function.

Given the functions Q(t), M(t) and R(t) over an appropriate time period, frequency of occurrence distributions can be readily derived for the various magnitudes of the observed or estimated values of Q, M and R. Thus, the time history data are transformed into frequency of occurrence distributions. For purposes of future estimations, the frequency of occurrence distributions become expected probability density functions.

When the frequency distributions for Q, M and R as defined above are determined, they may be utilized to generate information useful in the reliability analysis and upgrading of an SCS. For example, it would be useful to generate the following information (Section 4 presents several examples):

1. The number of violations to be expected without and with any SCS scheme.

2. The percentage of production lost if the SCS scheme is a load reduction program.
3. The percentage use of high and low sulfur fuel in a fuel switching SCS program.
4. The dependence of the number of violations, production lost and/or percentage use of high and low sulfur fuel upon the implementation threshold (γ), model calibration, meteorological forecasting skill, and/or the difference in sulfur content of the two switching fuels.

3.3.2 A Mathematical Application of the Concept

This sub-section presents a mathematical approach that may be used to apply the concepts presented in Section 3.3.1.

Define P_X as the probability density function for the variable X. Then the probability of the variable X having a value between a and b is

$$F_X = \int_a^b P_X(\zeta)\, d\zeta$$

Assume that there exist probability density functions for M and Q, and we wish to generate a frequency distribution for C when no SCS is operating. If A is any concentration value, ε is a variable and Q and M are independent of each other and random variables, then

$$P_C(C = A) = \Big[P_Q\,(Q = \varepsilon) \cdot P_M\,(M = A/\varepsilon)$$

$$+ \; P_Q\,(Q = 2\varepsilon) \cdot P_M\,((M = A/2\varepsilon) + \text{---}$$

$$+ \; P_Q\,(Q = n\varepsilon) \cdot P_M\,(M = A/n\varepsilon) + \text{---} \Big] \; \Delta\varepsilon$$

or, in the limit as $\Delta\varepsilon$ approaches 0

$$P\,(C = A) = \int_o^\infty P_Q\,(Q = \zeta) \cdot P_M\,(M = A/\zeta)\; d\xi$$

or

$$P_C\,(A) \quad = \int_o^\infty P_Q\,(\zeta) \cdot P_M\,(A/\zeta)\; d\zeta$$

Expressing the operator above by *,

$$P_C = P_M * P_Q$$

This equation states that the probability density function for maximum ground-level concentrations can be derived from the convolution of the probability density functions for M and Q. Therefore, the frequency distribution of ground-level concentrations for an uncontrolled plant can be determined from determinations of M and Q.

Once P_C is known, the graphs corresponding to Figure 3-1B can be displayed, and the probability of violating standards is directly known.

Consider next the case when the SCS is operating. In this case $C_c = Q_c \cdot M$ where subscript c denotes the functional value when the SCS is operating. Q_c is no longer independent of meteorology since the operation of the SCS depends on meteorological forecasting.

P_Q will, therefore, also be generally dependent upon P_M and will vary for different control strategies. For computer solutions to the correlated integration, the dependence of these quantities upon each other can be readily simulated.

Assuming that the error ratio R is independent of M and of Q and given P_R, P_M, and P_Q it is possible to use the control strategy rules for determining Q_c to numerically evaluate P_{Cc} under the SCS control.

In this case $C_p = M \cdot Q \cdot R$. The value of Q_c is determined in each case from the predicted value of concentration C_p and from the strategy (e.g., strategy 1 or 2). From the resulting distribution of Q_c, the value of P_{Cc} is obtained from the equation

$$P_{Cc} = P_{Qc} * P_M$$

Note the parallel nature of this equation and the equation for P_C.

This means that the existing frequency distribution of ground level concentrations for a plant can be determined from archived measurements of Q and M, and from records of air quality forecasting accuracy during operational use of the SCS to determine R.

3.4 Isolating Component Error

This section proposes a method for isolating the error induced by three of the major components of an SCS--meteorological forecasting, emission forecasting, and air quality modeling. The individual errors can then be assessed and combined (e.g., by utilizing the concepts presented in Section 3.3.2) to estimate the overall system reliability.

For the first part of this analysis, assume that emission forecasting uncertainty is negligible. Given that assumption, the method requires that the following three (maximum) concentration values be recorded for each forecasting time during a period of several months or more of SCS operation:

- The model predicted concentration using predicted meteorological parameters. (This concentration value is the basis of the SCS control action which will affect concentrations T hours later.)
- The model predicted concentration using observed meteorological parameters.
- The maximum concentration recorded by the monitoring network.

The procedure combines the above recorded data in a way that isolates the error in air quality forecasting due to meteorological forecasting uncertainty from the error due to model uncertainty.

Recall the formulation developed in Section 3.3.1 for ground level concentration:

The observed maximum concentration is assumed to be $C_o = Q \cdot M$.

The predicted maximum concentration is assumed to be $C_p = Q \cdot M \cdot R$ where the Error Ratio R is the ratio

$$R = C_p/C_o$$

R is a function which contains contributions from all sources of error and uncertainty which prevent a perfect air quality forecast ($C_p = C_o$). These sources of uncertainty arise from each component of the SCS--meteorological forecasting, emissions forecasting, and air quality modeling. Consider the following formulation of R:

$$R = R_q \cdot R_w \cdot R_m$$

where R_q, R_w, and R_m are the error ratios for emissions prediction, meteorological (weather) forecasting, and air quality modeling respectively.

In the absence of emission source uncertainty,

$$R = R_w \cdot R_m \ .$$

Define the following model predicted concentration values. The predicted concentration using predicted meteorological parameters is given by:

$$C_p\ (Q,M_p) = Q \cdot M_p = Q \cdot M \cdot R.$$

This concentration value is the basis of the SCS control action which will affect concentrations T hours later. The predicted concentration using observed meteorological parameters is given by:

$$C_p\ (Q,M_o) = Q \cdot M_o$$

C_o is the maximum concentration recorded by the monitoring network.

Hence,

$$\frac{C_p\ (Q,M_p)}{C_p\ (Q,M_o)} \cdot \frac{C_p\ (Q,M_o)}{C_o} = \frac{C_p\ (Q,M_p)}{C_o} = R$$

That is, the error ratio R can be expressed as the product of two ratios. The first ratio is the quotient of two model predictions using the same model, the same source emissions and different meteorology. It is an error ratio isolating the effect of meteorological forecasting on the net error ratio, R. The second ratio is the quotient of two concentration values based on the observed source emissions and observed meteorological parameters. The numerator is a model prediction, and the denominator is a monitored concentration value. It is an error ratio isolating the effects of model accuracy on R. The first ratio satisfies the requirements for R_w and the second ratio satisfies the description of R_m, so that

$$R = R_w \cdot R_m$$

where

$$R_w = \frac{C_p\ (Q,M_p)}{C_p\ (Q,M_o)} \quad \text{and } R_m = \frac{C_p\ (Q,M_o)}{C_o}$$

In practical operation of the SCS, $C_p\ (Q,M_p)$ will be computed or determined at every forecast time and recorded. Then T hours later the value of C_o will be recorded. Simultaneously, it is a simple matter to determine the value $C_p(Q,M_o)$, using the observed meteorological parameters. If these three values are recorded at every forecast time and every forecast verification time, the ratios R_w, R_m, and R can be routinely computed.

To consider the possibility of uncertainty in emissions forecasting, define the following additional model predicted concentration values. The predicted concentration using predicted meteorological parameters and predicted source emissions is given by:

$$C_p\ (Q_p,M_p) = Q_p \cdot M_p = Q \cdot M \cdot R$$

This concentration value is the basis of the SCS control action which will affect concentrations T hours later. The predicted concentration using predicted source emissions and observed meteorological parameters is given by:

$$C_p\ (Q_p,M_o)$$

$C_p\ (Q_o, M_o)$ is the predicted concentration using observed source emissions and observed meteorological parameters.

It is clear that,

$$\frac{C_p\ (Q_p, M_p)}{C_p\ (Q_p, M_o)} \cdot \frac{C_p\ (Q_p, M_o)}{C_p\ (Q_o, M_o)} \cdot \frac{C_p\ (Q_o, M_o)}{C_o} = R$$

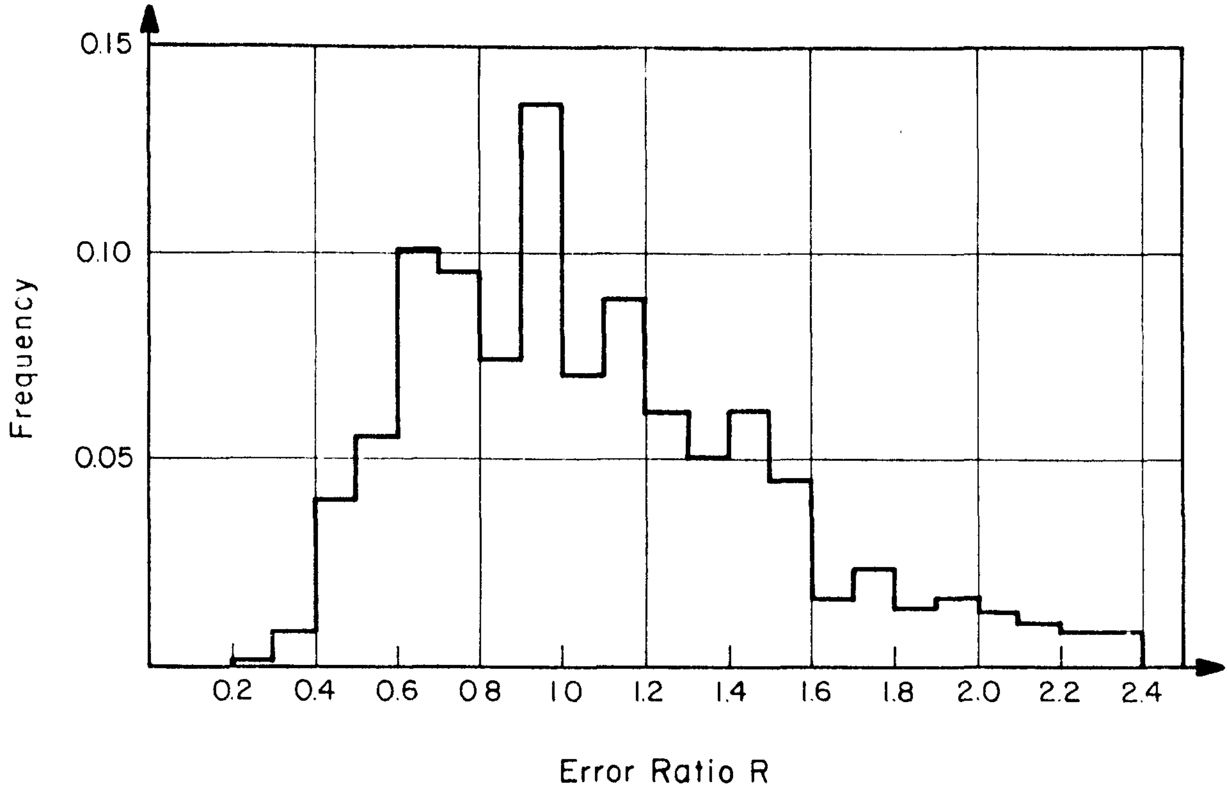
That is the error ratio R can be expressed as the product of three ratios. Similar to the case with no source error, the first and last ratios represents R_w and R_m, respectively. The second ratio is a quotient of concentration predictions using the same meteorological parameters and the same model but different source emissions. It is an error ratio isolating the effects of source emission uncertainty and errors on the Error Ratio R.

The presence of source emission errors requires that four concentration ratio values, R_w, R_m, R_q and R be determined for each time. The distribution of R which is generated is available for verification and upgrading of the SCS by means of the procedures described in Section 3.3 and applied in Section 4.

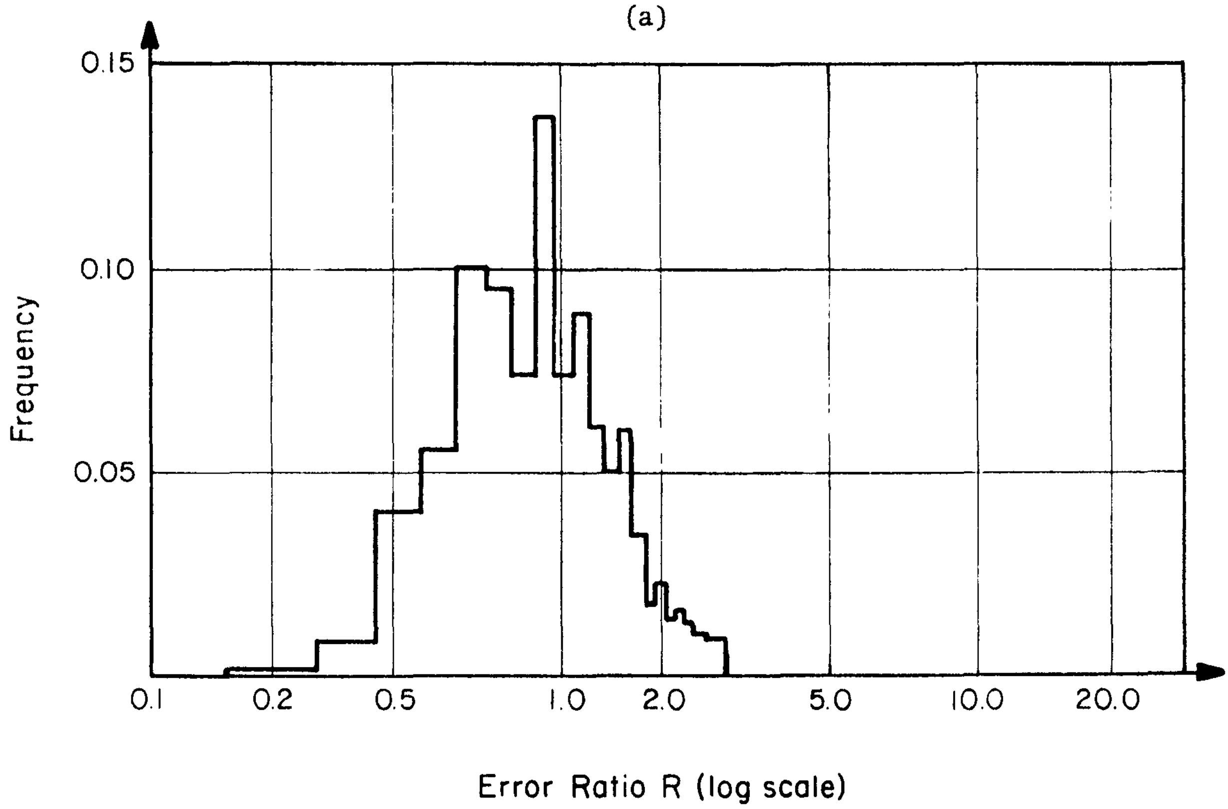
Finally, the distribution of the error ratio, R must be determined for each SCS application. A preliminary estimate of the character of the ratio can be made from data collected from an existing air quality monitoring/forecasting network (AIRMAP - operated by Environmental Research and Technology, Inc.). The AIRMAP network for the Boston area consists of SO_2 monitors which continuously monitor and record air quality levels. Experienced forecastors predict 24-hour average concentration levels at each receptor for the time period beginning 12 hours after the time of the forecast. A one year record of both observed concentrations and predicted concentrations for each day of 1973 was available. Maximum predicted concentrations and maximum observed concentrations were compared for each day to generate the distribution of R for this potential SCS network.

Figure 3-3A illustrates the resulting distribution of R for the Boston AIRMAP network. The median value of R is nearly 1.0 indicating no significant bias in prediction. Also, the frequency of R values approaches zero as R approaches either zero or values much larger than 1.0. Figure 3-3B is the same distribution with R represented on a logarithmic scale. The distribution is nearly log-normally distributed. For the example analyses which follow in Section 4, a log-normal distribution of R will be assumed.

It should be noted that the R distribution derived from the Boston AIRMAP system is for a metropolitan area and may not be applicable to a region characterized by an isolated source. However, it was the best available for the examples presented in Section 4. The use of this specific R distribution in the example applications is based on the assumption that one could predict air quality levels resulting from isolated source emissions with accuracies comparable to those associated with predicting air quality levels at specific receptors in a multiple source region.



(a)



(b)

Figure 3-3 Distribution of the Error Ratio R for the Boston AIRMAP Network

4. EXAMPLE RELIABILITY ANALYSIS

4.1 Test Case Conditions and Assumptions

The reliability analysis concepts presented in Section 3 have been applied* to several example hypothetical supplementary control systems. The examples are designed to illustrate the utility of the analysis technique as well as to illustrate the dependence of the reliability of an SCS upon the various independent parameters which influence SCS reliability.

The source data and the meteorological inputs are appropriate to an actual source. However, because we wish only to isolate and illustrate the effect on reliability of changes in the SCS structure, the inputs have been simplified. Assumed input information is given as follows:

- The source is a single 828-ft. stack.
- The meteorological data are based on a 5-year stability-wind rose from a nearby airport. Estimates of the frequency of inversion conditions and of inversion break-up fumigations are only approximate.
- Terrain is essentially ignored except for its effect on the stability-wind rose.

From the source data and the meteorological inputs detailed above, the Meteorology Function M and the Emissions Function Q can be defined. At any time, the Meteorology Function is predicted by a Gaussian point-source dispersion model for unit SO_2 emissions.

*Plans are underway to document, in the form of a user manual, the computer program that was utilized in the examples presented in this section (see Preface).

The distribution of M is determined from the stability-wind rose. The maximum downwind model prediction for each weather condition is assigned the corresponding frequency from the stability-wind rose and the frequency distribution of M is constructed. The Emissions Function Q is assumed for these examples to be constant and equal to the full load emissions to simulate conditions in the absence of an SCS. The frequency distribution of Q is, therefore, very simple. The probability of full load is 1.0 and all other values have probability zero.

Specification of the SCS is based upon several parameters. A range of values for each parameter is considered in the examples below to represent a wide range of possible SCS operations.

Two SCS types are examined: (1) a single option switch plan, and (2) a continuous option plan. The single option plan is representative of fuel switching. Implementation of the SCS reduces emissions by the fraction β in all cases. The continuous option switch plan is representative of process curtailment. Implementation of the SCS reduces emissions by exactly that fraction necessary to bring the maximum ground level concentration below a prescribed threshold. These two SCS types were chosen for study from an infinite set of SCS types which can be investigated by this probability analysis technique.

The distribution of the Error Ratio R is assumed to be a log-normal distribution, well specified by a geometric mean value $\overline{R}$ and by the standard deviation of the distribution σ.

The characteristics of the distributions for R were chosen to be similar to the observed distribution of R described for the AIRMAP network in Section 3.4. The log-normal shape and the width of each sample distribution are similar to those corresponding to this distribution. Error Ratio will be carefully specified for each example below.

As described in Section 3.4, the Error Ratio R can be expressed as the product of three ratios, R_w, R_q, and R_m. The majority of examples below consider the total function R without considering the individual component contributions separately. However, for one set of examples, $R = R_w \cdot R_q$ where both R_w and R_q have a significant probability of being different from 1.0. In this case, the distributions of R_w and R_q are both considered.

Each SCS, regardless of type, is assumed to have a switch threshold. If the predicted value of the maximum ground-level concentration is projected to exceed the switch threshold, the SCS emission reduction action is initiated. Obviously, the highest acceptable switch threshold is the air quality standard. Because of uncertainty in air quality forecasts, the switch threshold, γ, is usually some fraction of the standard.

4.2 Dependence of SCS Reliability on Various Influencing Factors

The following examples have been provided in order to isolate the effect of changes in each of the pertinent variables which influence reliability. These variables include: $\bar{R}$, the geometric mean of the error ratio R; σ, the standard deviation of the error ratio distribution; γ, the threshold value of the predicted maximum concentration above which some operational process adjustment is made; and β, the ratio of the sulfur content of the low sulfur fuel to the sulfur content of the high sulfur fuel used in a fuel switch SCS.

Example 1 - What is the effect on SCS reliability of changing the value of σ for the Error Ratio R?

Reduction of the value of σ for the Error Ratio R is a desirable objective of every SCS operation. If σ could be made negligibly small, the SCS could be perfectly reliable with a minimum loss of production or fuel costs for the source. A non-zero value of σ results from the presence of unbiased errors in meteorological forecasting, estimation of emissions, or modeling results. A reduction in σ would be expected from any of the following system improvements:

- Additional or improved meteorological data used in predicting the meteorological parameters which are input for air quality forecasts. Unless R_w is very near 1.0 or the system is operating near the predictability limit for each parameter, some improvement through added meteorological support is expected. Among the possible improvements in meteorological support might be atmospheric sounding data, on-site wind measurements, NWS teletype or facsimile circuits, a wind field generator model, a faster data reduction system, or simply more frequent observations of important meteorological parameters.
- More experienced or more capable meteorological personnel. Because personnel gain experience as the system is operated, the σ of the system should become smaller with time.

- An improved model. As a forecasting model is updated through system experience, a reduction in σ is to be expected.

- An improved emission schedule forecast system. This improvement might be gained by more thorough production planning or it might involve more careful fuel or materials analysis, better emissions monitoring, or better plant process monitoring.

Table 4-1 summarizes the results of this example analysis. Note that all SCS operating parameters are the same for each SCS option except that σ is varied. The first column in the summary table describes the six SCS options and the NO SCS option (for comparison). The second column contains the frequency of violations of a 1-hour standard of 0.5 ppm expected to occur with the indicated control strategy. The third column contains the fraction of low cost fuel (higher sulfur content) which can be used. The remaining fraction of fuel must be more expensive (lower sulfur content) fuel. The fourth column contains the fraction of the time that full production is possible assuming that the SCS process curtailment is the only constraint.

Clearly, any of the six SCS plans reduces the frequency of violations by at least a factor of 2 but, interestingly, no more than a factor of 3.4. By improving forecast accuracy for the fuel switching cases, SCS reliability is noticeably improved. Since the fuel switching constant $\beta = 0.25$ is overly conservative in most cases, nearly every switch action results in concentrations

Table 4-1

Effects on SCS Reliability of Changing the Value of σ for the Error Ratio R

Each SCS plan below has the following parameter values:

Fuel switching fraction $\beta = 0.25$

Switching threshold $\gamma = 0.5$

Geometric Mean of Error Ratio $\overline{R} = 1.0$

Width of Error Ratio distribution σ, is variable

SCS Control Strategy	Total Frequency of Violations	Fraction of Low Cost Fuel	Fraction of Time at Full Production
NO SCS	0.16432	1.000	1.000
SCS #1: FUEL SWITCHING $\sigma = 0.5$	0.06605	0.754	1.000
SCS #2: FUEL SWITCHING $\sigma = 0.4$	0.06291	0.768	1.000
SCS #3: FUEL SWITCHING $\sigma = 0.2$	0.04875	0.808	1.000
SCS #4: PROCESS CURTAILMENT $\sigma = 0.5$	0.08216	1.000	0.918
SCS #5: PROCESS CURTAILMENT $\sigma = 0.4$	0.08216	1.000	0.948
SCS #6: PROCESS CURTAILMENT $\sigma = 0.2$	0.08216	1.000	0.961

below standards. Therefore, improved accuracy of prediction (reduced σ) results in fewer potential violations escaping control. Since the switch threshold γ = 0.5 ppm is exactly the standard, there is no conservatism in the process curtailment forecasts. Although improved forecast accuracy reduces the magnitude of violating concentrations, the number of violations remains the same. These examples indicate that some conservatism is desirable for an efficient SCS strategy. Ways of including conservatism are discussed later.

Improved forecast accuracy can have possible economic and social benefits despite the probable added expense. For the fuel switching examples, use of valuable low sulfur fuel is reduced from .25 to .23 and finally to .19 of the total fuel used as forecasting accuracy is improved. Meanwhile, SCS reliability is also improved. Note that full production is assumed to be possible regardless of fuel type. For the process curtailment cases, the percentage of full production is increased as forecast accuracy improves. Meanwhile, SCS reliability is maintained at the same level.

Example 2 - What is the Effect on SCS reliability of changing the value of $\overline{R}$ for the Error Ratio R?

The geometric value of the Error Ratio, $\overline{R}$, is less than 1.0 if concentrations are characteristically underpredicted, greater than 1.0 if concentrations are characteristically overpredicted, and 1.0 if there is no systematic bias in prediction. It is easy for a system to achieve a value of $\overline{R}$ = 1.0 by simply reducing each forecast value by the required amount to bring the mean of past values to 1.0. It is generally desirable, however, to intentionally operate an SCS conservatively to prevent a high frequency of violations which are near but higher than the standard. The limits on reliability of a nonconservative SCS were illustrated in the previous example analysis. One method of operating a conservative SCS is to maintain an Error Ratio mean $\overline{R}$ greater than 1.0.

An air quality forecast model which overpredicts provides a means of achieving $\overline{R}$ greater than 1.0. Most air quality models overpredict because "worst case" conditions such as persistent meteorology and conservative plume rise are assumed.

Similarly, meteorological and emission predictions used for air quality projections are often chosen to be "worst case" forecasts. For example, predicting fumigation conditions for all clear mornings would produce a value of $\overline{R}$ greater than 1.0, but may be necessary to prevent contravention of standards on those several mornings when inversion breakup is a problem.

The example analysis which follows is designed to investigate the effect of changing $\overline{R}$ on SCS reliability, leaving all other SCS parameters unchanged. Table 4-2 includes the results of the operation of six hypothetical SCS schemes and the NO SCS case.

Again, each of the six SCS plans reduces the frequency of violations by a considerable amount. The increased conservatism of air quality prediction, manifested in increased values of $\overline{R}$, reduces the frequency of violations of the standard for both fuel switching and process curtailment. For fuel switching, 43 of every 44 violations can be eliminated using an SCS with $\overline{R} = 2.0$.

The economic penalty for the indicated improvements in air quality is shown in the final two columns of Table 4-2. With $\overline{R} = 2.0$, lower sulfur fuel is required 59% of the time for operation of the fuel switching plan. For process curtailment, a negligible violation frequency is accomplished by reducing maximum possible production by 39%. Unlike reducing σ, increasing $\overline{R}$ above 1.0 has no compensating economic savings.

Example 3 - What is the effect on SCS reliability of changing the value of the switch threshold γ ?

The previous example analysis investigated the improvement in SCS reliability effected by conservative air quality forecasting. Another method of improving SCS reliability is through the use of a switch threshold less than the standard. Similar to making

Table 4-2

Effects on SCS Reliability of Changing the Value of $\overline{R}$ for the Error Ratio R

Each SCS plan below has the following parameter values:

Fuel switching fraction $\beta = 0.25$
Switching threshold $\gamma = 0.5$
Geometric mean of error ratio $\overline{R}$ is variable
Width of error ratio distribution $\sigma = 0.5$

SCS Control Strategy	Total Frequency of Violations	Fraction of Low Cost Fuel	Fraction of Full Production
NO SCS	0.16432	1.000	1.000
SCS #1: FUEL SWITCHING $\overline{R} = 1.0$	0.06606	0.754	1.000
SCS #7 FUEL SWITCHING $\overline{R} = 1.5$	0.00876	0.521	1.000
SCS #8: FUEL SWITCHING $\overline{R} = 2.0$	0.00370	0.413	1.000
SCS #2: PROCESS CURTAILMENT $\overline{R} = 1.0$	0.08194	1.000	0.918
SCS #9: PROCESS CURTAILMENT $\overline{R} = 1.5$	0.01306	1.000	0.836
SCS #10: PROCESS CURTAILMENT $\overline{R} = 2.0$	0.00000	1.000	0.609

conservative predictions, this control technique compensates for tendencies to underpredict since most underprediction errors will result in "violations" of the threshold which are still below the standard.

Table 4-3 displays the results of the example analysis for six hypothetical SCS plans with switch thresholds of varying value.

Systematic improvement in SCS reliability is evident for both the fuel switching cases and the process curtailment cases as the switch threshold is made a smaller fraction of the air quality standard.

Systematic reduction in economic benefit manifested in fractional fuel usage data and fraction of full production data is also evident. Similar to maintaining the value of $\overline{R}$ greater than 1.0, a conservative switch threshold is a simple tool for improving SCS reliability; but an overall loss of plant efficiency is a probable effect of the control strategy.

Example 4 - What is the effect on SCS reliability of changing the fuel switching fraction β ?

Although choice of a fuel switching fraction β is most likely determined by the availability of fuel types, it is interesting to observe the effect of changing the value of β. One can hypothetically achieve any value of β by blending fuels of known sulfur content, but engineering problems prohibit this generality in most cases.

TABLE 4-3

EFFECTS ON SCS RELIABILITY OF CHANGING THE VALUE OF THE SWITCH THRESHOLD γ

Each SCS plan below has the following parameter values:

Fuel Switching Fraction	$\beta = 0.25$
Switching Threshold	γ is variable
Geometric Mean of Error Ratio	$\overline{R} = 1.0$
Width of Error Ratio Distribution	$\sigma = 0.5$

SCS CONTROL STRATEGY	TOTAL FREQUENCY OF VIOLATIONS	FRACTION OF LOW COST FUEL	FRACTION OF FULL PRODUCTION
No SCS	0.16432	1.000	1.000
SCS #1: Fuel Switching $\gamma = 0.5$	0.06606	0.754	1.000
SCS #11: Fuel Switching $\gamma = 0.4$	0.03500	0.615	1.000
SCS #12: Fuel Switching $\gamma = 0.3$	0.01562	0.526	1.000
SCS #2: Process Curtailment $\gamma = 0.5$	0.08194	1.000	0.918
SCS #13: Process Curtailment $\gamma = 0.4$	0.05641	1.000	0.873
SCS #14: Process Curtailment $\gamma = 0.3$	0.02557	1.000	0.801

Three SCS plans with values of β of 0.25, 0.30, and 0.40, respectively were investigated. No appreciable change in SCS reliability or in plant production was observed. Apparently, the value β used in all three cases is very conservative; that is, each time a switch is implemented to a lower sulfur content fuel a greater than necessary reduction in concentration is achieved. Therefore, increasing the value of β toward 1.0 has no effect on violation frequency for values of β less than 0.5.

Example 5 - What is the effect on SCS reliability of maintaining a conservative value of $\overline{R}$ for the error ratio R and changing the value of γ ?

The preceding examples indicate that significant improvement in air quality can be expected from any one of many reliable SCS plans. It is not possible to define which SCS is both reliable enough for acceptance by control agencies and economically practical enough for acceptance by plant operators. It is likely that some combination of the preceding example SCS systems would be optimum for most operations.

Furthermore, it is conceivable that an operating SCS will require upgrading due to demands for more SCS reliability or due to demands for more cost effective operation by the plant management. In this eventuality it is likely that some combination of the preceding SCS changes would be optimum for the particular operation.

It is, therefore, important and interesting to observe the effects of more than one parameter change on SCS reliability. Table 4-4 includes six example SCS plans which observe the effects of changing the switch threshold γ and employing a conservative mean value of the Error Ratio R.

Comparing SCS number 7 and the three fuel switching plans in Table 4-4, it is clear that increased conservatism yields successively smaller increments of improvement in reliability until the SCS reaches its limit of reliability under the fuel switching plan. For process curtailment a comparison of SCS number 9 and the three plans included in Table 4-4 indicate a greater improvement in SCS reliability with decreasing value of the switch threshold. Values of γ less than 0.3 are unnecessary since only a negligible frequency of violations is expected at a value of $\gamma = 0.3$.

Note that SCS number 19 expects less than 0.1 violations per year and achieves more than 66% of full production. Considering no other complexities in evaluating SCS reliability, SCS number 19 accomplishes the most acceptable reliability with maximum plant production of all SCS plans considered in these examples.

Example 6 - How can emission error be incorporated into the analysis?

Each of the example analyses considered so far in this section considers the Error Ratio R to be some hypothetical log-normally distributed function. No attempt has been made to simulate the effects of uncertainties in the individual components of the SCS. The following example analysis will consider SCS schemes which have

TABLE 4-4

EFFECTS ON SCS RELIABILITY OF OPERATING WITH A CONSERVATIVE VALUE OF $\overline{R}$ AND CHANGING χ

Each SCS plan below has the following parameter values:

Fuel Switching Fraction	$\beta = 0.25$
Switching Threshold	γ is variable
Geometric Mean of Error Ratio	$\overline{R} = 1.5$
Width of Error Ratio Distribution	$\sigma = 0.5$

SCS CONTROL STRATEGY	TOTAL FREQUENCY OF VIOLATIONS	FRACTION OF LOW COST FUEL	FRACTION OF FULL PRODUCTION
No SCS	0.16432	1.000	1.000
SCS #15: Fuel Switching $\gamma = 0.4$	0.00471	0.450	1.000
SCS #16: Fuel Switching $\gamma = 0.3$	0.00370	0.395	1.000
SCS #17: Fuel Switching $\gamma = 0.2$	0.00370	0.372	1.000
SCS #18: Process Curtailment $\gamma = 0.4$	0.00353	1.000	0.784
SCS #19: Process Curtailment $\gamma = 0.3$	0.00000	1.000	0.664
SCS #20: Process Curtailment $\gamma = 0.2$	0.00000	1.000	0.572

meteorological error distributed like the Error Ratios of the preceding examples, but which also have emission errors. According to the discussion in Section 3,

$$R = R_W \cdot R_Q \cdot R_M$$

For these examples, we assume $R_M = 1.0$, therefore

$$R = R_W \cdot R_Q$$

We will assume that R_W has a log-normal distribution with $\overline{R_W} = 1.0$ and $\sigma_W = 0.5$. Furthermore, we will assume that

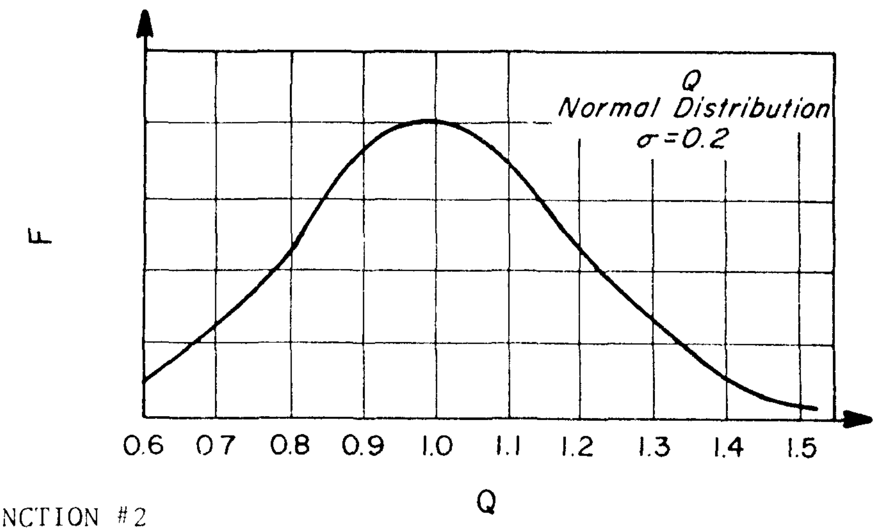
$$R_Q = \frac{Q_p}{Q_o} \; ;$$

that is, that the error in emission rate Q is measured simply by the ratio of predicted Q to the observed Q for that time.
Then,

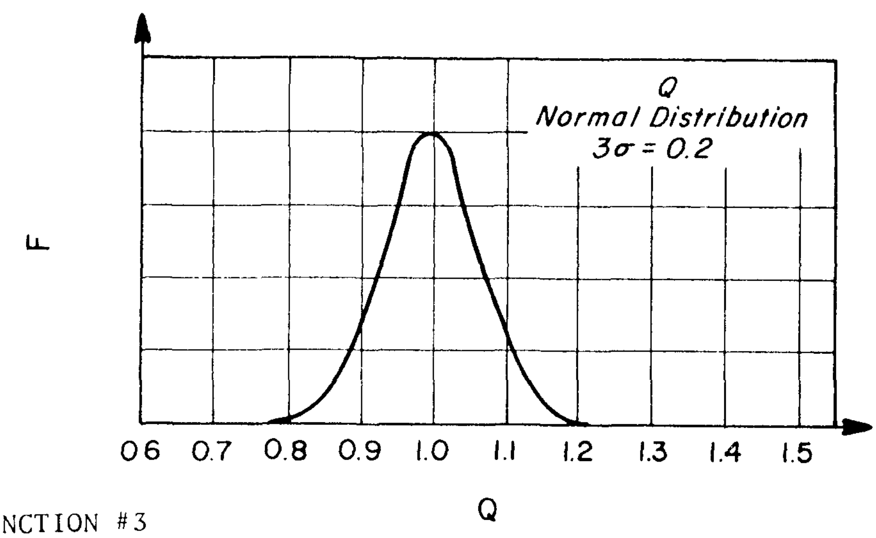
$$R = \frac{Q_p}{Q_o} \; R_W$$

It is reasonable to expect that $\frac{Q_p}{Q_o}$ has either a normal or a "top-hat" distribution. The example below considers both of those possibilities. The hypothesized distributions for R_W and R_Q are combined to form a distribution for R. Figure 4-1 illustrates the three distributions of $\frac{Q_p}{Q_o}$ used. They are designated as Q functions 1, 2 and 3.

Q FUNCTION #1



Q FUNCTION #2



Q FUNCTION #3

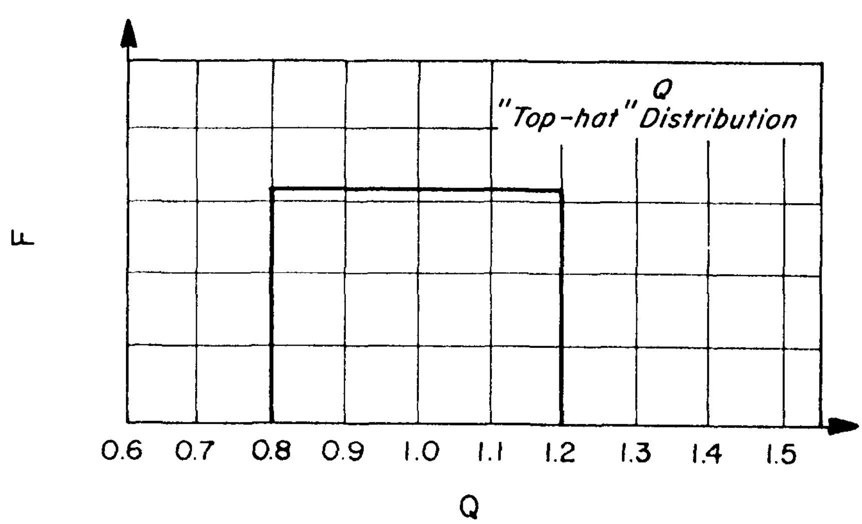


Figure 4-1 Three Frequency Distributions of the Ratio Q_p / Q_o .

Table 4-5 summarizes the results of the analysis using the combined Error Ratios. The frequency of violations for all six example SCS plans is greater than the frequency of violations for the corresponding SCS with no emissions error (SCS number 1 or SCS number 2). Improvement in SCS reliability is achieved as σ of the distribution is reduced. The "top-hat" emission error distribution is associated with a reliability intermediate between the two normally distributed emission error functions.

4.3 Further Applications of the Probability Analysis of SCS Reliability

It is likely that in many applications the Error Ratio R will not be independent of the meteorology function M. If conditions of very predictable strong winds are responsible for many high SO_2 levels, for example, it would be incorrect to use an Error Ratio R derived from more difficult to predict light wind cases. A different Error Ratio for each of several meteorological categories is likely. The probability analysis should be performed separately for each category; then the resulting frequency distributions can be added together.

It is also possible that several process curtailment actions are available for use but that a continuous option plant is not practical. This would be the case for an operation with integral units which can be either shut down or operated at full capacity. Such an SCS is easily investigated by the probability analysis.

Generally, SCS plans would have M functions which are not independent of the Q functions. The principal cause of this

TABLE 4-5

INCORPORATION OF EMISSIONS ERROR INTO THE RELIABILITY ANALYSIS

Each SCS plan below has the following parameter values:

Fuel Switching Fraction	$\beta = 0.25$
Switching Threshold	$\gamma = 0.5$
Geometric Mean of Error Ratio	$\overline{R} = 1.0$
Width of Error Ratio	$\sigma = 0.5$

SCS CONTROL STRATEGY	TOTAL FREQUENCY OF VIOLATIONS	FRACTION OF LOW COST FUEL	FRACTION OF FULL PRODUCTION
No SCS	0.16432	1.000	1.000
SCS #21: Fuel Switching Q Error 1	0.07079	0.765	1.000
SCS #22: Fuel Switching Q Error 2	0.06837	0.764	1.000
SCS #23: Fuel Switching Q Error 3	0.06943	0.766	1.000
SCS #24: Process Curtailment Q Error 1	0.08582	1.000	0.920
SCS #25: Process Curtailment Q Error 2	0.08397	1.000	0.921
SCS #26: Process Curtailment Q Error 3	0.08523	1.000	0.921

dependence is plume rise which is determined by both wind and stability (meteorology) and by heat flux through the stack (emissions). The probability analysis would require modifications to handle this interdependence of M and Q. For a given emission source this would require the specification of different M functions (incorporating the effects of differences in plume rise) for each significantly different source emission rate category.

For the examples in this Section, heat flux through the stack has been assumed to be fairly constant regardless of load. It is instructive to investigate in some detail the effect that changes in emission rate can have on ground-level concentration.

For a 36 day period in March and April of 1971, SO_2 emission rates, flue gas rates, and exit temperatures were compared for the 828-ft example stack. Exit temperatures are very constant, and flue gas rates are not a strong function of emission rate. A linear regression analysis to relate heat flux and emission rate for the stacks indicates that heat flux is reduced by just 8.0% when emissions are reduced by 50%. Many processes contribute effluent to the stack and effluent characteristics vary according to the stage of each process.

For power plants, on the other hand, the volumetric flow rate is a strong function of emission rate. Since exit temperatures vary by only about 10% over the range of possible power plant loads, heat flux is also strongly related to emission rate. In fact, the heat flux is nearly proportional to emission rate over the range of possible loads.

Assuming the plume rise formulation of Briggs (1969), the effect of changing emission rates on maximum ground-level concentrations can be assessed. Using a standard Gaussian diffusion model, maximum short-term concentrations were compared for the example plant under full load and half load conditions. An 8.0% reduction in heat flux was assumed. Under each weather condition, the maximum concentrations under half load conditions was no more than 53% and no less than 50% of the concentrations under full load conditions. A linear "roll-back" of concentrations with emissions seems appropriate in this case.

For a typical power plant, a 50% reduction in heat flux is expected to accompany a 50% reduction in emissions of SO_2. Under each weather condition, the maximum concentration predicted by the diffusion model under half load conditions was no more than 81% but no less than 61% of concentrations under full load conditions. Csanady (1973) developed a generalized technique of comparing emission reduction with maximum concentration reduction when heat rate is linearly related to emission rate. The hypotheses of the technique are most applicable to a point source under unstable atmospheric conditions. Figure 4-2 illustrates the result of this technique when heat rate is assumed proportional to emission rate. Maximum concentrations under half load conditions are expected to be 63% of concentrations under full load conditions. The effect of other fractional load reductions can be estimated from Figure 4-2. Clearly a linear roll-back of concentrations with emissions is not valid in this case.

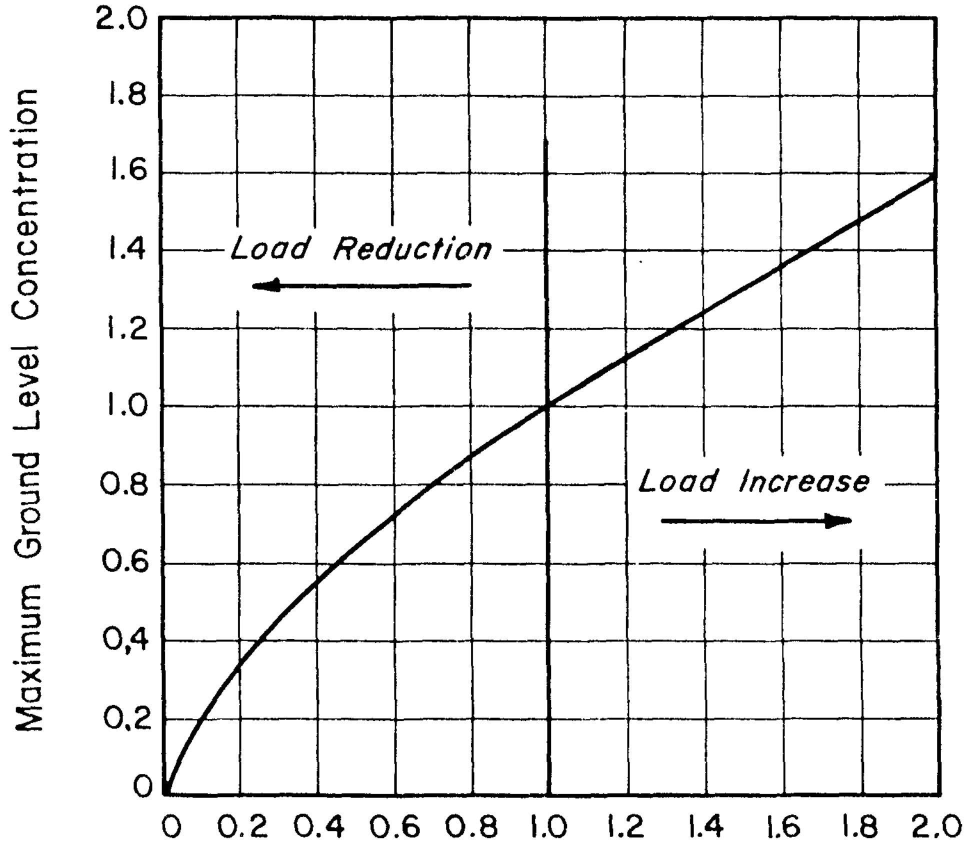


Figure 4-2 Effects of Emission Reduction on Maximum Ground Level Concentrations when Heat Rate through the Stack is Proportional to Emission Rate

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