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Evaluating Power Plant Control Strategies for Air Toxics

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INTRODUCTION

The 1990 Clean Air Act Amendments (CAAA) set out the new federal regulatory requirements for air toxics covering 189 listed chemical species.[1] Affected sources fall into some 766 categories or sub-categories which can be combined into 18 broad industry groups, including "Fuel Combustion," "Waste Treatment and Disposal" and "Radionucleide Emitters." Thus, electric power plants, particularly coal-fired facilities, could become subject to new regulatory requirements as the air toxics provisions of the 1990 CAAA are developed.

This paper reviews the status of the CAAA provisions as they affect the electric utility sector. An air toxics research program sponsored by the Electric Power Research Institute (EPRI) then is briefly described. One element of this program -- a computer-based probabilistic assessment model -- illustrates the analytical capability being developed to aid utilities in evaluating power plant control strategies for air toxics.

THE 1990 CLEAN AIR ACT AMENDMENTS

Under the 1990 CAAA, industrial sources emitting 10 tons per year (tpy) or more of any one of the 189 listed substances, or 25 tpy of a combination of substances, could automatically be required to apply "maximum available control technology" (MACT). Additional controls could be required if EPA finds an unacceptable level of remaining risk to public health after MACT is applied.

Title III of the 1990 Amendments to the Clean Air Act requires the Environmental Protection Agency (EPA) to categorize major sources of specifically listed hazardous air pollutants by November 15, 1991 and most area sources by November 15, 1995. Under a ten-year rolling schedule, EPA must then promulgate regulations covering all listed source categories. Electric utilities, however, are not initially subject to these Title III requirements.

Section 112(n) requires EPA to perform a study of the hazards to public health reasonably anticipated to occur from emissions of hazardous air pollutants from electric steam generating units after the imposition of the other requirements of the 1990 Amendments. In the study report, due to Congress by November 15, 1993, EPA must also develop and describe alternative control strategies for hazardous emissions which may warrant regulation. EPA must regulate electric utilities under Title III if "appropriate and necessary" after considering the results of the study.

Two other studies required by the 1990 Amendments may also impact electric utilities. Section 112(n)(1)(B) and (C) call for studies of mercury emissions from, among other sources, electric utilities. One of these studies, to be conducted by the National Institute of Environmental Health Sciences, will define threshold mercury exposure for adverse human health effects. Section

112(m) requires a fourth study which includes the health and environmental effects of deposition of hazardous air pollutants in the Great Lakes, the Chesapeake Bay, Lake Champlain and coastal waters. If EPA concludes that further regulation is required as a result of this study, then electric utilities could be included in those regulations

A POWER SYSTEMS EVALUATION MODEL

While the electric utility industry is not the primary focus of the CAAA air toxics provisions, EPRI already has undertaken a program to study utility air toxics and their control. The EPRI program on air toxics -- known as PISCES (Power Plant Integrated Systems: Chemical Emissions Study) -- consists of several major products and activities including, (1) a database of published information on trace species for conventional fossil fuel power plants; (2) a probabilistic computer model to estimate power plants emissions; (3) a field monitoring program to collect new data; (4) development of emission control technology selection guidelines; and (5) a sampling and analytical methods reference guide for trace chemical measurements. Descriptions of these and related EPRI activities appear elsewhere.[2,3,4]

This paper focuses on applications of the power plant chemical assessment model. The purpose of the model is to allow utilities to evaluate the performance of a given plant configuration with respect to multi-media emissions of chemical substances. The model provides probabilistic estimates of the mass flow rates of all solid, liquid and gaseous streams emanating from the plant, plus quantitative estimates of the associated trace species emissions. Descriptions of the model and illustrative results have been reported previously.[5,6] Here, we elaborate on how the model may be used in conjunction with the PISCES database to evaluate emission levels and control strategies for air toxic species.

Evaluating Control Strategies

As indicated earlier, the 1990 Clean Air Act Amendments suggest that annual emissions in excess of specified levels could be one mechanism for triggering air toxic control requirements. What determines the magnitude of such emissions? For a coal-fired power plant there are five key parameters. The plant size and capacity factor are the primary determinants of the annual average flows through a facility. In addition, the annual emissions of trace species depends on, (1) the composition of coal and other major raw materials into the plant (e.g., reagents and water), (2) the "partitioning" of trace species between the bottom ash stream and the flyash stream in the boiler, and (3) the removal efficiencies of various flue gas treatment systems particularly the electrostatic precipitator (ESP) and the flue gas desulfurization (FGD) system, if any.

The power plant model accounts for all of these parameters, as well as other parameters that determine overall plant performance. A key complement to the model is the extensive database

developed for EPRI as part of the PISCES project.[7] This database, drawn mainly from the open literature, provides empirical information on trace species concentrations in all major power plant streams, as well as other power plant design and operational data. The database thus provides information on the performance of environmental control technologies, and on the partitioning of trace species across various plant components. To the extent that the data reveal uncertainties and variability in trace species input quantities and control technology performance, the probabilistic capability of the computer model can accurately reflect such uncertainties in the mass balance calculations.

Evaluation of a control strategy thus involves, (1) configuring the power plant and fuel type of interest; (2) setting model parameters to reflect the size, design and performance of the system, and the properties of all fuels and reagents input to the plant; then (3) obtaining results for trace species emissions, either in deterministic or probabilistic form. Emission results either may serve as the end point of an evaluation (e.g., levels do or do not exceed some specified limit), or may serve as an input to a more comprehensive analysis, such as an environmental risk assessment. Note that in their probabilistic form, emission rates carry a *likelihood of occurrence,* something not explicitly incorporated in current CAAA language, but implicit in point value estimates of plant emissions.

Model Applications

Early testing of the model software focused on validation of the mass and energy balance calculations that determine major plant stream flow rates. Trace species flow rate calculations rely on empirical "partition factors" for conserved species (e.g., trace elements), plus "emission factors" for other substances formed within the plant (e.g., trace organics formed during combustion in the boiler). While the model is multi-media in scope, the present paper emphasizes applications to air pollution control.

The utility of the model for air toxics control strategy evaluation depends strongly on the availability of auxiliary data to quantify the various partition factors needed to track chemical species. Here we illustrate how the PISCES database was used together with the model in an initial case study to quantify the emissions of seven trace species from a coal-fired power plant.

The case study involved using the model and database to analyze a power plant located in western Europe. The plant configuration (Figure 1) consisted of a tangentially-fired boiler and a cold-side ESP. The plant burned European bituminous coal, samples of which provided the data used for this analysis. All model input parameters for the power plant and coal trace species concentration were provided by the European utility participating in this study. The seven selected trace species

Figure 1. Power Plant Case Study

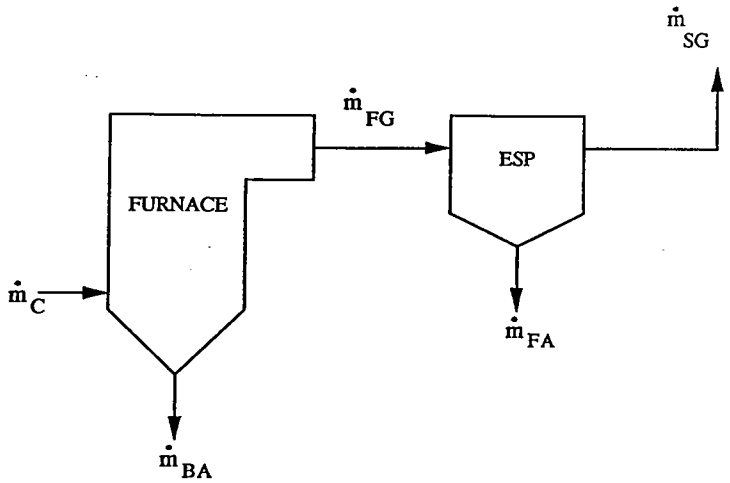
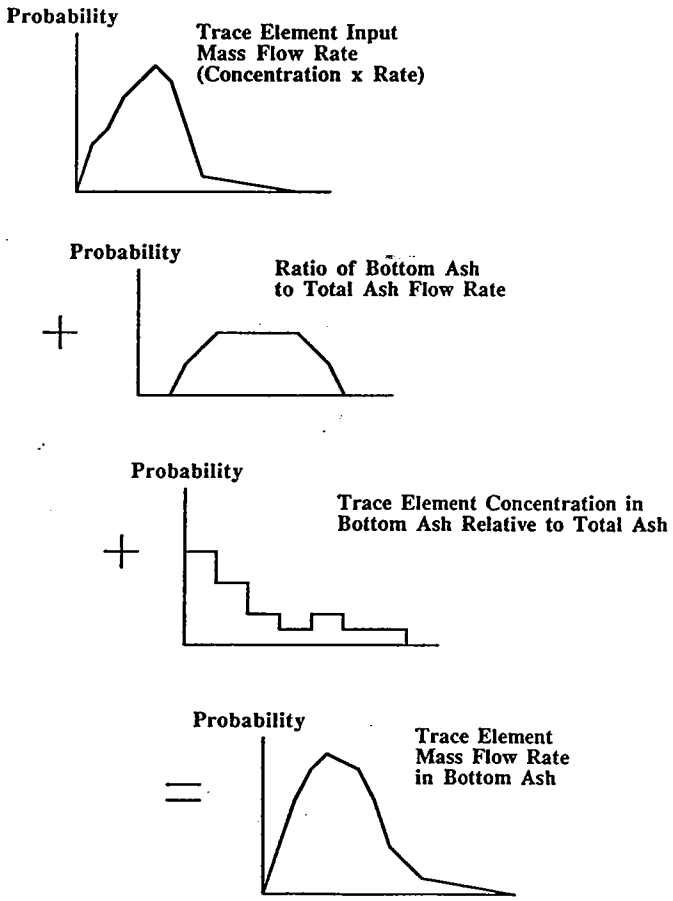


Figure 2. Model Approach to Calculating Trace Emissions



analyzed were arsenic, cadmium, chromium, mercury, nickel, selenium and vanadium.

The model input parameters provided by the utility are summarized in Table 1. All other model parameters utilized model defaults. The utility assigned uncertainties of ±5% to the boiler efficiency, and to the fraction of ash reporting to the flue gas stream as flyash. To incorporate this uncertainty, the nominal parameter values were multiplied by a normal distribution with a mean of 1.0 and a standard deviation of 1.67%. This normal distribution changes the mean value by approximately 5% at three standard deviations.

Table 1. Plant and Fuel Input Parameters for the Case Study

Plant Characteristics	Coal Characteristics (as fired)
Plant Capacity, MW	HHV, Btu/lb
Steam Cycle Heat Rate, Btu/kWh	Carbon, wt %
Boiler Efficiency, %	Hydrogen, wt %
Capacity Factor, %	Oxygen, wt %
Boiler Excess Air, %	Sulfur, wt %
Air Preheater Leakage, %	Nitrogen, wt
Furnace Type	Moisture, wt %
Ash to Flue Gas, wt %	Ash, wt %
Particulate Limit, lb/MBtu	Trace Species (ppmw)

Figure 2 illustrates the basic procedure used to calculate the mass flow rates of trace species entering and leaving the boiler. Similar procedures apply to the ESP. The uncertainty distributions for each input value and partition factor determine the data requirements for the model.*

The uncertainty in coal trace metal content was reported as data from three separate coal samples. Some of the concentration data were reported as less than a specified value, which indicates that the concentration falls between zero and the maximum value. For analysis purposes, this data was converted to numeric values equally distributed between zero and the specified value. For example, all three data points for selenium were "less than 1 ppmw." These three data points were converted to nominal values of 0.25, 0.50, and 0.75 ppmw, respectively. For mercury, two data points less than 0.1 ppmw were converted to nominal values of 0.033 and 0.067 ppmw.

The data for trace species concentration also had to be represented as an uncertainty distribution. Since there were only three data points, a fractile distribution was chosen to represent the data. A

* In developing the model, attention also had to be paid to the types of data that are available. Thus, to some extent, model parameters reflect the ways in which data typically are reported.

fractile distribution requires a sorted list of data points, and produces an uncertainty distribution which has equal probability between each point. With only three data points, there is a 50% chance of the result lying between the minimum and middle values, and a 50% chance of the result lying between the middle and maximum values.

Additional information also was needed to estimate the partitioning of trace species in the furnace and ESP. This information was obtained from the PISCES database. The species partition factors for the furnace were based on plants burning bituminous coal which had reported values for the total ash content of coal, as well as values for the concentration of the trace species in both the coal and bottom ash streams. Table 2 shows the number of data points available for each species at the time of the analysis.** For the database plants, the concentration of trace species in bottom ash was compared to the concentration in coal ash. This ratio estimates how well the trace species are retained in the bottom ash. Values less than one indicate that the trace species has a preference to exit with the flue gas, while values above one indicate that the trace species tends to be concentrated in the bottom ash. Figure 3 shows the histograms for the seven chemical species analyzed. As can be seen in these figures, chromium, nickel, and vanadium tend to be partitioned about the same as in coal ash while arsenic, cadmium, mercury, and selenium tend to exit the furnace in the flue gas, consistent with the more volatile nature of these substances.

Table 2. Number of Data Points for Developing the Furnace and ESP Partition Factors

Species	Furnace[a]	ESP[b]
Arsenic	11	13
Cadmium	9	5
Chromium	11	14
Mercury	9	3
Nickel	13	15
Selenium	13	9
Vanadium	13	7

[a] Data from up to 13 plants. [b] Data from 4 plants.

The ESP partition factor (removal efficiency) was based on data from bituminous coal-fired power plants with a total particulate removal efficiency of 99% or more (as at the plant being analyzed). This limitation was imposed because the literature indicates that trace species removal is generally correlated to the total particulate removal efficiency. The total removal efficiency was used to normalize all trace species data. The normalized ratio estimates how well the trace species are removed in the ESP relative to total particulates. Values between 1.00 and 1.005 indicate that a trace species is removed as well or better than total particulates, while values less than 1.00 indicate that the species is removed less efficiently. Figure 4 shows the histograms obtained for the seven

**Note that the database has been augmented since the time of this study.

Figure 3. Ratio of Species Concentration in Bottom Ash to the Concentration in Coal Ash

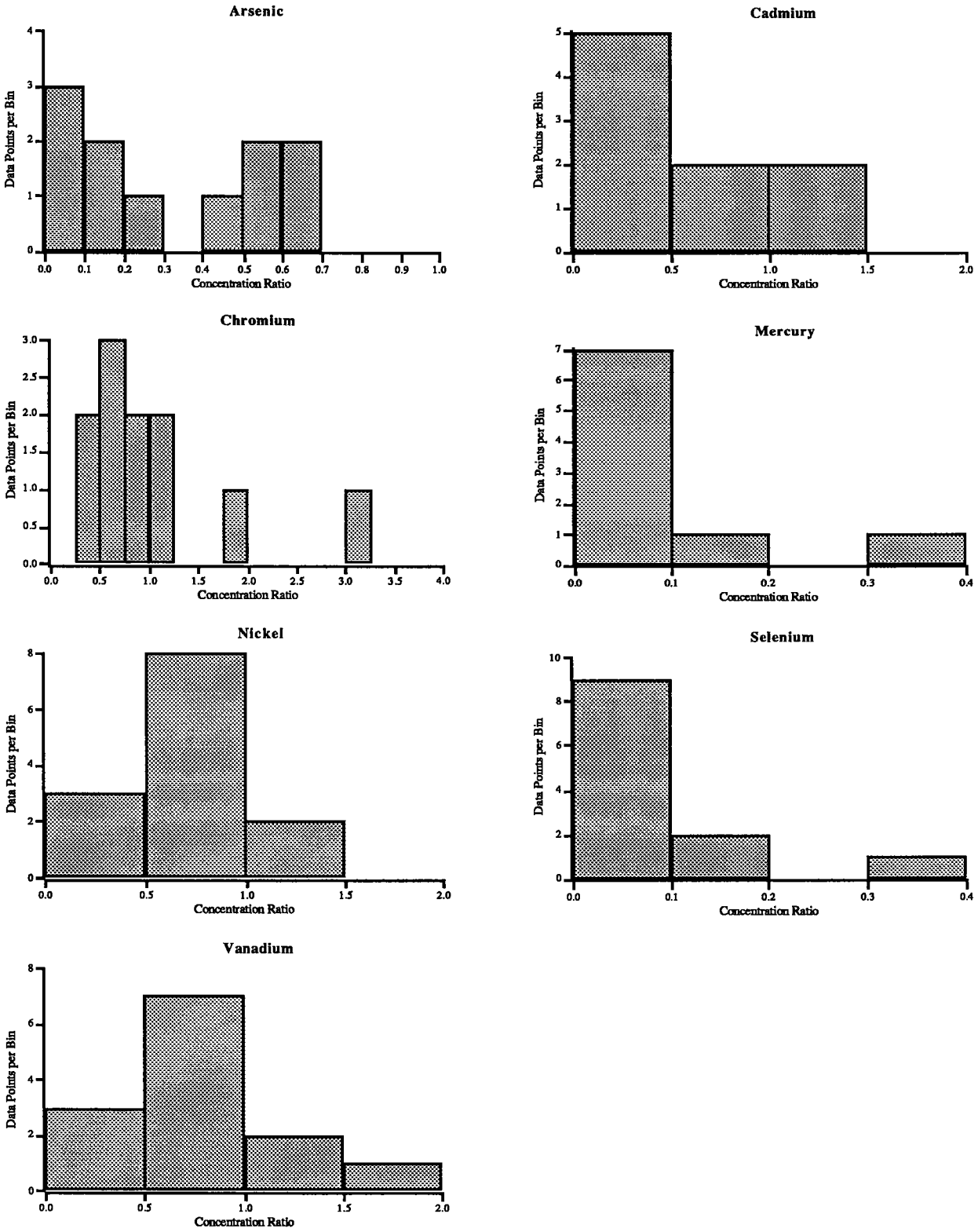
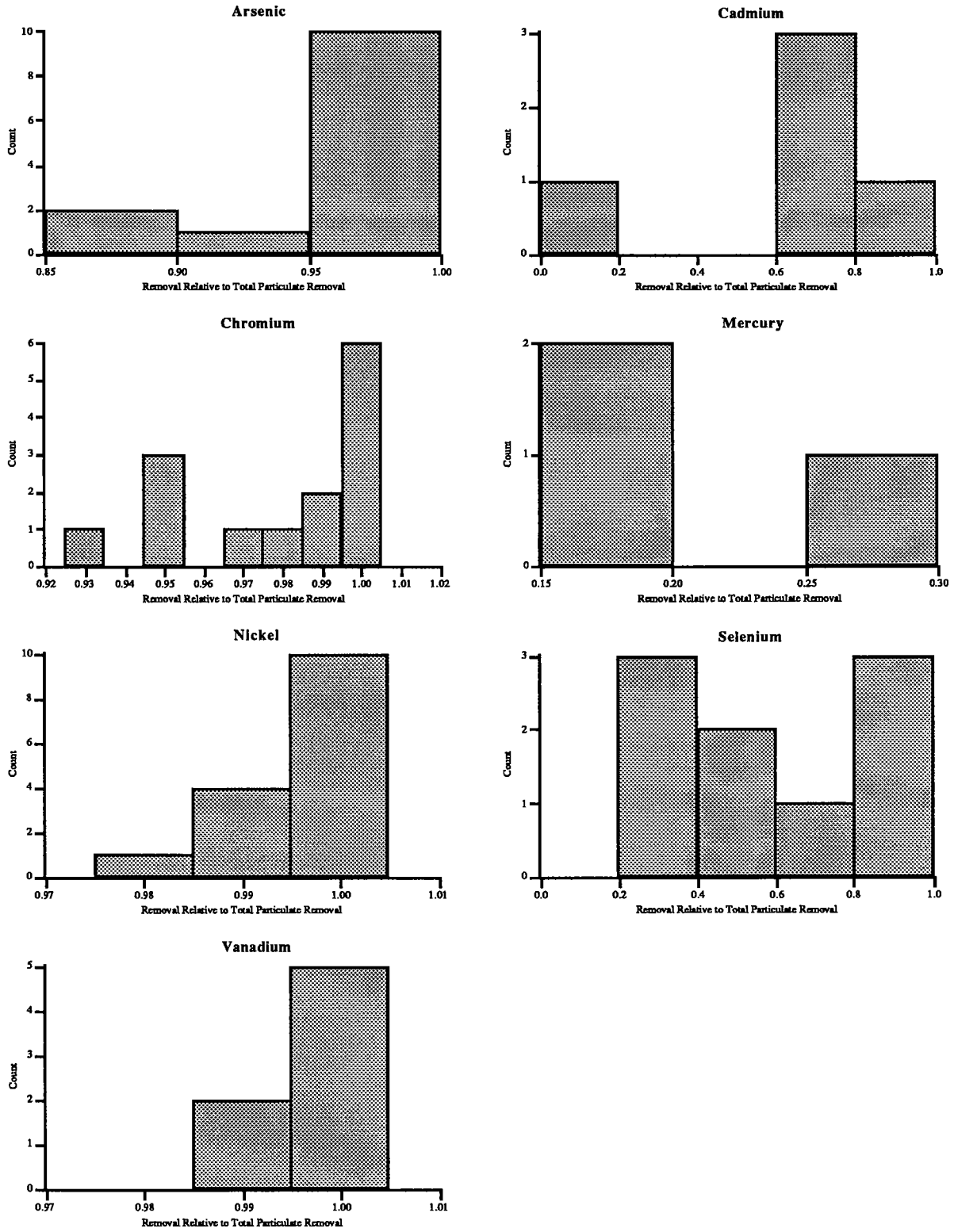


Figure 4. Removal of Trace Species in ESP Relative to the Total Particulate Removal Efficiency



chemical species, representing data from four power plants.

Given the data and assumptions outlined above, the computer model was used to predict the probabilistic mass flow rates and concentrations of trace species in the coal, bottom ash, collected flyash, and stack gas. All probabilistic results were generated using median Latin Hypercube sampling with a sample size of 200. Figures 5 - 7 show the probabilistic mass flow rates for the trace species in each major stream exiting the plant. Figure 8 shows the probabilistic concentrations of trace species in the collected flyash. In these figures, the trace species have been grouped by volatility. The less volatile species -- chromium, nickel, and vanadium -- have a reported coal concentration that is one to two orders of magnitude higher than the more volatile species. However, the results show that the furnace and ESP remove more of these elements than the less volatile substances. The net result is that emissions of the heavy metals is within an order of magnitude of the more volatile elements. The probabilistic results for each species, however, show a several-fold variation in the mass flow rates that might be realized.

Comparisons of Model Results and Data

As is often the case with trace species data, the only measurements available from the utility were trace species concentration in the coal and collected flyash. Table 3 shows the reported concentration in collected flyash and the corresponding range and cumulative percentile predicted by the model. In general, the model and data agreed well for cadmium, chromium, selenium, and vanadium. For arsenic and nickel the model predicted higher flyash concentrations than reported, while for mercury the measured values exceeded the model estimates. There are several possible reasons for the differences between measured and predicted values: (1) measurement error and variability in the coal and/or flyash samples; (2) limited data on which to base furnace and ESP partition factors, and (3) differences between European and U.S. coals and power plant characteristics. The most likely explanations for the differences are measurement errors and limited performance data. While it was not possible to assess the accuracy of the coal and flyash concentration data, at least the measurements for mercury are suspect since the reported data were not internally consistent. Two of the reported concentrations for mercury in coal were below the detection limit of 0.1 ppmw, with corresponding concentrations in collected flyash of 2 and 3 ppmw (see Table 3). However, a simple mass balance using the computer model showed that even if the coal mercury concentration were 0.1 ppmw and all of this mercury were captured in the flyash, the maximum flyash concentration would be only 1.84 ppmw; i.e., less than the two values reported. Since a significant portion of mercury is known to volatilize and exit with the flue gas, the maximum concentration in flyash actually would be much less than 1.8 ppmw. This indicates the likelihood of errors either in the mercury concentration in coal and/or the mercury concentration in flyash.

Figure 5. Calculated Mass Flow Rate of Trace Species in Bottom Ash

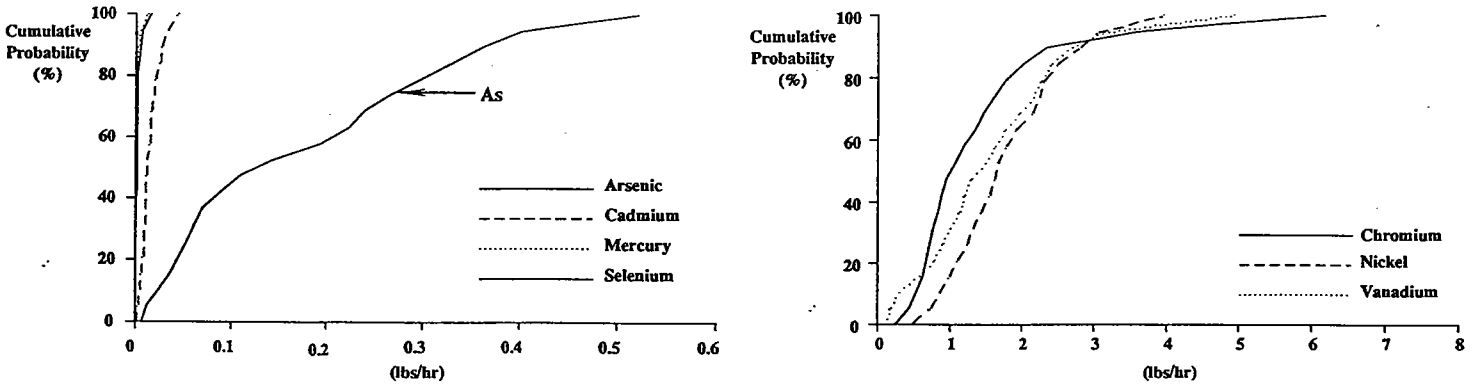


Figure 6. Calculated Mass Flow Rate of Trace Species in Collected Flyash

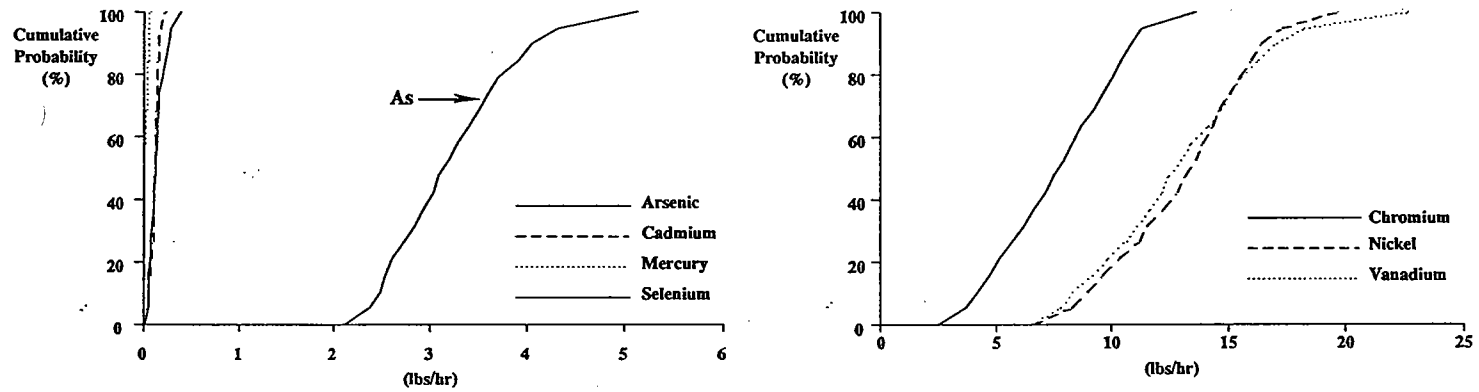


Figure 7. CalculatedMass Flow Rate of Trace Species Exiting Stack

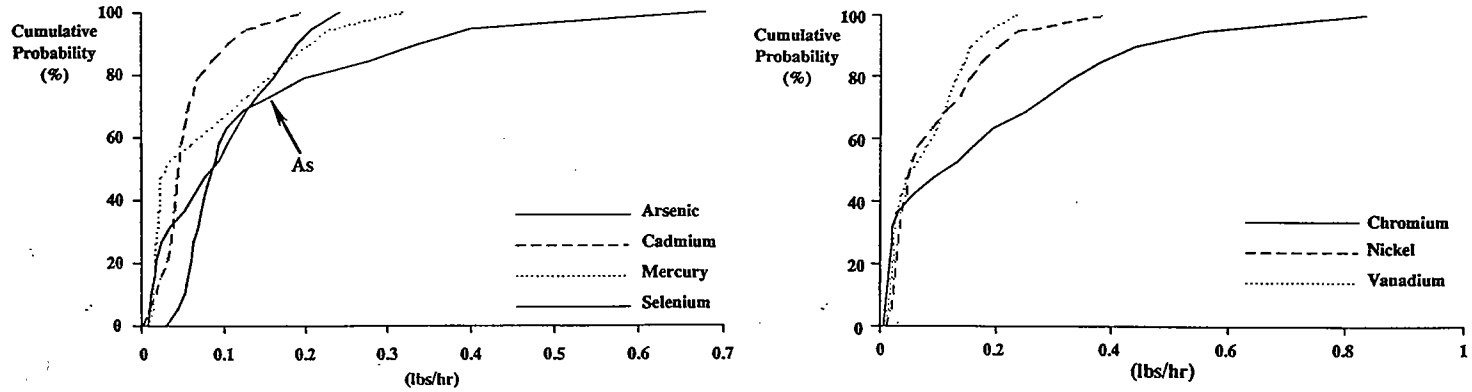


Figure 8. Concentration of Trace Species in Collected Flyash

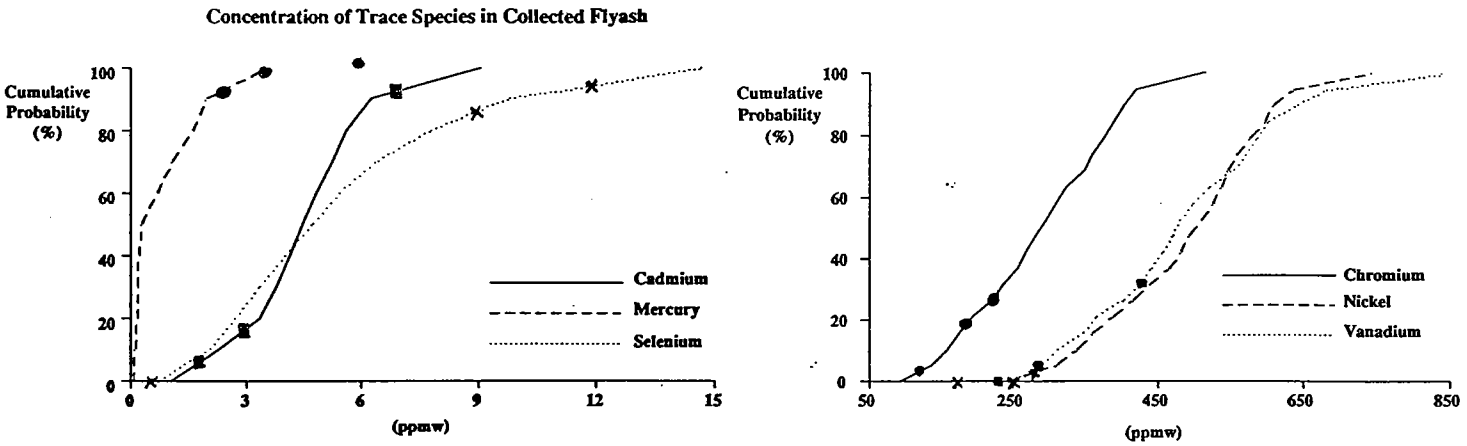


Table 3. Comparison of Model Results with Measured Samples for Collected Flyash

Species	Measured Values (ppmw)			Calculated Values in (ppmw)	
	Coal	In Coal	In Flyash	Cumul. %	Range
As	A	10	44	<0	77 - 180
	B	7	71	<0	
	C	6	64	<0	
Cd	A	0.3	2	7	1.1 - 9.0
	B	0.4	7	96	
	C	0.5	3	17	
Cr	A	9	122	3	75 - 470
	B	21	191	18	
	C	27	227	26	
Hg	A	0.7	6	>100	0.09 - 3.6
	B	<0.1	3	100	
	C	<0.1	2	88	
Ni	A	19	249	0	270 - 740
	B	34	175	<0	
	C	40	289	2	
Se	A	<1	12	97	0.74 - 15
	B	<1	9	86	
	C	<1	<1	1*	
Va	A	18	215	<0	240 -810
	B	32	271	3	
	C	41	411	31	

* Percentile given for a value of 1.0.

Other qualitative aspects of the reported data also suggest that measurement error may be at least partially responsible for differences between data and model values. For example, Table 3 shows the coal and corresponding flyash concentration data for each of the three test samples. In a number of cases, the trace element concentration in flyash does not increase with increasing concentration in coal, as would be expected. Indeed, in some cases (e.g., arsenic), the highest concentration in coal corresponds to the lowest concentration in flyash. This again suggests that measurement uncertainties are a likely contributor to the differences of up to a factor of two between model results and data.

Undoubtedly, the limited partition factor data extracted from the PISCES database is another contributing factor. Since the available data reflected a relatively small number of power plants (particularly for the ESP), a relatively small change in the partition factors could change the concentration in flyash significantly. For example, if about 30% more arsenic were captured in the bottom ash and 30% less arsenic were removed in the ESP, the cumulative distribution of arsenic in the flyash would range from 35 to 101 ppmw, enclosing all of the data values reported in the case study. The changes needed in the partition factors for nickel would be about the same, while changes in the partition factors for chromium and vanadium need only to be 16% different to encompass all the utility data. This suggests that the uncertainty distributions reflected by the current PISCES dataset are probably narrower than a more complete dataset would reveal. Also, the quality of existing data cannot be absolutely assured despite the screening applied to published literature studies.

Lessons Learned

This case study points to two critical needs for applying the power plant computer model to trace element analysis. First, the accuracy of all measurement data needs to be better assessed to evaluate the true uncertainty in reported quantities, and to facilitate comparisons between model results and data. Secondly, it would be desirable that the PISCES database be expanded so that coal quality, furnace partitioning and control technology performance can be more rigorously assessed for trace species. Additional data also would allow the uncertainty distributions used in the model to more accurately reflect the variability in performance of different classes of coal-fired power plants and control technologies.

FUTURE PLANS

To better assess and model the multi-media emissions of trace species, EPRI now is engaged in an extensive program of field testing to acquire additional data on power plant trace species emissions and control technology performance. Details of this test program are described in other EPRI reports.[2] Field monitoring data will be coupled with a related EPRI program to assess the health and environmental risks of air toxics emissions.[3] Furthermore, in cooperation with other electric

utility industry groups, EPRI will be working closely with EPA and DOE in their on-going assessments of utility air toxics emissions.

Future plans also call for further development of the power plant chemical assessment model and the associated database to include a number of advanced technologies of interest to the utility industry. Such technologies include fluidized bed combustion systems, integrated coal gasification combined cycle systems, slagging combustors, municipal waste combustion, and gas turbines. The existing set of model control technology options for conventional power plants also will be expanded to allow utilities even greater flexibility in evaluating control strategies for air toxics. Multi-media impacts on other waste and water streams also will be evaluated through on-going activities in those areas as well.

ACKNOWLEDGEMENT

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