# MODELING UNCERTAINTIES IN IGCC SYSTEM PERFORMANCE AND COST

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## ABSTRACT

This paper discusses the development of performance and cost models for integrated gasification combined cycle (IGCC) systems. Because few IGCC concepts have been demonstrated at a large scale, there is considerable uncertainty regarding the commercial scale performance and cost of these systems. The key feature of this work is the use of a probabilistic approach to performance and cost modeling, in contrast to conventional deterministic (point-estimate) methods. The development of selected IGCC engineering and cost models and the use of the probabilistic approach is illustrated for a specific process area.

## INTRODUCTION

Integrated gasification combined cycle (IGCC) systems are a promising new approach for the clean and efficient use of coal for power generation. However, there is still very limited experience with these systems. Uncertainties in the performance of IGCC systems may arise in the development of new processes (e.g., new gasifier designs), or in new applications of conventional technologies to an IGCC system (e.g., gas turbines fired with medium-BTU coal gas). Uncertainties in performance may, in turn, lead to uncertainties about the required sizes of process equipment, consumption of materials, or parasitic power requirements of a particular process. Furthermore, even if process performance is known with certainty, there is typically uncertainty in the cost of equipment, maintenance, operation, consumables, byproduct credits, and waste disposal. Failure to fully account for uncertainties in process performance and cost often results in misleading estimates for comparative analysis and planning, particularly for pioneer process plants [1].

In this paper, a new method for evaluating the performance and cost of IGCC power systems is presented. The main features of this approach include:

- Engineering performance and cost models for technologies of interest
- A probabilistic modeling capability to incorporate uncertainties in an analysis
- Specification of uncertainties using expert judgment and data analysis
- Exercising the models to answer questions such as:
    - What is the range of uncertainty in measures of process viability (e.g., efficiency, emissions, cost)?
    - What are the factors that contribute most to overall uncertainty?
    - What are the implications for technology applications, process design, research planning and cost estimation?

## BACKGROUND AND SCOPE

A number of IGCC performance models have been developed by the U.S. Department of Energy's Morgantown Energy Technology Center (DOE/METC) [2] using ASPEN, a chemical process simulator [3]. One limitation of ASPEN has been the ability to analyze uncertainties. Typically, sensitivity analysis is employed in which only one or two parameters are varied at a time in a simulation containing hundreds of independent variables. Thus, important interactions or cases could be overlooked. Another limitation of the existing IGCC process models has been a lack of directly coupled cost models, which has prevented the simultaneous evaluation of process performance and economics in a single computer simulation. The work described in this paper has addressed both of these limitations.

To explicitly characterize uncertainties in processes simulated in ASPEN, a general probabilistic modeling capability has been developed and implemented [4]. To evaluate the process economics of selected IGCC systems, new cost models, which estimate capital and annual costs, also have been developed [5]. The present paper describes the development of these models and gives an example application in the probabilistic ASPEN environment. Potential applications of the probabilistic modeling method then are briefly summarized.

## PERFORMANCE AND COST MODELS

Three IGCC systems for which ASPEN performance models previously have been developed by DOE/METC were selected for cost model development. The three IGCC systems represent different approaches for the gasification of coal and purification of the resulting fuel gas prior to firing in a gas turbine combined cycle. These include systems using: (1) an oxygen-blown fluidized-bed gasifier with "cold" (i.e., temperatures of approximately 100 $^{o}$F) fuel gas cleanup (representing a baseline technology); (2) an air-blown fluidized-bed gasifier with "hot" (i.e., temperatures of about 1,100 $^{o}$F) fuel gas cleanup and gasifier in-bed desulfurization; and (3) an air-blown fixed-bed dry-ash gasifier with hot gas cleanup.

An example of one of the ASPEN performance models is shown schematically in Figure 1. The performance models calculate mass and energy balances for the processes and track environmentally important chemical species. Figure 1 represents an air-blown system with hot gas cleanup. The major plant sections which are modeled and the major stream flows between process areas are shown. The model utilizes ASPEN's modular features to represent specific process unit operations and their interconnecting material, heat, and work streams.

In the new work described here, cost models for each of the three IGCC systems were developed based on a review of approximately 30 comprehensive conceptual design studies prepared for DOE, the Electric Power Research Institute (EPRI), and the Gas Research Institute (GRI), as well as other studies which focused on specific process components [5]. The models provide "preliminary" estimates of process capital and operating costs based on the standard method developed by EPRI [6]. To link process flowsheet parameters with economic cost models, the approach was to model costs at the level of major plant sections for each IGCC technology. For each system, there are approximately a dozen major process sections.

The direct capital cost of each process section was modeled separately. Analytical relationships between direct cost and key performance parameters were developed from published data, typically based on regression analysis. By summing the individual section costs, the total direct cost of each

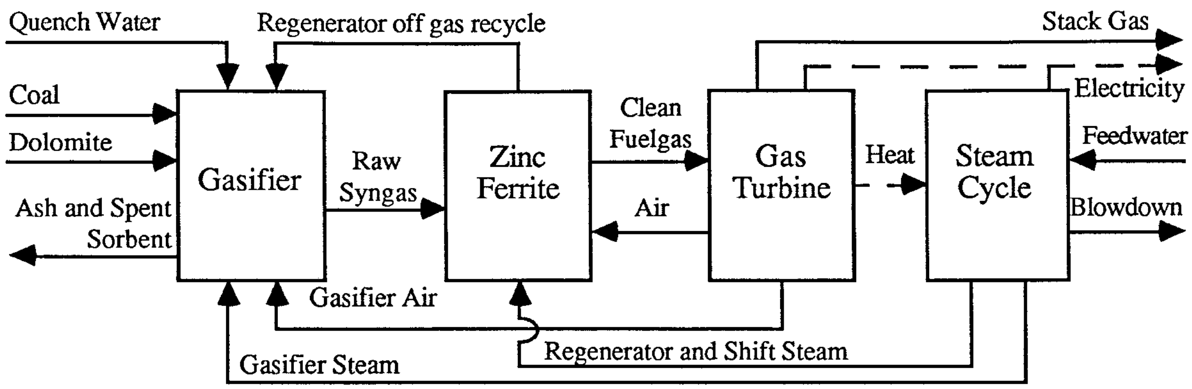


Figure 1. Conceptual Diagram of ASPEN Flowsheet of Air-Blown Fluidized Bed Gasifier IGCC System with In-Bed Desulfurization and Zinc Ferrite Process

IGCC system is sensitive to approximately two dozen performance parameters, in addition to process design parameters such as the number of operating and spare trains of equipment.

For each IGCC system, the total capital cost is then obtained as the sum of: (1) the total direct cost for all major process areas; (2) indirect costs, such as engineering and home office fees; (3) contingency costs; (4) allowance for funds during construction; (5) preproduction (startup) costs; and (6) initial catalysts and chemicals inventory costs. Models for each of these components were developed using standard costing methods [5]. For example, indirect costs typically are expressed as fractions of the total direct cost. A special case, however, is the inclusion of contingency costs. In conventional deterministic analysis, contingencies costs represent the additional capital requirement expected as a result of uncertainties in process performance and site-specific factors. In this regard, EPRI distinguishes between "process" and "project" contingency costs. The probabilistic modeling capability now included in ASPEN, however, allows uncertainties in process costs to be quantified explicitly. Thus, for a probabilistic analysis, the process contingency cost is no longer needed, and only the project contingency factor is retained. Of course, the cost models developed here also can be used in a deterministic mode. In this case, both project and process contingency factors are included. A more complete discussion of contingency costs in the context of probabilistic modeling can be found in Reference 5.

In addition to capital cost models, models for annual costs of IGCC systems also have been developed. These include fixed (e.g., operating labor and maintenance) and variable (e.g., consumables) costs. The consumption rates of consumables are modeled based on data from published studies. The annual cost models also include byproduct credit for sulfur recovery.

The total revenue requirement for an electric power plant is often the key parameter of interest, and is typically expressed as the cost of electricity. The cost of electricity model for each system includes economic and financial parameters, plus models for the power consumption of major plant sections, which are required to determine the net plant power output . All cost models have been coded in Fortran and implemented as subroutines along with the ASPEN performance models [5].

The development of direct capital cost equations for each process area is the fundamental building block of the IGCC cost models. Therefore, we present below a more detailed discussion of the considerations involved in direct cost model development, together with an example. An example of an annual cost model for the same process area is also given. The models are then used to illustrate the probabilistic modeling capability.

## EXAMPLE OF COST MODEL DEVELOPMENT

There are three major considerations in developing cost models, including: (1) the state of technology development for the process of interest; (2) the intended use of the cost model; and (3) the availability of data from which to develop relationships between cost and performance. These considerations are inter-related. In the case of technologies not yet commercially demonstrated, performance information typically is available either from experimental studies with small-scale systems, or from conceptual design studies which attempt to project the performance of a commercial-scale system. Cost data are often reported in the conceptual studies at a limited level of detail on the basis of major plant sections rather than for specific pieces of equipment. Therefore, the appropriate level of detail for a cost model of a new technology is one that captures the key relationships between performance and cost at the level of major plant sections.

Most of the direct capital cost models were developed using regression analysis based on data from conceptual design studies. An example of a regression approach to direct cost model development has been previously reported [7]. In this paper, an alternative approach is illustrated, based on equipment size estimates and published cost curves. The selected example is for a coal gas desulfurization system based on the fixed bed zinc ferrite process. Regression analysis was not possible for this process area because of the scarcity of sufficiently detailed design studies.

In the fixed bed zinc ferrite process, low molecular weight sulfur (primarily $H_2S$) is removed from the coal gas by reaction with a sorbent consisting of zinc ferrite ($ZnFe_2O_4$) in extruded 3/16 inch diameter by 1/2 inch long pellets. The sorbent is held in a fixed bed in a pressure vessel, through which the coal gas flows vertically. Absorption occurs until outlet sulfur "breakthrough." The coal gas is then diverted to a second zinc ferrite reactor vessel. The spent sorbent in the first vessel undergoes regeneration, yielding an offgas containing sulfur dioxide. The offgas may be processed for recovery of a sulfur or sulfuric acid byproduct or, in IGCC systems featuring gasifier in-bed desulfurization, the offgas may be recycled to the gasifier.

Because the zinc ferrite plant section consists primarily of vertical pressure vessels, a preliminary direct cost model was developed based on published pressure vessel cost curves [8]. A design basis by Kasper [9] was used to develop models to size each reactor vessel. Other process area direct costs were estimated based on a recent design study [10]. In addition, a comparison of the cost model prediction and the cost estimate from another study [11] was made to verify the model.

The first step in estimating the zinc ferrite process area direct capital cost is to estimate the total initial sorbent charge. The overall absorption reaction is:

$$6\ ZnFe_2O_4 + 18\ H_2S + 5\ H_2 + CO \rightarrow 6\ ZnS + 12\ FeS + 23\ H_2O + CO_2 \qquad (1)$$

The maximum theoretical sulfur loading in spent sorbent is about 35 percent. However, the theoretical maximum is not likely to be achieved in practice. Therefore, a relationship between the required sorbent charge and the sorbent sulfur loading was developed. The sorbent charge is estimated as follows:

$$S_c = \left(\frac{N_T}{N_O}\right)\left(\frac{32 - 10.67\ L_s}{L_s}\right) M_S\ t_a \qquad (2)$$

where,

$S_c$ = Total sorbent charge to all zinc ferrite reactor vessels, lbs
$N_T$ = Total number of reactor vessels

$N_O$ = Number of on-line reactor vessels at full load
$L_s$ = Long-term sorbent sulfur loading, weight percent of spent sorbent
$M_s$ = Molar flow rate of low molecular weight sulfur species (e.g., H2S), lbmole/hr
$t_a$ = Absorption cycle time, hours

The number of on-line vessels at full load is estimated iteratively based on the coal gas volume flow rate, the volume of required sorbent, and constraints on the design of the zinc ferrite reactor vessels. These constraints include maximum vessel size, space velocity, and superficial gas velocity. The values of these constraints are variables that can be changed by a model user.

Cost curves for vertical pressure vessels from Ulrich [8] were converted to an analytical form using regression analysis. The cost of the pressure vessels depends on the vessel internal diameter, length, and operating pressure. The cost of auxiliary equipment, such as sorbent handling, piping, valving, and control systems was estimated by difference between the pressure vessel cost and the total direct cost reported in a recent design study [10]. For simplicity it was assumed that the cost of auxiliaries is a multiplier of the pressure vessel cost. The resulting direct capital cost model for the zinc ferrite process area, adjusted to a user-specified year, is:

$$DC = 1.477\, f_1(p)\,[f_2(d) + f_3(d)h]\, N_T \left(\frac{PCI}{351.5}\right) \tag{3}$$

where,

$$f_1(p) = 2.5 + 0.093p^{0.64}$$
$$f_2(d) = 4.1 - 4.35d + 0.96d^2 - 0.039d^3$$
$$f_3(d) = 0.23 + 0.17d - 0.018d^2 + 7.9\times10^{-4}d^3$$

and,

DC = Direct capital cost of the zinc ferrite process area, \$1,000
p = Operating pressure, psia
d = Internal diameter of the pressure vessels, ft
h = Height of the pressure vessels, ft
PCI = *Chemical Engineering* Plant Cost Index (for a user-specified year)

In the EPRI cost method, the cost of the initial sorbent charge is not included as part of the direct cost, but is reported separately as an initial cost for catalyst and chemical inventory.

Annual costs for the zinc ferrite process area include fixed operating costs for maintenance and variable operating costs for sorbent replacement. Makeup zinc ferrite sorbent is required to replace sorbent lost due to attrition. The operating cost associated with sorbent replacement is given by:

$$VOC_{ZF} = \frac{8{,}760\, c_f}{2\, t_a}\, r_a\, S_c\, UC_{zf} \tag{4}$$

where,

$VOC_{zf}$ = Variable operating cost for zinc ferrite sorbent replacement, \$/year
$c_f$ = Plant capacity factor, fraction of year at equivalent full load
$r_a$ = Sorbent attrition rate, weight percent per absorption/regeneration cycle
$UC_{zf}$ = Unit cost of zinc ferrite sorbent, \$/lb

The discussion of the zinc ferrite process area illustrates the development of a direct capital cost and an annual operating cost model. For a more complete discussion of the capital and annual cost models of the selected IGCC systems, see Frey and Rubin [6].

## SENSITIVITY ANALYSIS

A sensitivity analysis of the direct cost model for the zinc ferrite process area section is shown in Figure 2. The two curves represent two levels of sulfur concentration in the coal gas, representing typical values for IGCC systems with and without sulfur removal upstream of the zinc ferrite process unit. The direct cost is also shown to be sensitive to the long-term achievable sorbent sulfur loading. This example also illustrates the limitations of sensitivity analysis; although the model is sensitive to many parameters, only one or two parameters can be varied at a time to graphically illustrate the behavior of the model. Furthermore, while the ranges of input variables in a sensitivity analysis may represent judgments regarding "best" and "worst" outcomes, sensitivity analysis provides no information as to the likelihood of different outcomes.

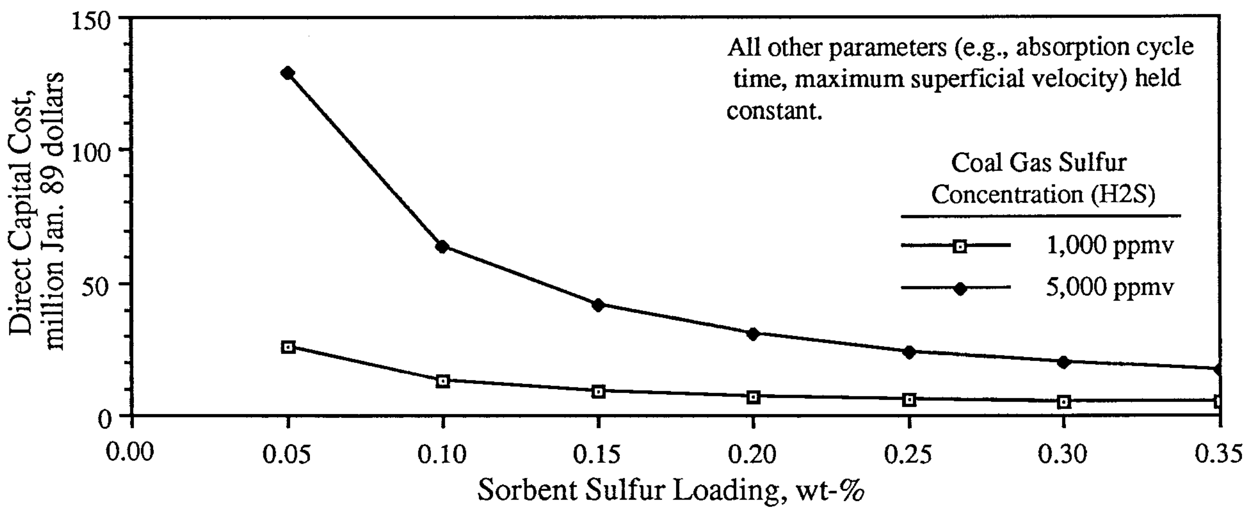


Figure 2. Sensitivity of Zinc Ferrite Direct Capital Cost

## A PROBABILISTIC ANALYSIS FRAMEWORK

The newly implemented capability for systematic analysis of uncertainties in ASPEN is based on a program developed by Iman and Shortencarier, which uses Latin hypercube sampling (LHS), a variant of Monte Carlo simulation [4,12] . With the new capability, several types of probability distributions (e.g., uniform, normal, and others) are available for characterizing uncertainty in flowsheet variables. The characterization of uncertainties in process technologies requires data analysis or judgments regarding the possible variation in each model parameter.

The probabilistic software environment in ASPEN also includes options for analyzing the results of a probabilistic simulation. For output variables selected by the user, the probabilistic simulation reports both a graph and table of the cumulative distribution function (cdf). In addition, a program developed by Iman, Shortencarier, and Johnson [13] has been integrated into ASPEN to quantify the sensitivity of model outputs to each of the uncertain input distributions [4]. The methods available for analysis of the model results include partial correlation coefficients and standardized regression coefficients for linear correlations, plus partial rank correlation coefficients and standardized rank regression coefficients for nonlinear correlations.

## A SIMPLE EXAMPLE

Use of the probabilistic modeling capability to characterize the uncertainty in the performance and cost of a process technology is illustrated with a simple example. The example is also intended to demonstrate some of the generic types of insights that may be obtained from probabilistic analysis. The example uses the performance and cost model of the zinc ferrite process area. Four model parameters were assigned probability distributions as shown in Table I. These include two performance and two cost parameters. Four different types of probability distributions were used to show the flexibility of representation available in the probabilistic modeling environment. These variables were given arbitrary ranges for this simple example. (The process of eliciting engineering judgments about uncertainties in the form of probability distributions is not addressed in the current paper.) The sorbent sulfur loading and capital cost uncertainty both affect the total direct cost, while the sorbent sulfur loading, attrition rate and unit cost affect the variable operating cost of this process area.

Table I. Illustrative performance and cost uncertainties.

| Parameter | Units | Distribution | Range (Mode)[a] |
|---|---|---|---|
| Sorbent Sulfur Loading | wt-% | Uniform | 10 - 20 |
| Sorbent Attrition Rate | wt-%/cycle | Normal | 0.15 - 0.25 |
| Sorbent Unit Cost | $/lb | Triangle | 2 - 5 (3) |
| Capital Cost Uncertainty | % of direct cost | Lognormal | -20 to 65 |

[a] For uniform and triangle distributions, the range is the 100 percent probability range. For other distributions, the range is the 99.8 percent probability range. All costs are January 1989 dollars.

### Running the Simulation

The probabilistic simulation was run on a DEC Vaxstation 3200 computer. The coupled performance and cost models required approximately 200 CPU seconds to execute a single deterministic simulation. The total run-time for a probabilistic simulation is a linear function of the number of samples. Alternatively, in the special case where uncertainties in only selected variables in the cost model subroutine are of interest, the cost models can be run stand-alone. In stand-alone mode, the results of a single deterministic simulation of the IGCC performance model must be given as input to the cost model. The cost model subroutine can then be run as a standard Fortran program (for deterministic analyses) or as a subroutine linked to the probabilistic capability in ASPEN (for probabilistic analyses). Because the uncertainties in Table I apply only to variables in the cost model subroutine, the cost model was run in stand-alone mode. The execution time for the stand-alone cost model with 500 samples was 300 CPU seconds.

Although the run-time for a single stochastic simulation is larger than for a single deterministic analysis, statistical analysis on the input and output data can be used to identify trends, without need to re-run the analysis. In contrast, one would have to run deterministic cases many times to identify trends, with the additional complication of interpreting results from individual runs with no explicit measure of the *likelihood* of each outcome. In addition, in practical problems with many input variables which may vary simultaneously, the combinatorial explosion of possible scenarios becomes unmanageable. Thus, the interpretation of results from stochastic analysis is much easier and more meaningful compared to sensitivity analysis.

### Uncertainty in Model Outputs

From the probabilistic simulation, frequency distributions for variables calculated in the performance and cost models can be estimated. For this example, the results for three calculated variables are summarized graphically. Uncertainty in one performance variable, the total initial zinc ferrite sorbent charge to all reactor vessels, is shown in Figure 3. Figure 4 shows the result of alternative assumptions regarding model input uncertainties on the direct capital cost for the zinc ferrite process area. Figure 5 shows the effects of alternative assumptions regarding uncertainties on the variable operating cost for makeup zinc ferrite sorbent.

The results of a probabilistic simulation provide information regarding both the range of possible values that may be obtained and the likelihood of obtaining various outcomes. It is common to use the cdf to estimate the median (50th percentile value) and the 80 percent probability range for the distribution. For example, from Figure 3 the median value for the sorbent charge is about 31 million lb, while the 80 percent probability range (encompassing the range between the 10th and 90th percentiles of the distribution) is from about 24 to 43 million lb. The median is a measure of the central tendency of the distribution, while the 80 percent range reflects the variance of the distribution.

### Interactions of Uncertainties

Uncertainties in model input performance parameters, when propagated through a model, result in uncertainties in calculated quantities such as key stream flow rates. The simple example above illustrates how uncertainty in just one input parameter (sorbent sulfur loading) affects the required initial sorbent charge. In turn, uncertainties in plant performance parameters have direct implications for plant costs. For example, as discussed previously, the direct capital cost of the zinc ferrite process area is sensitive to the required volume of sorbent. In the probabilistic simulation, this performance variable is uncertain. This leads to uncertainty in the size and number of pressure vessels, and hence direct capital cost, as shown in Figure 4. The resulting 80 percent probability range for direct cost due to performance uncertainty only is from \$33 to \$58 million.

For technologies in early stages development there is often additional uncertainty in the cost of a process area, even if the sizing parameters were to be known precisely. For example, preliminary cost estimates may not capture all of the costs that would be revealed by a final estimate based on more detailed engineering analysis. Therefore, the process area cost as reported in recent studies may be underestimated. Potential problems that could be encountered in a commercial-scale plant, such as corrosion or fouling, also may not be anticipated. In many cases, only limited data regarding process performance (often from small-scale tests) exists to develop a design basis for a commercial scale system. Hence, current cost estimates could prove incorrect.

If desired, probabilistic analysis can be used to represent judgments about the likelihood that actual process area direct costs might differ from currently estimated values for a given set of performance data. As an illustration, the uncertainty factor for the process area direct cost specified in Table I represents a judgment that capital costs for a commercial plant are more likely to increase rather than decrease from current estimates for reasons such as the ones described above. As shown in Figure 4, the effect of this additional uncertainty, in conjunction with uncertainty in sorbent sulfur loading, is to shift the probability distribution for capital cost upward and to increase the variance of the distribution. The median value of direct cost is increased by about \$6 million,

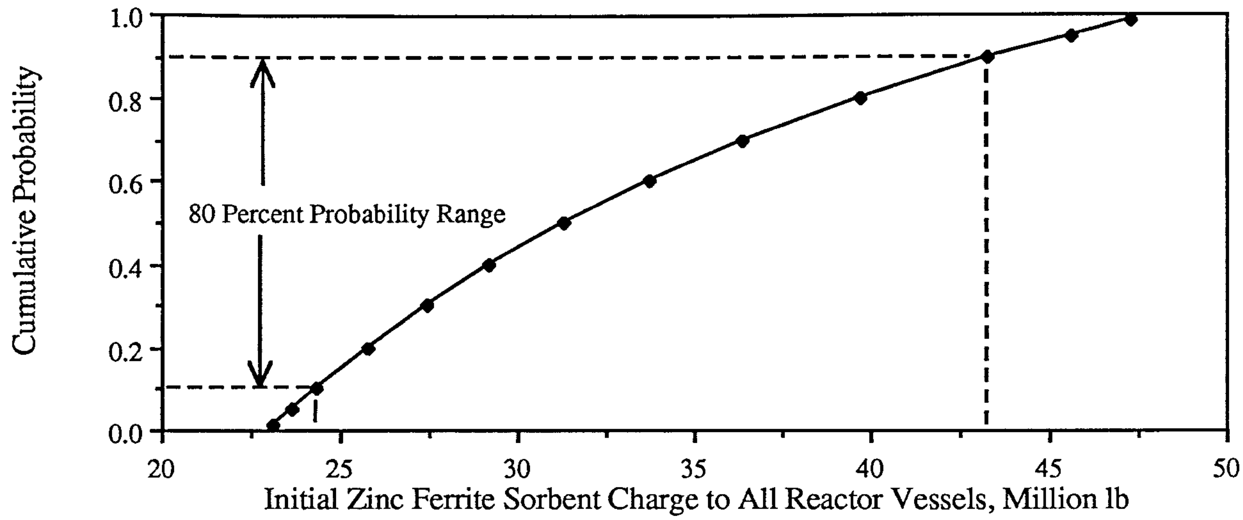


Figure 3. Illustrative Uncertainty in Sorbent Charge Due to Sorbent Sulfur Loading Uncertainty

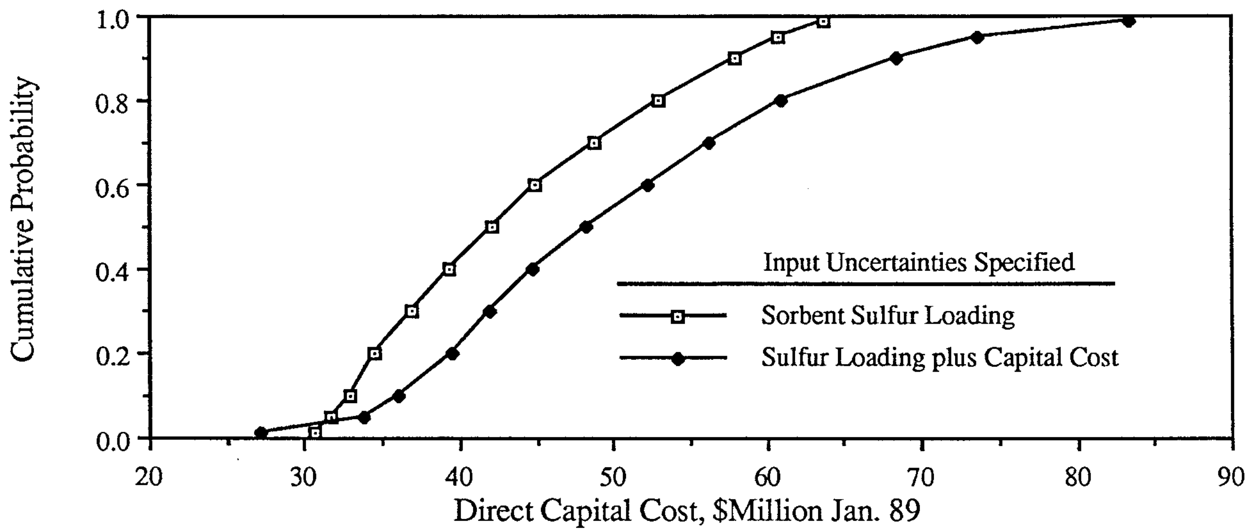


Figure 4. Illustrative Uncertainty in Direct Capital Cost of the Zinc Ferrite Process Area

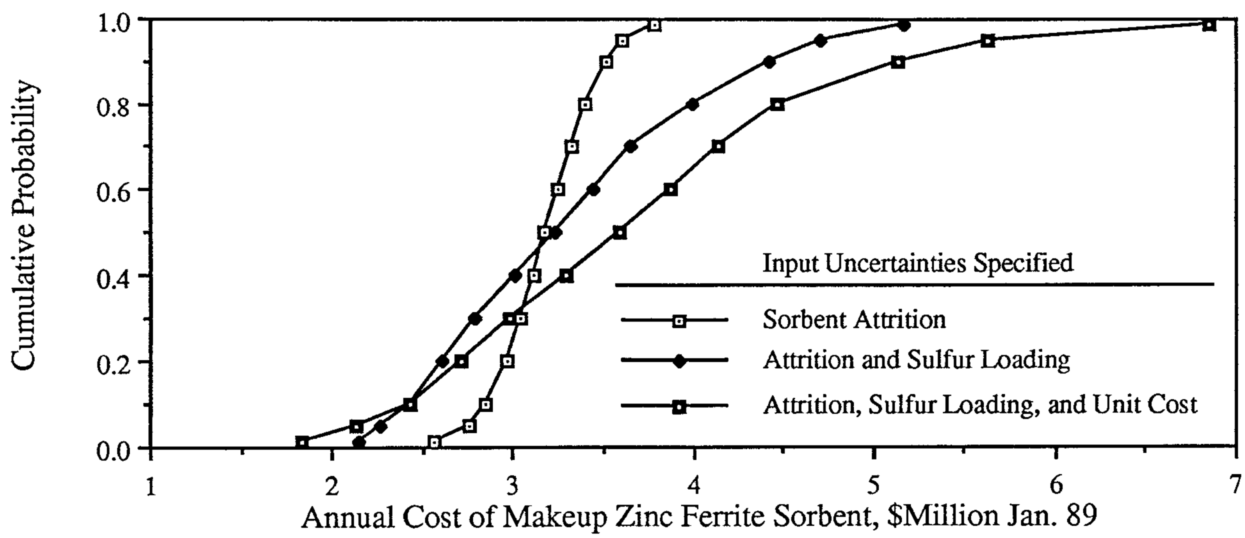


Figure 5. Illustrative Uncertainty in Variable Operating Cost for Zinc Ferrite Sorbent Replacement

and the magnitude of the 80 percent probability range is over $30 million, compared to $25 million for the case with uncertainty in sorbent sulfur loading only.

An example of uncertainty in the variable operating cost of the zinc ferrite process area is shown in Figure 5. The figure shows the interactions of uncertainties in sorbent attrition rate, sorbent sulfur loading, and the unit cost of the sorbent on the annual sorbent replacement cost. The uncertainty in makeup sorbent cost considering only uncertainty in sorbent attrition encompasses an 80 percent probability range of about $0.7 million. If uncertainty in sorbent sulfur loading is considered in addition, the magnitude of the 80 percent probability range increases to almost $2 million per year. Finally, when uncertainty in the sorbent unit cost is also considered, the 80 percent probability range is from $2.4 to 4.4 million per year. Because the relationship between sorbent sulfur loading and the sorbent charge is nonlinear, and because the uncertainty in unit cost is assumed to be positively skewed, the uncertainty in makeup sorbent cost also is positively skewed. Thus, the mean makeup sorbent cost ($3.7 million/year) is slightly larger than the median cost of $3.6 million per year.

As with any model analysis, the results obtained depend strongly upon the input assumptions. The above examples simply illustrate the methodology involved in examining uncertainties probabilistically. Where different judgments or data exist regarding key uncertainties, the model allows the implications of these differences to be examined systematically.

### Identification of Key Uncertainties

Another major advantage of probabilistic analysis techniques over sensitivity analysis is the capability to identify, in the context of a single analysis, the specific model input parameters which most significantly influence uncertainty in model output parameters when many parameters are varying simultaneously. While a number of regression analysis techniques can be applied to identify key uncertainties, the simplest method is correlation analysis. The partial correlations between model input and output probability distributions are easily computed, and provide a measure of the linear dependence of one distribution on another. In the example above, the uncertainty in sorbent sulfur loading was most highly correlated with uncertainty in both direct capital cost and sorbent makeup cost, with partial correlations of -0.85 and -0.71, respectively. The uncertainty in the sorbent unit cost also had a high correlation (0.63) with the sorbent makeup cost.

## CONCLUSION

While often overlooked, uncertainties in the performance and cost of new energy technologies may result in a large variance in the key measures used for process evaluation and decision-making. The use of a probabilistic modeling approach permits the explicit and quantitative representation of uncertainties, and an assessment of their impact on overall plant performance and cost. Key uncertainties then can be identified and targeted for further investigation. Thus, probabilistic modeling can be a valuable tool for representing the current level of understanding about a new process, and for planning future research more effectively.

In future work, detailed case studies involving IGCC systems will be performed. These studies will focus on the use of the probabilistic capability for IGCC system analysis, including more realistic representations of uncertainties in process performance and cost. Procedures for eliciting engineering judgments about uncertainties in the form of probability distributions will be developed and applied in the case studies. Given a set of judgments about parameter uncertainties, the performance and cost models will then be used to show: (a) interactions of simultaneous uncertainties in performance and cost; (b) ways to identify key uncertainties; and (c) probabilistic comparisons of the performance and cost of alternative IGCC systems for different uncertainty assumptions. The emphasis of the case studies will be to demonstrate how the probabilistic modeling approach can be used as a tool for research planning and process assessment.

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