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Gas Turbines, Gas Engines and Combined Cycle I

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PennWell Conferences & Exhibitions
Kaap Hoorndreef 30, 3563 AT Utrecht
PO Box 9402, 3506 GK Utrecht
The Netherlands

Phone: +31 30 2 650 963
Fax: +31 30 2 650 928
E-mail: nel @ pennwell.com
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Gas Turbines, Gas Engines and Combined Cycle II

Diesel Engines and Gas Engines, and Refinery Oil Power Plants

Operating Experience I

Operating Experience II

PROBABILISTIC MODELING OF GASIFICATION REPOWERING FOR AN OIL REFINERY IN POLAND

H. Christopher Frey
Department of Civil Engineering
North Carolina State University
Raleigh, NC 27695-7908, USA
Tel: + 1 919 515 1155, Fax: + 1 919 515 7908
E-mail: frey@eos.ncsu.edu

Ziemowit Iwanski
Program Manager
Institute of Power Engineering (IEn-NPC)
ul. Augustowka 5
02-981 Warsaw, Poland
Tel and Fax: + 48 22 648 83 78

ABSTRACT

Risk is the probability of an adverse outcome. Technological risks include the possibility of poor performance, high emissions, and high cost compared to other technology options. Probabilistic analysis provides a systematic framework for the evaluation of technological risks. Probabilistic analysis involves the quantification of uncertainty in process simulation model inputs using probability distributions, the propagation of uncertainties through the model, and evaluation of model results to characterize the range and likelihood of possible values for model outputs. Probabilistic evaluations enable the consequences of uncertainties in the inputs to detailed engineering-economic models to be displayed and evaluated. By identifying the sources of high risk outcomes, it is possible to prioritize research on new technologies so as to minimize such risks. Furthermore, probabilistic analysis may be used to compare competing technologies under uncertainty. The existence of uncertainty poses challenges to the optimization of advanced power generation and environmental control technologies. In this paper, methods for probabilistic analysis and optimization of process technologies are described. Preliminary work to apply the probabilistic methods to evaluate gasification repowering for an oil refinery in Poland is also discussed. The probabilistic approach yields important insights regarding process design, technological risks, cost estimation, management of research and development, and strategic planning.

1.0 INTRODUCTION

Gasification systems are a promising approach for clean and efficient power generation as well as for polygeneration of a variety of products, such as steam, sulfur, hydrogen, methanol, ammonia, and others (Heaven, 1996; Philcox and Fenner, 1996). As of 1996, there were 354 gasifiers located at 113 facilities worldwide. The gasifiers use natural gas, petroleum residuals, petroleum coke, refinery wastes, and coal as inputs, and produce liquid and gaseous fuels, chemicals, and electric power. In recent years, gasification has received increasing attention as an option for repowering at oil refineries, where there is currently a lack of high-value markets for low-value liquid residues and coke (Simbeck, 1996).

The complexity of gasification systems implies that it is difficult to evaluate all possible combinations of gasification systems based upon the relatively small population of demonstration and commercial plants. For each of the major components of a typical gasification system flowsheet (e.g., fuel feed, gasification, syngas cooling, syngas cleanup, power generation, byproduct recovery), there are many possible options. Limited performance and cost data for first generation systems, coupled with uncertainties associated with a potentially large number of alternative process configurations, motivates a systematic approach to evaluating the risks and potential pay-offs of alternative concepts.

Technology assessment models are typically developed for the purpose of providing a point-estimate which may be intended to serve as an accurate and precise prediction of some quantity (e.g., thermal efficiency, total capital cost). The purpose of such analyses are to provide decision makers with a best-estimate that can be used in comparison with other assessments or to develop design targets or budgetary cost estimates. However, quantitative measures of the accuracy and precision of model predictions are usually not developed, because no information on model or input uncertainty is accounted for quantitatively. Deterministic estimates for the performance and cost of new process technologies are often significantly biased toward optimistic outcomes (Merrow *et al.*, 1981). Such biases can lead to serious misallocation of resources if decisions are made to pursue research and development on a technology whose risks were not properly quantified.

To explicitly represent uncertainties in gasification systems and other process technologies, a probabilistic modeling approach has been developed and applied. This approach features: (1) development of sufficiently detailed engineering models of performance, emissions, and cost; (2) implementation of the models in a probabilistic modeling environment; (3) development of quantitative representations of uncertainties in specific model parameters based on literature review, data analysis, and elicitation of technical judgments from experts; and (4) modeling applications for cost estimating, risk assessment, and research planning. The methods have been applied to previous case studies of gasification and other advanced power generation and environmental control systems (e.g., Frey and Rubin, 1991; Frey and Rubin 1992a&b; Frey *et al.*, 1994; Frey and Rhodes, 1996).

In this paper, we describe the methodology for quantitative analysis of the risks and pay-offs of new technologies, and describe how these methods will be applied to the evaluation of gasification repowering for an oil refinery in Poland. The purpose of the gasification repowering case studies is to evaluate the technical, environmental, and economic feasibility of gasification repowering, as an alternative to more conventional technologies, to produce electric power, steam, sulfur, and potentially other byproducts at an existing oil refinery. This project is aimed at identifying strategic approaches for a general direction for industrial plant repowering, with a special focus on the use of available feedstocks, such as heavy residual oil, at refineries. In such applications, it is not acceptable to have significant risks of economic or technological failure, since the economic competitiveness of the entire refinery may be at stake. Thus, a systematic approach to risk analysis is needed.

2.0 REVIEW OF METHODS FOR EVALUATING UNCERTAINTIES IN PROCESS TECHNOLOGIES

Insight into the risks of a new technology is obtained by evaluating the implications of alternative model input assumptions. For example, local sensitivity analyses are commonly used, in which the value of one or a few model input parameters are varied, usually from "low" to "high" values, and the effect on a model output parameter is observed. Meanwhile, all other model parameters are held at their "nominal " values. In practical problems with many input variables which may be uncertain, the combinatorial explosion of possible sensitivity scenarios (e.g., one variable "high", another "low," and so on) becomes unmanageable. Furthermore, sensitivity analysis provides no insight into the *likelihood* of obtaining any particular result. Thus, while they indicate that a range of possible values may be obtained, sensitivity results do not provide any explicit indication of how a decision-maker should weigh each possible outcome.

A more robust approach to risk analysis is the use of numerical simulation methods for propagating probability distributions through models, as illustrated conceptually in Figure 1. Unlike sensitivity analysis, probabilistic analysis yields direct quantitative insight into both the possible range and the relative likelihood of values for model outputs. Numerical simulation methods are not limited to the use of parametric probability distributions for model inputs and can accommodate empirical distributions and other user-defined distributions. Probabilistic analysis helps decision makers understand both the potential pay-offs as well as the downside risks of a new technology compared to other alternatives. Probabilistic analysis also enables the identification of key sources of uncertainty, or risk, which can be targeted for further research.

3.0 DEVELOPING INPUT ASSUMPTIONS FOR PROBABILISTIC ANALYSIS

There are several types of uncertainty in trying to predict the commercial-scale performance and cost of a new process technology. These include statistical error, systematic error, variability, and lack of an empirical basis for concepts that have not been tested. Uncertainties may apply to

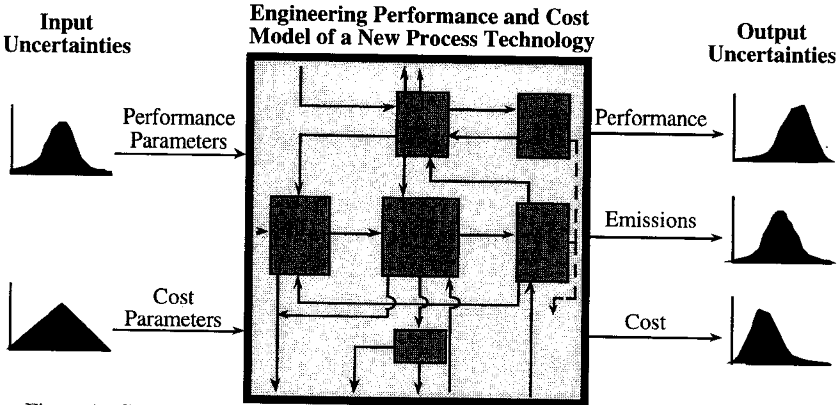

Figure 1. Conceptual Diagram of Probabilistic Approach to Technology Risk Analysis

different aspects of the process, including performance variables, equipment sizing parameters, process area capital costs, requirements for initial catalysts and chemicals, indirect capital costs, process area maintenance costs, requirements for consumables during plant operation, and the unit costs of consumables, byproducts, wastes, and fuel. Model parameters in any or all of these areas may be uncertain, depending on the state of development of the technology, the level of detail of the performance and cost estimates, future market conditions for new chemicals, catalysts, byproducts, and wastes, and so on (e.g., Frey and Rubin 1992a).

Using probabilistic methods, model input assumptions are given probability distributions, rather than single numbers. Examples of the types of distributions that may be employed are shown in Figure 2. The selection of a distribution depends on the nature of the uncertain variable and the type of information available to estimate its uncertainty. The ideal case is to have a large amount of representative data that can be used to describe variability in a model input, such as the composition of feedstocks or the removal efficiency of an environmental control system, using statistical techniques.

However, in most cases, data that are representative of the problem we wish to address are not available. For example, while there is a growing amount of data regarding the performance of gasification systems using a variety of coal feedstocks, there are less data regarding the performance of such systems when heavy residual oil is the feedstock. Thus, in some cases considerable judgment is required to characterize uncertainties in model inputs.

Formal methods exist for encoding the judgment of experts regarding probability distributions for a specified quantity. One such method is the Stanford/SRI protocol. We briefly describe this protocol based upon material in Morgan and Henrion (1990) and Merkhofer (1987). Elicitation protocols are typically designed to overcome some known sources of bias based upon heuristics that people often use to construct estimates of probability distributions. These heuristics include: (1) availability; (2) representativeness; and (3) anchoring and adjustment. Availability refers to bias introduced because an expert may tend to focus on information that is most easily recalled, rather than upon all possibly relevant information. Representativeness is the tendency to infer patterns from small amounts of data which may in fact be unjustified due to random aspects that underly some of the information. Anchoring and adjustment is the tendency to fixate on a particular point estimate, and then to make insufficient adjustments away from the point estimate when estimate the range and likelihood of possible values for a quantity. All of these biases can lead to "overconfidence," which is the assignment of too narrow a range of values to an uncertain quantity.

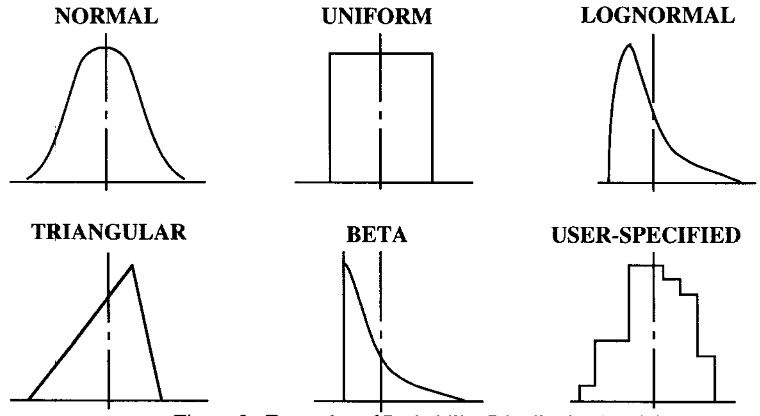

Figure 2. Examples of Probability Distribution Models

Expert elicitation is typically most effective when the process is conducted by an elicitor. The elicitor must first establish a rapport with the expert, which is Step 1 in the Stanford/SRI protocol. In Step 2, the expert and the elicitor agree on the specific model inputs for which judgments are to be obtained. This step includes a clear definition of each input, so that there is no ambiguity regarding factors such as the design basis. In the third step, the elicitor attempts to counteract the typical heuristics used by experts, as outlined above, by getting experts to consider as large a body of relevant evidence as practical. Only then, in the fourth step, is the expert asked for judgments regarding the quantity. These judgments may be encoded using a variety of techniques, depending upon the expert's familiarity with probability distributions. Finally, in the last step, efforts are made to verify the robustness of the expert's judgment, by comparing expert responses based upon different encoding methods and asking the expert to comment on the results recorded by the elicitor.

4.0 PROPAGATING DISTRIBUTIONS THROUGH A MODEL

In order to analyze uncertainties, a probabilistic modeling environment is required. A typical approach is the use of Monte Carlo simulation (e.g., Morgan and Henrion, 1990). In Monte Carlo simulation, a model is run repeatedly, using different values for each of the uncertain input parameters each time. The values of each of the uncertain input parameters are generated based on the probability distribution for the parameter. If there are two or more uncertain input parameters, one value from each is sampled simultaneously in each repetition in the simulation. Over the course of a simulation, perhaps 20, 50, 100, or even more repetitions may be made. The result is a set of sample values for each of the model output variables, which can be treated statistically as if they were an experimentally or empirical observed set of data.

Although the generation of sample values for model input parameters is probabilistic, the execution of the model for a given set of samples in a repetition is deterministic. The advantage of Monte Carlo methods, however, is that these deterministic simulations are repeated in a manner that yields important insights into the sensitivity of the model to variations in the input parameters, as well as into the likelihood of obtaining any particular outcome. Monte Carlo methods also allow the modeler to use any type of probability distribution for which values can be generated on a computer, rather than to be restricted to forms which are analytically tractable.

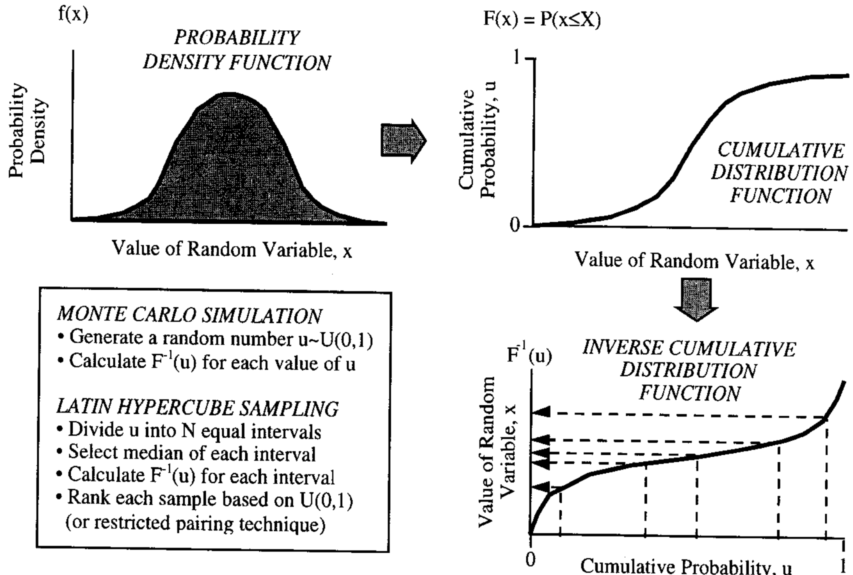

Figure 3. Conceptual Approaches to Numerical Simulation of Probability Distributions Based Upon Monte Carlo Simulation and Latin Hypercube Sampling

4.1 Monte Carlo Simulation

The generation of random variables using Monte Carlo simulation is done using a variety of methods. In order to illustrate the general concept behind Monte Carlo simulation, we briefly describe one of these, which involves the use of the inverse cumulative distribution function (cdf) of a probability distribution. A more detailed discussion can be found in Ang and Tang (1984). In random Monte Carlo simulation, a pseudo-random number generator is used to generate uniformly distributed numbers between 0 and 1 for each uncertain variable. The sample values for the random variables are calculated using the inverse cdf functions based on the randomly generated fractiles. This approach is shown schematically in Figure 3. Sample values are generated for each random variable in the model. For a given iteration of the model, one random value for each of the model inputs is used. A single value of the model outputs are calculated. The process is repeated until the desired number of model iterations is completed.

4.2 Latin Hypercube Sampling

An alternative to random Monte Carlo simulation is Latin Hypercube Sampling (LHS). In LHS methods, the fractiles that are used as inputs to the inverse cdf are not randomly generated. Instead, the probability distribution for the random variable of interest is first divided into ranges of equal probability, and one sample is taken without replacement from each equal probability range. However, the ranking (order) of the samples is random over the course of the simulation, and the pairing of samples between two or more random input variables is usually treated as independent. In median LHS, one sample is taken from the median of each equal-probability interval, while in random LHS one sample is taken at random within each interval.

LHS methods guarantee that values from the entire range of the distribution will be sampled proportional to the probability density of the distribution. Therefore, the number of samples required to adequately represent a distribution is less for LHS than for random Monte Carlo sampling. LHS is generally preferred over random Monte Carlo simulation. Restricted pairing techniques are available for the purpose of inducing correlations between variables in LHS (Iman and Conover, 1982).

5.0 ANALYZING RESULTS

The results of a probabilistic simulation are alternative realizations of the values of each model output. These data can be analyzed using empirical cumulative distribution functions to provide information regarding the range and likelihood of values for each model output. Summary statistics, such as the mean, standard deviation, and 95 percent probability range, can also be calculated. An important advantage of numerical methods for probabilistic simulation is that they enable evaluation of the sensitivity of the model outputs with respect to uncertainty in each of the model inputs. The importance of sensitivity analysis is illustrated in Figure 4. Using sensitivity analysis, it is possible to begin the probabilistic analysis without making great expenditures of resources on the characterization of input uncertainties. Based upon a preliminary characterization of uncertainty, probabilistic results may be obtained and analyzed to identify which of the model inputs contributed most to uncertainty in the model outputs of concern. For the most sensitive model inputs, the estimates of uncertainty may be refined by collecting more data or more rigorously eliciting the judgments of experts. Then the analysis is repeated to confirm the key sources of uncertainty, or to identify new key sources of uncertainty. The process is repeated as necessary until a stable set of sensitive inputs are identified. In this manner, project resources can be focused on characterizing uncertainties only for those inputs which matter the most. It is typically the case that only a handful of input uncertainties significantly affect model results. For example, in a case study of an externally-fired combined cycle system, only 4 of 35 uncertain model inputs significantly contributed to uncertainty in levelized total costs (Frey and Agarwal, 1996).

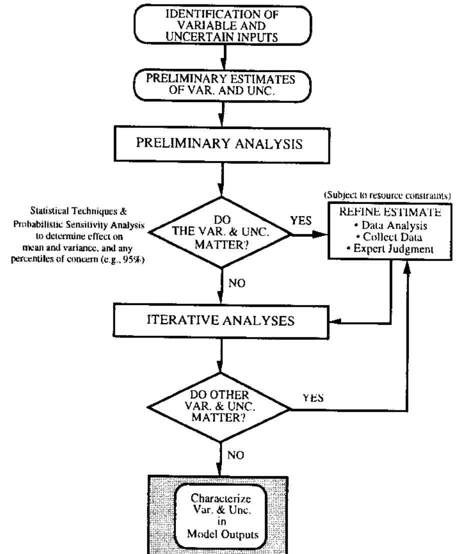

Figure 4. Conceptual Approach to Screening and Iteration In Probabilistic Analysis

One method for identifying key sources of uncertainty is to calculate the sample correlation coefficients between a model output and each uncertain model input. Sample correlation coefficients are a simple but useful tool for identifying the linear correlations between uncertain variables. Other techniques are available in software packages such as one developed by Iman, Shortencarier, and Johnson (1985). Frey and Rubin (1992a) describe other methods for identifying key uncertain model inputs.

6.0 PROBABILISTIC PROCESS MODELING USING ASPEN

ASPEN (Advanced System for Process ENgineering) is a FORTRAN-based deterministic steady-state chemical process simulator developed by the Massachusetts Institute of Technology (MIT) for the U.S. Department of Energy to evaluate synthetic fuel technologies (MIT, 1987). ASPEN includes generalized unit operation "blocks" (e.g., chemical reactions, pumps) and an extensive physical property database. In addition, ASPEN includes convergence algorithms for

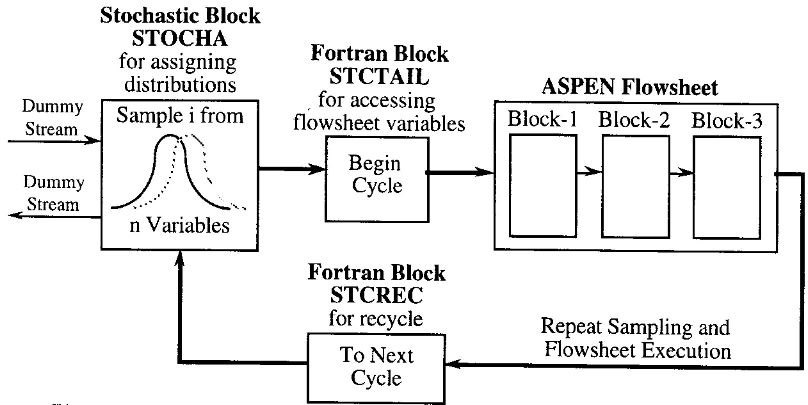

Figure 5. Simplified Schematic of Probabilistic Approach to Technology Risk Assessment Using the ASPEN Chemical Process Simulator

calculating results in recycle and closed loop systems. The latter are typically implemented by using a "design specification," in which a flowsheet variable is iteratively manipulated until another selected flowsheet variable converges to a set point within a user-specified tolerance. Thus, any process plant may be represented by specifying: (a) unit operation blocks; (b) their interconnections via material, heat, and work streams; and (c) convergence loops for obtaining interative solutions. In addition, users may include their own models using "FORTRAN blocks." Thus, ASPEN is a flexible and powerful environment for simulating mass and energy balances.

A probabilistic modeling capability for uncertainty analysis has been added to the public version of the ASPEN simulator. To implement the stochastic modeling capability, ASPEN's modular nature has been utilized. The stochastic simulation module is based on public domain programs (Iman and Shortencarier, 1984; Iman *et al.*, 1985). A new unit operation block, called STOCHA, has been added to the ASPEN unit operation library. The structure of this block and its use are briefly described. Details are provided elsewhere (Rubin and Diwekar, 1989).

The unit operation block, STOCHA, characterizes the uncertainty in model input parameters in terms of probability distributions, and analyzes their effect on selected output variables. To link STOCHA to the ASPEN flowsheet, two Fortran blocks are needed. The stochastic modeling approach involves the following steps: (i) specification of uncertainties in key input parameters in terms of probability distributions; (ii) specification of the correlation structure of any interdependent model inputs; (iii) sampling of the distributions in an iterative fashion, using random Monte Carlo simulation or Latin Hypercube sampling; (iv) propagation of the effects of uncertainties through the process flowsheet; and (v) application of graphical and statistical techniques to analyze the results.

Figure 5 shows the use of the stochastic block for uncertainty analysis of a flowsheet. The cycle for stochastic simulation consists of: (a) the stochastic block, STOCHA, for generating i samples from the probability distributions for n uncertain flowsheet variables selected by the user; (b) the Fortran block, STCTAIL, for accessing the uncertain flowsheet variables at the beginning of a repetition and assigning to them the sample values from their associated probability distributions; and (c) the Fortran block, STCREC, for data output collection and recycling to the next repetition.

An example of a probabilistic analysis of an integrated gasification combined cycle (IGCC) system is given in Figure 6. This example is based upon an ASPEN simulation model for an air-blown dry-ash Lurgi gasifier-based IGCC system with hot gas cleanup. Details regarding this case

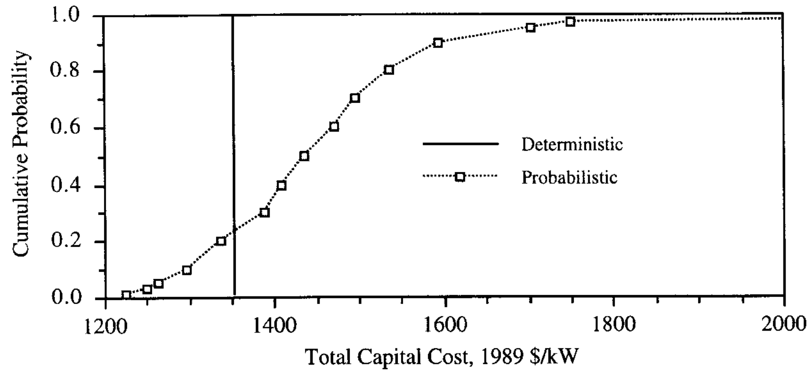

Figure 6. Example Results from Stochastic Simulation of IGCC Systems: Uncertainty in Total Capital Cost for a Bituminous Coal Air-Blown Dry-Ash Lurgi Gasifier-Based System with Hot Gas Cleanup and Selective Catalytic Reduction.

study are given by Frey (1997). The IGCC model was run on a DEC VAXStation 3200 mini-computer using the public version of ASPEN with the stochastic modeling capability. The model results are for a system with a 15.0 pressure ratio and 1,288 °C firing temperature gas turbine. The nominal plant size is 710 MW, based upon three gas turbines. Interactions among uncertainties in plant performance and cost parameters lead to uncertainties in key measures of cost used for process evaluation. As shown in Figure 6, the uncertainty in the total plant capital cost covers a wide range, from about $1,200/kW to over $2,000/kW. The mean and median of the plant costs are both approximately $1,450/kW. A deterministic "best guess" analysis of this technology, which did not account for uncertainty, indicated a cost of $1,350/kW. There is a 75 percent chance that the capital cost would be higher than this estimate, which includes so-called "contingency" allowances intended to account for both performance- and project-related uncertainties. In the probabilistic estimate, contingency factors are replaced with explicit representations of uncertainty in direct costs. Figure 6 suggests that use of the deterministic cost estimate would expose a decision-maker to a substantial chance of a cost overrun. Using statistical analyses as previously described, the model inputs which contribute most to uncertainty in total capital cost were found to be the gasifier coal throughput, project allowance cost, gas turbine direct cost, and desulfurization capability of the mixed metal oxide sorbent used for hot gas cleanup.

In addition to probabilistic simulation, new methods for optimization have been implemented into the public version of the ASPEN process simulator. Probabilistic analysis and optimization methods can be used together to optimize the design of process technologies under uncertainty. Stochastic optimization has been employed in case studies of IGCC and EFCC systems (Rubin *et al.*, 1996; Frey and Agarwal, 1996). When combined with probabilistic analysis, optimization methods provide a powerful tool for the design of clean technologies. Optimization is especially critical for gasification systems because of the wide variety of feedstocks, products, and technologies that can be configured to meet site-specific needs (Bjorge *et al.*, 1996).

7.0 GASIFICATION REPOWERING OF AN OIL REFINERY IN POLAND

Oil refining is likely to become a key market for gasification technologies, due to the lack of high-value markets for low-quality residuals and petroleum coke (Simbeck, 1996). Examples of current gasification projects which either use heavy residual oil as a feedstock and/or which are located at a refinery include (Preston, 1996; Koenders *et al.*, 1996):

- Texaco El Dorado project in Kansas, which started up in the summer of 1996, is a cogeneration facility at an oil refinery that uses hazardous refinery wastes as fuel.
- ISAB Energy is a 500 MW system for gasifying asphalt from the ISAB Sicily refinery to produce steam, power, and hydrogen using the Texaco gasification process.
- API Energia is a 250 MW system for gasifying visbreaker residue from the API refinery in Falconara, Italy to produce steam and power using the Texaco gasification process.
- Sarlux is a 500 MW system for gasifying visbreaker residue to produce steam, power, and hydrogen using the Texaco gasification process.
- Shell Pernis combined cycle refinery project in the Netherlands is scheduled for startup in the spring of 1997. The plant will produce hydrogen for direct use in refining and 100 MW_e of cogenerated power using the Shell gasification process.

Here we consider a preliminary design for gasification repowering based upon the characteristics of an oil refinery located in Plock, Poland. The refinery is currently undergoing modernization in order to compete in a free market. The refinery produces 1 million tonnes per year of heavy vacuum residue, which contains approximately 85 weight percent carbon, 11 weight percent hydrogen, and between 3.0 and 3.5 weight percent sulfur. In addition, the residue contains approximately 17 to 40 ppm (by weight) of sodium and no more than 250 ppm of vanadium and 100 ppm of nickel. The refinery is already proceeding with the installation of a new hydrocracker, which will enable utilization of approximately one half of the current heavy residual mass flow rate. Thus, it is not necessary to consider production of hydrogen as the primary purpose for this particular repowering project.

The purpose of the assessment of gasification repowering is to determine whether the gasification of remaining heavy residuals competes with other approches for power and steam generation in Poland. The refinery currently generates electrical power using aging natural gas-fired boilers. The reliability of future natural gas supplies is both an economic and political issue. Most of Poland's natural gas is imported from Russia. The existing pipeline from Russia to Poland is over 20 years old and is increasingly unreliable. At the same time, plans for a new pipeline, which is under construction, have been subject to delays. There are additional economic incentives for industries in Poland to become more "vertically integrated" due to the imposition of value added tax (VAT) on fuels purchased from outside the company, but not for fuels produced and consumed within the company. However, any process that is incorporated into the refinery must satisfy basic requirements for technical and economic feasibility. These requirements include reliability, efficiency, compliance with environmental regulations and avoidance of the risk of fines for noncompliance, and competitive costs. Thus, the aim of this study is to provide planners at the Plock refinery and elsewhere with an independent estimate which might be helpful to define company strategy regarding power generation in general and regarding preselection of applicable technologies for refinery repowering in particular.

The probabilistic risk analysis approach described in previous sections will be a critical aspect of the independent analysis of both the risks and potential pay-offs of technology options for refinery repowering. An overall conceptual framework for the systems which we will evaluate is given in Figure 7.

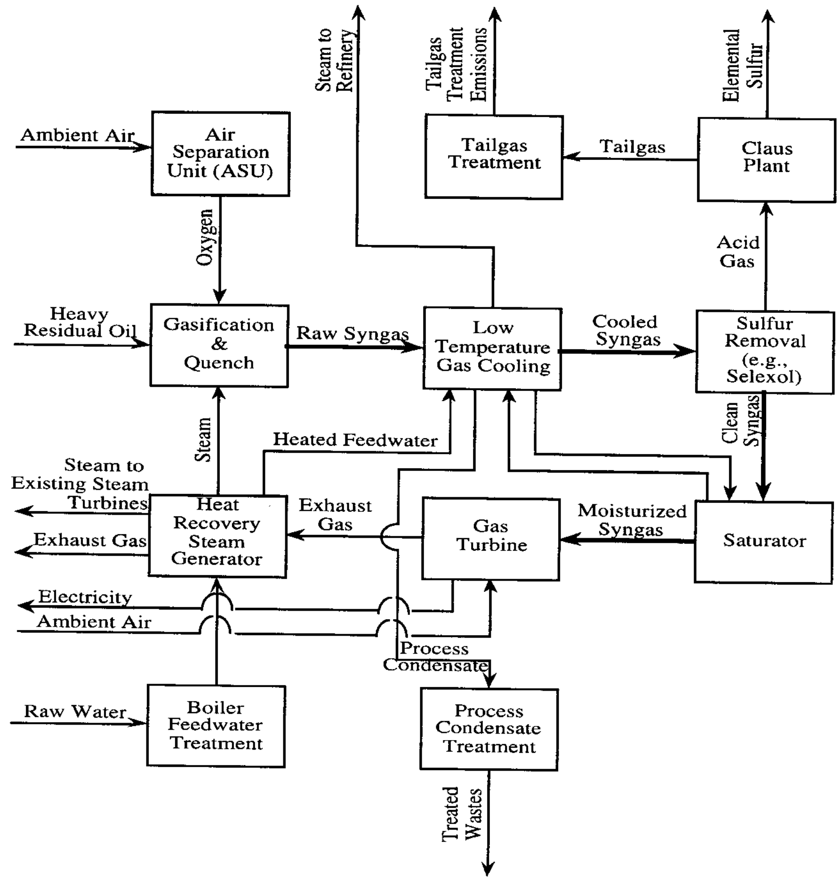

Figure 7. Simplified Schematic of Refinery Repowering Gasification Combined Cycle and Cogeneration System Using Existing Steam Turbines

The heavy residual from the refinery may be gasified in an entrained-flow gasifier. Oxygen from an air separation unit is used to partially oxidize the heavy residual. The thermal energy from partial combustion is used internally for endothermic gasification reactions, which convert the carbon in the feed and the hydrogen in both the feed and inlet water and steam to a syngas containing primarily CO and H_2, respectively. The gasification process typically includes either a series of high temperature heat exchangers or, as assumed here, a water quench, to cool the hot syngas from approximately 1,260 °C to approximately 350 °C. A low temperature gas cooling step reduces the syngas temperature to approximately 40 °C. As a result of syngas cooling, some process condensates may be formed which must be sent to a process condensate treatment system. The low temperature syngas enters a solvent-based process, such as Selexol, for separating acid gases (e.g., H_2S) from the syngas. The desulfurized syngas enters a saturator, where moisture is added for the primary purpose of control of nitrogen oxides emissions. The moisturized syngas is combusted in a gas turbine, where electric power is generated. The gas turbine exhaust is routed to a heat recovery steam generator (HRSG) for thermal energy recovery. In this case, the steam from the HRSG is to be used primarily with existing refurbished steam turbines at the refinery. Some steam is also used for the gasification process, and heated boiler feedwater is sent to the low temperature gas cooling system for generation of low pressure steam for use in the refinery and the saturator. The acid gases from the sulfur removal step are sent to a Claus plant for byproduct sulfur recovery. The Claus plant may include a tailgas treatment system (e.g, Beavon-Stretford or other). The combination of gas quenching, solvent-based acid gas removal, tailgas treatment, and syngas moisturization will lead to relatively low emissions of particulate matter, sulfur dioxide, and nitrogen oxides.

We describe the major plant sections and plans for future studies regarding these in more detail in the following sections.

7.1 Air Separation

The Air Separation Unit (ASU) can be developed as either a stand-alone, over-the-fence, facility or as an integral part of the gasification plant. The primary purpose of the ASU is to provide oxygen for use in the gasifier. The nitrogen produced by the ASU can be used for pneumatic transport and purging. There is a trade-off between the purity level of the oxygen, the cost of the ASU, and the cost of the gasification system. These trade-offs will be evaluated using the ASPEN process model. The typical oxidant purity level required for the gasifier is 95 percent. Possible additional options to consider are various levels of integration of the ASU with the gas turbine, such as the use of extraction air from the gas turbine compressor as input to the ASU, and the subsequent use of nitrogen from the ASU as input to the turbine for power augmentation. While such levels of integration may offer efficiency advantages, they increase the complexity of both the design and the control of the plant. This in turn increases the technological risks. Preliminary operating experience with an integrated ASU at the El Dorado plant has been successful. The ASU must be designed to provide oxygen at a pressure that matches the gasifier pressure, which in turn may be dictated by the pressure ratio of the gas turbine (Smith and Noga, 1996).

7.2 Gasification

Of the three major types of gasifiers (fixed bed, fluidized bed, and entrained flow), we will focus upon the use of entrained flow gasification for the oil refinery repowering study. Entrained flow gasifiers typically operate at much higher temperatures than the other two types of gasifiers, and are usually designed as oxygen-blown systems. The high temperatures increase the reaction rates of the gasification reactions, and therefore enable the gasification of a wide variety of feedstocks. Because these types of gasifiers operate at high temperatures, they produce a large amount of sensible heat in the raw syngas. This in turn implies that the methods chosen for gas cooling will have a significant impact upon overall plant efficiency.

There are a variety of commercially-available entrained flow gasifiers. We will describe one example based upon the Texaco gasifier. Development of the Texaco entrained flow gasifier began in the 1940s at Texaco's Montebello, California facility. The Texaco gasifier has been used in over 80 commercial installations for the partial oxidation of oil and natural gas to produce carbon dioxide and hydrogen for industrial purposes. More recently, since the early 1970s, development of the Texaco gasifier has focused more upon coal gasification for chemical production and power generation. The Texaco gasifier uses a slurry feed system, which is considered to be a more reliable feed system than dry solids handling systems. Using slurry feed, it is possible to provide the feed and operate the gasifier at high pressures. The high temperature gasification process results in relatively low levels of condensible hydrocarbons and of methane (Simbeck *et al.*, 1983). The Texaco gasifier has been used in numerous demonstration and commerical projects including, for example, the Polk Power Station Repowering coal-fueled IGCC and the El Dorado waste-fueled gasification projects previously mentioned. The Texaco gasifier is being used in several project in Italy involving the gasification of heavy residuals.

A concern with any gasifier, and especially high temperature ones, is the life of the refractory linings. Good controls are required to maintain gasifier temperatures at acceptable levels to ensure good refractory life.

7.3 Heat Recovery and Gas Cooling

There is a trade-off between initial capital cost and net plant thermal efficiency embodied in the decisions regarding what technologies to use for high temperature syngas cooling. The least expensive technologies involve water quenching of the syngas, with no heat recovery. This approach can lead to humidification of the gas and the formation of process condensates. An alternative approach involves the use of radiative and convective heat exchangers to cool the gas and to generate steam. This approach is more capital intensive, but also results in higher plant efficiency. Since capital cost is likely to be a significant constraint in Eastern European markets, we will focus our considerations on a quench-based syngas cooling approach. Furthermore, the presence of metals in the high temperature syngas, due to metals in the gasifier feedstock, can adversely affect boiler tubes and other surfaces in high temperature heat exchangers (Del Bravo *et al.*, 1996).

Sour water that is condensed from the syngas in the low temperature heat recovery system of the plant can be used for slurry preparation and, therefore, can be recycled to the gasifier. A sour water treatment system, such as that used at Wabash, is likely to be required to strip dissolved gases from the water and to prepare excess sour water for discharge from the plant. Recycled process water is used for slurry preparation in many existing plants, such as the Wabash and Polk stations.

Low temperature gas cooling is a relatively well-established component of gasification systems and is not expected to pose significant problems. Early experience with the Wabash and Polk power stations have indicated good performance of the low temperature cooling systems. It is important to ensure that there is sufficient gas cleanup to avoid the presence of chlorides that can damage the heat exchangers, as detailed in the next section.

7.4 Gas Cleanup

While a significant amount of research has been focused upon the development of hot gas cleanup (HGCU) systems, such as ceramic candle filters and high temperature desulfurization process involving mixed metal oxide sorbents, HGCU is likely to be too risky for application to oil refinery repowering in Eastern Europe on a commercial basis at this time. Such systems are not fully demonstrated in terms of long term reliability. Furthermore, it is likely that a variety of additional components, such as removal systems for chlorides and alkali, would be required to protect the gas turbine. Therefore, although HGCU offers the potential for higher thermal efficiencies and possibly lower capital costs, we will focus upon evaluation of more conventional cold gas cleanup (CGCU) systems.

While processes such as Selexol are effective at removing H_2S from the syngas, they are less effective at removing COS. Therefore, a catalytic COS hydrolysis step may be required, which introduces additional pressure drop and cost (Kubek *et al.*, 1996). At the Wabash River Coal Gasification Repowering Project (WRCGRP), the gas cleanup system experienced poisoning of the COS catalyst due to chlorides and trace amounts of arsenic in the syngas. Localized chloride stress corrosion cracking was identified in some downstream heat exchangers. Since the installation of a water-based wet scrubber, chloride and trace metal loadings in the syngas are reported to have been significantly reduced (Amick *et al.*, 1996). Solvent-based and wet scrubbing processes are typically effective at removing precursors to fuel-NO_x formation, such as HCN and NH_3, from the syngas (Kubek *et al.*, 1996). Thus, our base case design will feature the use of wet scrubbing and solvent-based acid gas removal processes. It is well known that solvent-based acid gas removal systems can experience problems with foaming. However, this operational problem can usually be corrected with the use of defoaming agents (e.g., Black and McDaniel, 1996).

A Claus plant and tailgas treatment system are well-established commerically-available technologies which are utilized in many other gasification plant designs, including those aimed at gasification of refinery wastes (e.g., Del Bravo *et al.*, 1996).

Few data are currently available to accurately and precisely characterize hazardous air pollutant (HAP) emissions from gasification-based systems. For example, under U.S. Department of Energy sponsorship, the Energy and Environmental Research Center at the University of North Dakota has conducted a review of available HAP emissions data for advanced coal-based power systems (Erickson *et al.*, 1996). These systems include: (1) Tidd Station, which is a bubbling-bed pressurized fluidized bed combuster (PFBC) with a two-stage cyclone and an electrostatic precipitator (ESP) for particulate matter control and a dolomite bed for sulfur control; (2) Louisiana Gasification Technology Incorporated (LGTI) plant in Plaquemine, Louisiana, which features an oxygen-blown entrained-flow gasifier followed by a venturi scrubber and a Selectamine absorber for particulate and acid gas removal, respectively; (3) General Electric Hot Gas Cleanup Unit (HGCU), which employs an air-blown fixed bed gasifier to generate syngas for a zinc titanate-based desulfurization system; and (4) Cool Water, which was used to demonstrate coal-based gasification using a Texaco gasifier, water scrubber, and Selexol system for acid gas removal.

Erickson *et al.* (1996) indicate that of the three gasification systems tested, only the LGTI should be considered to be valid. The total HAP emissions for 11 trace metals (Sb, As, Be, Cd, Cr, Co, Cu, Pb, Mn, Hg, Ni, Se) from LGTI are reported to be less than 15 lb per 10^{12} BTU (6.5 g/TJ). The mercury emissions for LGTI are reported to be approximately 3 lb per 10^{12} BTU (1.3 g/TJ). Emission measurements for chromium and nickel were considered suspect because of possible contamination from the sampling probe. Based upon equilibrium calculations, it is expected that most of the trace metals, with the likely exception of mercury, will exist primarily in solid form associated with particulate matter. Therefore, low temperature scrubbing systems are expected to be effective at removing a large portion of most HAPs from the syngas. The available information suggests that cold gas cleanup systems should present less uncertainty and risk regarding the possibility of unacceptably high HAP emissions than hot gas cleanup systems. However, currently data are not readily available regarding HAP emissions from gasification systems utilizing heavy residual oil feedstocks.

Further information is required regarding the long term performance of gas cleanup systems in reducing trace species to levels low enough to allow for long gas turbine hot gas path life. Other types of risk-related issues to be considered include, for example: (a) corrosion, erosion, and deposition in critical components of the plant; (b) potential gas flow distribution problems, such as channeling; (c) durability of key components, such as catalysts; (d) reliability of solids-handing equipment; (e) equipment prices; and (f) prices of consumables and byproducts.

7.5 Gas Turbines

There is increasing experience regarding the use of gas turbines with syngas. For example, WRCGRP features a General Electric MS7001FA gas turbine capable of 192 MW electrical output when fired on syngas. The gas turbine includes redesigned compressor and turbine stages. The blade temperatures have been more evenly distributed for syngas operation compared to oil-based operation. Some early modifications to the syngas module, piping from the syngas module to the gas turbine, and syngas purge control were required. Otherwise, the first 1,000 hours of gas turbine operation on syngas were apparently successful (Amick *et al.*, 1996). At the Polk power station, which also employs a General Electric 7F gas turbine, early efforts to make the transition from firing of distillate oil to syngas and back to distillate oil were successful (Black and McDaniel, 1996).

More advanced gas turbines typically operate at higher pressure ratios. The GE 7F unit operates with a pressure ratio of approximately 15 and firing temperatures of approximately 1316 C. In contrast, the "H" technology gas turbines, which are anticipated to be available beginning in 1998, will operate at higher temperatures (1427 C) and higher pressure ratios (e.g., 23 or more), requiring gasifiers to operate at temperatures of 34 atmospheres or more. This in turn will motivate changes in the design of air separation units for many gasification plants (Bjorge *et al.*, 1996).

7.6 Integration with the Oil Refinery

There are a number of considerations regarding integration of the gasification system with the oil refinery. These considerations are inherently site-specific. For example, at Plock, there is no need to provide hydrogen to the refinery. The main requirements are for steam and electric power. The repowering project would utilize existing steam turbines that are currently operated with natural gas-fired boilers. There may be opportunities to more fully integrate the gasification system with the refinery. However, the feasibility of such opportunities must be evaluated not only from a technological perspective, but also from operational, economic, and business perspectives. It may be simpler and more practical, in terms of plant staffing, control, operation, and financing, to maintain the gasification plant as a separate "over the fence" entity associated with the refinery, rather than as an integral part of the refinery.

8.0 CONCLUSIONS

In this paper we have described a methodology for detailed analysis and management of the risks and potential pay-offs of process technologies using quantitative analysis of uncertainty and process simulation. Probabilistic analysis methods enable the risks of poor technology performance, high emissions, and high cost to be identified. In addition, they enable the key sources of these risks to be identified. Therefore, it is possible to target additional data collection or research to the areas of the technology that are most responsible for unacceptable risks. In addition, screening and iteration in probabilistic analysis enables project resources to be focused upon the most sensitive model inputs. The comparison of alternative process designs under uncertainty, and stochastic optimization and stochastic programming methods, can be used to develop process designs that minimize risks and that are robust to uncertainties in model inputs. The results of these analyses are more realistic technology assessments than those based upon single point estimates.

We describe a case study for repowering of an oil refinery in Poland using gasification technology. A basic process flowsheet is presented. As part of future work, the probabilistic methodology described here will be applied to detailed analysis of the performance, emissions, and cost of gasification-based refinery repowering options. The analyses will be based upon ASPEN process simulation models and the development of probabilistic input assumptions using the methods described in this paper. The probabilistic case studies are intended to realistically address sources of both technological and economic risks in order to determine whether gasification-based repowering is a competitive and reliable option for industries in Poland.

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BIOGRAPHICAL INFORMATION

Speaker : H. Christopher Frey

Author(s) : H. Christopher Frey and Ziemowit Iwanksi

Company : North Carolina State University

Dr. Chris Frey is an Assistant Professor of Civil Engineering at North Carolina State University.

He conducts research regarding the performance, emissions, and cost of power generation and environmental control systems. Examples of recent projects for which Dr. Frey was the Principal Investigator include:

(a) a study of energy and environmental technology needs in developing countries; and

(b) quantitative analysis of uncertainty for advanced coal based power generation systems for purposes of research planning

His experience includes work as an environmental engineer at Radian Corporation and as an Environmental Science and Engineering Fellow at the U.S. Environmental Protection Agency. Dr. Frey currently serves as a consultant to industry and government regarding uncertainty analysis and its application to energy and environmental systems.

Dr. Frey has a Bachelor of Science degree in Mechanical Engineering from the University of Virginia, and from Carnegie Mellon University received a Master of Engineering degree in Mechanical Engineering and a Doctor of Philosophy degree in Engineering and Public Policy.