EVALUATION METHOD FOR ADVANCED ACID RAIN COMPLIANCE TECHNOLOGY[a]

By H. Christopher Frey[1] and Edward S. Rubin[2]

ABSTRACT: Technological innovation in emissions control of acid rain precursors has made possible increasingly stringent control requirements for coal-fired power plants. A key challenge for potential process adopters is evaluation of the uncertainties in performance and cost inherent in any new control technology. Uncertainties can be explicitly characterized using probabilistic modeling techniques such as Monte Carlo simulation. A robust approach to evaluating advanced systems is illustrated via a case study based on the fluidized bed copper oxide process. An engineering performance and cost model of this process was developed. Selected input parameters were assigned probability distributions based on data analysis and expert judgments. The model then was exercised in a probabilistic modeling environment. The modeling applications illustrate how uncertainty may be included in process evaluation. In particular, the likely cost savings and risks of a new technology compared to conventional technology can be estimated under varying design and uncertainty assumptions. The results can be used for decisions regarding process design trade-offs, technology selection, and research planning in the face of uncertainty.

INTRODUCTION

Advances in coal-fired power-plant emission-control systems have made feasible increasingly stringent control levels. The acid rain provisions of the 1990 Clean Air Act Amendment also establish a strong incentive to achieve low emission levels. Advanced technologies are thus likely to play an increasingly important role. Such technologies feature an integrated approach to power-plant and emissions-control system design with the potentially key benefits of system simplification, efficiency improvement, and cost reduction.

However, uncertainties in performance and cost are inherent in any system that has not been demonstrated at full scale. Uncertainty can be associated with statistical error in test data, scale-up risks, differences in test conditions relative to full-scale operation, and variability in feedstock properties or composition. There may be uncertainty regarding capital, maintenance, and operating costs, particularly for new types of process equipment. The price of consumable materials also may be uncertain over the life of a plant.

A key challenge for technology developers is to evaluate uncertainties in the performance and cost of a new concept. Computer modeling of new technologies can provide insights into the feasibility, optimal design, applications, and risks of a new process. Mass and energy balances charac-

---

[a] Presented at the March 11–13, 1991 ASCE specialty conference, Energy in the 90's, held at Pittsburgh, PA.

[1] Res. Assoc., Dept. of Engrg., and Public Policy and Ctr. for Energy and Envir. Studies, Carnegie-Mellon Univ., Pittsburgh, PA 15213.

[2] Alumni Prof. of Envir. Engrg., and Sci., and Dir., Ctr. for Energy and Envir. Studies, Carnegie-Mellon Univ., Pittsburgh, PA.

Note. Discussion open until September 1, 1992. To extend the closing date one month, a written request must be filed with the ASCE Manager of Journals. The manuscript for this paper was submitted for review and possible publication on June 29, 1991. This paper is part of the ***Journal of Energy Engineering***, Vol. 118, No. 1, April, 1992. ©ASCE, ISSN 0733-9402/92/0001-0038/$1.00 + $.15 per page. Paper No. 2117.

terizing process performance can be developed based on ongoing experimental work. Uncertainties in performance can be explicitly characterized using probabilistic modeling techniques such as Monte Carlo simulation. Similarly, uncertainties in cost may also be modeled.

Information generated during technology research and development (R&D) can be used to make decisions regarding research strategies. Of concern to process developers is the prioritization of research needs and an understanding of the barriers that exist between a conceptual design and commercial adoption of an environmental-control technology. Which technologies are the most promising for further process development? What conditions favor the selection of the new technology? What specific technical areas require more research? What economic and cost uncertainties affect the economic feasibility of the technology? How much funding should reasonably be committed to further research?

This paper presents a research planning method that can be used to help answer these questions. The salient features of the method include the following.

- Development of engineering performance and cost models.
- A probabilistic modeling capability to incorporate uncertainties.
- Judgments regarding uncertainties, likely applications, and the outcome of additional research.
- Exercising of the models to answer key questions such as: What are the key process design trade-offs?, What uncertainties most affect the overall costs?, What are the potential payoffs and risks vis-à-vis conventional technology?, and What is the likely effect and value of additional research?
- Decision analysis to select a course of action.

An example of a technology innovation for pollution control of a coal-fired power plant is used to illustrate the research planning method just outlined.

INTEGRATED ENVIRONMENTAL CONTROL

With the prospect of increasingly stringent emission control the concept of integrated environmental control has evolved. The concept has several dimensions. One is a multimedia approach to pollution control. Another is the integrated use of precombustion, combustion, and postcombustion control methods (as distinct from one approach alone). A third dimension is the development of new processes for combined pollutant removal in lieu of separate processes for individual pollutants. Thus, integrated environmental control represents good design practice and provides opportunities to minimize costs for a given set of emission-reduction requirements (Carr 1986).

A conventional emission-control system for a new coal-fired power plant typically consists of a wet-limestone flue-gas desulfurization (FGD) system for 90% SO_2 control, an electrostatic precipitator (ESP) for over 99% particulate matter (PM) removal, and combustion controls for about 50% NO_x reduction. The spent limestone reagent used in the FGD system is disposed of with the power plant solid waste. These systems are all commercially available and well-demonstrated. However, recent commercial experience in Japan and Germany with selective catalytic reduction (SCR) indicates that 80–90% postcombustion NO_x removal may be feasible (Robie et al. 1989).

The DOE Pittsburgh Energy Technology Center (PETC) has conducted research on a number of advanced control technologies. One of these is the fluidized-bed copper oxide process. Unlike a wet FGD/SCR system, the copper oxide process: (1) Combines SO_2 and NO_x removal in a single reactor vessel; (2) is regenerative (i.e. the reagent is reused rather than disposed of); and (3) produces a saleable sulfur or sulfuric acid byproduct, in contrast to the sludge produced by FGD systems (Drummond et al., unpublished, 1985). Schematic diagrams of a baseline FGD/SCR and an advanced, integrated copper oxide–based system are shown in Figs. 1 and 2, respectively.

Fig. 2 illustrates the key features of the copper oxide process. A sorbent, consisting of copper-impregnated aluminum oxide spheres, circulates between a fluidized-bed reactor, where SO_2 in the flue gas is removed by reaction with copper oxide in the sorbent, and a regenerator, in which SO_2 is evolved in a reaction of the sulfated sorbent with methane. The SO_2-rich gas from the regenerator is sent to an elemental sulfur or a sulfuric acid plant for byproduct recovery. Factors such as the fluidized-bed height and the amount of copper in the sorbent influence the sorbent mass flow rate. NO_x is removed by reaction with ammonia, which is injected into the flue gas upstream of the absorber. The absorber reactions are exothermic, increasing the temperature of the flue gas. This energy can be recovered in

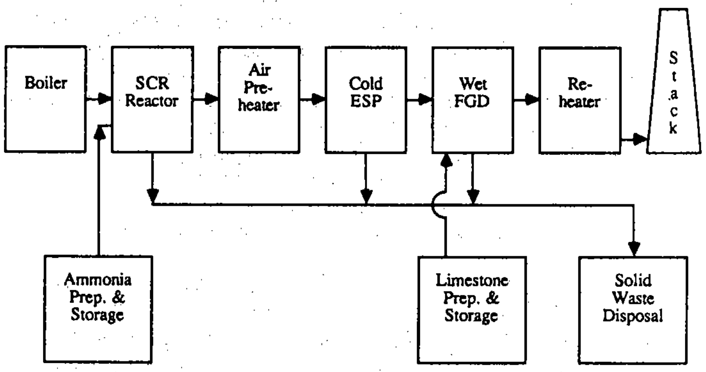

FIG. 1. Power Plant Design with FGD/SCR Emission-Control System

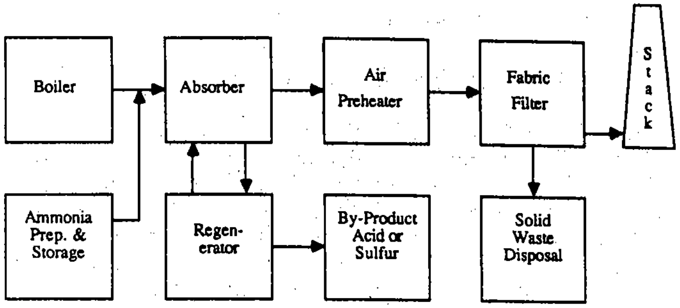

FIG. 2. Power Plant Design with Copper Oxide Emission-Control System

the power plant furnace through additional preheating of the combustion air by the power plant air preheater, which cools the flue gas.

PROBABILISTIC ENGINEERING MODEL

The copper oxide process is in an early phase of development, with limited test data and no commercial operating experience. Uncertainties in system performance at the commercial scale lead to uncertainties in capital and operating costs. Furthermore, even if process performance were known with certainty, uncertainties regarding the costs of equipment and reagents would remain. To explicitly characterize these uncertainties, and to evaluate the overall uncertainty in process costs, a probabilistic engineering modeling framework was developed.

Analytic models for a conventional pulverized coal (PC) power plant, coal-cleaning processes, and selected conventional and advanced postcombustion pollution-control systems are available in the integrated environmental control model (IECM), developed by Rubin et al. (1986). Details of the IECM's copper oxide process, power plant air preheater, and sulfuric acid recovery plant models are described elsewhere (Frey 1987).

The models characterize mass and energy balances for key process equipment. The capital-cost models are based on equipment cost estimates from the literature, adjusted for plant size using key process stream flow-rates and exponential scaling factors. Indirect capital costs and variable and fixed operating costs are also calculated using a standard approach (EPRI: "TAG" 1986). Constant 1985 dollars, which are exclusive of inflation, are used in this analysis.

To characterize uncertainties in advanced emission-control systems, the IECM is implemented in a probabilistic modeling environment (Henrion and Wishbow 1987). Uncertainties in process parameters can therefore be characterized using a variety of user-specified probability distribution functions. The resulting uncertainty distributions for model outputs are calculated using median Latin hypercube sampling, a variant of Monte Carlo simulation.

Probabilistic modeling has several advantages over traditional sensitivity analysis. In probabilistic analysis, the values of any number of parameters may vary *simultaneously*, and the *likelihood* of obtaining particular results is explicitly estimated. Furthermore, statistical analysis on the model input and output data can be used to identify trends (e.g., key input uncertainties affecting output uncertainties) without needing to rerun the analysis. This permits the identification of key input parameters when many other parameters are simultaneously uncertain.

CASE STUDY: COPPER OXIDE VERSUS FGD/SCR

To illustrate the application of the research planning method, an integrated emission-control system consisting of coal clearning, the copper oxide process, byproduct recovery, and energy recovery, was compared with a conventional system consisting of wet FGD and SCR. Table 1 summarizes some of the key parameters, including emission constraints and base plant design, assumed for this analysis. Both deterministic (nominal point-estimate) values and probability distributions are indicated. Table 2 summarizes the different coals considered, including both unwashed and cleaned (30% sulfur reduction on an energy basis) coals. The main emphasis here is on applying the research priorization methodology to the copper oxide process, assuming the FGD/SCR system as benchmark. Thus, the key inputs and distributions assigned to the copper oxide emission control system are summarized in Table 3. Additional details regarding modeling assumptions for the FGD/SCR system are reported by Frey and Rubin (1991).

TABLE 1. Selected Input Parameter Assumptions for Case Studies

Model parameter (1)	Deterministic (nominal) value (2)	Probability distribution (3)	Values (σ as % of mean) (4)
	(*a*) Emission Constraints		
Nitrogen oxides	90% reduction	—	—
Sulfur oxides	90% reduction	—	—
Particulates	0.03 lb/MBtu	—	—
	(*b*) Power Plant Parameters		
Gross capacity	522 MW	−1/2 normal	1.8%
Gross heat rate	9,500 Btu/kWh	Normal	7%
Capacity factor	65%	Normal	2.5%
Excess air (boiler, total)	20%, 39%	—	—
Ash to flue gas	80%	—	—
Sulfur to flue gas	97.5%	—	—
Economizer outlet temp	700°F	—	—
Preheater outlet temp	300°F		

TABLE 2. Selected Properties of Coals Used for Case Studies (As-Fired Basis)

Coal property (1)	Illinois No. 6 Coal		Pittsburgh Coal	
	Run of mine (2)	Washed[a] (3)	Run of mine (4)	Washed[a] (5)
Heating value, Btu/lb	10,190	10,330	13,400	12,900
Sulfur, wt %	4.36	3.09	2.15	1.66
Carbon, wt %	57.0	57.7	74.8	72.1
Hydrogen, wt %	3.7	4.0	4.6	4.5
Oxygen, wt %	7.2	8.4	5.3	5.4
Nitrogen, wt %	1.1	1.1	1.4	1.3
Moisture, wt %	12.3	17.5	2.7	7.9
\$/ton (at mine)	26.10	30.68	33.40	34.99
\$/ton (transport)	7.90	7.90	7.90	7.90

[a] Model results for a 30% sulfur reduction on a lb/MBtu basis using conventional coal cleaning (level 3 plant design)

The selection of parameters for probabilistic representation was based on a review of reported information, statistical analysis, and judgments by process developers and Rubin et al. (1988) and Frey (1991). The uncertainties are intended to represent the possible ranges that could be obtained in mature (i.e. fifth-of-a-kind) commercial units.

Identification of Key Uncertainties

Interactions among uncertain input variables result in uncertainties in total costs, which are often a key basis for comparative analysis. Research

TABLE 3. Nominal Parameter Values and Uncertainties for Advanced Environmental Control System

Model parameter (1)	Deterministic (nominal) value (2)	Probability distribution (3)	Values (or σ as % of mean) (4)
	(a) Copper Oxide Process[a]		
Fluidized-bed height	48 in.		
Sorbent copper loading	7 wt–%		
Regeneration efficiency	99.2%	–1/2 normal	20%[b]
Fluidized sorbent density	400 kg/m^3	Normal	10%[b]
Standard error, Cu/S ratio	0	Normal	$\sigma = 0.39$[c]
Sorbent attrition	0.06%	Normal	41%[b]
Ammonia stoichiometry	(calc)	Normal	6.25%[b]
Regeneration temperature	900°F	Normal	2%[b]
Number of operating trains	4	Chance	10% at 1[d]; 20% at 2[d]; 40% at 3[d]; 30% at 4[d]
Number of spare trains	1	Chance	50% at 0[d]; 50% at 1[d]
Sorbent cost	$5.00/lb	–1/2 normal	25%[b]
Methane cost	$4.50/mscf	1/2 normal	25%[b]
Ammonia cost	$150/ton	Uniform	$150–225/ton[e]
Sulfuric acid cost	$40/ton	–1/2 normal	30%[b]
Sulfur cost	$125/ton	–1/2 normal	30%[b]
Absorber direct capital cost	calc	Uniform	$1.0x$–$1.5x$[c]
Solids heater DCC	calc	Uniform	$1.0x$–$1.5x$[c]
Regenerator DCC	calc	Uniform	$1.0x$–$1.5x$[c]
Solids transport DCC	calc	Uniform	$1.0x$–$2.0x$[c]
Sulfur recovery DCC	calc	Uniform	$1.0x$–$1.2x$[c]
Total capital cost	calc	1/2 normal	10%[b]
	(b) Fabric Filter		
Air-to-cloth ratio	2.0 a cu ft m/sq ft	–1/2 normal	10%[b]
Bag life	calc	Normal	25%[b]
Energy requirement	calc	Normal	10%[b]
Bag cost	$0.80/sq ft	Normal	5%[b]
Operating cost	calc	Normal	15%[b]
Total capital cost	calc	Normal	15%[b]
	(c) Solid Waste Disposal		
Land cost	$6,500/acre	Normal	10%[b]
Direct cost	calc	Normal	10%[b]
Operating cost	calc	Normal	10%[b]

[a] As part of integration of the copper oxide process with the base power plant, the plant air preheater is resized to maintain an exit flue gas temperture of 300°F.

[b] Standard deviation as % of mean value.

[c] Standard deviation.

[d] Probabilities of obtaining specific values.

[e] Actual value.

Note: a cu ft m = actual cubic feet per minute; mscf = 1,000 standard cubic feet.

can provide additional information about the uncertain input variables, resulting in changes in their uncertainty distributions (such as the mean or standard deviation) and, in turn, in the overall uncertainties of the technology. Therefore, it may be fruitful to target research to the uncertainties that contribute most to the risk of technology failure.

The key uncertainties were identified by estimating correlations between total levelized cost and the input uncertainties included in Table 3. Correlations provide a measure of the linear dependence of one distribution on another. Scatter plots can also be used to visually identify nonlinear dependencies that may not be well characterized by correlation coefficients.

The factors that contributed most to uncertainty in the total levelized cost were uncertainties in sorbent attrition, regeneration efficiency, and copper-to-sulfur molar ratio, with correlations of 0.55, -0.41, and 0.41, respectively. These are the most sensitive parameters in the model over the ranges of values considered. Scatter plots did not reveal any strong nonlinear dependencies. These results suggest that further research on the copper oxide process should focus on improving understanding of these key factors to reduce the risks of the technology.

Characterizing Uncertainty in Capital Costs

In deterministic cost estimates, a contingency is an additional cost that is expected to occur, but is not included explicitly in the estimate. Contingency costs are often estimated using simple rule-of-thumb multipliers applied to installed equipment cost estimates. The Rand Corporation conducted a survey of 18 companies in the chemical and petroleum industries to determine the actual methods used to develop contingency factors (Milanese 1987). The study concluded that contingency factors are often badly underestimated. Rand recommends greater and more formalized use of experience, the use of the Delphi technique to get multiple expert inputs, and the inclusion of costs associated with risks and innovation.

A probabilistic modeling approach supplants the contingency-factor approach by incorporating expert knowledge about uncertainties explicitly and at a more disaggregated level (e.g., for specific performance and cost parameters). Furthermore, while contingency factors provide no insights into the specific performance or cost parameters that contribute most to the process technical and economic risks, a probabilistic approach permits identification and ranking of key uncertainties, as discussed earlier.

The Electric Power Research Institute (EPRI) uses two types of contingency factors: project and process contingency (EPRI: "TAG" 1986). The project contingency is intended to cover costs that would result from a more detailed design of a definitive project at a specific site. In the present analysis, a project contingency of 25% is assumed for the copper oxide process, based on an earlier study (Drummond et al., unpublished, 1985). The process contingency is intended to quantify additional costs expected due to uncertainty in the future commercial-scale performance and cost of a new technology. This contingency factor is reduced as a technology proceeds from bench scale to full commercial use. However, there is little substantive discussion of how these factors should be derived.

The contingency factor should be selected based on understanding of the associated probability of cost overrun. An example of this type of analysis is shown in Fig. 3, which shows the results of a probabilistic analysis of the capital cost of the copper oxide process. The mean value of the distribution was $111,000,000. For a completely deterministic case using nominal values

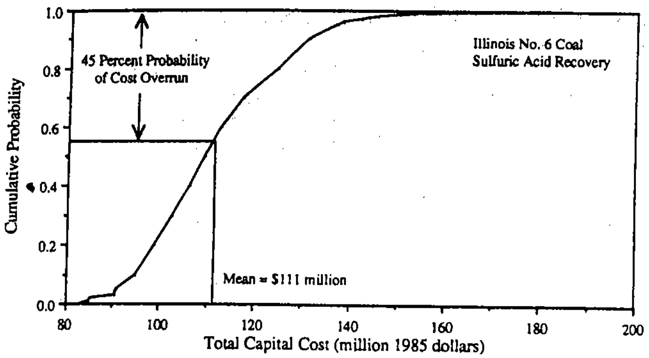

FIG. 3. Uncertainty in Total Capital Costs for Copper Oxide Process

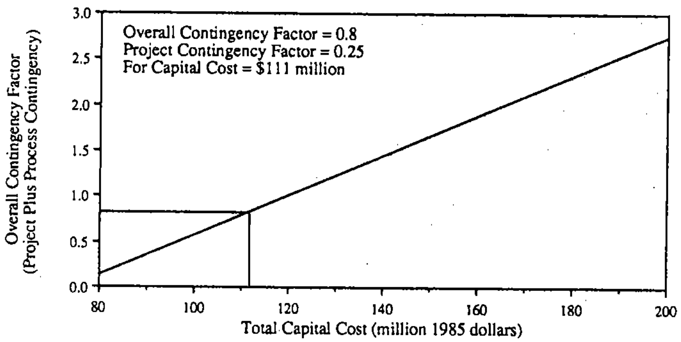

FIG. 4. Overall Contingency Factor and Total Capital Costs

with no contingencies the cost was $74,000,000. As illustrated in Fig. 4, the mean value of the probabilistic analysis corresponds to a deterministic contingency factor of 80% overall, or a 55% process contingency in addition to the 25% project contingency. The probability of an overrun at this contingency factor was 45%. A more risk-averse decision maker would elect a higher contingency factor, giving a lower probability of cost overrun.

The contingency factor estimated in this fashion is significantly higher than the value of 55% overall assumed in previous analyses (Drummond et al., unpublished, 1985). The difference is largely due to the uncertainties assigned to the regeneration efficiency and the capital costs for each major process section, which are skewed. The fact that the original rule-of-thumb estimate appears to be too low is consistent with the results of the Rand study.

Optimizing Design Parameters

An analysis of process performance and cost trade-offs was done to select optimal values of key copper oxide design parameters such as fluidized-bed height, air-preheater size, weight percent of copper in the sorbent, and sulfur-recovery option. Furthermore, the model was used to identify potential market niches based on coal characteristics.

The evaluation of design trade-offs considered performance and cost interactions between the copper oxide process and the balance of the power plant system, as well as interactions within the process itself. The objective was to minimize the overall cost of the pollution control system, including SO_2, NO_x, and PM removal, solid-waste handling, and coal cleaning. Any changes to the base plant related to the emission-control system were charged to the pollution-control system. Furthermore, because design decisions may be affected by uncertainties, analyses of trade-offs were based on probabilistic estimates of the costs associated with various designs. The details of this analysis were reported elsewhere (Frey and Rubin 1991). Two examples are summarized here.

One process-integration issue is the recovery of energy added to the flue gas in the fluidized-bed absorber. A deterministic best-guess analysis indicated that there was an overall cost penalty to enlarging the air preheater to recover this energy. However, a probabilistic analysis indicates that an enlarged air preheater provides an overall cost savings. The difference in results is due to skewed uncertainties assigned to key parameters in the probabilistic model. Furthermore, the model accounts for downstream effects, such as the size of the fabric filter, which are often neglected by process developers. The cost of the fabric filter is reduced by the larger air preheater, because the fabric-filter inlet flue-gas temperature, and the corresponding volumetric flue-gas flow rate, are reduced.

Coal cleaning also affects process costs. Because many of the costs of the copper oxide process are sensitive to sorbent flow rate, which in turn is proportional to the sulfur content of the coal, a reduction in the coal sulfur content through coal cleaning can reduce process costs. In contrast, the FGD/SCR system is comprised of two separate reactor vessels for SO_2 and NO_x control, both of which are proportional in cost primarily to the flue-gas flow rate and not significantly influenced by coal cleaning. Fig. 5 shows the mean levelized pollution control costs of each component of the copper oxide system associated with various levels of coal preparation for an Illinois No. 6 coal. Fig. 5 illustrates the strong relationship between copper oxide process costs and coal sulfur content, and the incremental costs associated with coal cleaning. For medium- and low-sulfur coals, the increased costs of coal cleaning are larger than the reduction in copper oxide process costs.

In the following comparisons of FGD/SCR and copper oxide systems, optimal levels of coal cleaning are used. There is no coal cleaning for FGD/SCR systems and copper oxide systems with the Pittsburgh coal, and there

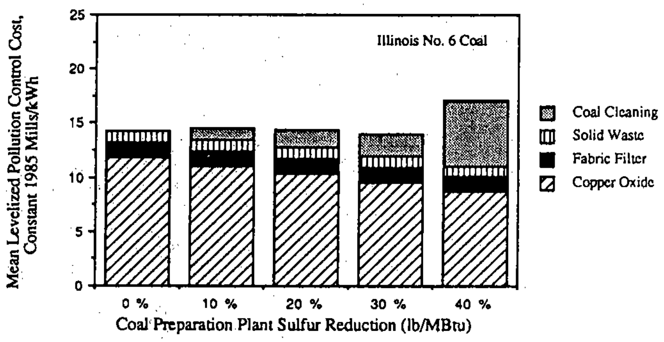

FIG. 5. Mean Levelized Pollution-Control Cost versus Sulfur Reduction from Coal Cleaning

is 30% coal-sulfur reduction for copper oxide systems with the Illinois No. 6 coal.

COMPARATIVE ANALYSIS: COPPER OXIDE VERSUS FGD/SCR

Four probabilistic comparisons of the copper oxide and FGD/SCR systems were made for two coals and for two copper oxide byproduct recovery options. These comparisons provide information about the likely cost savings and risks of the advanced emission control technology.

Because several of the input parameter distributions are common to both systems (e.g., financial parameters, base plant characteristics, solid-waste disposal, and ammonia cost), there is a positive correlation between the cost distributions for the two systems. Therefore, in determining the distribution for the cost *differences* between the copper oxide and FGD/SCR systems, the cost distribution samples for both systems were paired accordingly.

Fig. 6 shows the differences in levelized costs between the FGD/SCR and copper oxide systems. In all cases, the copper oxide process is likely to be less expensive than the FGD/SCR system; however, for the higher sulfur coal there is a substantial risk that the copper oxide process will be more expensive. Taking the case with sulfur recovery as an example, there is nearly a 30% probability that the new process will have higher cost than conventional technology.

The risk of higher cost can be quantified using the partial mean of the cost difference distribution for all negative values. The downward and upward partial means are defined as (Buck and Askin 1986)

$$\mu_d(x) \equiv \int_{-\infty}^{0} x f(x)\, dx \quad \text{(1)}$$

$$\mu_u(x) \equiv \int_{0}^{\infty} x f(x)\, dx \quad \text{(2)}$$

where $f(x)$ is the probability density function for the random variable x. In our example, the downward partial mean is -0.8 mills/kWh and the upward partial mean is 2.5 mills/kWh. These sum to the distribution mean. The conditional partial mean is based on the partial mean and the probability that a loss or grain has occurred. For example, the expected value of a loss, given that a loss has occurred, is

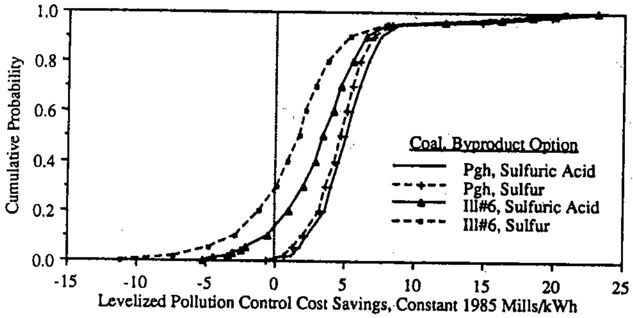

FIG. 6. Comparison of Levelized Pollution-Control Cost Savings for Copper Oxide versus FGD/SCR Systems: Effect of Coal and By-Product Recovery Option

$$\mu_{d|x<0}(x) \equiv \frac{\mu_d(x)}{P(x<0)} \quad \text{(3)}$$

where $P(x < 0)$ = probability that the random variable x has a value less than zero. The expected value of a gain, given that a gain has occurred, is defined similarly. For our example, the expected value of a loss is 2.8 mills/kWh if a loss occurs, and the expected value of a gain is 3.5 mills/kWh if a gain occurs.

The information provided by this analysis can be used to answer questions about the risks and potential payoffs of the new technology. While the copper oxide process is unlikely to be commercialized for another 5–15 years, process research will ultimately be used to make decisions about what emission-control system to use for a specific application. Therefore, it is reasonable to look at the decision a hypothetical process adopter would make with currently available information vis-à-vis information expected to be yielded from research over the next several years.

The opportunity loss from a decision to adopt the copper oxide process is given by the downward partial mean (Moore and Chen 1984). The downward partial mean is the same as the expected value of perfect information (EVPI) for the case in which the loss function, $L(x)$, of a potential adopter is represented as linear for all negative outcomes and zero for all positive outcomes, i.e.

$$E[L(x)] = \int_{-\infty}^{\infty} L(x) f_x(x)\, dx \quad \text{(4)}$$

where

$$L(x) = x, x < 0 \quad (5a)$$

$$L(x) = 0, x > 0 \quad (5b)$$

The downward partial mean is the maximum amount that a decision maker (with the given loss function) would be willing to pay to obtain perfect information to avoid the downward risk. Although research is unlikely to completely resolve uncertainties, research that leads to a reduction in the probability of a loss through process improvements has value as information to a potential process adopter. The value of information is one measure by which to bound the expenditures on research, development, and demonstration (RD&D).

CONDITIONAL EXPECTED VALUE OF ADDITIONAL RESEARCH

While additional research may reduce the downward risk of a new technology, it can also lead to incremental improvements, which would, in turn, increase the expected value of cost savings compared to conventional technology. The value of research may thus be estimated based on incremental increases in the expected cost savings, rather than on the reduction in downside risk.

Several factors must be considered in determining the value of research. First, judgment is required to estimate the likely results from a research effort. The value of research depends also on the circumstances of actual adoption of the new technology, which determines the ultimate cost savings compared to other technology. Judgment is required regarding the likely plant sizes, by-product markets, coal characteristics, and other influencing factors that will face the new technology. It is unlikely that any single cost estimate can be used for such an analysis; rather, several case studies representative of different applications may be required. A third factor is the possibility of simultaneous improvement in competing processes.

Here we consider the effect of possible research results on the comparative costs of the copper oxide versus FGD/SCR systems. It is assumed that research can reduce the uncertainties in several key process variables. Because the key uncertainties in process cost are related to regeneration, solids transport, and the stoichiometric copper-to-sulfur ratio, it is assumed that new research would be focused on these areas. Table 4 shows illustrative assumptions made about the reduction of uncertainties in regeneration efficiency, regeneration temperature, the equipment costs for the regenerator and solids-transport system, sorbent attrition, and the copper-to-sulfur molar ratio.

Four case studies are used to illustrate that the value of research is conditional on applications, although no attempt is made to forecast the diffusion of the copper oxide process into commercial use. For simplicity, it is assumed that the FGD/SCR pollution-control system is relatively mature, and that, as an approximation, there will be no incremental improvements in FGD/SCR system costs.

Levelized cost differences based on Illinois No. 6 coal and elemental sulfur recovery are shown in Fig. 7 for levelized costs. Shown are differences based on current information, and selected results based on information from further research. The assumptions about additional research reduced the variance of the cost difference distributions, but also reduced the skewness (due to assumptions about the regeneration efficiency). Thus, the assumed research outcomes have reduced the downside risk and increased the expected cost savings of the new technology.

TABLE 4. Case Studies for Reduction in Copper Oxide Process Uncertainties due to Research

Model parameter (1)	Nominal value (2)	Probability distribution (3)	Values (or σ as % of mean) Prior to research (4)	After research (5)
		(a) Regenerator		
Regeneration efficiency	99.2%	– 1/2 normal	20%	5%
Regeneration temperature	900°F	Normal	2%	1%
Reageneration direct capital cost	calc	Uniform	1.0*x*–1.5*x*	1.1*x*–1.4*x*
		(b) Solids Transport		
Sorbent attrition	0.06%	Normal	41%	10%
Solids transport direct capital cost	calc	Uniform	1.0*x*–2.0*x*	1.1*x*–1.8*x*
		(c) Absorber		
Standard error, Cu/S ratio	0	Normal	σ = 0.39	σ = 0.2

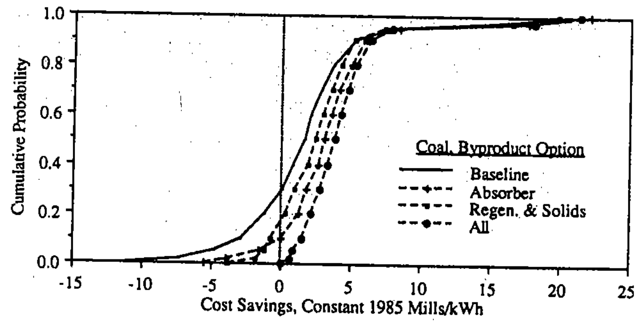

FIG. 7. Levelized Pollution-Control Cost Savings for Copper Oxide/Sulfur Plant System, Washed Illinois No. 6 Coal: Effect of Illustrative Research Outcomes

The results from additional research for all four cases are summarized in Table 5 using the statistics discussed previously. These statistics include the probability of the copper oxide process being more expensive than an FGD/SCR system, the downward partial mean, the downward and upward conditional partial means, and the mean for the entire cost-difference distribution. The hypothesized research results reduced the downward partial mean of the cost differences for all cases, and therefore reduced the risk of an opportunity loss to a potential process adopter.

The mean cost difference with more research for all targeted process areas was higher than for current estimates. It can be seen in Table 5 that the value of research in terms of cost improvements was significantly greater than the reduction in downside risk. Thus, the value of research may be greater than the EVPI discussed previously because of skewness in key uncertainties.

IMPLICATIONS FOR RESEARCH PLANNING

The data summarized in Table 5 can be used to answer a number of key questions such as the following.

- Is one technology preferred over another?
- Is additional research merited?
- What should be the research strategy?
- How much is additional research worth?
- Under what conditions does the decision strategy change? (i.e., how robust is the decision strategy?)

These questions can be answered using decision analysis. The discretization of the continuous probability distributions given in Table 5 facilitates the use of relatively simple decision trees to evaluate research strategies. An example of such a decision tree based on the case with high-sulfur coal and elemental sulfur recovery is given in Fig. 8. First, we will consider decisions based on expected cost savings, and then briefly consider a more detailed decision model incorporating the risk attitudes of a decision maker and the time value of research outcomes.

The tree in Fig. 8 includes three types of decisions. The first is a choice between advanced and conventional systems based on current knowledge.

TABLE 5. Results of Research Information Case Studies: Comparison of Levelized Total Pollution Control Costs for Copper Oxide versus Conventional FGD/SCR

Research area (1)	Probability of a loss (%) (2)	Downward partial mean (mills/kWh) (3)	Expected value of loss (mills/kWh) (4)	Expected value of a gain (mills/kWh) (5)	Mean (mills/kWh) (6)	Reduction in risk (mills/kWh) (7)	Value of research (mills/kWh) (8)
(*a*) Sulfuric Acid Recovery, Washed Illinois No. 6 Coal							
Baseline	15	−0.27	−1.7	4.6	3.6	—	—
Solids transport	10	−0.13	−1.4	4.2	3.6	0.14	0.0
Absorber	9	−0.16	−1.8	4.8	4.2	0.11	0.6
Regeneration	7	−0.09	−1.3	4.8	4.4	0.19	0.8
Regeneration and solids transport	2	−0.02	−1.1	4.5	4.4	0.25	0.8
All	0	0	0	5.1	5.1	0.27	1.5
(*b*) Sulfur Recovery, Washed Illinois No. 6 Coal							
Baseline	29	−0.81	−2.8	3.5	1.7	—	—
Solids transport	17	−0.25	−1.5	3.7	2.8	0.56	1.1
Absorber	11	−0.23	−2.0	4.1	3.4	0.58	1.7
Regeneration	18	−0.28	−1.6	3.8	2.8	0.53	1.1
Regeneration and solids transport	17	−0.17	−1.0	3.7	2.9	0.64	1.2
All	0	0	0	4.3	4.3	0.81	2.6
(*c*) Sulfuric Acid Recovery, Unwashed Pittsburgh Coal							
Baseline	1	>−0.01	−0.3	5.6	5.5	—	—
Solids transport	1	>−0.01	−0.3	5.6	5.5	0	~0.0
Absorber	1	>−0.01	−0.5	5.9	5.9	0	0.4
Regeneration	0	0	0	6.0	6.0	<0.01	0.5
Regeneration and solids transport	0	0	0	6.0	6.0	<0.01	0.5
All	0	0	0	6.4	6.4	<0.01	0.9
(*d*) Sulfur Recovery, Unwashed Pittsburgh Coal							
Baseline	2	>−0.01	−0.4	5.2	5.1	—	—
Solids transport	1	>−0.01	−0.4	5.2	5.1	0	~0.0
Absorber	2	>−0.01	−0.3	5.6	5.5	0	0.4
Regeneration	<1	>−0.01	>−0.1	5.6	5.6	0	0.5
Regeneration and solids transport	0	0	0	5.6	5.6	<0.01	0.5
All	0	0	0	6.0	6.0	<0.01	0.9

In this example, the copper oxide process without additional research is shown to have a positive expected cost savings. A second decision regards obtaining perfect information that would resolve all downside risks of the new process. The elimination of downside risk increases the expected value by 0.81 mills/kWh, and this is the EVPI. A third decision regards further R&D as discussed previously. The expected values of each research option were larger than for the current state of knowledge, indicating that additional research is merited. The most fruitful research strategy was to target all three major process areas. Compared to current information, such a strategy increases the expected value of the process by 2.6 mills/kWh; this is the basis for bounding expenditures on further research. These differences are summarized in Table 5 as the "Value of research" (column 8).

The risk attitude of a decision maker can be considered by using expected utility, rather than expected cost savings, as the basis for decision making. Utility is a measure of the personal value a decision maker places on a specific outcome and may differ from the associated monetary value (Dawes

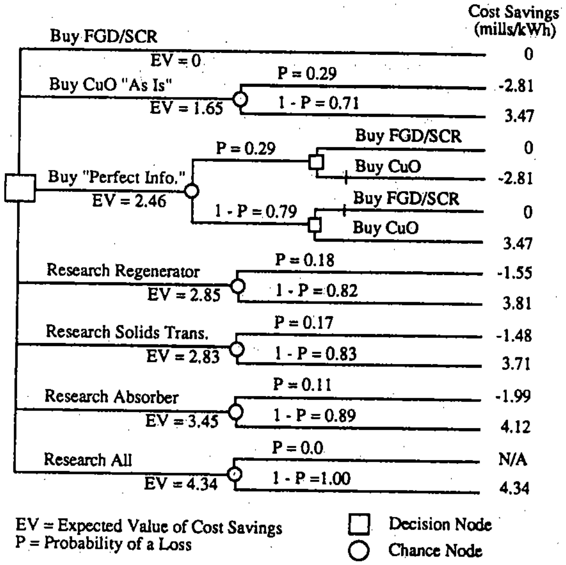

FIG. 8. Decision Tree for Copper Oxide Process Research Planning: Example for Illinois No. 6 Coal and Elemental Sulfur Recovery

1988). Furthermore, because research results may not be obtained for 5–15 years, the time value of the outcomes can be modeled using discounting. One possible utility function for a decision model is thus

$$u(x) = \left[\frac{x(i, n) - x_l(i, n)}{x_h(i, n) - x_l(i, n)}\right]^b \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

For a risk-neutral decision maker, $b = 1$. A risk-averse ($b < 1$) decision maker tends to be conservative and prefers a sure outcome over an alternative with a slightly higher expected value and a risk of a loss. Conversely, a risk-seeking ($b > 1$) decision maker is willing to forfeit an increase in expected value to take a risk. Examples of utility functions are plotted for normalized values of x and selected values of b in Fig. 9. A nominal value of $b = 0.6$ (risk averse) was used in the expected utility analysis.

The effect of discounting outcomes of research is to reduce their expected utility. For our example, research into all areas is preferred by a risk-averse decision maker if the payoff from research is obtained within 10 years at a discount rate less than about 20%. If the time to payoff exceeds 20 years, the discount rate would have to be less than 10% for this strategy to have the highest expected utility. Research results could reasonably be expected in the next 5–15 years. Thus, the best research strategy for high-sulfur coal applications is to wait for the results of further research. Only an extremely risk-seeking decision maker would choose to accept the copper oxide process as is. However, for the medium-sulfur coal, the robust strategy, considering risk attitude, discount rate, and time until research payoff, is to accept the copper oxide process as is, without further research.

As noted, the increase in expected value from research in all areas is 2.6 mills/kWh for the example case. This would be a savings of about $7,000,000

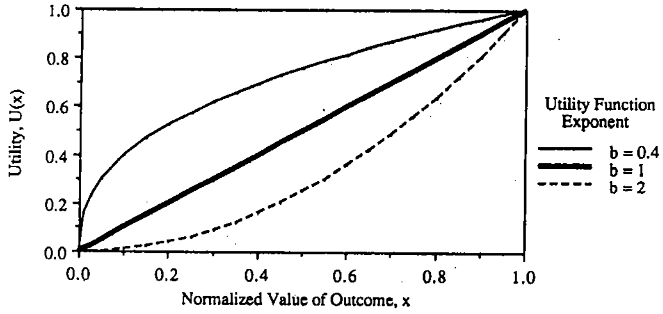

FIG. 9. Power Utility Function

annually for each 500 MW power plant at a capacity factor of 65%. The actual amount to be spent on research depends on how many and what size high-sulfur coal power plants would be expected to use the copper oxide process with elemental sulfur recovery.

Of course, a decision maker may not have the luxury of waiting for the outcomes of further research. The decision model can be expanded to consider other power-generation technology alternatives that may be required sooner. However, the model results suggest that, even without additional research, the copper oxide process is likely to yield cost savings over conventional technology.

COSTS OF DEMONSTRATION

Can results expected from research be obtained at a cost consistent with the estimated value of the research? To answer this question, it is important to consider the costs incurred in developing and demonstrating the technology. Of all the costs of RD&D, the first-of-a-kind plant costs are by far the most expensive. The Rand Corporation has conducted a number of studies regarding cost growth for first-of-a-kind plants using a data base containing 106 cost estimates prepared, at various stages of development, for 44 chemical process plants. From the data base, a regression equation for capital-cost growth from estimated to actual costs was developed, based on factors such as the complexity and newness of the technology (Hess, et al. 1987). Application of this equation to the copper oxide process indicates that capital cost growth of a factor of 2.3 can be expected. Thus, any cost differences between different applications will be magnified for the demonstration plant. For example, using the deterministic assumptions in Table 3 and the Rand cost-growth model, the capital cost of a 125 MW copper oxide demonstration unit with an unwashed Illinois No. 6 coal was estimated to be $56,000,000. For an unwashed Pittsburgh coal, the estimated capital cost of a demonstration unit of the same size was $9 million less. The value of research must be weighed against these and other research costs.

CONCLUSIONS

A probabilistic engineering model can be used during the research phase of a technology to provide insights into important design trade-offs and key uncertainties. In some cases, the integrated model of the copper oxide process provided insights into performance trade-offs that were contrary to common assumptions, and the incorporation of uncertainties led to a different result than deterministic analysis. Thus, the model applications yielded important insights that would otherwise have been overlooked.

Probabilistic cost comparisons between conventional and advanced technology can be used to estimate the likely cost savings and the risks of a new technology. These comparisons may be changed by future research. The probabilistic engineering model and a decision model provided a framework for evaluating judgments regarding the outcomes of research. The value of the research, coupled with judgment about the extent and nature of technology diffusion, can be used to bound research expenditures. Whether research is feasible depends also on the costs of the first commercial-scale demonstration plant. Because these costs are potentially large, care must be exercised in the selection of an appropriate first application.

As with any other modeling approach, the results here depend on the assumptions made regarding both deterministic and uncertain model inputs. A key benefit of probabilistic analysis is to force process engineers to think more systematically about the ranges and likelihoods of possible values for multiple model-input parameters, rather than settle on a best-guess point estimate. The results of probabilistic analysis provide more meaningful estimates of the risks and payoffs of new technology than deterministic or sensitivity analysis. Using probabilistic techniques, process engineers can make more fully informed decisions regarding process design, technology selection, and research planning in the face of uncertainty.

ACKNOWLEDGMENTS

This work was supported under contract DE-AC22-87PC79864 for the U.S. Department of Energy Pittsburgh Energy Technology Center. However, all assumptions and conclusions appearing in this paper are those of the writers alone.

APPENDIX I. REFERENCES

Buck, J. R., and Askin, R. G. (1986). "Partial means in the economic risk analysis of projects." *Engrg. Economist*, 31(3), 189–211.

Carr, R. C. (1986). "Integrated environmental control in the electric utility industry." *APCA/ASME/EPRI 3rd Symp. on Integrated Envir. Controls*, Pittsburgh, Pa.

Dawes, R. M. (1988). *Rational choice in an uncertain world.* Harcourt Brace Jovanovich, San Diego, Calif.

"TAG—Technical assessment guide, volume 1: Electricity supply." (1986). *EPRI P-4463-SR*, Electric Power Research Institute (EPRI), Inc., Palo Alto, Calif.

Frey, H. C. (1987). "Performance and economic model of the fluidized bed copper oxide process," thesis presented to Carnegie Mellon University, at Pittsburgh, Pa., in partial fulfillment of the requirements for the degree of Master of Engineering.

Frey, H. C. (1991). "Probabilistic modeling of innovative clean coal technologies: Implications for technology evaluation and research planning," thesis presented to Carnegie Mellon University, at Pittsburgh, Pa., in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

Frey, H. C., and Rubin, E. S. (1991). "Probabilistic evaluation of advanced SO_2/NO_x control technology." *J. Air and Waste Mgmt. Assoc.*, 41(12), 1585–1593.

Henrion, M., and Wishbow, N. (1987). *Demos user's manual: Version 3.* Carnegie Mellon University, Pittsburgh, Pa.

Hess, R. W., Merrow, E. W., and Pei, R. Y. (1987). "An application of the pioneer plants study methodology to a first-of-a-kind MHD central station." *N-2368-DOE*. Rand Corporation, Santa Monica, Calif.

Milanese, J. J. (1987). "Process industry contingency estimation: A study of the ability to account for unforeseen costs." *N-2386-PSSP*. Rand Corporation.

Moore, W. T., and Chen, S.-N. "The value of perfect information in capital budgeting decisions with unknown cash flow parameters." *Engrg. Economist*, 29(1), 41–51.

Robie, C. P., Ireland, P. A., and Cichanowicz, J. E. (1989). "Technical feasibility and economics of SCR NO_x control in utility applications." *Symp. on Stationary Combustion Nitrogen Oxide Control, Volume 2: EPRI GS-6423*, Elecric Power Research Institute (EPRI), Palo Alto, Calif.

Rubin, E. S., Salmento, J. S., Barrett, J. G., Bloyd, C. N., and Frey, H. C. (1986). Modeling and assessment of advanced processes for integrated environmental control of coal-fired power plants. *Report*, Carnegie Mellon University, Pittsburgh, Pa.

Rubin, E. S., Salmento, J. S., and Frey, H. C. (1988). "Evaluating combined SO_2/NO_x processes." *Proc. 4th Symp. on Integrated Envir. Control: EPRI Report No. GS-6519*, Electric Power Research Institute (EPRI), Palo Alto, Calif., 6-1–6-15.

APPENDIX II. NOTATION

The following symbols are used in this paper:

b = risk attitude exponent;
i = discount rate (decimal);
n = time period (years);
x = discounted outcome of given alternative;
x_h = discounted upper limit of x for all alteratives; and
x_l = discounted lower limit of x for all alternatives.

APPENDIX III. CONVERSIONS TO SI UNITS

To Convert	To	Multiply By
acre	Ha	0.405
Btu/kWh	J/kWh	1,054
cu ft	m^3	0.0283
in.	m	0.0254
lb/MMBtu	kg/GJ	0.4307
pound mass (lb)	kg	0.454
short ton	metric ton	0.9072
sq ft	m^2	0.0923