Chapter 4
Alternatives to Monitoring Instrumentation

Alternatives to the installation of traditional CEM systems have been, and can be, used to monitor emissions. These alternatives are often applicable to sources where independent monitoring instrumentation may not be required to meet the goals of a regulatory program. To monitor process and control equipment performance, certain NSPS sources employ "parameters," such as pressure drop, temperature, or water injection rates (see Chapter 2, NSPS Parameter Monitoring Requirements and Table 2-3), instead of installing CEM systems. Similar provisions are included in other federal and state monitoring requirements. Sources regulated under the air toxics or the "enhanced monitoring" provisions of the 1990 Clean Air Act Amendments are likely to have the flexibility to consider such options.

Alternative monitoring options include: 1) using parameters as indicators of proper operation and maintenance practices, 2) using parameter values directly as surrogates for emissions determinations, 3) using parameters in models that calculate emissions, 4) performing mass balance calculations, or 5) employing a CEM system to monitor a more easily analyzed gas as a surrogate for one that is more difficult to analyze. Deciding whether to use an alternative method depends upon the application and how the data will be used. To assist in such decisions, the basic principles of these techniques as well as their advantages and limitations will be discussed in this chapter.

4.1 Parameter Monitoring

Parameter monitoring has been used in a variety of ways in regulatory programs. These are summarized in Figure 4-1.

Beginning with the original application of the monitoring process and control equipment performance, parameter monitoring has extended to providing a basis for the calculation of source emissions. Emission calculations have been performed since the original development of air pollution control equipment in the form of engineering design calculations (for example, see Mycock, 1995). Design engineers typically will attempt to determine equipment performance from operational parameters. In terms of air pollution control equipment, the question facing the engineer is, if I vary this parameter, or if I vary that parameter, will the pollutant emissions increase or decrease?

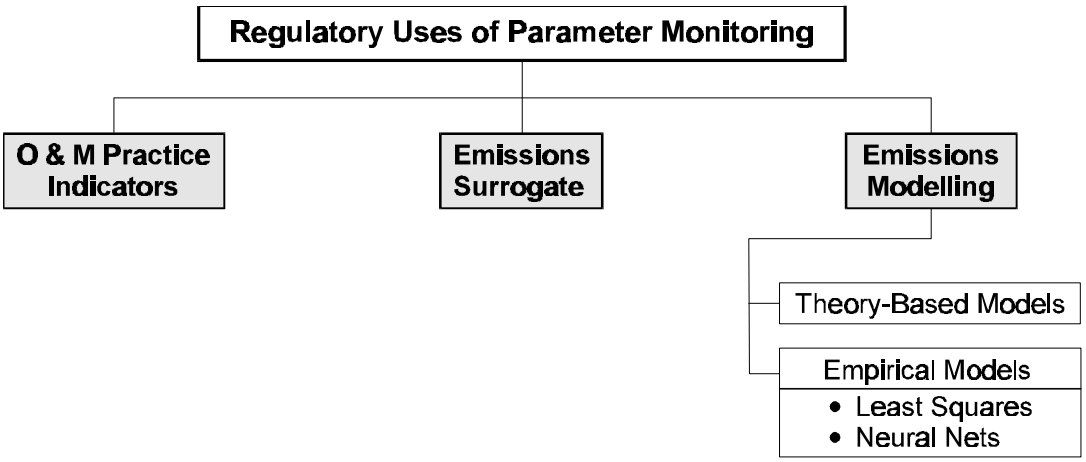

Figure 4-1. Uses of parameter monitoring in regulatory programs.

This question also has drawn the attention of regulatory agencies, and due to relationships between parameter values and emissions, has led to the reporting of parameter data to both federal and state agencies. The original regulatory use of parameter data and CEM data was to indicate whether process and control equipment were being operated properly. A continued record of unsatisfactory parameter data could result in a notice and finding of violation of operation and maintenance requirements. A subsequent requirement to perform a source test for determining compliance with an emission standard might also result.

A more direct application of parameter data is to use it as a surrogate for emissions. Rather than requiring the determination of emissions by CEM systems or a manual method, a surrogate parameter level is established which is correlated to the emissions standard. An exceedance of this parameter level could then be used for enforcement and a source test may not be necessary (depending upon the applicable regulation or permit requirements).

An extension of the use of parameter data is to "predict" the performance of the process or control equipment from the parameter data. If the process is well understood, first principle (i.e, theoretical or phenomenological) calculations may be performed. Another technique is to "correlate" parameter data to emissions data. An initial study is performed by varying and monitoring process and control equipment parameters while monitoring emissions using reference methods or CEM systems. One can then correlate the data to develop a statistical model that can "predict" emissions.

Both theoretical and statistical emission models based on process and control parameter inputs are used today to meet emission monitoring requirements. A number of states have accepted their use, and the federal proposals addressing the 1990 Clean Air Act enhanced monitoring requirements have been receptive to their application (USEPA, 1993, Bivins, 1996).

The different uses of parameters, illustrated in Figure 4-1, provide a means for agencies to track control equipment performance and emissions without the application of CEM systems or performing source tests. Although in some cases the data may not be as accurate as that obtained from independent test methods, such levels of accuracy may not be necessary. For stable, nonfluctuating sources having low emissions relative to the compliance limit, data that can assure compliance with the standard may have a higher inaccuracy than that generally acceptable (e.g., >20% of the reference method or >10% of the standard), but may still be defensible. For example, if a stable source has a VOC emission limit of 50 ppm, but normally emits 5 ppm, even with 100% uncertainty (±5 ppm), one could still assume that the source is in compliance. However, the acceptability of such uncertainty depends on the use of the data. Moreover, this scenario may not be acceptable if the emission limit is 10 ppm or the data were to be used in a market trading program.

4.2 Parameters and Sensors

A parameter is a property whose value can characterize or determine the performance of process or control equipment. Such properties may be temperature, pressure drop, liquid to gas ratios, percent oxygen, or even the position of a damper.

The values of parameters are determined by "sensors." In the broadest sense, a sensor is "a device that receives and responds to a signal or stimulus (Fraden, 1993)." A thermocouple or resistance temperature device (RTD) may be used to measure temperature, a pressure transducer to measure pressure drop, flow monitors to measure liquid to gas ratio, an oxygen monitor sensor to measure percent oxygen, and a simple on-off switch to monitor the damper position. Sensors normally are assumed to be some mechanical, electrical, or chemical device that generates an electrical response, but human perception also can serve to determine parameter values. For example, the visible emissions observer performing EPA Method 9 is determining a value for the parameter, opacity, which may characterize the performance of a bag house or an electrostatic precipitator. Or, in an iron and steel plant (NSPS subpart AA), each shift operator may note the furnace static pressure, again a parameter.

In process and control equipment, sensors tend to be simple devices that generate an electrical response. They do not, in general, incorporate sophisticated linearization and calibration features such as those used in CEM systems. They are basically the stripped down version, the sensing elements incorporated in CEM systems. For example, the zirconium oxide electrocatalytic cells used in many CEM oxygen analyzers are the same type of cells used as "sensors" in automobiles for engine and emissions control.

4.3 Parameter Monitoring Used as an Indicator of Equipment Operation and Maintenance

As discussed in Chapter 2, plant operational parameters or control equipment parameters have been specified in the New Source Performance Standards for certain source categories. In these applications, the parameter data are intended to determine whether the process or control equipment is operating properly. Proper operation, in turn, means that the plant equipment is operating in a manner such that the emissions limits (standards) are most likely being met. In NSPS applications, parameter data may indicate possible problems in plant performance, but compliance with emission standards traditionally has been determined by source testing (or in some cases, CEM systems) under specified operating conditions.

The use of the parameter values varies depending upon the regulation. In the simplest case, a regulation merely may require that the parameter values be determined, such as in the NSPS requirements for monitoring the pressure drop across wet scrubbers used to control particulate emissions in the phosphate fertilizer industry, coal preparation plants, ammonium sulfate manufacture, etc. (CFR Subparts T, U, V, W, Y, and PP, respectively). No recording or reporting requirements are given for these examples, but the required permanent record can be used by the regulatory agency to assess plant operations and target problem facilities for follow-up actions.

State programs also have used parameter monitoring for determining the adequacy of plant operation and maintenance practices. Many programs include general provisions in state implementation plans re-quiring good engineering practice in the operation and maintenance of control equipment.

4.4 Parameter Monitoring Used as a Surrogate for Emissions

An extension to requirements for monitoring and recording operational parameters is to establish some trigger value for the parameter. Here, a parameter baseline or trigger value is established during a source test, where the source test is conducted to determine compliance with the emissions standard (lbs/hr, ppm, etc.). This trigger value then can be used in one of two ways: 1) it can trigger a reporting requirement, analogous to reporting excess emissions by sources with CEM systems, or 2) it can be used directly as a surrogate for an emission compliance limit.

4.4.1 Parameter Monitoring as a Surrogate for Reporting Excess Emissions

Parameter values can be used as surrogates for emission values to report problems in the operation and maintenance of emission control equipment. A typical regulatory statement for parameter monitoring for particulate control equipment is:

> "...report to the Administrator, on a semiannual basis, all measurements (pressure loss and water supply pressure) over any 3-hour period that average more than 10% below the average levels maintained during the most recent performance test in which the affected facility demonstrated compliance with the mass standards..." (40 CFR 60.143 Subpart N).

Here, one assumes that the facility is operating at or below its compliance value and that the parameter values reflect the operating conditions of the control device (usually a wet scrubber) at that level. If parameter levels fall within a range of acceptable values established during the compliance test, one assumes that the scrubber is continuing to operate in a manner where the facility is in compliance with the underlying emission limit. In this sense, the parameter value stands in as a surrogate for the emission compliance value.

Note, however, in the example given, that the trigger level is not at the parameter level determined during the compliance test, but at a level 10% lower. In a typical venturi scrubber, an increase in pressure drop increases the particulate removal efficiency of the scrubber. A decrease in the pressure drop means that less particulate matter will be removed. Since the sensor measurement accuracy may be ±5% and since some inaccuracies may have occurred in the source testing, the pressure drop is allowed to decrease by 10% from the baseline level before it is required to be reported. For even greater flexibility, some regulations allow a reduction of 30% before reporting is required (see for example, 40 CFR 60, Subpart HH, lime manufacturing plants).

Many other examples could be given of this use of parameters as surrogates for emissions. In Subpart GG, gas turbines using water injection to control NO_x emissions must report any one hour period where the water-to-fuel ratio falls below the value determined to demonstrate compliance. Incinerator temperatures in Subpart MM, RR, and other coatings operations are to be reported when they change from some specified compliance level.

If parameter values fall below such trigger levels, the agency may require the source to improve its operation and maintenance practices, or may require a compliance test be performed to determine if the source is meeting its emissions standards. Also, if sensors installed to monitor equipment performance are not operating properly, parameter data will no longer be useful and a compliance test again may become necessary.

4.4.2 Parameter Monitoring for Direct Compliance

A new approach appeared in a 1993 proposal for enhanced monitoring (EPA, 1993) where parameter monitoring was proposed as a method for determining directly the compliance of a source with emissions standards. In this approach, the source owner or operator would be required to "justify that a known and consistent relationship exists between the emissions subject to an applicable limitation or standard and the parameters being monitored." This is not much different from using parameters as a surrogate limit in excess emissions monitoring, as prescribed in certain NSPS requirements. The differences are that:

- The parameter level is used as a surrogate for the emissions standard.
- The source owner would be required to establish the parameter value or values that would assure that the source is in compliance with the emissions standard.

That established parameter value has been called the "demonstrated compliance parameter limit," or DCPL. Although the proposed enhanced monitoring rule was withdrawn in April 1995, the concept of the DCPL, the stand-in or surrogate emissions standard, still remains.

The question as to how parameter limits actually relate quantitatively to emission values depends on the underlying relationship, the accuracy and precision of the emission measurement method, averaging periods, and other factors. To answer this in practice, one must obtain further information by testing at different operational levels. One can correlate the parameter values with emissions over a narrow range of operating conditions to establish the DCPL. A typical performance curve for a venturi scrubber is given in Figure 4-2. Here, as the pressure drop across the venturi throat increases, the efficiency in removing particulate matter increases.

At some point on the curve, a pressure drop will correspond to the compliance value, the emissions standard for the facility. Some variability will exist in the testing procedures used to establish the correlation and in the accuracy of the sensor used to determine ΔP. This range of variability is shown by the confidence intervals in the figure. The agency may therefore not accept a 1:1 correlation between the emissions standard and the correlation, but establish the surrogate standard, P_{std}, at a higher value to account for the variability. If the pressure drop is maintained at the DCPL value or higher,

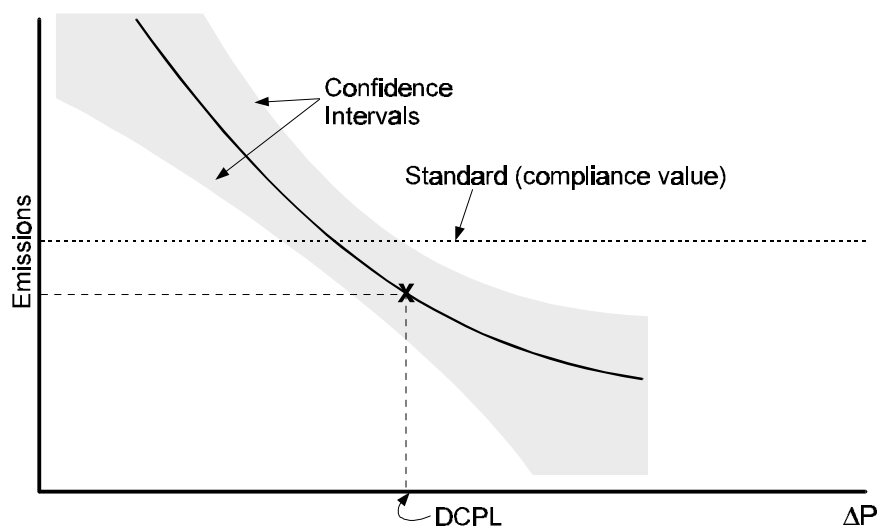

Figure 4-2. Operational parameters correlated to emissions. Establishing the demonstrated compliance parameter limit (DCPL).

some assurance exists that the emissions standard is being met, within the uncertainty of the correlation.

Many examples of using parametric monitoring to demonstrate compliance with emissions regulations have been published. Bills (Bills, 1995) describes applications in the pharmaceutical industry for thermal oxidation systems, condensers, and adsorption systems used to control VOC emissions. In these applications, direct measurements of multiple gaseous components in the process gas streams became overly complicated and resource intensive. Instead of using sophisticated monitoring instrumentation, simpler parameter monitoring approaches were adopted in exchange for accepting more stringent "worst case" DCPLs.

This use of parameter surrogates in place of using CEM systems to monitor emissions may appear straightforward. However, as in all emission monitoring techniques, the method is application dependent. In determining the appropriateness of the method, one should consider the following factors:

- The relationship between the parameter or parameters should be straightforward.
- The relationship should hold for all operating conditions.
- The correlation between emissions and the parameter should have a high degree of confidence with narrow confidence and tolerance intervals.

Parameter surrogates are most appropriate when the relationship is a simple one, such as in using incinerator temperature for VOC control, or water-to-fuel ratio for gas turbine NO_x control. For the method to be practical, no other operating variables should affect the correlation significantly. If they do, they should be included in the correlation, which will then make the correlation more complicated and more uncertain. These issues are discussed in detail by Evans (Evans, 1994).

The DCPL approach is similar to a predictive method since the DCPL value is established on past data or performance data to predict present compliance with emissions standards. It differs from the statistical predictive emission monitoring (PEM) models in that it is less refined (see Evans, 1994) and is established over a narrow range of operating conditions. In a DCPL approach, parameter values such as pressure drop, temperature, or supply pressure are reported to the agency. In a predictive method, emissions values calculated by the model from parameter values are reported to the agency.

4.5 Emission Modeling - Predictive Emissions Monitoring Systems

Many applications occur where parameter relationships to emissions are more complicated than establishing a simple DCPL and sensor determined parameters might be better incorporated into a predictive emission monitoring (PEM) model, or system. In the PEM model approach, emission values are calculated by the model from the input parameter values.

When developing a predictive model, parameter and emissions data are accumulated under various operating conditions. Then the data are used to develop the model. Two approaches are possible:

1) If the source or control equipment operation is well understood, first principles calculations can be made to determine the emissions. Based upon the physical and chemical effects of operating parameters on emissions, the actual emissions may be determined. This approach is often called the "first principles" or "phenomenological" approach.

2) If the effects of operating parameters on emissions are not well understood, or if theoretical calculations become too complicated, statistical methods may be applied. Linear and nonlinear regression techniques have been used successfully in many situations. Neural net methods also have become popular in these applications.

No one modeling approach can be said to be the "best." As with CEM systems, one must consider tradeoffs in each application. Both first principle and statistical models have passed relative accuracy tests in specific applications (Hung, 1994, Clapsaddle, 1995, Clapsaddle, 1996).

Predictive systems are basically empirical models. Even the first principle approaches use past data for evaluation purposes. The theory establishes the form and mathematical functions of the model, and test data commonly are used to introduce empirical constants to fine-tune the model. In building these models a test program must be developed that can provide representative emissions and parameter data over the probable, expected range of operating conditions of the emission source.

4.5.1 First Principle Models

Models can be developed from the fundamental theory associated with the operation of a process or a pollution control device. Depending on the process, principles of thermodynamics, chemical kinetics, fluid flow, and so on, may be applied. First principle models have been applied to calculate nitrogen oxide emissions for can-type gas turbines (Hung, 1993, 1994, 1995). Also, theoretical design equations have been developed for most types of air pollution control equipment: particulate scrubbers, gas absorbers, condensers, electrostatic precipitators, etc.

First principle models provide for an understanding of a process and the relative importance of the input parameters to its performance. A pure first principles model does not depend upon historical data and can be used over the full range of process operation.

4.5.1.1 Semi-empirical Models

Theoretical design equations can give good qualitative information, but quantitative information having the accuracy necessary to be legally enforceable usually is not obtainable without empirical correlation. Not all of the effects of process variables may be known and the values of the necessary input parameters may not be of sufficient accuracy to give correct results. The problem here is that most devices are too complex. Calculating emissions from first principles often requires too much information to be practical. For example, in the "infinite throat model" for Venturi particulate scrubbers a knowledge of the particle size and droplet size is necessary (Yung, 1977). In practice, one would have to integrate over the particle size distribution to obtain a realistic number. Unfortunately, the distribution of particle sizes in a flue gas is both difficult and expensive to determine accurately. The model may be good for design applications, but because of the requirement for accurate input data, is limited in practical applications for emissions calculations.

A compromise to this problem is to develop a semi-empirical model. In a Venturi scrubber example, the "contact power" theory (Calvert, 1972), the efficiency of the scrubber in removing particulate matter is related to the power required to move the process gas and liquid through the system. The exponential relation developed depends upon empirical constants determined by experiment. The net result is a model that incorporates some physical understanding of the process, but which is fine-tuned with experimental data --- the semi-empirical model.

Hung (Hung, 1993) has developed a semi-empirical model for annular (can) type gas turbines to calculate NO_x emissions. Based on operating conditions, ambient conditions, combustor geometry, and the type of fuel used, the model has been used to generate data comparable to that obtained from CEM systems. The strength of the model does depend upon the quality and amount of test data used in the semi-empirical correlation (Hung, 1994).

4.5.1.2 Mass Balance Calculations

A much simpler version of the theoretical approach is to calculate mass balances in the process. Theoretically, for an uncontrolled emissions source, "what goes in should go out." For fossil-fuel-fired boilers, sampling and analysis for sulfur in fuel has been allowed as an option to CEM systems for certain Part 60 and Part 75 sources regulated by EPA. Fuel analysis is particularly convenient for oil and gas fired boilers, where fuel flow rates are easily determined and the sulfur content is homogeneous. For coatings operations the emission of volatile organic compounds (VOCs) can be calculated from the VOC content of the coating (paint) and solvents and the amount of paint and solvent used. Mass transfer calculations have been used for estimating emissions in very small emission sources such as those found in electroplating operations and degreasers (Siebert, 1995).

Comparisons between mass balance calculations and CEM systems do not always come out as expected. When the plant operating engineer's mass balance calculations and the environmental engineer's CEM results do not agree, winning the argument may be less important than who is right, especially where emissions up the stack correspond to loss of product. In the case of heat rate calculations vs CEM systems, Cashin (Cashin, 1996) has addressed the many issues involved in such debates.

4.5.2 Empirical Modeling

When developing a model from physical, chemical, or engineering principles is not possible, a statistical approach may be applicable. Beginning with the effect of only one parameter on equipment performance, we could first assume a linear relationship between the parameter and emissions. That is, if a change occurs in the parameter x, the emissions y will change by a constant factor, b, according to:

$$y = a + bx$$

where a and b are the intercept and the slope, respectively, of the regression equation.

In practice, one desires a model that will be valid under a range of values of x. Thus, a number of tests would be conducted to obtain data that might appear as that shown in Figure 4-3.

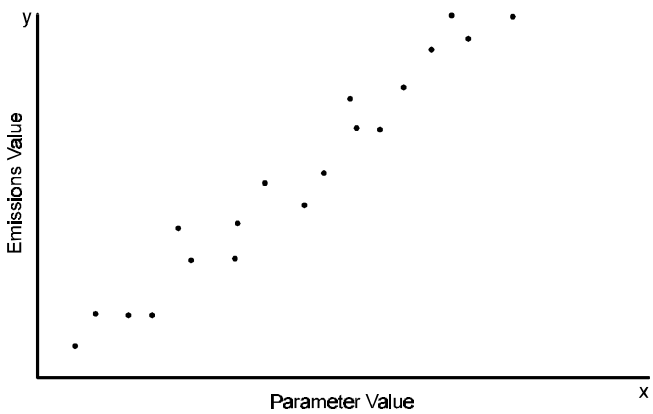

Figure 4-3. Test data. Emissions as a function of the parameter values, x.

Obviously scatter occurs in the emissions data. The scatter in y is due to uncertainties and variability in the emissions measurements because of problems in measurement, difficulties in keeping process variables (parameters) other than x constant during the testing, and to unknown variables that may be affecting the process.

In the statistical methods, the goal is to find an equation that best summarizes the test data and predicts emissions to within an acceptable level of confidence. Based upon the quality of the input data and the choice of parameter or parameters or, based on past data, how confident are we in our equation predicting future values?

Statistics can answer these questions for us and many statistical methods have been developed to fit curves to data and qualify the results. The least squares linear regression and multiple linear regression techniques are very useful in this regard. The extended statistical method of neural nets has also been useful in providing greater flexibility for nonlinear expressions.

4.5.2.1 Least Squares Linear Regression Techniques

The least squares technique is one of the simplest methods used to fit a line to emissions/parameter data. In the example above, if y is a linear function of the parameter x, the line y = a + bx is such that if one takes the deviation from each point to the line and squares the deviations, the constants a and b in the equation will be such that the sum of the squares is the smallest possible value (Figure 4-4).

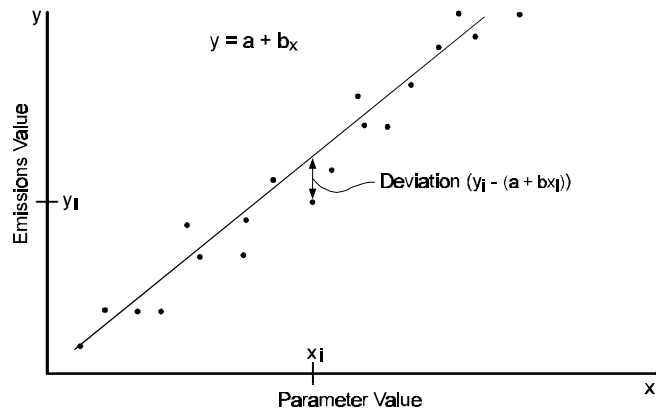

Figure 4-4. Linear regression of test data.

In mathematical terms a and b are calculated to be such that

$$\sum(y_i - (a + bx_i))^2 = \text{a minimum value}$$

One can show that the values for a and b which define the line of minimum deviation (the regression line), can be calculated from n data sets (x_i, y_i) as follows:

$$a = \frac{\sum x_i^2 \sum y_i - \sum x_i \sum x_i y_i}{n\sum x_i^2 - (\sum x_i)^2}$$

$$b = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{n\sum x^2 - (\sum x_i)^2}$$

The calculations are tedious if performed manually, however. Computer programs are available to do such routine calculations easily and rapidly.

The determination of a and b is not a matter of guess or iteration. In this statistical method, an underlying assumption is that the value of x has negligible error or is free from error. It assumes that the deviation lies principally in the measurement of y, in this case, the emissions.

Other assumptions in the method exist, but the main point here is that the values of a and b are mathematically determined and depend only on the original test data. If the dependence of y on x should change because of a change in operations, system degeneration, or faulty determination of x, the best line will no longer be valid.

4.5.2.2 Multiple Linear Regression

More than one parameter may influence the value of y (the emissions). The equation for y may then appear as:

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \ldots + b_kx_k$$

for k parameters. This is the more likely case in emissions applications and techniques of multiple linear regression can be used. The approach is similar to that given for simple linear regression, but a set of k simultaneous linear equations are solved to determine the values of b_o to b_k. In multiple regression, the effect of one parameter on the emissions can be determined while the other parameters are kept constant.

Linear regression statistical techniques have been used widely to develop PEM system models. Published examples most often address monitoring NO_x emissions from industrial boilers. Evans (1995) has developed a PEM NO_x model for a gas-fired boiler using two parameters, % excess O_2 and flue gas temperature. Macak (Macak, 1988), using multiple linear regression techniques, developed a model for a natural gas-fired boiler using three equations, each used over different load ranges, and each using two to three different parameters.

4.5.2.3 Higher Order Multiple Linear Regression

Higher order linear models may be used to provide curve fits to data (Draper, 1981). In the case of more than one parameter, the regression expression may include higher orders of the input variables and incorporate expressions such as:

$$y = a + bx + cx^2$$

For multiple input parameters both polynomials and polynomial cross-products may be included:

$$y = b_o + b_1x_1 + b_2x_2^2 + b_3x_1x_2 + b_4x_1x_2^2 + \ldots..$$

These expressions are termed linear regression equations since they are linear in terms of the regression coefficients. The first expression is a second order linear equation. The second expression is a third order linear equation.

4.5.2.4 Nonlinear Least Squares Regression

Nonlinear models express the model output (emissions) as a nonlinear function of the regression coefficients (a, b,...). The nonlinear function may be a power function, or a logarithmic or exponential function of the regression coefficients. Examples of nonlinear models include:

$$y = a + x^b$$

$$y = a + \log(bx)$$

$$y = a + e^{-bx}$$

The constants for nonlinear models are determined by iteration techniques similar to those in linear regression. Some non-linear forms present significant mathematical complexity and require numerical methods rather than analytic solutions.

Many more mathematical options are available in the nonlinear and multiple order curve-fitting techniques. One may be able to represent the initial input data well with such models, but a danger exists in "overfitting" the data. One can "correlate" or fit a curve between any two sets of numbers, but if no actual relationship exists between them, future predictions will not necessarily be valid.

Clapsaddle (Clapsaddle, 1995, 1996) has used polynomial expressions to represent emissions in gas and oil-fired boilers. Four to six parameters such as fuel oil flow rate, air flow rate, excess O_2, fuel gas flow rate, air damper position, air heater outlet temperature, fuel bound nitrogen, were used in the various models. Snyder, et. al. (Snyder 1996) used up to five parameters in nonlinear models for predicting NO_x and CO emissions from stationary gas turbines.

4.5.2.5 Neural Network Models

Neural network models have been applied recently to model source emissions. Although the neural network methods are inherently mathematical, analogies can be made to biological learning processes. The regression methods discussed so far provide a model that is calculated by using a set of equations. In the neural net method, the model constants are not calculated, but are determined by iteration. The constants in the model are varied incrementally until a set of constants is obtained that will reproduce the actual emissions of the input data set. Least squares regression methods are still used in neural net models to minimize the residual differences between the test emission data and the model predicted emissions.

In developing neural network models, extra sets of constants are introduced into what are called "hidden layers (or nodes)." These constants, in conjunction with nonlinear functions, can weight the importance or unimportance of different input parameters in contributing to a given result. This "weighting" also is done by an iterative process. This weighting process is similar to what neurons do in the brain, hence the word "neural."

Neural network procedures are somewhat of a "brute force" approach in statistical model development. The procedures use the iterative capabilities of the computer to choose optimum constants that best represent how a process operates. The method is powerful since most process operations are complicated and the interrelation between input parameters is not always well understood. The approach is similar to using a computer to numerically integrate an integral that is too complex to solve analytically.

Neural network models do offer some greater flexibility in optimizing system operations. Since the contribution of the various parameters to the operations is better understood, this information can be fed back to improve system performance. Neural network process optimization models have been said to have been developed for the chemical, petro-chemical, semiconductor, and mining industries (Keeler, 1993).

In one study, 21 input parameters, selected from 120, were used to develop an NO_x prediction model for a gas fired boiler (Collins, 1994). Clements, et. al. (Clements, 1996) applied both multiple linear regression methods and neural network techniques to develop PEM models to predict NO_x, CO, O_2, and stack gas flow rates for gas turbines and reciprocating gas engines. In this study comparing the two types of models, regression coefficient (R^2) values were found to be better for the neural network analysis than for linear regression analysis. **Note**: R^2 values give a measure of the "fit" of the model to the data, but are not necessarily an indicator of which model will provide the best prediction from new data (Evans, 1995).

4.5.3 Model Development

A typical approach to model development is to first review all potential operational parameters that affect emissions, determine the full operating range for each parameter, examine potential cross para-meter interaction, and then develop a test matrix to evaluate the effect of parameter changes on the emissions (Clapsaddle, 1996). The emissions are then characterized according to the test plan and a regression model developed from the test data. Evans (Evans, 1994) proposes a similar approach that emphasizes care in the selection of model parameters. The test must concentrate on parameters that have an effect on emissions. Inclusion of parameters that have negligible effects will complicate the test without commensurate improvements in the model. The main problem in developing models is in not recognizing parameters that can affect emissions. This "lurking parameter", being as simple as an open or closed damper, can easily invalidate any model (Evans, 1994).

A model should be developed over a sufficient period of time where a full range of operating conditions can be correlated to the emissions. During this time both accurate emissions data and sensor data are required. If either inaccurate sensor or emissions data are used to build the model, the model itself will be inaccurate.

Usually more than one model is examined when developing a PEM system. Different combinations of parameters and both linear and nonlinear regression equations may be used to examine those having the best fit with the data. An examination of residuals, confidence intervals, and regression coefficients typically are examined in the evaluation process (Evans, 1995).

A relative accuracy test audit (RATA) used to certify CEM systems is not necessarily sufficient to validate a PEM model (Eghneim, 1996). The RATA normally is conducted at only one operating condition of the source. For a PEM system, if that operating condition were to be one under which the correlation were developed, the system should obviously pass. A truer evaluation would be to conduct a RATA, or RATAs, at operating conditions different from those used to develop the correlation. To be "predictive," the model must provide true emissions values from parameter data not previously provided to the model.

4.5.4 Model Quality Assurance

In NSPS requirements for operations monitoring, sensor calibrations are required to be checked annually. The manufacturer of a sensor is expected to deliver a product to specified levels of precision and accuracy. These levels are chosen to be within an acceptable range for the intended application, usually ±5% of reading. However, users often assumed incorrectly that the performance of a sensor will remain constant with time. The calibration may drift over time, the sensor may become fouled, or it might not work at all. Plant maintenance routines provide for inspection of these devices, but the sensors most critical to plant operation usually receive the most attention.

If a parameter monitoring program is to be initiated, the sensors used to provide parameter values for a model or correlated relation must provide values at consistent levels of precision and accuracy. To do otherwise leads to faulty data, just as would a poorly calibrated or malfunctioning analyzer of a CEM system. A quality assurance program institu-ted to as-

sure that the sensor data continues to be valid is as essential in PEM systems as a preventive maintenance program is in a CEM system (Macak, 1996, DeFriez, 1996). The "once yearly" check for a sensor may no longer be sufficient and quarterly or monthly preventive maintenance procedures may be necessary to ensure the continued validity of the model.

PEM systems do, however, have the capability of performing self-diagnostics and making adjustments for poor sensor data. If redundant sensors are installed in a system, the PEM system might switch to another operating sensor after one fails. Algorithms can be instituted to perform cross-checks, or reality checks for sensors. Historical data might even be substituted for missing data until a faulty sensor is replaced or the PEM system may model the sensor data itself from other input variables. However, the regulatory acceptability of these substitution procedures has not been addressed in most state or federal monitoring programs, except for a few instances (for example, see 40 CFR 75 Appendix C).

EPA historically has required daily calibration checks for monitoring instrumentation so as to provide for legally defensible data for each operating day. The necessity of providing a means for assuring data quality on a routine basis is as important in PEM systems as it is in CEM systems (Eghneim, 1996).

4.5.5 Model Limitations

The availability of least squares regression and neural net software enables one to correlate any two data sets by a variety of methods. However, the ease of doing this can create problems if basic assumptions of the method are ignored. Using extensive sets of past performance data may not be valid if the data were obtained under different or unknown operating conditions. If site conditions change (such as a change in emission controls or a change in fuel type) new test data must be obtained.

Including or excluding parameters without examination or justification can result in complicated models that are not robust - they may be valid for only one set of conditions, give the same emissions results for different sets of parameters, or give nonsensical results outside and within the expected range of applicability. The key for a good PEM model is to design a thorough experimental test program that examines the effect of selected parameters on emissions and to understand the statistical correlation methods and assumptions used to mathematically develop the model (see Evans, 1994, 1995).

4.6 Issues in Parameter Monitoring

The use of parameter monitoring techniques to determine source emissions offers an alternative to the installation of CEM systems. Parameter-based models can be relatively inexpensive to develop and they can provide process information and feedback that can be used to increase plant efficiency and reduce emissions.

Decisions regarding the use of parameter methods, particularly the PEM systems, often reduce to the issue of PEM system versus CEM systems. Pre-dictive methods have been promoted actively by commercial firms that market the technique. Introducing an innovative technique is difficult, and marketing programs in this area have exhibited biases with respect to both technical and commer-cial issues in order to gain industry and agency acceptance (e.g., Samdani, 1994, Steven, 1994). One particular marketing point that is emphasized frequently is the relative cost of CEM systems versus PEM systems, with the implication that PEM systems constitute a lower cost option. As we shall see in Chapter 6, technical applicability is the most important criteria for selecting a monitoring system and initial capital cost should not be the sole criterion.

Parameter models do offer some significant advantages as a monitoring technique, but one must remember that a model is still a model. It can give present information based upon past data or it can predict future information based upon hypothetical data. But a model is always tied to the past operation of the process and the present sensor data. This is in contrast to manual reference test methods or CEM systems, which provide measurements that are relatively independent of the process and its past history.

As we have seen above, predictive systems are developed by correlating parameter data with emissions data over a range of conditions. The correlation will continue to be valid if those condi-tions are maintained and the sensors provide input data at the same level of quality as provided during the correlation testing. However, of interest to both plant operators and regulatory agencies is what happens under upset conditions, what are the emissions when the process is not operating properly (see for example, Macak, 1996). Since most correlations are not developed under such conditions, the model predictions will either be incorrect during the period of malfunction or the model may flag the data as "missing." In the first case, the data will be misleading (Figure 4-5b); in the second case, no data will exist (Figure 4-5c).

The scenarios of Figures 4-5a and 4-5b may be convenient for the source required to report periods of excess emissions, but not desirable for the regulatory agency. A more complete model would be able to determine that the upset occurred through appropriate sensing devices, and would then switch to an alternate model or algorithm to account for the upset. The problem here is multifold. First, one would have to be aware of all possible upset conditions. One would then have to either initiate or simulate the possible upset conditions and obtain reference emission data to develop the alternate models. This could be prohibitively expensive, or impossible if one could not or did not wish to produce the upset conditions during the development effort. Another approach might be to establish "control limits," or limiting conditions for the model. When the process operates outside these limits, the model will be out-of-control and data cannot be used. Such limits would be analogous to the 40 CFR 60 Appendix F out-of-control limits for a CEM system.

For example, in gas turbine models, NO_x emission predictions are based upon the inherent assumption that the turbine is maintained and operated under the conditions under which the model was developed. Should water injection nozzles become plugged, or water distribution in the turbine become uneven, the model becomes invalid. The wear and tear on a system, the normal degeneration of system components due to continual operation will remove the system from the baseline conditions from which the model was developed. These issues are similar to those associated with CEM systems, since a CEM system must be maintained properly to operate under the conditions at which it was certified. As with CEM systems, a program of quality control, of checking model performance and sensor performance, must be instituted to ensure that the model continues to represent current conditions.

PEM model maintenance issues are therefore very important. Just as with CEM systems, when a component is modified or replaced, the question of recertification arises when the model is modified. Agency guidance in this area is still developing, but questions posed by Clappsaddle are pertinent (Clapsaddle, 1995): "Can periodic adjustments be made to the PEM model equation (without recertification)? If a RATA on the PEM shows inaccuracies, can the PEM model be adjusted and then accepted until the next required quality assurance (QA) audit? How many times can a PEM fail a QA audit before a regulatory agency requires that the PEM be replaced?" Other questions arise with regard to techniques used in "sensor validation." If a sensor is replaced, is the model still valid? Is recertification required? If a sensor fails and sensor data are reconstructed to substitute and maintain data availability, should the model be certified under those conditions and other possible sensor data substitution scenarios? (See DeFriez, 1996 for a discussion of sensor issues.) If a model contains different algorithms for different operating conditions, should the model be certified at each operating condition?

The cost issue has become distorted considerably in PEM system vs CEM system arguments. PEM system costs are often compared inappropriately to the costs associated with CEM systems installed to meet the requirements of the Part 75 acid rain program. In Part 75, the hardware precision and accuracy requirements and detailed data acquisition and handling systems (DAHS) specifications necessary to legitimize data for allowance trading justified higher costs. Sys tems installed to meet the NO_x or VOC monitoring requirements of a state Title V permit program are not required to meet such stringent specifications, and their costs are consequently much less.
Many CEM system suppliers now offer CEM systems at prices comparable to commercial PEM systems. When one considers the correlation testing necessary to develop a PEM system model and the certification testing necessary to validate the model, initial capital costs are often comparable. Also, if the original correlation becomes invalid due to process changes or system degeneration, the correlation testing would have to be redone. The ongoing quality assurance costs can be comparable between the two methods. These cost issues are further discussed in Chapter 6 of this manual.

Those required to monitor non-criteria pollutants may have the flexibility to choose between a CEM and PEM system to meet the requirements of future rulemaking. Depending on the application, the two techniques can be competitive both in terms of cost and accuracy. However, one of the most powerful

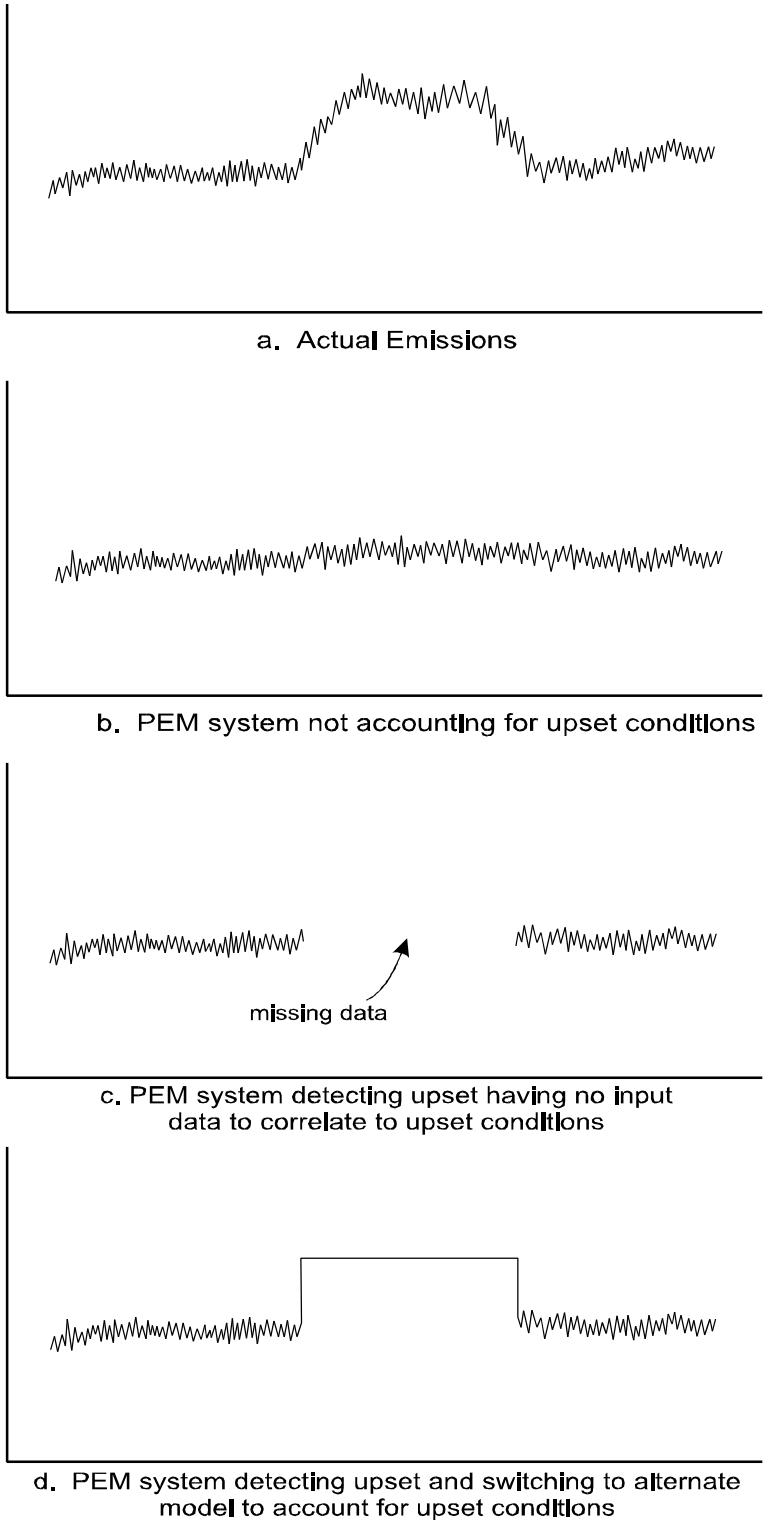

Figure 4-5. Emissions calculations (PEM system predictions) based upon upset conditions not accounted for by the model.

options is the combination of two methods (DeFriez, 1996, Macak, 1996). With a combined CEM/PEM system, the PEM system can serve as a backup to the CEM system, as in the prescribed techniques can be competitive both in terms of cost and accuracy. However, one of the most powerful options is the combination of the two methods C-EM/PEM system, the PEM system can serve as a backup to the CEM system, as in the prescribed methods of the acid rain CEM program (40 CFR 75). Or, a CEM system can serve as a backup to a PEM system. When a sensor validation program causes the PEM system to invalidate data and report missing data due to failed sensors or an unrecognized operating condition, the CEM system can fill in the missing data gap. The CEM system can provide the data where it may be most needed, the period of plant upset conditions not accounted for by the PEM model.

The final decision in choosing a monitoring method, whether a CEM or a PEM system, depends upon how the data will be used and the constraints of the application. Questions need to be asked about whether a DCPL or predictive model will meet monitoring requirements, will the method be sufficient for demonstrating compliance, or will the data be accurate enough for a trading program? A consideration of these questions should involve an evaluation of cost, regulatory, and technical issues; none should be considered solely.

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