9

Optimal Air Pollution Control Strategies

In general, the goal of air pollution abatement is the meeting of a set of air quality standards (see Table 1.9). Air pollution abatement programs can be divided into two categories:

1. Long-term control
2. Short-term control (episode control)

Long-term control strategies involve a legislated set of measures to be adopted over a multiyear period. Short-term (or episode) control involves shutdown and slowdown procedures that are adopted over periods of several hours to several days under impending adverse meteorological conditions. An example of a short-term strategy is the emergency procedures for fuel substitution by coal-burning power plants in Chicago when SO_2 concentrations reach certain levels (Croke and Booras, 1969).

Figure 9.1 illustrates the elements of a comprehensive regional air pollution control strategy, consisting of both long- and short-term measures. Under each of the two types of measures are listed some of the requirements for setting up the control strategy. The air quality objectives of long- and short-term strategies may be quite different. For long-term control, a typical objective might be to reduce to a specified value the expected number of days per year that the maximum hourly average concentration of a certain pollutant exceeds a given value. On the other hand, a goal of short-term control is ordinarily to keep the maximum concentration of a certain pollutant below a given value on that particular day.

The alternatives for abatement policies depend on whether long- or short-term

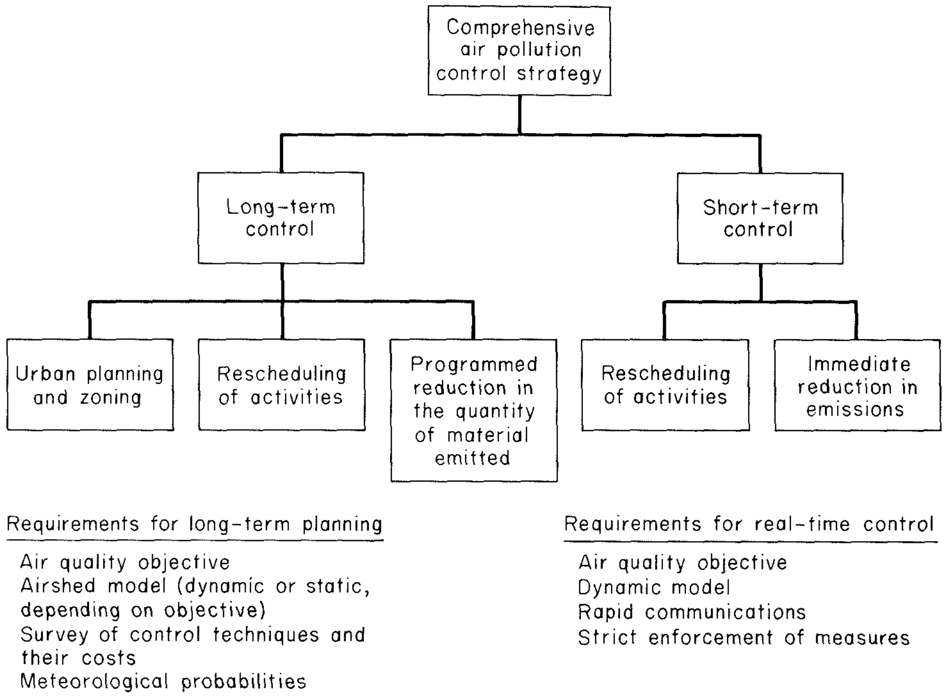


Figure 9.1 Elements of a comprehensive air pollution control strategy for a region.

control measures are being considered. Some examples of long-term air pollution control policies are:

- Enforcing standards that restrict the pollutant content of combustion exhaust
- Requiring used motor vehicles to be outfitted with exhaust control devices
- Requiring new motor vehicles to meet certain emissions standards
- Prohibiting or encouraging the use of certain fuels in power plants
- Establishing zoning regulations for the emission of pollutants
- Encouraging the use of vehicles powered by electricity or natural gas for fleets

Short-term controls are of an emergency nature and are more stringent than long-term controls that are continuously in effect. Examples of short-term control strategies are:

- Prohibiting automobiles with fewer than three passengers from using certain lanes of freeways
- Prohibiting the use of certain fuels in some parts of the city
- Prohibiting certain activities, such as incineration of refuse

The objectives of a short-term control system are to continuously monitor concentrations at a number of stations (and perhaps also at the stacks of a number of important emission sources) and, with these measurements and weather predictions as a basis, to prescribe actions that must be undertaken by sources to avert dangerously high concentrations. Figure 9.2 shows in schematic, block-diagram form a possible real-time control system for an airshed. Let us examine each of the loops. The innermost loop refers to an automatic stack-monitoring system of major combustion and industrial sources. If the stack emissions should exceed the emission standards, the plant would automatically curtail its processes to bring stack emissions below the standard. The emission standards would normally be those legislated measures currently in force. The next loop represents a network of automatic monitoring stations that feed their data continuously to a central computer that compares current readings with air quality "danger" values. These values are not necessarily the same as the air quality standards discussed earlier. For example, if the air quality standard for SO_2 is 0.14 ppm for a 24-h average, the alert level might be 0.5 ppm for a 1-h average. In such a system one would not rely entirely on measurements to initiate action, since once pollutants reach dangerous levels it is difficult to restore the airshed quickly to safe levels. Thus we would want to predict the weather to 3 to 48 h in advance, say, and use the information from this prediction combined with the feedback system in deciding what action, if any, to take.

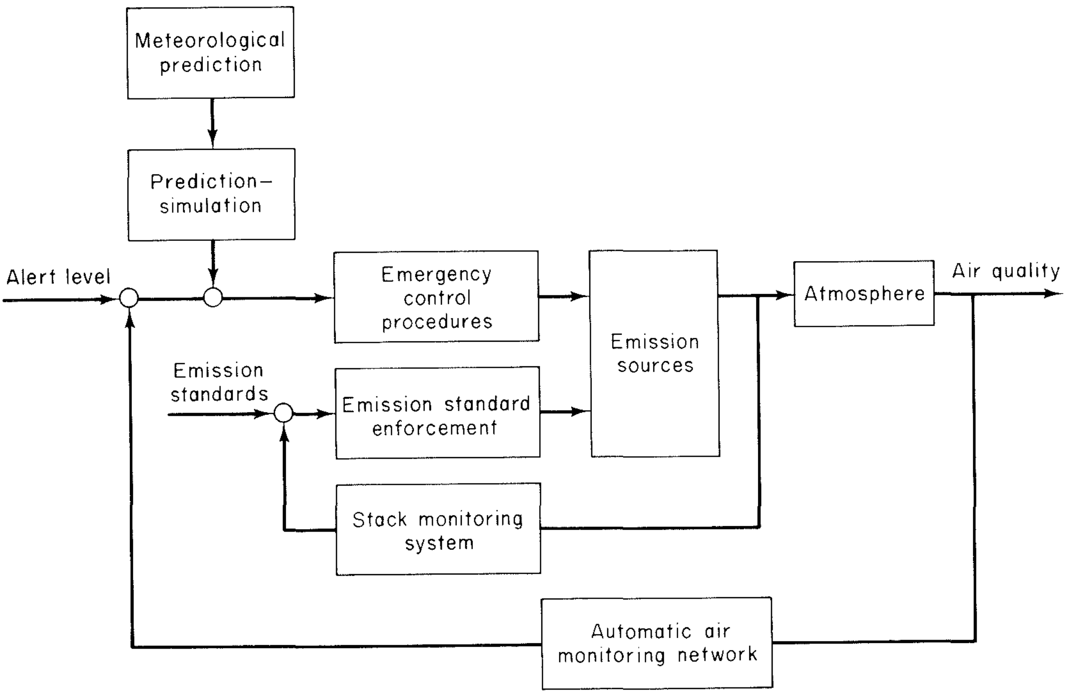


Figure 9.2 Elements of a real-time air pollution control system involving automatic regulation of emission sources based on atmospheric monitoring.

We refer the interested reader to Rossin and Roberts (1972), Kyan and Seinfeld (1973), and Akashi and Kumamoto (1979), for studies of short-term air pollution control.

9.1 LONG-TERM AIR POLLUTION CONTROL

Let us focus our attention primarily on long-term control of air pollution for a region. It is clear that potentially there are a number of control policies that could be applied by an air pollution control agency to meet desired air quality goals. The question then is: How do we choose the "best" policy from among all the possibilities? It is reasonable first to establish criteria by which the alternative strategies are to be judged.

Within the field of economics, there is a hierarchy of techniques called cost/benefit analysis, within which all the consequences of a decision are reduced to a common indicator, invariably dollars. This analysis employs a single measure of merit, namely the total cost, by which all proposed programs can be compared. A logical inclination is to use total cost as the criterion by which to evaluate alternative air pollution abatement policies. The total cost of air pollution control can be divided into a sum of two costs:

1. *Damage costs:* the costs to the public of living in polluted air, for example, tangible losses such as crop damage and deteriorated materials and intangible losses such as reduced visibility and eye and nasal irritation
2. *Control costs:* the costs incurred by emitters (and the public) in order to reduce emissions, for example, direct costs such as the price of equipment that must be purchased and indirect costs such as induced unemployment as a result of plant shutdown or relocation

We show in Figure 9.3 the qualitative form of these two costs and their sum as a function of air quality; poor air quality has associated with it high damage costs and low

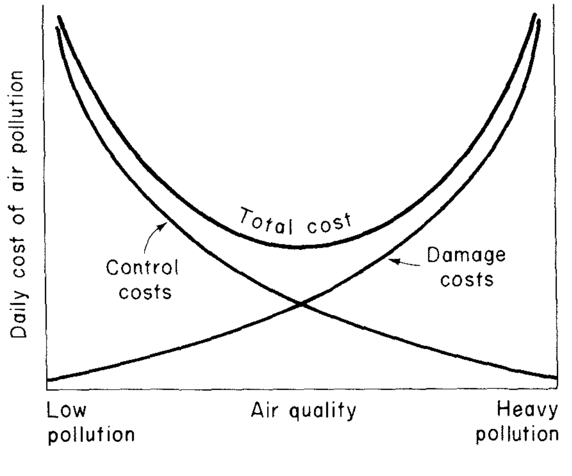


Figure 9.3 Total cost of air pollution as a sum of control and damage costs.

control costs, whereas good air quality is just the reverse. Cost/benefit principles indicate that the optimal air quality level is at the minimum of the total cost curve. The key problem is: How do we compute these curves as a function of air quality? Consider first the question of quantifying damage costs.

Damage costs to material and crops, cleaning costs due to soiling, and so on, although not easy to determine, can be estimated as a function of pollutant levels (Ridker, 1967). However, there is the problem of translating into monetary value the effects on health resulting from air pollution. One way of looking at the problem is to ask: How much are people willing to spend to lower the incidence of disease, prevent disability, and prolong life? Attempts at answering this question have focused on the amount that is spent on medical care and the value of earnings missed as a result of sickness or death. Lave and Seskin (1970) stated that "while we believe that the value of earnings foregone as a result of morbidity and mortality provides a gross underestimate of the amount society is willing to pay to lessen pain and premature death caused by disease, we have no other way of deriving numerical estimates of the dollar value of air pollution abatement." Their estimates are summarized in Table 9.1. These estimates are so difficult to make that we must conclude that it is generally not possible to derive a quantitative damage-cost curve such as that shown in Figure 9.3.

There are actually other reasons why a simple cost/benefit analysis of air pollution control is not feasible. Cost is not the only criterion for judging the consequences of a control measure. Aside from cost, social desirability and political acceptability are also important considerations. For example, a policy relating to zoning for high and low emitting activities would have important social impacts on groups living in the involved areas, and it would be virtually impossible to quantify the associated costs.

It therefore appears that the most feasible approach to determining air pollution abatement strategies is to treat the air quality standards as constraints not to be violated and to seek the combination of strategies that achieves the required air quality at minimum cost of control. In short, we attempt to determine the minimum cost of achieving a given air quality level through emission controls (i.e., to determine the control cost curve in Figure 9.3).

In the case of the control cost curve, it is implicitly assumed that *least-cost* control

TABLE 9.1 ESTIMATED HEALTH COSTS OF AIR POLLUTION IN 1970

Disease	Total annual estimated cost (millions of dollars)	Estimated percentage decrease in disease for a 50% reduction in air pollution	Estimated savings incurred for a 50% reduction in air pollution (millions of dollars)
Respiratory disease	4887	25	1222
Lung cancer	135	25	33
Cardiovascular disease	4680	10	468
Cancer	2600	15	390
			2100

Source: Lave and Seskin (1970).

strategies are selected in reaching any given abatement level. There will usually be a wide assortment of potential control strategies that can be adopted to reduce ambient pollution a given amount. For instance, a given level of NO_x control in an urban area could be achieved by reducing emissions from various types of sources (e.g., power plants, industrial boilers, automobiles, etc.). The range of possible strategies is further increased by alternative control options for each source (e.g., flue gas recirculation, low-excess-air firing, or two-stage combustion for power plant boilers). Out of all potential strategies, the control cost curve should represent those strategies that attain each total emission level at minimum control cost.

9.2 A SIMPLE EXAMPLE OF DETERMINING A LEAST-COST AIR POLLUTION CONTROL STRATEGY

Let us now consider the formulation of the control method–emission-level problem for air pollution control, that is, to determine that combination of control measures employed that will give mass emissions not greater than prescribed values and do so at least cost. Let $E_1, \ldots, E_N$ represent measures of the mass emissions* of N pollutant species (e.g., these could be the total daily emissions in the entire airshed in a particular year or the mass emissions as a function of time and location during a day); then we can express the control cost C (say in dollars per day) as $C = C(E_1, \ldots, E_N)$. To illustrate the means of minimizing C, we take a simple example (Kohn, 1969).

Let us consider a hypothetical airshed with one industry, cement manufacturing. The annual production is 2.5×10^6 barrels of cement, but this production is currently accompanied by 2 kg of particulate matter per barrel lost into the atmosphere. Thus the uncontrolled particulate emissions are 5×10^6 kg yr^{-1}. It has been determined that particulate matter emissions should not exceed 8×10^5 kg yr^{-1}. There are two available control measures, both electrostatic precipitators: type 1 will reduce emissions to 0.5 kg bbl^{-1} and costs 0.14 dollars bbl^{-1}; type 2 will reduce emissions to 0.2 kg bbl^{-1} but costs 0.18 dollar bbl^{-1}. Let

X_1 = bbl yr^{-1} of cement produced with type 1 units installed

X_2 = bbl yr^{-1} of cement produced with type 2 units installed

The total cost of control in dollars is thus

$$C = 0.14X_1 + 0.18X_2 \tag{9.1}$$

We would like to minimize C by choosing X_1 and X_2. But X_1 and X_2 cannot assume any values; their total must not exceed the total cement production,

$$X_1 + X_2 \leq 2.5 \times 10^6 \tag{9.2}$$

and a reduction of at least 4.2×10^6 kg of particulate matter must be achieved,

$$1.5X_1 + 1.8X_2 \geq 4.2 \times 10^6 \tag{9.3}$$

*Note that E_i is 0 if i is purely a secondary pollutant.

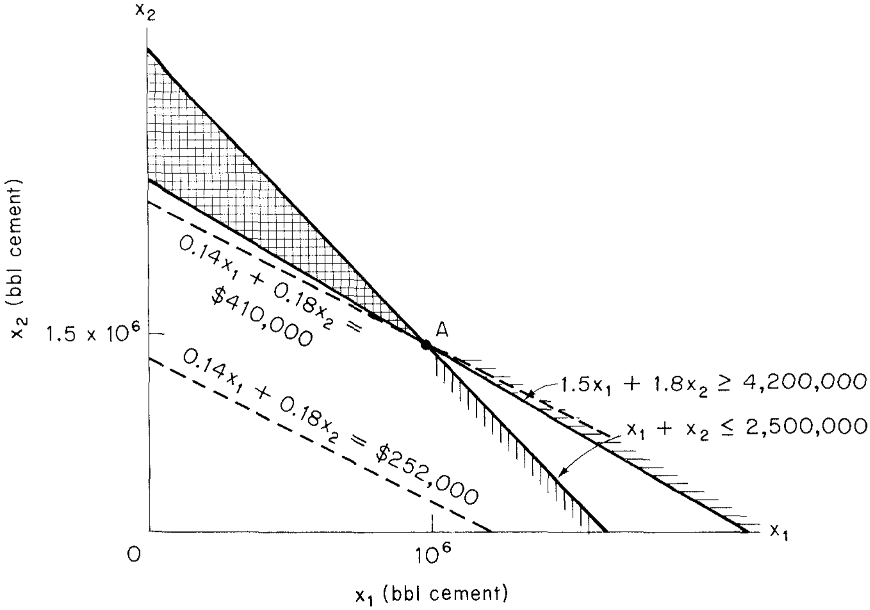


Figure 9.4 Least-cost strategy for cement industry example (Kohn, 1969).

and both X_1 and X_2 must be nonnegative,

$$X_1, X_2 \geq 0 \tag{9.4}$$

The complete problem is to minimize C subject to (9.2)–(9.4). In Figure 9.4 we have plotted lines of constant C in the X_1-X_2 plane. The lines corresponding to (9.2) and (9.3) are also shown. Only X_1, X_2 values in the crosshatched region are acceptable. Of these, the minimum cost set is $X_1 = 10^6$ and $X_2 = 1.5 \times 10^6$ with $C = 410,000$ dollars. If we desire to see how C changes with the allowed particulate emissions, we solve this problem repeatedly for many values of the emission reduction (we illustrated the solution for a reduction of 8×10^5 kg of particulate matter per year) and plot the minimum control cost C as a function of the amount of reduction (see Problem 9.1).

The problem that we have described falls within the general framework of *linear programming* problems. Linear programming refers to minimization of a linear function subject to linear equality or inequality constraints. Its application requires that control costs and reductions remain constant, independent of the level of control.

9.3 GENERAL STATEMENT OF THE LEAST-COST AIR POLLUTION CONTROL PROBLEM

The first step in formulating the least-cost control problem mathematically is to put the basic parameters of the system into symbolic notation. There are three basic sets of variables in the environmental control system: control cost, emission levels, and air quality. Total control cost can be represented by a scalar, C, measured in dollars. To allow systematic comparison of initial and recurring expenditures, control costs should be put in an "annualized" form based on an appropriate interest rate. Emission levels for N types of pollutants can be characterized by N source functions, $E_n(\mathbf{x}, t)$, $n = 1, \ldots, N$, giving the rate of emission of the nth contaminant at all locations, $\mathbf{x}$, and times, t, in the region. The ambient pollution levels that result from these discharges can be specified by similar functions, $P_h(\mathbf{x}, t)$, $h = 1, \ldots, H$, giving the levels of H final pollutants at all locations and times in the area under study.

Actually, air quality would most appropriately be represented by probability distributions of the functions $P_h(\mathbf{x}, t)$. In specifying ambient air quality for an economic optimization model, it is generally too cumbersome to use the probability distributions of $P_h(\mathbf{x}, t)$. Rather, integrations over space, time, and the probability distributions are made to arrive at a set of *air quality indices*, P_m, $m = 1, \ldots, M$. Such indices are the type of air quality measures actually used by control agencies. In most cases, they are chosen so as to allow a direct comparison between ambient levels and governmental standards for ambient air quality.

The number of air quality indices, M, may be greater than the number of discharged pollutant types, N. For any given emitted pollutant, there may be several air quality indices, each representing a different averaging time (e.g., the yearly average, maximum 24-h, or maximum 1-h ambient levels). Multiple indices will also be used to represent multiple receptor locations, seasons, or times of day. Further, a single emitted pollutant may give to rise to more than one type of ambient species. For instance, sulfur dioxide emissions contribute to both sulfur dioxide and sulfate air pollution.

Among the three sets of variables, two functional relationships are required to define the least-cost control problem. First, there is the control cost–emission function that gives the minimum cost of achieving any level and pattern of emissions. It is found by taking each emission level, $E_n(\mathbf{x}, t)$, $n = 1, \ldots, N$, technically determining the subset of controls that exactly achieves that level, and choosing the specific control plan with minimum cost, C. This function, the minimum cost of reaching various emission levels, will be denoted by G,

$$C = G[E_1(\mathbf{x}, t), \ldots, E_N(\mathbf{x}, t)] \tag{9.5}$$

Second, there is the discharge–air quality relationship. This is a physicochemical relationship that gives expected air quality levels, P_m, as functions of discharge levels, $E_n(\mathbf{x}, t)$. For each air quality index, P_m, this function will be denoted by F_m,

$$P_m = F_m[E_1(\mathbf{x}, t), \ldots, E_N(\mathbf{x}, t)], \quad m = 1, \ldots, M \tag{9.6}$$

With the definitions above, we can make a general mathematical statement of the minimal-cost air pollution control problem. To find the minimal cost of at least reaching air quality objectives P_m°, choose those

$$E_n(\mathbf{x}, t) \qquad n = 1, \ldots, N$$

that minimize

$$C = G[E_1(\mathbf{x}, t), \ldots, E_N(\mathbf{x}, t)] \tag{9.7}$$

subject to

$$F_m[E_1(x, t), \ldots, E_N(x, t)] \leq P_m^\circ \qquad m = 1, \ldots, M$$

Thus one chooses the emission levels and patterns that have the minimum control cost subject to the constraint that they at least reach the air quality goals.

9.4 A LEAST-COST CONTROL PROBLEM FOR TOTAL EMISSIONS

The problem (9.7), though simply stated, is extremely complex to solve, because, as stated, one must consider all possible spatial and temporal patterns of emissions as well as total emission levels. It is therefore useful to remove the spatial and temporal dependence of the emissions and air quality. Let us consider, therefore, minimizing the cost of reaching given levels of total regional emissions. We assume that:

- The spatial and temporal distributions of emissions can be neglected. Accordingly, the discharge functions, $E_n(x, t)$, $n = 1, \ldots, N$, can be more simply specified by, E_n, $n = 1, \ldots, N$, that are measures of total regionwide emissions.
- The air quality constraints can be linearly translated into constraints on the total magnitude of emissions in the region of interest.
- The problem is static (i.e., the optimization is performed for a fixed time period in the future).
- There are a finite number of emission source types. For each source type, the available control activities have constant unit cost and constant unit emission reductions.

With these assumptions, the problem of minimizing the cost of reaching given goals for total emissions can be formulated in the linear programming framework of Section 9.2. Table 9.2 summarizes the parameters for this linear programming problem. The mathematical statement of the problem is as follows: Find X_{ij}, $i = 1, \ldots, I$ and $j = 1, \ldots, J_i$ that minimize

$$C = \sum_{i=1}^{I} \sum_{j=1}^{J_i} c_{ij} X_{ij} \tag{9.8}$$

subject to

$$\sum_{i=1}^{I} \sum_{j=1}^{J_i} e_{in}(1 - b_{ijn}) X_{ij} \leq E_n \qquad \text{for } n = 1, \ldots, N \tag{9.9}$$

$$\sum_{j=1}^{J_i} A_{ij} X_{ij} \leq S_i \qquad \text{for } i = 1, \ldots, I \tag{9.10}$$

and

$$X_{ij} \geq 0 \qquad \text{for } i = 1, \ldots, I; \; j = 1, \ldots, J_i \tag{9.11}$$

TABLE 9.2 PARAMETERS FOR THE LEAST-COST PROBLEM FOR TOTAL EMISSIONS

Parameter		Definition
X_{ij}	$i = 1, \ldots, I$ $j = 1, \ldots, J_i$	The number of units of the jth control activity applied to source type i (e.g., the number of a certain control device added to 1980 model year vehicles or the amount of natural gas substituted for fuel oil in power plant boilers). The total number of source types is I; the number of control alternatives for the ith source type is J_i.
c_{ij}	$i = 1, \ldots, I$ $j = 1, \ldots, J_i$	The total annualized cost of one unit of control type j applied to source type i.
C		The total annualized cost for the control strategy as specified by all the X_{ij}.
E_n	$i = 1, \ldots, N$	The uncontrolled (all $X_{ij} = 0$) emission rate of the nth pollutant as specified by all X_{ij} (e.g., the resultant total NO_x emission level in kg day^{-1}). There are N pollutants.
e_{in}	$i = 1, \ldots, I$ $n = 1, \ldots, N$	The uncontrolled (all $X_{ij} = 0$) emission rate of the nth pollutant from the ith source (e.g., the NO_x emissions from power plant boilers under no controls).
b_{ijn}	$i = 1, \ldots, I$ $j = 1, \ldots, J_i$ $n = 1, \ldots, N$	The fractional emission reduction of the nth pollutant from the ith source attained by applying one unit of control, type j (e.g., the fractional NO_x emission reduction from power plant boilers attained by substituting one unit of natural gas for fuel oil).
S_i	$i = 1, \ldots, I$	The number of units of source type i (e.g., the number of 1980 model year vehicles or the number of power plant boilers).
A_{ij}	$i = 1, \ldots, I$ $j = 1, \ldots, J_i$	The number of units of source type i controlled by one unit of control type j (e.g., the number of power plants controlled by substituting one unit of natural gas for fuel oil).

In this linear programming problem, (9.8) is the objective function, and (9.9)–(9.11) are the constraints. Equation (9.9) represents the constraint of at least attaining the specified emission levels, E_n. Equations (9.10) and (9.11) represent obvious physical restrictions, namely not being able to control more sources than those that exist and not using negative controls.

Solution techniques are well developed for linear programming problems, and computer programs are available that accept numerous independent variables and constraints. Thus the solution to the problem is straightforward once the appropriate parameters have been chosen. The results are the minimum cost, C, and the corresponding set of control methods, X_{ij}, associated with a least-cost strategy for attaining any emission levels, E_n.

More generality is introduced if we do not translate the air quality constraints linearly into emission constraints. Rather, we may allow for nonlinear relationships between air quality and total emissions and can include atmospheric interaction between emitted pollutants to produce a secondary species. The general least-cost control problem can then be restated as: Choose

$$E_n \qquad n = 1, \ldots, N$$

to minimize

$$C = G(E_n) \tag{9.12}$$

subject to

$$F_m(E_n) \le P_m \qquad m = 1, \ldots, M$$

Here $G(E_n)$ represents the minimum cost of attaining various total emission levels. This function can be found by linear programming. The functions, $F_m(E_n)$, represent the air quality–emission relationships. These can be found by a variety of means, such as empirical/statistical or physicochemical models (Seinfeld, 1986). If linear functions are adopted for the $f_m(E_n)$, this case degenerates into that above. In general, however, the air quality–emission relationships can be nonlinear and can involve interactions between two or more types of emissions.

A hypothetical example of the solution to (9.12) for two emitted contaminants (E_1, E_2) and two final pollutants (P_1, P_2) is illustrated in Figure 9.5. The axes of the graph measure total emission levels of the two contaminants, E_1 and E_2. The curves labeled C_1, C_2, and so on, are iso-cost curves determined by repeated application of a linear programming submodel. Along any curve labeled C_k, the minimum cost of reaching any point on that curve is C_k. As emission levels fall (downward and to the left in the graph), control costs rise. Thus $C_1 < C_2 < \ldots < C_5$. The air quality constraints are represented by the two curves, P_1 and P_2, derived from a nonlinear air quality–emission level relationship. The constraint of at least reaching air quality level P_1 for the first pollutant requires that emissions be reduced below the curve. The constraint that air quality be at least as good as P_2 for the second pollutant requires that emissions be reduced to the left of the P_2 curve. The emission levels that satisfy both air quality

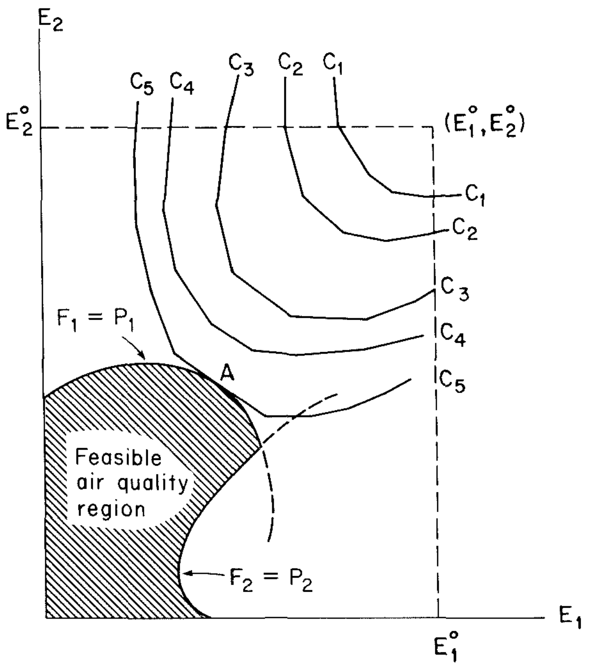


Figure 9.5 Iso-cost lines in the plane of emission levels of two pollutants, E_1 and E_2, showing a feasible region of air quality defined by the curves $F_1(E_1, E_2) \le P_1$ and $F_2(E_1, E_2) \le P_2$.

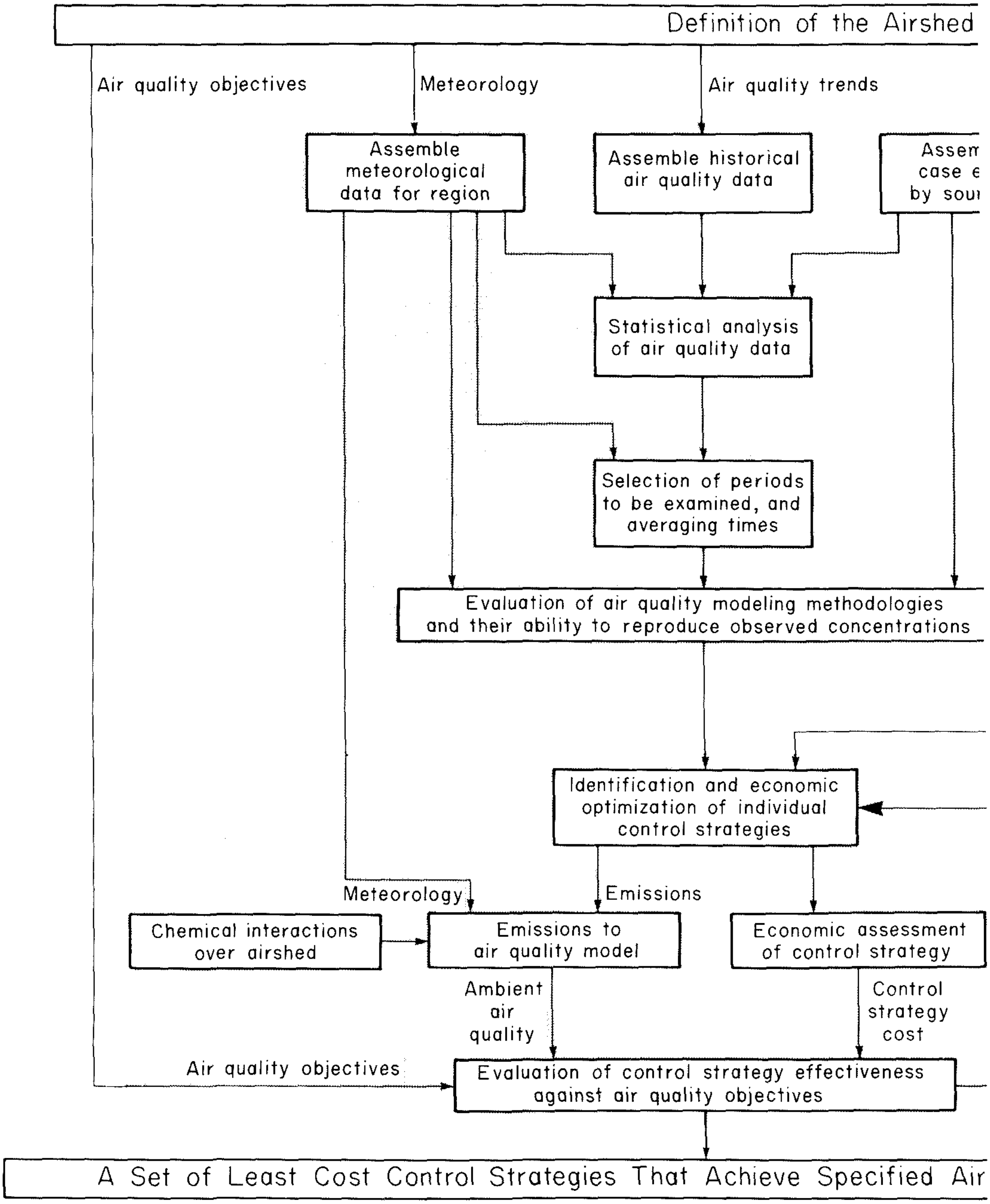
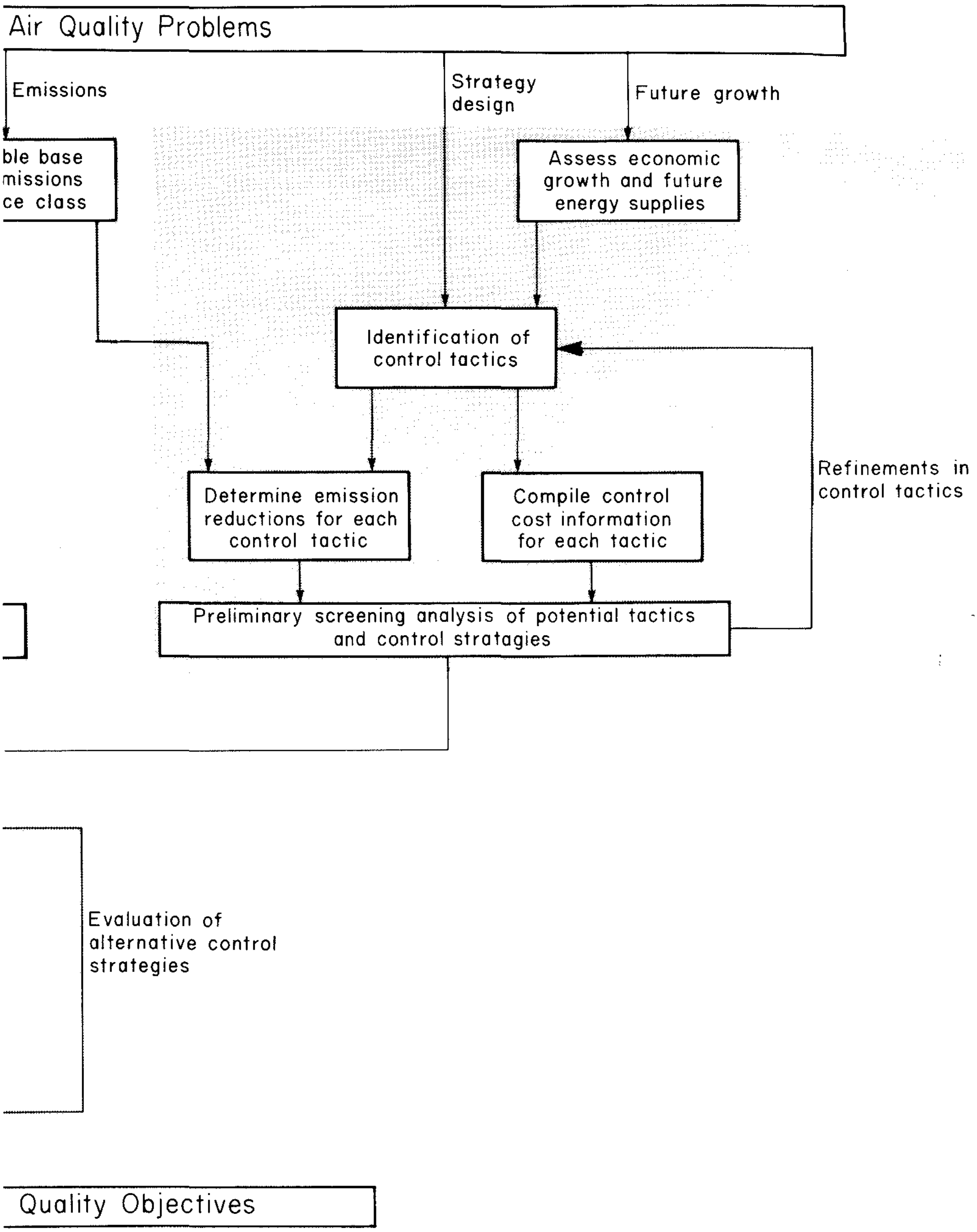


Figure 9.6 Comprehensive structure of the problem of determining a least-cost set of control actions to achieve specified air quality in an airshed.


Air Quality Problems
Emissions
Strategy design
Future growth
ble base
missions
ce class
Assess economic growth and future energy supplies
Identification of control tactics
Refinements in control tactics
Determine emission reductions for each control tactic
Compile control cost information for each tactic
Preliminary screening analysis of potential tactics and control stratagies
Evaluation of alternative control strategies
Quality Objectives

constraints lie in the crosshatched admissible air quality region. The minimum cost of meeting the two air quality constraints is C_5 and the solution is to reduce emissions to point A.

For applications of mathematical programming to air pollution control, we refer the reader to Kyan and Seinfeld (1972, 1974), Bird and Kortanek (1974), Trijonis (1974), Kohn (1978), and Cass (1981). In addition, Sullivan and Hackett (1973), Schweizer (1974), and Dejax and Gazis (1976) have considered the optimal electric power dispatching problem to achieve air quality constraints.

Figure 9.6 gives a comprehensive picture of the air quality control problem for an airshed. The large block in the upper left-hand portion of Figure 9.6 indicates the air quality modeling aspects, whereas that in the upper right-hand portion summarizes the identification of control tactics. Both inputs then feed into the overall economic optimization in the box in the lower part of the figure. This figure thus attempts to summarize the material in this chapter indicating how the various components of the airshed abatement problem must be attacked.

PROBLEMS

9.1. For the example in Section 9.2 calculate and plot the total cost C as a function of the level of emission reduction.

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