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Evaluating the Risk-Reduction Benefits of Wind Energy

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FOREWORD

Quantifying of the value of wind power integrated in a utility system is central to electric technology resource selection and deployment decisions. Many of the positive attributes of wind power are normally considered to be non-monetary in nature. This makes evaluation in a market driven primarily by price difficult. Many members of the renewables community believe that including a qualitative or subjective assessment of these attributes in traditional Integrated Resource Planning processes or in a restructured, delaminated utility business environment results in the characteristics being under-valued or ignored.

Recently, however, the issue of uncertainty and risk has received more attention. Utility financial losses caused by higher than expected plant costs and lower than expected growth in demand in the 1980s, coupled with uncertainty from the introduction of competition through restructuring, has resulted in explicit consideration of new risk management strategies.

This study examines the costs and risks of two resource options, a gas-fired combined cycle plant and a wind plant, using a decision analysis framework. A case study, using generation and economic characteristics of Texas Utilities Electric, a large investor owned utility, was used to illustrate the concepts.

This report is written by a group of experts with experience in utility modeling and decision making, and renewable energy evaluation. They have shown that accounting for risk makes wind energy appear more attractive than if the examined risk attributes are not considered . The benefit allocation between generation plant owner and electric consumer depends on market structure . By approaching the analysis from the perspective of a utility, we hope that the methods and results will motivate electric market players to explicitly consider the risk reduction attributes of wind in future deliberations on technology selection.

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EVALUATING THE RISK-REDUCTION BENEFITS OF WIND ENERGY

EXECUTIVE SUMMARY

The question of uncertainty and risk in electric utility resource planning has received considerable attention in recent years. During the 1980s, many utilities suffered losses because of unexpectedly high plant construction costs and low growth in electricity demand. Since then, the introduction of competition to the electric industry has created additional risks for power companies. No longer will utilities be able to count on regulatory protections and a base of captive consumers to provide a stable market and adequate return on their investments. New risk management strategies will have to be considered.

One approach to managing risk is for a utility company to invest in diverse power sources such as wind power plants. Since wind plants consume no fuel, can be built in relatively small increments with short construction lead times, and generate no pollutants, it is often said that they offer significant protection from risks associated with conventional fossil-fuel power plants. Until recently there have been few efforts to quantify these benefits, however.

This study compares the costs and risks of two competing resource options, a gas-fired combined cycle plant and a wind plant, both utility-owned, through decision analysis. The case study utility is Texas Utilities Electric, a very large investor-owned company serving an area with substantial, high-quality wind resources. We chose a specific moment in the future—the year 2003—when the utility currently plans to build a large fossil-fueled power plant, and examined the implications for the utility's expected revenues, costs, and profits if a wind plant were to be built instead. The uncertain inputs include fuel prices, environmental regulations (specifically, CO_2 controls), wind and conventional power plant availability, and load growth. A regulated market scenario and two unregulated market scenarios—a power pool like that operating in the United Kingdom and a market dominated by short- and medium-term fixed-price contracts—were examined.

The initial findings of this study suggest that risk should be an important consideration in evaluating competing wind and gas-fired combined cycle plants. For the most part, accounting for risk makes wind energy appear more attractive than gas-fired power plants, as the benefits of reduced exposure to fuel-price and environmental regulatory risks outweigh the greater uncertainty in the annual average availability of wind plants. The magnitude of the benefit for utility customers ranges up to $7.8/MWh under traditional regulation but is smaller or negative in unregulated markets. The benefit for utility plant owners ranges up to an extra 1 to 1.5 percent return on equity in a power pool market—where profits are most driven by short-term fuel prices—but is smaller in other market settings. (See table.)

As these findings suggest, the allotment of risks between shareholders and customers may have a significant impact on how favorably each group perceives wind energy. In a

Summary Results: Risk Benefits of Wind Energy

Market Scenario	As Perceived by Customers ($/MWh)		As Perceived by Shareholders (% ROE)	
	Low	*High*	*Low*	*High*
Regulated	3.4	7.8	~ 0	~ 0
Power Pool	(2.3)	(1.3)	1	1.5
Fixed Contracts	2.9	6.7	0.2	0.5

regulated market, utility company shareholders see few of the risks of fossil fuels and hence have little incentive to invest in risk-mitigation options such as wind power. This helps explain why few utilities have eagerly embraced wind technology. Our study indicates that an unregulated market will provide a greater incentive for utility investment in wind energy based on risk considerations alone. (Other factors, such as a higher discount rate hurdle, may work against wind power, however.) Although the risk incentive is theoretically largest in a power pool, the extreme volatility of prices in such a market may serve to mask the incentive to a considerable degree. A market dominated by fixed-price contracts may be most favorable to wind, as the risk benefits will then be distributed more or less evenly between customers and utility company shareholders, giving both a modest incentive to go with wind.

Most importantly, this study demonstrates that decision analysis can be a useful tool for estimating the risk-reduction benefits of wind energy under a range of market conditions. Analytical tools like this should help inform traditional methods of utility resource planning as well as regulatory and legislative efforts to create a level playing field for wind and other renewable technologies in a deregulated electricity market.

Finally, the report identifies several areas in which further research would be helpful:

1. The SRP model or similar tools should be applied to exploring the benefits of modularity and short construction lead times. Large conventional power plants have construction lead times (excluding licensing and permitting) ranging from two to five years or longer, compared to the one year typically required for wind power plants. Longer lead times increase the risk that the financial attractiveness of a power plant investment will diminish between the time substantial construction funds are first committed to the time the plant goes into operation. Factors that may affect the financial attractiveness include fluctuating loads, fuel prices, and environmental regulatory costs.

2. A related question is the need to consider the value of delaying a large capital investment such as a wind power plant until conditions are better known. The benefit of delaying investment may work against wind power since it requires more capital investment and hence more risk than some other options.

3. There needs to be more study of appropriate probability distributions for the uncertain input parameters, particularly environmental regulatory costs. One option would be to

conduct a survey of energy and environmental experts, including managers of utility companies and independent power producers.

4. Further work should be done to define appropriate risk aversion factors for both utility managers and power consumers. A literature search would be useful. In addition, focus groups and similar polling techniques could be applied to measure risk aversion.
5. The pros and cons of various approaches to measuring risk should be evaluated in greater depth. In particular, the capital asset pricing model and the decision analysis approach used here should be systematically compared. Our results suggest that the very large risk premium estimated by Awerbuch[1] for gas-fired power plants (upwards of 7 ¢/kWh) is unjustified. It is important to understand why the two approaches disagree.
6. Finally, it would be interesting and potentially useful to see if analytical short cuts could be developed that would yield good results without the degree of effort demanded by probabilistic simulations. An approach that is more easily grasped and applied by non-experts could help communicate the importance of risk issues to decision makers such as utility managers and investors.

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[1] Shimon Awerbuch, "Measuring the Costs of Photovoltaics in an Electric Utility Planning Framework," *Progress in Photovoltaics*, vol. 1, 153-164 (1993).

EVALUATING THE RISK-REDUCTION BENEFITS OF WIND ENERGY

1. INTRODUCTION

The question of uncertainty and risk in electric utility resource planning has received considerable attention in recent years.[1] During the 1980s, many utilities suffered financial losses because of unexpectedly high plant construction costs and low growth in electricity demand. In addition, the introduction of competition to the electric industry is creating new risks for power companies. No longer will utilities be able to count on regulatory protections and a base of captive consumers to provide a stable market and adequate return on their investments. Alternative risk management strategies will have to be considered instead.

One approach to managing risk is for a utility company to invest in diverse power sources such as wind power plants. Since wind plants consume no fuel, can be built in relatively small increments with short construction lead times, and generate no pollutants, it is often said that they offer significant protection from risks associated with conventional fossil-fuel power plants. So far there have been few efforts to quantify these benefits, however.[2]

This report presents the results of a study to systematically evaluate and quantify the risk-reduction benefits of wind power (and by extension, other renewable resources) for a case study utility system. The study uses probabilistic decision analysis, a method in which the costs and risks of alternative decisions are compared and evaluated through computer simulations. The decision to be assessed is whether to build a 400 megawatt (MW) gas-fired combined cycle power plant or a 1600 MW wind plant of equal firm capacity. The case study utility is Texas Utilities Electric, a very large investor-owned company serving an area with substantial, high-quality wind resources.[3] We chose a specific moment in the future—the year 2003—when the utility currently plans to build a large fossil-fueled power plant, and examined the implications for the utility's expected revenues, costs, and profits if a wind plant were to be built instead. The uncertain inputs include fuel prices,

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[1] Eric Hirst and Martin Schweitzer, "Electric-Utility Resource Planning and Decision-Making: The Importance of Uncertainty," *Risk Analysis* **10**, 137-146 (1990); C. J. Andrews, "Evaluating Risk Management Strategies in Resource Planning," Paper presented at the 1994 IEEE Power Engineering Society Summer Meeting (94 SM 520-7 PWRS); C. Studness, "Competition and Utility Financial Risks," *Public Utilities Fortnightly*, July 1 1993, pp. 31-32; and Enrique Crousillat and Spiros Martzoukos, *Decision Making Under Uncertainty: An Option Valuation Approach to Power Planning* (Washington, DC: The World Bank, 1991).

[2] For examples, see Eric Hirst, *Benefits and Costs of Small, Short-Lead-Time Power Plants and Demand-Side Programs in an Era of Load-Growth Uncertainty* (Oak Ridge, Tenn.: Oak Ridge National Laboratory, 1989); Shimon Awerbuch, "Market-Based IRP: It's Easy!!!" *The Electricity Journal* **8**, 50-67 (1995); and Thomas E. Hoff, Pacific Energy Group, *Integrating Renewable Energy Technologies in the Electric Utility Industry: A Risk Management Approach* (Golden, Colo.: National Renewable Energy Laboratory, 1996).

[3] TU Electric is planning to complete a 40 MW wind plant at Big Springs, Texas, in 1997.

environmental regulations (specifically, CO_2 controls), wind and conventional power plant availability (including variations in annual average wind speed), and load growth.

The study concludes that building a wind plant can have substantial value as a risk-reduction strategy. Its precise value depends on many factors, however, including whose perspective is being considered (e.g., ratepayers or utility shareholders) and how the market allocates risks among them. In a strictly regulated market, ratepayers are exposed to virtually all of the risk from fossil-fuel sources and therefore see virtually all of the risk-reduction benefit from wind power. It follows that utility managers—who represent primarily the interests of shareholders—have little or no incentive to invest in wind energy. However, the risks and risk benefits are more equally shared among customers and shareholders in an unregulated market, depending on the nature of contracts between the utility and its customers and whether power is traded through a pool. These findings should help inform discussions on the future structure of the utility industry and may help encourage utility companies to make greater investments in wind energy.

The paper begins with a general discussion of the concept of risk for electric utilities and describes briefly several methods of evaluating risk (section 2). There follows an overview of the model we used, the Strategic Resources Planning (SRP) model (section 3), as well as a detailed description of how the uncertain variables are treated (section 4). In section 5, we present the results of the study, and in section 6, we derive ranges of diversity values, in dollars per kilowatt or kilowatt-hour, for wind energy under various market scenarios and assumptions.

2. RISK AND ELECTRIC UTILITIES

2.1. Introduction

For most people risk is something to be avoided. In the financial world, however, risk is neither good nor bad, but is merely one of the characteristics that affects the value of an investment. The standard measure of financial risk is the variance, or spread, in a cost or revenue stream. As a rule, investors require higher payoffs from riskier investments. For example, so-called junk bonds are extremely risky compared to US Treasury bonds but offer a far greater expected yield. One of the basic functions of financial markets is to establish how much return investors will demand for an expected degree of risk.[4]

Risk, however, is often in the eyes of the beholder. Since the electric utility industry, in particular, operates for the public's benefit under regulatory oversight, it is important to consider not only the perspective of the shareholders who invest in the utility company but also that of the company's customers.[5] The risk perceived by each group is often very different. For the customers the principle risk lies in the variance of electricity rates. In a

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[4] There are many treatments of the relationship between risk and return in the financial literature. See, e.g., Richard A. Brealey and Steward C. Myers, *Principles of Corporate Finance* (New York: McGraw-Hill, 1991), chapters 7 and 8.

[5] This remains true even if the electric industry is restructured to allow greater competition, since critical aspects of the industry, particularly distribution services, will remain under regulation.

regulated market, rates are normally set by dividing the projected total cost of providing service (plus some profit margin for the utility shareholders) by the projected electricity demand. Consequently, the variances of these two factors determine the variance of rates. In an unregulated market, however, electricity rates may depend as much on the nature and degree of competition amongst both suppliers and customers, and on the contractual arrangements between them, as on the actual cost of producing and delivering a kilowatt-hour of electricity (just as the price of an airline ticket often bears little relation to the distance flown).

For utility companies and independent power producers, risk is usually measured by the variance in profits or return on equity. In the case of regulated utilities, many—but not all—of the risks to profits are eliminated or greatly reduced. Fuel costs are recovered directly through a surcharge on bills; the costs of building new power plants and of meeting new environmental and safety regulations are usually approved by regulators for recovery through rates; and perhaps most important, most customers are obliged to purchase power from their local utility no matter how expensive it is. Uncertain load growth remains a significant source of risk for utilities because rates are normally fixed for some period during which changing loads can affect revenues. Overall, however, the main risks for the utility originate in the regulatory system itself. Will a power plant be allowed into the rate base? Will the regulatory commission approve the utility's rate request?

With the introduction of competition, the utility's bottom line becomes much more sensitive to market forces. In the long run, the price charged by the utility must be at least enough to recover the costs of producing and delivering the power, including a profit sufficient to compensate power plant investors and utility shareholders for the risk of their investments. If that price is too high, however, a utility risks losing market share to competitors. Other factors besides price, such as environmental quality, may also affect a company's ability to attract and retain customers.

2.2. Methods of Studying Risk in Electric Utility Systems

Against this complex background, it is clearly very difficult to evaluate the risks of a generic utility investment—like a wind plant—in a comprehensive or conclusive way. Nevertheless, a number of techniques have been developed which can illuminate different aspects of the issue. Several approaches are described briefly here in rough order of increasing sophistication.[6]

Sensitivity Analysis. In this approach, the utility develops a resource plan based on expected values of fuel prices, loads, and other critical parameters. Then, the cost

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[6] For descriptions of several of these approaches, see Hoff, *Integrating Renewable Energy Technologies in the Electric Utility Industry*, op. cit., chapter 2; Elizabeth Olmsted Teisberg, "Methods for Evaluating Capital Investment Decisions Under Uncertainty," in Lenos Trigeorgis, ed., *Real Options in Capital Investment* (Westport, Conn.: Praeger, 1995); Eric Hirst and Martin Schweitzer, "Electric-Utility Resource Planning and Decision-Making: The Importance of Uncertainty," *Risk Analysis* **10**, 137-146; and C. J. Andrews, "Evaluating Risk Management Strategies in Resource Planning," Presented at the IEEE/PES 1994 Summer Meeting, July 24-28, 1994.

implications of possible changes in the input values are examined. For example, one might look at the effect of increasing gas prices by 10 percent relative to the base projection. Although probabilities may be attached to the perturbations, the exercise is usually performed to answer "what if" questions. A key shortcoming is that the resource plan is *not* re-optimized when studying the effects of changes in the input parameters, and thus the results can be unrealistic. However, it is useful for identifying the parameters that could have the greatest impact on future costs and for measuring the robustness of the proposed plan against changes in assumptions.

Scenario Analysis. This involves developing a set of optimal, least-cost resource plans based on internally consistent combinations of key assumptions, which are usually grouped around a "base case" or "most likely" prediction. For example, one scenario might assume strict environmental regulations, such as a CO_2 tax, combined with relatively low load growth; another might assume low fossil fuel prices, no new environmental regulations, and high load growth. By comparing the attributes of the various plans, one can identify common resource blocks that would constitute part of a robust resource plan that appears favorable under a range of conditions. Unlike sensitivity analysis, scenario analysis captures some aspects of dynamic resource planning since it provides an indication of how an optimal resource plan would be adjusted if the future were to unfold in a particular way. Generally speaking, however, it provides few quantitative results that can aid in reaching a decision on a particular power plant investment.

Static Discounted Cash Flow Analysis. This approach resembles the traditional method of analysis of power plant costs used by utilities for decades. The present values of the various cost and revenue streams of a proposed project are calculated. If the net present value—the amount by which expected revenues exceed expected costs—is positive, then the investment is deemed worthwhile, or if more than one power plant is under consideration, then the one with the highest net present value is chosen. (In a regulated market, requirements to meet a certain level of reliability may force the utility to build a power plant even if the expected net present value of the investment is negative.) The important distinction between static DCF analysis and the traditional method is that the analyst chooses a discount rate that corresponds to the apparent risk of the project, rather than using the utility's weighted average cost of capital (WACC). The reason is that the WACC reflects the risk to profits from the utility's entire resource portfolio and may consequently have little to do with the risk of the particular project under consideration. Generally speaking, using the WACC leads to wrong results.

Ideally, the discount rate should be based on the observed cost streams or net returns of projects which have similar risk profiles. If such information is not available, a theoretical model such as the capital asset pricing model (CAPM) may be used to estimate the appropriate value.[7] An added complication is that different cash flows within a project (such as fuel costs and revenues) may have different risk profiles and thus should be

[7] The CAPM relates discount rates (or equivalently, expected returns) to the covariance between a particular cost stream and the returns to a broadly diversified portfolio of assets such as a stock market index, as represented by the parameter ß (beta). It is described in more detail in a section 6.

discounted at different rates. It is often difficult to determine, *a priori*, which cash streams should be treated separately and how many individual discount rates are needed.

Static DCF analysis has been applied to utility investments with interesting results. One example, notable since it deals explicitly with renewable energy sources, is the work of Shimon Awerbuch. He has argued that using the WACC of a power company to calculate the present value of a proposed project can bias utility resource decisions heavily in favor of conventional energy technologies. The reason is that renewable resources such as photovoltaic and wind systems have cost streams that are largely fixed and hence nearly risk-free, whereas the fuel costs of conventional technologies tend to be negatively correlated with the general economy and hence appear quite risky (fuel outlays will tend to be high when the general economic condition is poor). According to Awerbuch, the effect of taking these differing risk profiles into account is to raise the levelized cost of energy (LCOE) for a gas-fired power plant from $0.08/kWh to $0.15-$0.28/kWh, while reducing the LCOE of a PV system from $0.24/kWh to $0.21/kWh.[8]

Although superior to traditional utility cost-effectiveness calculations, static DCF analysis presents some methodological and conceptual challenges. For one thing, it is difficult to estimate appropriate discount rates for some input parameters, particularly when the historical record is limited or market conditions are changing. For example, the assumption that gas prices are negatively correlated with stock market returns is based on a brief record of the past 25 years or so, a period which saw two major oil crises and the deregulation of the gas industry. Furthermore, static DCF analysis does not consider how the use of a power plant—or the development of the utility's entire resource portfolio—may change in response to changing conditions. This weakness may in some cases exaggerate the potential risk of certain investments. For example, if a utility were suddenly faced with increased gas prices it could choose to run its gas units less and perhaps build other power plants to replace their capacity.

Dynamic Discounted Cash Flow Analysis (Decision-Tree Analysis). This approach introduces dynamic planning to static DCF analysis. Distinct decision points are identified that when charted out resemble a tree with many branches; for that reason, it is sometimes called decision-tree analysis. At each point in the tree, the model attempts to make the best decision based on information available at the time. Probabilities are assigned to different parameters that may affect decisions, leading to a potentially huge number of probability-weighted "futures." The expected outcomes for each cost stream in each year are then discounted back to the present using the appropriate risk-adjusted discount rate.

Usually, the first decision in the tree is the one that is being analyzed. By tracing each branch of the tree after that decision is made, the net present value of both choices can be calculated and compared. This type of analysis, done properly, explicitly captures the dynamic and incremental nature of corporate planning and system operations.

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[8] Shimon Awerbuch, "Measuring the Costs of Photovoltaics in an Electric Utility Planning Framework," *Progress in Photovoltaics*, vol. 1, 153-164 (1993).

Although the method is more sophisticated than static DCF analysis and can produce more realistic results, it presents some of the same difficulties, such as the need to estimate risk-adjusted discount rates with often limited or unreliable data. In addition, like most other probabilistic techniques, it is computationally far more challenging. Each possible event (e.g., a change in fuel prices) must be characterized explicitly by a discrete magnitude and probability (or a continuous probability distribution) in each time period of the analysis. These probabilities must be based at least in part on subjective judgment. Moreover, the potential behavior of key decision makers must be modeled in a realistic fashion. Is every decision likely to be economically rational? What other considerations might come into play? Lastly, discount rates may change over time in unexpected ways.

Decision Analysis. This approach is similar in many respects to dynamic DCF analysis, with the important distinction that discounting is used only to reflect time preference, not risk. The discount rate is therefore a single, risk-free rate, such as the expected yield on US Treasury bonds. Risk is taken into account after the fact by applying a risk preference function (or utility function) to the distribution of possible outcomes. The risk preference function is an equation describing the level of risk a decision maker (e.g., a corporation) would be willing to accept for a given expected reward. The value of a proposed investment is usually expressed as a certainty equivalent, which is defined as how much the investment is worth to a decision maker today given the likely variability of its future returns.[9]

An example of the application of decision analysis to utility planning is provided in testimony by staff from the Pacific Gas and Electric Company in hearings before the California Energy Commission.[10] The analysts set out to determine a value that should be placed on resources that do not have variable fuel costs. They compared the predicted variability of energy costs for the PG&E system with, on the one hand, a gas-fired power plant addition, and on the other hand, with a "diverse" generating unit with constant fuel cost. Their conclusion was that the diversity value of such an addition is negligibly small—no more than $0.77/kW-year of diverse capacity.[11]

A key underlying difference between decision analysis and discounted cash-flow analysis is that the former attempts to model an individual's or a group's sensitivity to risk, whereas the latter relies on financial markets to determine the appropriate tradeoff between risk and reward. The results can be quite different. Individuals vary widely in their aversion or affinity for risk, and even corporate managers, who are supposed to act solely in the interest of their company's stock holders, may be influenced by personal factors such as fear of losing their jobs. The stock and bond markets, on the other hand,

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[9] The application of expected utility theory to decision analysis is described more fully in section 6.

[10] Jonathan M. Jacobs and Thomas E. Huntley, Pacific Gas and Electric Company, "Valuation of Fuel Diversity," Submitted for Hearings before the California Energy Commission (February/March 1992).

[11] Our study finds a much larger risk-reduction benefit from wind energy than suggested by the PG&E study. The discrepancy appears to come from two sources. First, the PG&E report assumed a relatively short time horizon over which the cumulative deviation of gas prices from the expected path is likely to be small. Second, the PG&E study did not consider environmental regulatory risks, perhaps the dominant source of risk in fossil-fuel investments.

reflect the average risk aversion of all of its investors. The challenge of decision analysis is to determine the appropriate risk preference function for a particular company, investor, customer class, or other stakeholder.

Options Valuation. This technique has been developed to a high degree of sophistication as a tool for analyzing options and futures markets. As several analysts have shown, it can also be applied to assessing power plants and similar capital investment decisions.[12] Options theory basically involves estimating the value of deferring an investment decision to a later time when more information is available to assess its worth. A call option, for example, allows the buyer to purchase a particular asset at some later time and at a specified price. If the value of the asset is above the option price at the time the option becomes available, then the investor can exercise the option and make a profit. If the asset value is below the option price, then the investor can choose not to exercise the option, and instead take a loss equal to the original option price. The reason such an option has a positive value is that the upside benefit is potentially unlimited whereas the downside risk is not. When applied to an investment such as a power plant, a typical outcome of options valuation is an estimate of how much the expected net present value must exceed zero for the investment to be worth making now rather than deferring to a later date. Decision-tree analysis is often used to make this determination.

Again, a critical issue is how to value risky cash flows. Instead of using discount rates, practitioners of options valuation typically refer to similar assets (known as twin assets) whose market value is already known. For example, the market value of a prospective oil field development could be estimated from that of comparable, existing oil fields. If no suitable twin asset is available, then the project may be broken down into individual components, each of which has a twin whose value can be determined. The obvious—but not always easy—challenge is to find or derive appropriate twin assets. If one is evaluating a widget factory, for example, and the only available twin is a factory that makes both widgets and gadgets, it may not be correct to simply subtract the value of a gadget factory from the value of the gadget-widget factory, since there may be benefits to combining both production processes under a single roof.

The most direct application of options valuation to utility planning is determining the value of small plant size, a short construction lead time, and modularity. A commitment to build a large power plant over several years entails a loss of flexibility. If fuel prices, load growth, and other factors change once the commitment is made, the plant may no longer be economic, yet the company may already have spent too much to back out of the investment. Options valuation techniques can determine the potential cost of this loss of flexibility, which may then be included in the comparison of competing generation options.

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[12] See, e.g., Robert S. Pindyck, "Irreversibility, Uncertainty, and Investment," *J. of Economic Literature* **23**, 1110-1148 (1991); and Henry D. Jacoby and Davig G. Laughton, "Project Evaluation: A Practical Asset Pricing Method," *The Energy Journal* **13**, No. 2, 19-47 (1992).

3. OVERVIEW OF THE STRATEGIC RESOURCES PLANNING MODEL

As the foregoing makes clear, there is no ideal or universally preferred way of evaluating risk in the context of utility planning. Rather, a variety of methods exist which can reveal different aspects of risk in a more or less quantitative fashion. For long-range strategic planning, scenario analysis may be the best approach, as it most clearly delineates between the possible strategic alternatives. For evaluating particular power plant investments, however, static or dynamic DCF analysis, decision analysis, and options valuation may be appropriate depending on the type of investment, the analytical resources and information available, and the kind of risks of interest to the analyst.

The approach adopted in this study is a probabilistic application of decision analysis. The decision to be evaluated is whether to build a 400 MW gas-fired combined cycle power plant or a 1600 MW wind power plant of equal firm capacity. The model assumes that this decision will be made at the end of 2001 and that the plant will go on-line in 2003. Up to 2001, conditions potentially affecting the decision—such as fuel prices and load growth—are not allowed to deviate from present expectations. After 2001, however, conditions are allowed to vary according to specified probability distributions. (See Figure 3.1.)

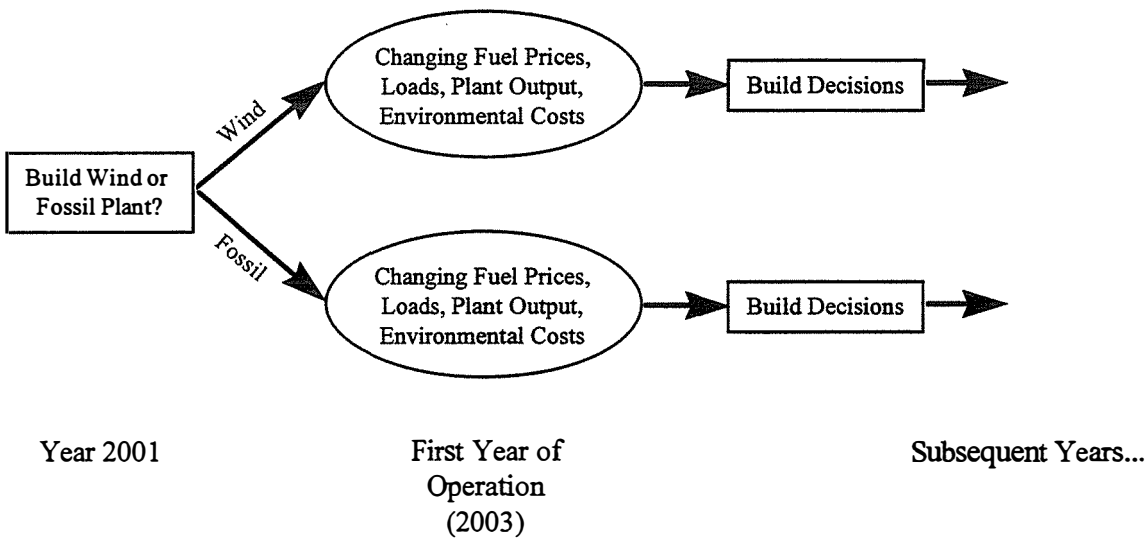

Figure 3.1. Decision tree schematic.

The model, known as the Strategic Resources Planning (SRP) model, calculates the expected cash flows and probability distribution of cash flows for each of the two possible decisions—the gas plant or the wind plant—in parallel, using Monte Carlo techniques to simulate the key uncertain variables. Future costs are discounted for time preference alone, at a nominal risk-free discount rate of 7.5 percent. Risk is taken into account by applying a utility function to the variances of revenue, cost, and net income.

The SRP model was originally developed by Charles River Associates and Convergence Research to analyze risks on the Pacific Northwest power grid. It was subsequently

adapted and extensively revised for this project. The spreadsheet-based model generates utility resource expansion plans and estimates fuel use and operating expenses over a 20- or 30-year period based on projected load growth, capital and operating costs, fuel prices, environmental costs, and other user-specified input parameters. The resource plans and projected costs differ with each Monte Carlo draw of the uncertain inputs. For example, if gas prices increase sharply relative to coal prices in a particular draw, the model will preferentially select coal or renewable resources instead of gas. The results of all the simulations are collected and presented as both an expected value and a probability distribution for any indicator of interest (such as cumulative revenue requirements or annual net cash flow).

The initial inputs to the model are designed to recreate TU Electric's 1995 integrated resource plan[13] (the most recent available) under deterministic conditions, i.e., assuming no uncertainty in fuel prices, load growth, and other critical parameters. Since the model creates hundreds of resource plans in any given scenario, the inputs and calculations must be simplified to reduce the computation time. The following sections summarize the general assumptions, characteristics of generating units, build and dispatch functions, financial calculations, and model outputs.

3.1. General Assumptions

Table 3.1 summarizes the general input assumptions for the model. Loads are projected from 1994 data, with corrections for anticipated DSM program savings. The fuel prices represent an approximate average for all generating units, both existing and new. Coal prices include both lower cost lignite and higher cost bituminous coal. Although TU Electric has some oil-fired generating capacity and a considerable amount of mixed oil-gas generating capacity, it is assumed that all of these units (with the exception of 20 MW of oil-fired steam generation) burn natural gas.

The starting year for calculations is 1996. All calculations are performed in nominal (inflated) dollars, assuming 3.5 percent annual inflation. The cost of debt and debt fraction include a small proportion of preferred stock. The cost of both debt and equity reflect conditions in 1994 and are assumed not to change with time. The fixed charge rate is calculated from the other input assumptions using standard utility accounting methods. Generating and transmission and distribution (T&D) asset figures are taken from TU Electric's FERC Form 1 filing, with minor adjustments to project the assets and depreciation to the base year. The great majority of the generating asset value is the Comanche Peak nuclear plant, which cost nearly $12 billion by the time it was completed in 1992. The model calculates depreciation expenses from the generating and T&D asset figures assuming a straight-line depreciation schedule and 40 year average book life. Non-generation expenses include primarily administrative overhead, customer service, and T&D operations and maintenance.

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[13] For a summary of the plan, see TU Electric, *TUE Plan 2004: An Energy Guide to the Future*, Dallas, Texas (1994). The complete plan is contained in hundreds of pages of testimony submitted to the Texas Public Utilities Commission. Data for this study were drawn from this testimony and from the company's Form 1 filing with the Federal Energy Regulatory Commission.

Table 3.1 General Assumptions*

Parameter	*Initial Value*	*Mean Growth Rate*
Loads		
Peak	18,497 MWp	1.93%/yr
Average	10,676 MWa	1.93%/yr
Fuel Prices		
Natural Gas	$2.10/MMBtu	5.5%/yr
Coal	$1.55/MMBtu	3.5%/yr
Nuclear	$0.77/MMBtu	4.3%/yr
Financial Inputs		
General Inflation Rate	3.5%	Fixed
Cost of Debt	8.51%	Fixed
Cost of Equity	10.78%	Fixed
Debt Fraction	49.85%	Fixed
WACC	9.64%	Fixed
Federal Tax Rate	35.0%	Fixed
Tax on Gross Revenues	9.5%	Fixed
Property Taxes and Insurance Rate	2.0%	Fixed
Fixed Charge Rate	14.84%	Fixed
Risk-Free Discount Rate	7.5%	Fixed
Assets and Non-Generation Expenses		
Generating Assets (Million $)	16,994	Determined by model
Undepreciated (Million $)	13,584	Determined by model
T&D Assets (Million $)	5,781	Proportional to peak load
Undepreciated (Million $)	3,584	Determined by model
Depreciation Period (Straight Line)	40 yrs	Fixed
Non-Generation Expenses (Million $)	705	Proportional to peak load

*Prices are in 1996 dollars. Inflation is included in fuel price inflation rates, discount rates, and costs of financing.

3.2. Existing and New Generating Units

The TU Electric system presently comprises nearly 22,000 MW of generating capacity broken down by fuel type as shown in Figure 3.2. Most plants are steam plants burning primarily natural gas, with distillate oil as a secondary fuel. However, these plants do not generally run at full capacity. The coal and nuclear power plants run in a baseload mode and generate most of the energy (see Figure 3.3). Table 3.2 below summarizes the operating costs and characteristics of the existing generating units. These data represent average or typical values drawn from TU Electric's FERC Form 1 filing and (in the case of outage rates) NERC data. Costs have been escalated to 1996 dollars. Purchased power contracts cannot be represented explicitly in the model. Instead, the fixed and variable operating and maintenance (O&M) costs shown in the table are chosen to yield approximately the correct annual purchased power expenses based on the FERC Form 1 filing.

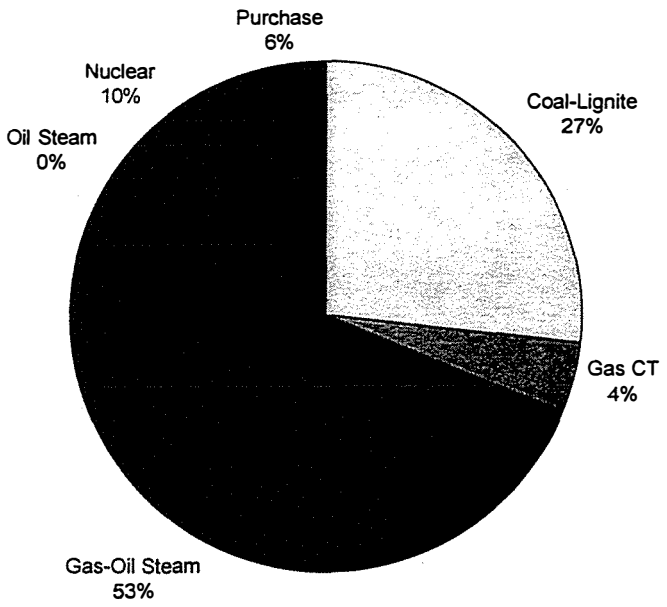

Figure 3.2. Breakdown of TU Electric generating capacity by type in 1996.

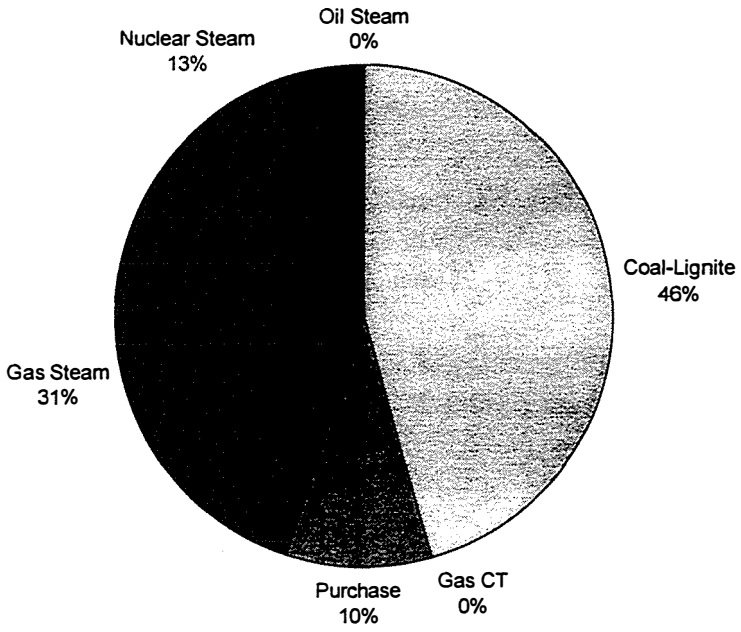

Figure 3.3. Breakdown of TU Electric generation by source in 1996.

Table 3.2 Characteristics of Existing Plants

	Coal-Lignite	Gas CT	Gas-Oil Steam (1)	Gas-Oil Steam (2)	Gas-Oil Steam (3)	Oil Steam	Nuclear	Purchase
Total Capacity (MW)	5845	975	1430	1340	8781	20	2300	1244
Average Size (MW)	1460	325	715	1340	675	20	2300	N/A
Average 1994 CF	67.7%	3.9%	52.6%	49.5%	25.5%	0.0%	72.5%	N/A
Scheduled Outage	10%	5%	10%	10%	10%	10%	18%	10%
Forced Outage Rate	6%	6%	6%	6%	6%	6%	11%	6%
Fixed O&M*	10.21	0.33	1.37	1.50	2.61	9.01	72.78	199.25
Variable O&M*	2.50	3.41	1.07	1.18	2.03	1.00	0.88	0.0
Heat Rate*	10,909	12,568	10,160	10,180	11,315	10,400	10,659	10,000

*Fixed O&M in $/kW-yr, variable O&M in $/MWh, heat rate in Btu/kWh.

New generating units can be of four types: pulverized coal, gas-fired combustion turbines (CTs), gas-fired combined-cycle units (CCs), and wind plants. The assumed characteristics of the new generating options are shown in Table 3.3.

The minimum plant size is intended to limit the number of computations needed to make build decisions. A smaller size requires more calculations, since each unit must be added successively to the mix until the capacity need in each year is met. To simplify the comparison of competing generating options, the minimum sizes (in terms of firm capacity) are assumed to be the same for all units. However, if peaking capacity is needed to "firm" a wind addition, the minimum size requirement for the peaking unit (a gas CT) is relaxed.

The capital and operating costs of the fossil-fuel units are estimated from TU Electric data. The gas-fired combined-cycle capital cost of $620/kW is based on data sheets for a 2-unit, 1300 MW plant planned for the end of the 1990s.[14] Smaller units would have higher capital costs.

The wind capital cost of $835/kW is derived from TU Electric's estimated cost of $1,013/kW, in 1996 dollars, for a 100 MW plant, discounted by 8 percent to reflect the accelerated tax depreciation available to renewable plants, and by another 10 percent to account for the much larger size of the proposed wind plant.[15] Unlike the fossil-fuel plant

[14] "Generating Unit Data Sheet: Combined-Cycle Combustion Turbine Units 2 and 3," TU Electric Integrated Resource Plan filing (1994). The estimated cost of the two units in 1994 dollars is approximately $752 million, including contingency and AFUDC, but not including transmission facilities, switchyard, makeup water supply, and gas supply pipeline. The cost is escalated to 1996 dollars at 3.5 percent per year. The initial 214 MW unit (Unit 1) for this plant is expected to cost approximately $909/kW in 1996 dollars.

[15] "Generating Unit Data Sheet: Wind 1." The estimated cost in 1994 dollars is 94.5 million, including contingency and AFUDC, but not including transmission facilities and switchyard. This is escalated to 1996 dollars at 3.5 percent per year. The discounting for tax depreciation assumes 5 year depreciation for the wind plant. The additional discounting assumes that the 1600 MW plant would be made up of four 400-

Table 3.3 Characteristics of New Plants

	Pulverized Coal	Gas CT	Gas CC	Wind
Minimum Plant Size	400 MW	400 MW	400 MW	1600 MW
Scheduled Outage Rate	10%	5%	5%	0%
Forced Outage Rate	5%	3%	3%	64%
Capacity Accreditation	100%	100%	100%	25%
Capital Cost	$1,450/kW	$590/kW	$620/kW	$835/kW
Escalation Rate	0.0%	0.0%	0.0%	-1.0%
Fixed O&M	$40.00/kW-yr	$4.60/kW-yr	$8.90/kW-yr	$8.00/kW-yr
Variable O&M	$1.21/MWh	$1.00/MWh	$1.20/MWh	$7.10/MWh
Heat Rate (Btu/kWh)	10,800	11,500	7,500	0

costs, which are fixed, the wind capital cost is assumed to decrease at a rate of one percent per year, so that by 2003 it reaches $780/kW ($845/kW without the tax depreciation adjustment). This is well within the range of current projections (see, e.g., EPRI *TAG*).

The forced outage rate for the wind unit is a proxy for the average capacity factor, i.e., a forced outage rate of 64 percent implies an average capacity factor of 36 percent. The capacity factor is entered this way so that the intermittent output of the wind plant is properly accounted for in the dispatch and build functions (described below). The average capacity factor of 36 percent is derived from wind data from Amarillo, Texas, assuming a 40 meter tower height and a power curve for the Enercon E-40 wind turbine (as described in section 3 below). The wind capacity accreditation represents the firm capacity value for the first 1600 MW of wind capacity.[16] Wind additions beyond 1600 MW will have smaller capacity values and will therefore require peaking additions to make up the requisite 400 MW of firm capacity.

3.3. Resource Selection and Dispatch Functions

The SRP model dispatches generating resources in order of increasing variable O&M and fuel cost, including environmental costs where applicable, to meet loads. For this purpose, the annual load duration curve is divided into four steps. It is assumed that all scheduled outages occur in the lowest-load block (comprising half the hours of the year). Forced outages are assumed to be distributed equally among all four load blocks. In the highest-load block, covering 5 percent of the hours, the average load equals 91.4 percent of the peak load. The coarseness of this representation of the load duration curve means

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MW plants, and that each plant would be 10 percent less expensive than the 100 MW plant assumed by TU Electric. (EPRI *TAG* estimates a 5 percent discount in going from 100 to 200 MW.)

[16] The 25 percent value is not based on any Texas-specific information, but is consistent with previous studies of wind capacity value on various utility systems. See Theresa Flaim and Susan Hock, *Wind Energy Systems for Electric Utilities: A Synthesis of Value Studies* (Golden, Colorado: National Renewable Energy Laboratory, 1984); M. C. Brower et al., *Powering the Midwest* (Cambridge, Mass.: Union of Concerned Scientists, 1993); and S. Bernow et al., reference.

that some peaking units never run in the model, but since their output is less than 0.5 percent of annual energy demand, the effect on system costs is negligible. The actual and simulated load duration curves are shown in Figure 3.4.

The build function determines which of the new generating units should be built in any given year. The function operates in two modes, the first when there is a need for capacity to meet reliability requirements—which occurs when accredited capacity falls below 1.15 times peak capacity—the other when no such need exists. Normally, additions occur only when a capacity need exists. But if fuel prices or environmental costs increase by a large enough margin, then existing units may effectively be retired and new units selected to take their place.

- In the first mode, the build function selects the resource with the highest long-term net benefit and adds it to the existing mix of units. (The net benefit equals the reduction in operating costs of the existing units minus the capital and operating costs of the proposed addition.) Long-term operating costs are simulated using levelized fuel prices, while levelized capital costs are calculated using a fixed charge rate. The firm capacity of the unit selected is subtracted from the capacity need. If the capacity need remains greater than zero, then the process is repeated.
- After meeting the capacity need, the function then evaluates whether any additional units should be built. The criterion that must be satisfied is that the net benefit of the addition must be positive *both* over the long term *and* in the first year of the addition.

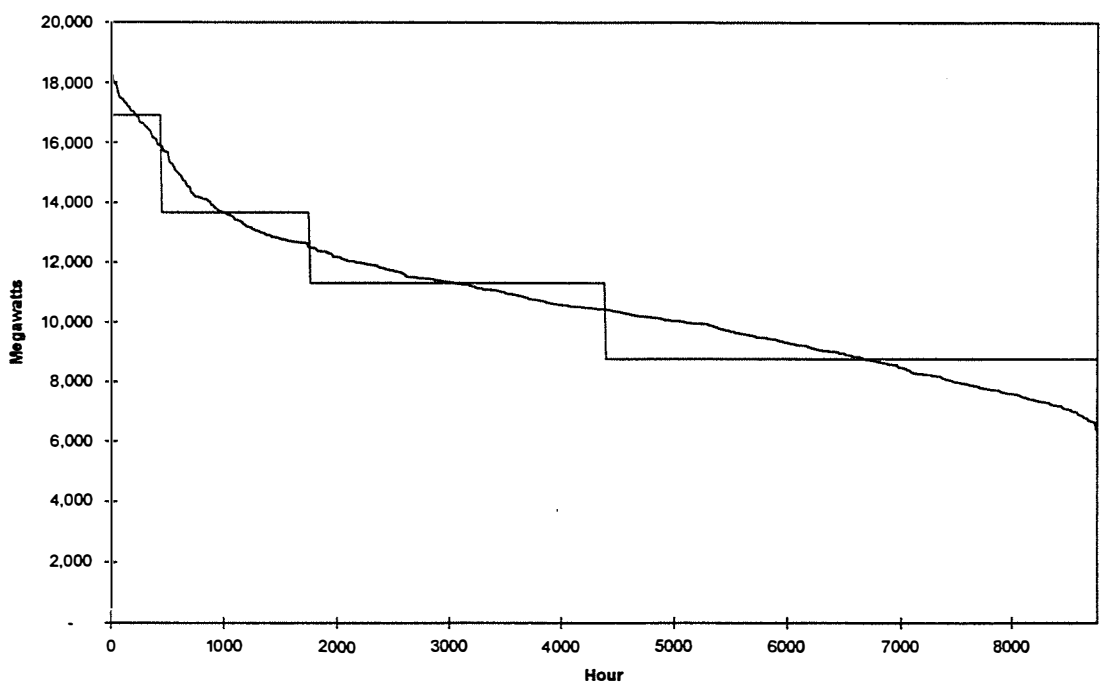

Figure 3.4. Projected and simulated load duration curves for TU Electric in 1996.

The build function first determines whether any of the possible additions meets the first criterion, assuming levelized fuel prices and a fixed charge factor. If so, it then determines whether the net benefit for the highest-long-run benefit resource is positive assuming current-year fuel prices and the first-year capital carrying charge. If so, then the unit is added to the mix. The process is then repeated until it is determined that none of the available resources meets both criteria.

3.4. Financial Calculations

The SRP model follows standard utility accounting practices to calculate revenues, costs, and net income. The basic formula for net income is the following:

(3.1) $I(t) = R(t) - E(t) - INT(t)$,

where

$I(t)$ = net income in year t

$R(t)$ = revenues in year t

$E(t)$ = operating expenses in year t

$INT(t)$ = interest expenses in year t.

In this model, revenues result entirely from the sale of electricity, and so equal the average electricity price (in $/MWh) times annual electricity sales (in MWh):

(3.2) $R(t) = p(t)S(t)$

The average electricity price is determined by the model in a manner that depends on the market setting, regulated or unregulated, and if the latter, the characteristics of the competitive market. These different cases are discussed individually in section 5.

The operating expenses are the total of fuel, operations, and maintenance expenses associated with power generation; plus taxes and book depreciation; plus non-generation expenses, e.g., for the transmission and distribution system, administrative overhead, and sales and customer service:

(3.3) $E(t) = GEN(t) + DEP(t) + TAX(t) + NONGEN(t)$

In the SRP model, generation expenses are calculated from the fixed and variable operating costs and fuel costs of the power plants on the system. Non-generation expenses are assumed merely to escalate with inflation and load growth. The tax is determined by the equation

(3.4)
$$\begin{aligned} TAX(t) &= R(t)\tau_R \\ &\quad + \left[R(t) - INT(t) - TAXDEP(t) - GEN(t) - NONGEN(t) - R(t)\tau_R\right]\tau_I \end{aligned}$$

where τ_R is the revenue or value-added tax rate, τ_I is the combined federal and state income tax rate, and $TAXDEP(t)$ is the tax depreciation. This can also be written as

$$
\begin{aligned}
TAX(t) = {} & R(t)\tau_R \\
(3.5) \qquad & + \left[R(t) - INT(t) - DEP(t) - GEN(t) - NONGEN(t) - R(t)\tau_R\right]\tau_I \\
& - \left[TAXDEP(t) - DEP(t)\right]\tau_I
\end{aligned}
$$

in which the last term, called the deferred tax, explicitly adjusts for the differing treatment of tax and book depreciation. From the start of the project to the end of its tax life, the deferred tax reduces the taxes paid; from then until the end of the asset book life, the deferred tax is recovered through an increase in the total tax. In the SRP model, deferred tax is ignored for all assets existing before 1996, and for any additions to non-generation assets after 1996, but is counted for new generating resources after 1996.

The SRP model also calculates the book return on equity, which is defined as the net income divided by the book equity:

$$
(3.6) \qquad ROE(t) = \frac{I(t)}{EQ(t)},
$$

where $EQ(t)$ is the equity portion of the net book value of the company's assets. Under rate-of-return regulation, electricity prices are set with the aim of providing a certain expected ROE. The actual ROE will fluctuate because of errors in predicting load growth and other factors, but normally it stays within a fairly narrow band. In unregulated markets, however, the ROE can vary over a much wider range.

3.5. Outputs

The SRP model generates five basic outputs: revenues, costs, net income (or cash flow), return on equity (or investment), and average sale price. These outputs are generated annually over 20 years from 2003 to 2022, for three different market scenarios: a regulated market, an unregulated power pool, and an unregulated fixed-price contract market. (These three scenarios are described in detail in section 5.) Lastly, the outputs are produced for each of the two decision choices that can be made, a wind plant or a gas-fired plant.

Since each simulation involves hundreds of Monte Carlo draws, it would be impractical to store every output from every draw. Instead, once the simulation has converged,[17] the mean and standard deviation of each output parameter are calculated for each year and stored in a spreadsheet. In addition, the cumulative net present value of each stream of outputs (calculated using the risk-free discount rate) is stored for each Monte Carlo iteration in a different spreadsheet. Thus, the model provides two different slices of the data which allow different kinds of analysis.

[17] Convergence is obtained when the standard error of revenues—equal to the standard deviation divided by the square root of the number of observations—for the two cases (wind and fossil) is less than or equal to 1 percent. Convergence is normally achieved in 150 to 400 iterations; the minimum is 150.

4. MODELING RISKS

The most critical component of the SRP model is its simulation of the uncertain inputs. Four uncertain inputs are considered: fuel prices, load growth, environmental costs, and plant availability (both wind and fossil). The first three are probably the most important ones in most situations, but the last is necessary to include in the evaluation of wind energy because wind power plants have considerably more uncertain availability on a day-to-day basis than fossil plants.

Each parameter is modeled somewhat differently from the others, as described below. However, they share the common characteristic that their probability distributions are assumed to be continuous (i.e., smooth rather than chunky) and to have a strong central tendency, meaning that they can be represented fairly well by normal (or Gaussian) probability density functions. This is not a necessary condition for modeling these risks in the SRP model, but it greatly eases the task of interpreting and presenting the results, for in such cases the means and standard deviations are well defined.

Where possible, we have relied on TU-specific historical or projected data to arrive at appropriate probability distributions for each parameter. This was not possible in the case of environmental risks, since the greatest future risk is that of CO_2 regulation, for which neither historical experience nor reliable projection is available. Nevertheless, there is a considerable body of literature on the potential costs of CO_2 controls that informs the choice of risk parameters. For the two variables whose behavior is most difficult to predict—fuel prices and environmental costs—we considered both high-risk and low-risk probability profiles.

4.1. Fuel Prices

The purchase of fossil fuels for use in power plants is one of TU Electric's largest expense items, constituting about $1.2 billion out of total operating revenues of $5.6 billion in 1994. It is also one of the most variable and unpredictable and hence important to simulate in this study.

Historical Data. TU Electric relies principally on coal and natural gas to run its fossil-fuel power plants. The coal units provide the bulk of the energy, while the natural gas units run on the margin, and hence determine the marginal cost of power for much of the year.

Historical data for TU Electric show that both coal and gas prices—but particularly gas prices—have been highly volatile over the past 20 years. (See Figure 4.1.) From 1976 to 1985, gas prices rose at an average real (inflation-adjusted) rate of 15.7 percent, while coal prices rose at an annual rate of 10.2 percent. From 1986 to 1993, gas prices fell at a 5.8 percent annual rate, while the rate of decline of coal prices averaged 1.5 percent.[18] The standard deviation in the annual real price changes for the entire period was 16.6 percent for gas and 10.2 percent for coal. These statistics are consistent with historical average fuel prices for the United States as a whole.

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[18] In this discussion, coal and lignite prices are quoted interchangeably.

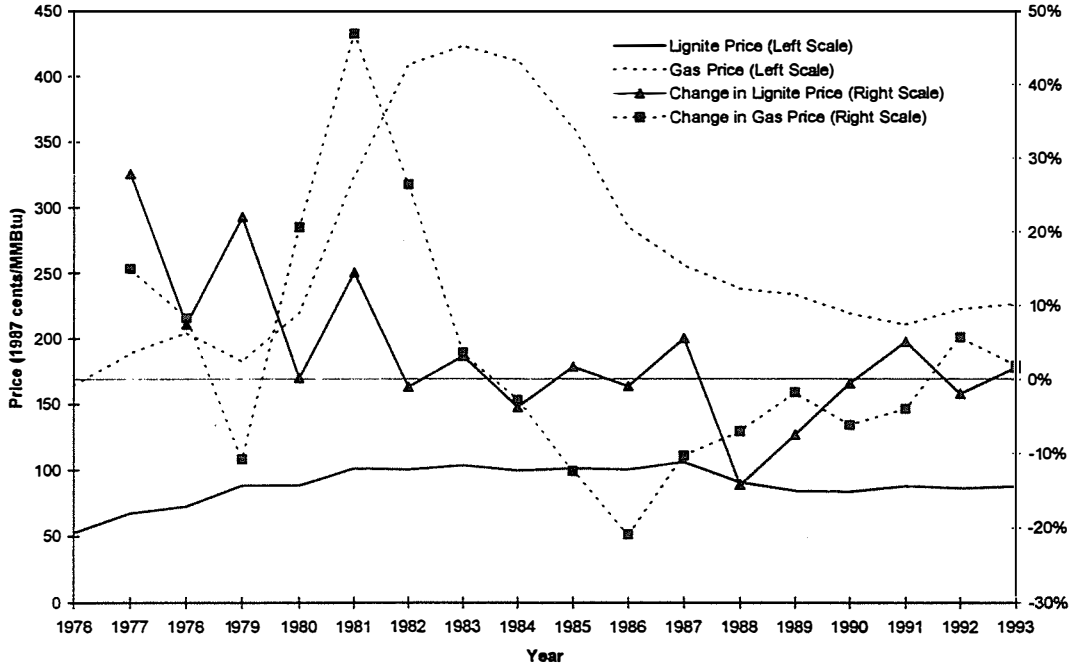

Figure 4.1. Historical gas and lignite prices and price changes for TU Electric, 1976-1993.

Interestingly, the data show a significant positive inter-temporal correlation in yearly fuel price changes. In other words, an increase in price in one year is more likely to be followed by another increase than by a decrease. Comparing each year's price change with the price change in the year following it, the correlation coefficient for the period 1967 to 1993 (using national data) is approximately 50 percent for natural gas. The correlation coefficient drops to zero as the time lag increases beyond 3 years. An inter-temporal correlation in coal prices is detectable, although smaller—about 20 percent for a one-year time lag—than for natural gas.

A significant correlation is also observed between contemporaneous coal and gas price changes. TU Electric data (covering 1976 to 1993) suggest a coal-gas correlation coefficient of 28 percent, whereas the coefficient for national data (1967 to 1993) is 40 percent. Both the inter-temporal and inter-fuel correlations are quite uncertain because of the limited number of data points in the historical record, however. The statistical standard error in each case is about 15 percentage points.

Forecasts. TU Electric's recent fuel price projections indicate that the company expects fuel prices to be much more stable in the future than they have been in the recent past. Filings for the 1995 Integrated Resource Plan show an expected real growth rate in gas prices of 1.9 percent per year from 1994 to 2014, with a possible high rate of 2.8 percent

and low rate of 0.5 percent.[19] The probability that the average growth rate will fall between the high and low values is estimated by the company to be 80 percent. TU Electric does not project a range of prices for lignite or western coal, despite the significant historical price volatility of these fuels. The average rate of price increase for both is expected to be close to zero.

TU's forecasts are consistent with, though slightly higher than, other recent forecasts. In *Annual Energy Outlook 1996*, the expected rate of growth in the price of natural gas purchased by electric utilities from 1994 to 2015 is 1.4 percent, with a probable range of 0.3 percent to 2.7 percent. The expected rate for coal is -0.3 percent, with a probable range of -0.6 percent to 0.0 percent.

Modeling Approach. Several different approaches to modeling fuel price fluctuations may be considered; none appears to be inherently superior to all others. Some analysts emphasize the tendency of fuel prices to return to some equilibrium level after temporary deviations caused by supply-demand imbalances. The equilibrium level itself is uncertain, however, and must be modeled independently. Others favor a model in which fuel prices follow a trend that varies randomly at intervals.[20] The trends can be combined with short-term price fluctuations (which we call price shocks). In both cases, one must rely on projections to determine appropriate ranges for the equilibrium or trend prices.

The approach we have taken is to assume that fuel price variations follow a random-walk process, with an allowance for temporary price shocks. This approach is easy to model, can be adapted to include inter-temporal correlations (as described below), and can readily simulate historical price changes. In a random walk (also known as a Wiener process), each annual change in price establishes a new starting point from which the next year's price is calculated. With the addition of annual price shocks, the equation can be written as follows:

$$(4.1) \qquad p_i = p_{i-1}\left(1+r_i^{walk}\right)\frac{1+r_i^{shock}}{1+r_{i-1}^{shock}} = p_0\prod_{j=1}^{i}(1+r_j^{walk})\frac{1+r_i^{shock}}{1+r_0^{shock}}.$$

Here, p_i is the fuel price in year i, r_i is the relative change in fuel price, the superscripts *walk* and *shock* refer to the random walk process and the one-year shock, respectively, and i=0 is the starting year. The expression in the denominator serves to eliminate the previous year's price shock, which by definition does not persist beyond that year. Thus, the long-term price evolution only depends on the random walk process.

The sequential price changes in the random walk may be either independent from one another or correlated to some degree. There may also be correlations between the prices of different fuels. Either case can be modeled by equating the change in one fuel price to a combination of a change in the other fuel price and a randomly generated change, e.g.,

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[19] These figures have been adjusted to remove TU's assumed inflation rate of 4 percent. The original figures were 6 percent (expected), 6.9 percent (high), and 4.5 percent (low).

[20] Paul L. Chernick et al., *Characterizing Utility Planning Risks* (Boston: Resource Insight, 1994).

(4.2) $r_i^{(1)} = a(r_i^{(2)} - \mu^{(2)}) + b_i + \mu^{(1)}$,

where the superscripts (1) and (2) refer to the different fuel price streams and μ is the mean rate of change in fuel price (1) or (2). The random number b_i is generated from a normal distribution of zero mean with a standard deviation given by:

(4.3) $\sigma = \sigma_1 \left(1 - \rho_{12}^{\ 2}\right)^{1/2}$,

where σ_1 is the observed standard deviation of the fuel price (1), and ρ_{12} is the observed correlation coefficient of fuel prices (1) and (2). The constant a is given by:

(4.4) $a = \frac{\sigma_1}{\sigma_2} \rho_{12}$.

(These equations are derived from the equation for the standard deviation of the sum of two series, $\sigma_3^{\ 2} = \sigma_1^{\ 2} + \sigma_2^{\ 2} + 2\sigma_1\sigma_2\rho_{12}$.)

The mean value of r_i is taken from TU Electric's median forecasts (in real terms, 1.9 percent for gas and zero for coal). For the standard deviations, we consider two cases. In the high-risk case, we assume that the historical standard deviation of about 16 percent for gas and 10 percent for coal will persist in the future, and that slightly more than half this deviation will be due to a random walk process and the rest to one-year price shocks. In the low-risk case, we choose the natural gas parameters to approximate the range of TU Electric's 20-year gas price forecast, while the one-year deviation is chosen so that the combined standard deviation matches recent gas price volatility of about 7 percent.[21] The corresponding figures for coal are simply scaled down from those of natural gas, since TU provides no range of coal price forecasts. The resulting assumptions are summarized in the table below.

Table 4.1 Assumed Fuel Price Variability

Fuel	*Case*	*Random Walk*		*One-Year Shock*	
		Mean	*Std. Dev.*	*Mean*	*Std. Dev.*
Natural Gas	High-Risk	1.9%	12%	0%	10%
	Low-Risk	1.9%	4%	0%	6%
Coal	High-Risk	0.0%	8%	0%	7%
	Low-Risk	0.0%	3%	0%	4%

[21] TU Electric's forecast implies a standard deviation in gas prices after 20 years of approximately 17 percent. In a random walk, the standard deviation of price at the end of n years equals the square root of n times the standard deviation of the annual changes. Thus, the implicit standard deviation in the annual price changes is 3.8 percent. About the lowest standard deviation observed for any appreciable period in the gas price record was 7 percent in the late 1980s and early 1990s. To match this, the one-year price volatility must be approximately 6 percent.

In most scenarios, no inter-temporal or inter-fuel price correlations are allowed. To test the effects of price correlations, however, we ran some cases in which the correlation coefficient between coal and natural gas prices is assumed to be 28 percent, and the one-year lag correlation for gas prices is 50 percent and for coal prices is 20 percent. (See sections 5 and 6 for a discussion of the results.)

4.2. Load Growth

Uncertainty in loads is another basic component of a utility's risk. To the extent that electricity prices are fixed for any period (either by regulation or through contracts with customers), changes in load will affect a utility company's revenues, and hence its profits. Changes in load can also affect electricity prices, since the load determines the price that must be charged to recover a utility's previous capital investments and also affects the kinds of generating units that must be run on the margin.

Historical Data. The past record shows that loads have been quite variable, although not nearly as variable as gas and even coal prices have been (see Figure 4.2). From 1977 to 1993, the average rate of TU Electric's load growth was 3.5 percent, with a standard deviation of 5 percent. For the country as a whole, the standard deviation in the change in annual energy demand was 4 percent from 1948 to 1993, and since 1970 it has been just 2.5 percent. It is to be expected that the variability of aggregate national demand will be lower than that of TU Electric's (or any other individual utility's) loads, since TU loads

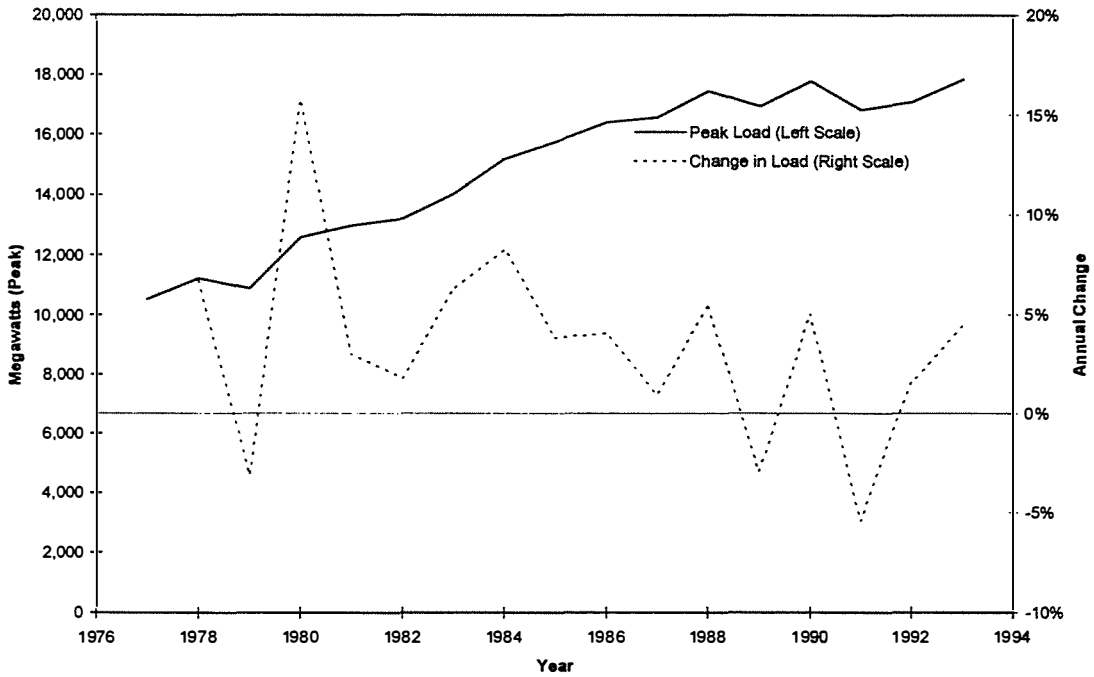

Figure 4.2. Historical peak loads and load growth for TU Electric, 1976-1994.

are influenced by regional weather and economic factors that do not affect the rest of the country.

In looking at the national data for the past 45 years, the correlation coefficient between load changes in successive years is approximately 50 percent. This correlation decreases only gradually as the time lag increases. This observation suggests a greater persistence in load trends than in fuel price trends. Much of the observed correlation, however, is the result of the abrupt drop in the average load growth rate that occurred around 1970. For the 22 years before 1970, the average load increase was 8.5 percent, whereas for the 23 years since it was just 3 percent. When data from one of these two periods are examined in isolation from the other period, the correlation between load growth rates in successive years virtually disappears.

The implication is that while loads may follow long term trends lasting 20 years or longer, short-term deviations from the underlying trend are largely independent from one year to the next. This makes sense, since most short-term fluctuations are caused by weather or changes in economic activity (such as local recession), whereas long-term load growth is driven by more persistent demographic, economic, and technological trends.

Load growth also appears to be correlated significantly with electricity prices (and indirectly, coal and gas prices). Analysis of national data shows that the contemporaneous correlation coefficient between retail electricity price changes and load changes is a reasonably strong -56 percent, i.e., a rise in electricity price is generally associated with a substantial drop in load growth. It is dangerous to infer causation in either direction from these data, however. While electricity prices may affect loads, changes in load growth may also in part cause changes in price—a drop in load may force utility companies to charge higher rates to cover their fixed costs, for example. Or it may be that both loads and prices are affected by other common factors. Since electricity has no ready market substitute, economists generally believe that the price elasticity of demand for electricity is quite low, and that short-term price changes have little impact. A large and enduring change in price, however, is likely to induce a noticeable drop in load growth.

Forecasts. TU Electric's most recent forecast suggests that the company expects the historical volatility and uncertainty in long-term loads to continue largely unchanged in the future. The company predicts an average rate of growth in peak loads of 2.5 percent (compared to the historical 3.4 percent) from 1994 to 2004, with a 40 percent chance that the rate may be as high as 3.9 percent and a 40 percent chance that it may be as low as 0.9 percent. The implied standard deviation of final loads in this forecast is 12 percent, which can be explained by a random walk with an annual standard deviation of 3.8 percent. (National-level forecasts of electricity demand are of little value in predicting TU Electric's loads and are consequently not considered.)

Modeling Approach. Once again, we simulate the uncertain parameter using a combination of a random walk process and one-year shocks. The equation for the change in load is, therefore,

$$(4.5) \qquad L_i = L_{i-1}\left(1 + r_i^{walk}\right)\frac{1 + r_i^{shock}}{1 + r_{i-1}^{shock}}.$$

The random variables r_i are generated from a normal distribution. Based on TU Electric's projections (and taking into account planned demand-side management efforts), we assume a mean value of r^{walk} of 1.93 percent, with a standard deviation of 3.8 percent to match the range of TU Electric's ten-year forecast. The one-year load shocks r_{shock} are assumed to have a mean of zero and standard deviation of 3.25 percent, yielding a total standard deviation in load changes of 5 percent. Annual energy demand is assumed to vary in an identical fashion, using the same values of r^{walk}, but with an independently generated shock. In other words, energy use and peak load move in tandem over the long term, but in any year they may diverge, thereby altering the shape of the load duration curve. These assumptions are summarized in Table 4.2.

Table 4.2 Assumed Load Growth Variability

	Random Walk		Load Shocks	
	Mean	*Standard Deviation*	*Mean*	*Standard Deviation*
Peak Load	1.93%	3.8%	0%	3.25%
Energy	1.93%	3.8%	0%	3.25%

Most scenarios assume no correlation between electricity price changes and load growth. In some runs, however, we have allowed a correlation coefficient between the change in load and the average change in electricity price in the preceding five years. This is accomplished as described earlier for coal-gas price correlations. The only complication is that the variance in electricity price is not specified in advance but rather is the result of variances in input fuel prices, loads, power plant availability, and environmental costs. Based on national historical data, the standard deviation of five-year average change in electricity prices is about 3.3 percent. Assuming a correlation coefficient of -0.20, the value of a in Eq. 4.5 is -0.23, and the standard deviation of the random variable b in Eq. 4.4 is 3.72 percent. The mean value of the electricity price change in Eq. 4.2 is the change under expected fuel prices, environmental costs, power plant availability, and load growth.[22]

4.3. Environmental Costs

Future environmental costs are more difficult to simulate because of the paucity of meaningful historical data on which to base predictions. And yet, the potential liability for electric utilities and their customers is large, and thus it is important to attempt to capture its effect. This is especially true for greenhouse-gas regulation, since CO_2 is produced by all power plants burning fossil fuels. Rather than attempt to model each of the potential environmental costs separately, we have chosen to use a proxy cost, the presumed cost of

[22] Note that when the price-load correlation is "turned on," the evolution of loads is different for the wind and fossil cases. Initially, the price is higher when the wind plant is built than when the fossil plant is built, resulting in slightly less demand.

CO_2 regulation. CO_2 is a good proxy because most pollutant emissions, like CO_2, are generally higher for coal-fired power plants than for gas-fired combined cycle systems. In addition, CO_2 appears to be the dominant—but not sole—source of environmental regulatory risk for TU electric. Because of the great uncertainty in CO_2 costs, both low-risk and high-risk scenarios are considered.

Historical Costs. It is first useful to consider the historical and current environmental cost burden for electric utilities. According to EIA data, the total investment by investor-owned utilities in environmental compliance costs, in mixed-year dollars as of the end of 1993, was $60.3 billion; TU Electric's investment was $2.4 billion. The expenses are broken down as follows:

Table 4.3 Historical Environmental Compliance Costs[23]

Item	*Cost of Compliance (Billion $)*	
	TU Electric	All IOUs
Air pollution control	$0.362	$25.14
Water pollution control	$1.245	$13.53
Solid waste disposal	$0.687	$5.28
Noise abatement	$0.007	$0.32
Esthetic measures	$0.027	$12.02
Restricted plant output	$0.050	$1.85
Miscellaneous	$0.000	$2.16
Total	$2.378	$60.30

Most of these costs have been incurred since the early 1970s with the passage of a variety of federal and state environmental laws and regulations. Although not overwhelming, they represent a significant fraction of total utility investment. TU's cumulative investment, for example, is about 10 percent of the gross book value of its assets.

Potential Non-Greenhouse Environmental Costs. A wide variety of pollutants and other environmental impacts are either not regulated or only partially regulated and may be subject to more stringent controls in the future. Several examples of these are discussed below.

Air toxics are in important class of largely unregulated pollutants which include mercury, cadmium, arsenic, chromium, and lead, and which are produced mainly by oil- and coal-fired power plants. High combustion temperatures vaporize these metals, and as the flue gas temperature falls, most condense on particulate matter. Thus, particulate controls (implemented in many power plants today) are an effective means of reducing their

[23] Energy Information Administration, *Financial Statistics of U.S. investor-Owned Electric Utilities 1993* (Washington, DC), Table 45.

output. However, not all toxics condense on particulates, and particulate controls are not 100 percent effective, so residual emissions occur. Once released into the environment, these substances are highly persistent and can cause chronic and acute health impacts in humans and animals that inhale or ingest them.

Title III of the Clean Air Act lists 189 hazardous air pollutants which are to be regulated on a source by source base. As yet, however, very few of them have been subjected to controls. Emissions from electric utilities are addressed separately in the Act, which directs the EPA administrator to study their public health hazards and determine regulations, if necessary. However, no major control initiatives appear imminent. A study by the Tellus Institute indicates that, based on the implied marginal control costs of these pollutants, regulations to reduce them beyond present levels could add 0.08-0.55 ¢/kWh to the cost of an oil-fired combined-cycle power unit and 0.06-1.19 ¢/kWh to the cost of a coal-fired unit.[24]

Sulfur dioxide combines readily with water vapor in the atmosphere to form acid rain, which is damaging to humans, vegetation, and goods. SO_2 also reacts to form sulfate aerosols, which are a large constituent of particulate matter. Sulfate aerosols are efficiently captured in the respiratory tract, producing symptom such as shortness of breath, chest tightening, wheezing and choking.

The 1990 Clean Air Act Amendments (CAAA) already require approximately a 50 percent reduction in utility emissions of SO_2. Further controls on this substance are consequently unlikely to be imposed in the near future. The principle source of risk for utilities is consequently in the price of emissions trading allowances. TU Electric has no plants requiring Phase I controls on SO_2 emissions. For Phase II compliance, it estimates that SO_2 emissions allowances will be valued at $215 (in 1995 dollars) in the year 2000, when Phase II of Title IV commences. The price of SO_2 allowances has recently fallen below $100, however, and we believe that a more likely price in 2000 is $150, with a lower bound of $130 and an upper bound of $175. By the year 2010, the potential spread in cost may be larger, ranging from about $100 to about $320 real, with an expected value of $150. Whatever the final cost, however, the potential risk for TU Electric is relatively modest. We estimate that an increase in the emissions allowance cost from $200 to $300 would increase TU Electric's annual operating costs by about 0.5 percent.

Nitrogen oxides and volatile organic compounds react together in the presence of sunlight and heat to form ground level ozone. Ozone is an extremely reactive gas which can damage human health, vegetation, and materials. It is a respiratory irritant that can cause shortness of breath, wheezing, and coughing. NO_x dissolves readily in water to form acid rain and contributes indirectly to the greenhouse effect.

NO_x and VOCs emissions permits have been traded for some time in the South Coast Air Quality Management District in southern California. Trading programs for these two ozone precursors are also being implemented in the Ozone Transport Region, which stretches from Maine to Virginia. TU Electric mentions in its IRP that "[a]dditional

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[24] Bruce Biewald et al., *Non-Price Factors of Boston Edison's Demand-Side Management Programs*, Vol. 2: Technical Report, Chapter 4 (Boston: Tellus Institute, 1994).

provisions of the amendments to the Clean Air Act require continuous emissions monitoring (CEM) as well as certain restrictions regarding oxides of nitrogen (NO_x) emissions." Further restrictions beyond those required in the CAAA are conceivable, though their likelihood is difficult to predict.

Should much stricter NO_x controls be established, a reasonable estimate of the expected control cost would be $1,000 per ton in the year 2000 and $1,500 per ton in the year 2010. For the year 2000, the lower bound might be $750, while the upper bound could be significantly higher at $5,000 per ton, if ozone non-attainment continued in urban areas (especially the Dallas-Fort Worth metropolitan area) in TU's service territory. Similarly, in the year 2010, the lower bound might be $1,000 per ton, while the upper bound might be $10,000 per ton, again in a scenario in which ground level ozone concentrations remained constant or increased. Values as high as these would have a noticeable impact on TU Electric's costs. For example, a NO_x control cost of $1000 per ton imposed in 2003 would increase TU Electric's operating costs by about $450 million, or 6 percent of projected annual revenues in that year.

Much the same can be said for VOCs. Strict controls could impose a cost of perhaps $2,500 per ton (with a $2,000 per ton lower bound and $10,000 per ton upper bound) in the year 2000. In the year 2010, the expected cost could be $3,000 per ton, with a $2,500 per ton lower bound and a $15,000 per ton upper bound.

Potential Greenhouse Gas Control Costs. Carbon dioxide is by far the largest contributor to greenhouse warming. Atmospheric levels of CO_2 are currently increasing at an annual rate of 0.4 percent. Various studies have shown that in order to achieve climate stabilization, there would have to be a reduction in CO_2 emissions relative to today's levels of around 40 percent by the year 2010 and 70 percent by the year 2030.

There is currently no regulation on CO_2 emissions in the United States, although the Clinton Administration is officially committed to limiting CO_2 emissions to 1990 levels by the year 2000 through primarily voluntary means. Some actions designed to offset CO_2 and other greenhouse gas emissions are being implemented, both privately and by government, including reforestation, coal-mine methane recovery, and methane collection and conversion in landfills.

Substantial controls on CO_2 emissions are highly unlikely in the immediate future but could be implemented within the next 10 to 15 years if scientific and international political concern about the problem continue to grow. Several countries, such as Germany, Austria, and the Netherlands, have made more-or-less firm commitments to substantial CO_2 reductions by 2000 or 2005. There is also growing consensus in the scientific community regarding the seriousness of the greenhouse problem. In 1995, the Intergovernmental Panel on Climate Change, the official scientific advisory group to world governments, concluded that human-generated greenhouse gases are already having a measurable effect on the earth's temperature. This finding has recently led the United States to adopt a policy favoring mandatory international CO_2 controls.

Estimates of the marginal cost of controlling CO_2 emissions vary widely.[25] "Top-down" econometric studies generally predict a high cost based on relatively low estimates of the price elasticity of fossil-fuel demand and high estimates of the costs of competing non-fossil energy technologies. "Bottom-up" studies, which analyze in detail the costs to meet various energy end-use demands, lead to much lower estimates, and generally assert a failure of the market to take advantage of cost-effective CO_2-reduction opportunities. The former results in estimates in the range of $25 to $150 per ton to achieve reductions of 20 to 50 percent from 1990 levels. The latter lead to estimates of $10 to $25 per ton to achieve similar reductions. A few states have adopted CO_2 externality values falling on the low end of these ranges. For example, the California Public Utilities Commission adopted a value of $8.7 per ton of CO_2, while the Massachusetts Department of Public Utilities proposed $24 per ton.

Whatever the probability of strict CO_2 controls in the future, we believe a fair range of estimates for the probable cost of control under a likely emissions trading regime would be $5 to $35 per ton. While these estimates are considerably lower than the control costs produced by some top-down models, much higher costs are unlikely to be politically feasible. Moreover, experience with the SO_2 trading allowances regime suggests that relatively low-cost options for reducing CO_2 emissions will appear once regulation creates a demand for them. To give an idea of the potential impact of CO_2 regulation, we estimate that a cost of $15 per ton imposed in 2003 would add $1.5 billion, or 18 percent, to TU Electric's projected annual revenue requirements.

Modeling Approach. Modeling environmental costs, whether using a CO_2 proxy or some other means, raises some unique issues. One is to determine how the environmental regulation would be implemented. At least three possibilities can be considered:

- a pollution cap or mandated reduction (the command-and-control option)
- auction and trading of emissions allowances
- a pollution fee or tax.

These different policies could have different impacts on the utility and its customers. A strict pollution cap is the most direct but probably also least economically efficient, since every utility would have to meet the same target, no matter how costly that might be. A pollution fee or tax would be economically efficient, but also perhaps highly unpopular in today's political climate. A mechanism for recycling tax revenues into the general economy—perhaps directly back to the utility customers—would be needed.

With the relative success of the SO_2 emissions trading market created under the CAAA, it seems likely that a future CO_2 reduction regime would adopt the second approach. In an emissions trading market, the price of emissions allowances should be equal to the average marginal cost of controlling the emissions for all utilities participating in the market. That cost, in turn, will depend on how deep the mandated reductions are (i.e., on

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[25] Stephen S. Bernow et al., *Valuation of Environmental and Human Health Risks Associated with Electric Power Generation: A Discussion of Methods and a Review of Greenhouse Gas Studies* (Boston: Tellus Institute, 1994).

the total number of emissions allowances auctioned to power generators). A very sharp cut in CO_2 emissions could well imply an emissions allowance price of $35 per ton or higher; more modest restrictions, or a cap at 1990 levels, could result in a price of perhaps $5 per ton or less.

Although very different in concept and implementation from a CO_2 tax, an emissions trading regime can be modeled as a tax. The reason is that, in an efficient trading market, each utility would purchase emissions allowances until the cost of the allowances equaled its own marginal cost of CO_2 control. Thus, every utility would end up paying the same amount in proportion to its pre-regulation CO_2 emissions. In the SRP model, the ersatz tax is applied to the price of fossil fuels in proportion to the fuel's CO_2 emissions. Its cost is absorbed into the variable operating cost of the power plants and thereby alters the dispatch and build decisions as well as the utility's total operating expenses.

There remains the question of the timing, probability distribution, and expected magnitude of the CO_2 tax or control. We assess two risk scenarios:

- The high-risk scenario assumes a probability of 70 percent that some kind of CO_2 regulation will be imposed between 2003 and 2022, with a mean value of the imposed cost of $25 per ton (1996 dollars).
- The low-risk scenario assumes only a 30 percent chance of CO_2 regulation between 2003 and 2022, with a mean imposed cost of $25 per ton (1996 dollars).

The probability of a CO_2 regulation being imposed in any given year is assumed to be constant and independent of the probability in any other year. Thus, the cumulative probability of CO_2 control rises from zero to the predicted value (70 percent or 30 percent) at the end of the 20 year period (Figure 4.3, top). The model assumes that the CO_2 control, once imposed, will remain unchanged for the remainder of the 20 year period and that its cost will escalate with inflation. The randomly generated cost is taken from a normal distribution with a zero mean from which only positive values are accepted (Figure 4.3, bottom). The standard deviation of this distribution is given by the equation,

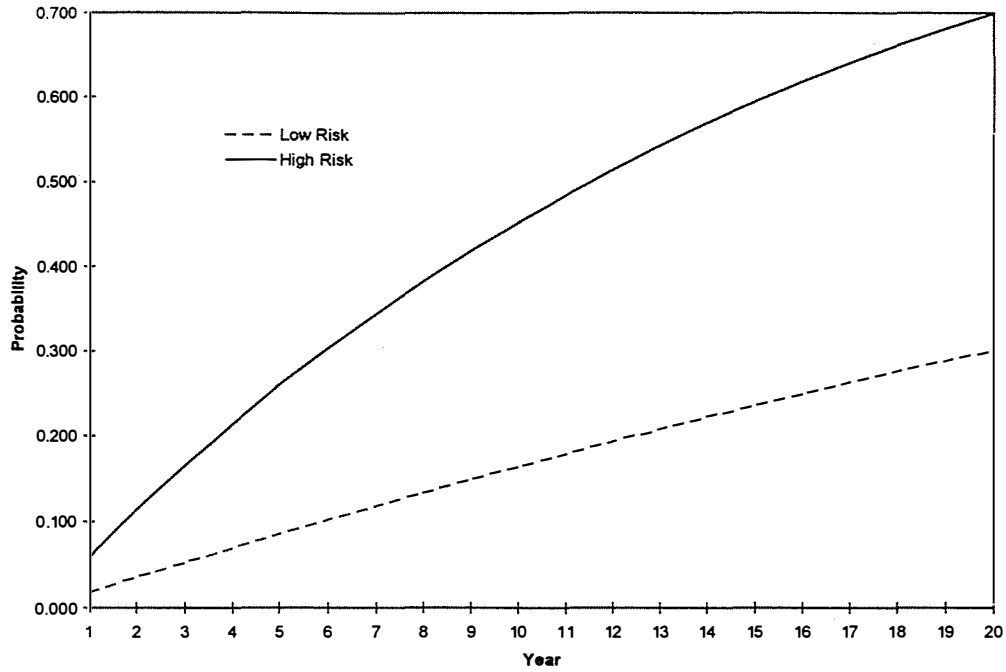
$$(4.6) \qquad \sigma = \sqrt{\frac{\pi}{2}}\mu,$$

where μ is the desired mean. So, for a desired mean control cost of $25 per ton, the standard deviation of the normal distribution from which it is drawn should be $31.3 per ton.[26]

4.4. Plant Availability

The fourth type of risk modeled in this study is that of plant availability. This is frequently ignored in utility resource planning as it is generally assumed that predicted forced and scheduled outage rates accurately reflect year-to-year performance. This can

[26] Note that the expected CO_2 control cost is less than the mean of the distribution, since there is a non-zero probability that no cost will be imposed. The true (undiscounted) expected value in the high-risk case is $17.5 per ton (70 percent × $25), and in the low-risk case it is $7.5 per ton (30 percent × $25).



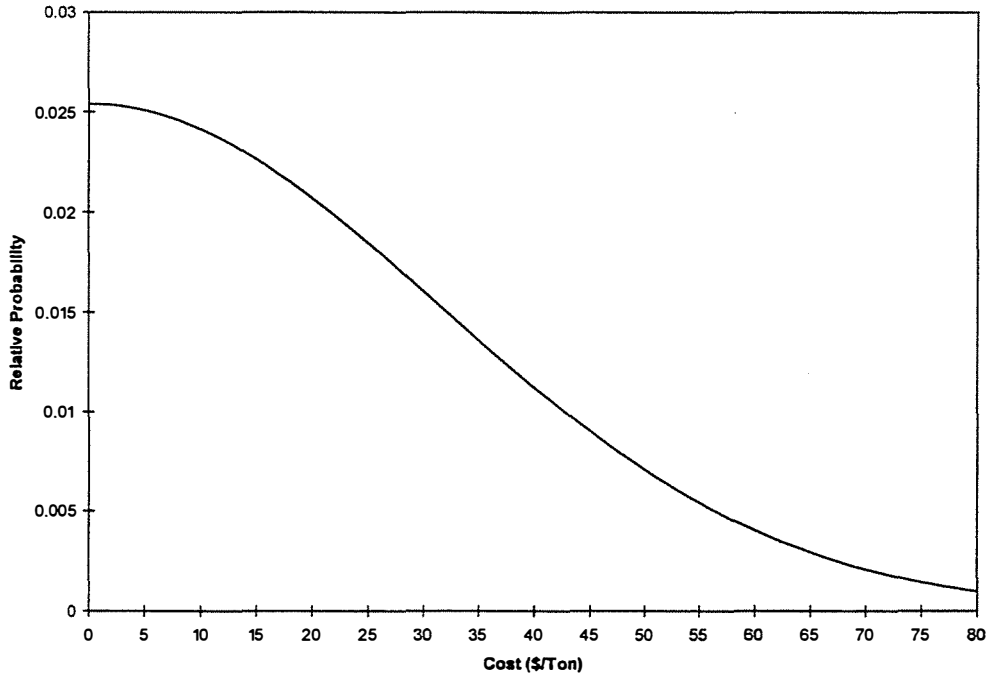


Figure 4.3. Modeling the risks of environmental regulation. Top: The probability of CO2 regulation (low-risk and high-risk profiles). Bottom: Probability distribution of CO2 control costs assuming regulations imposed.

be a dangerous assumption, however, especially when a utility system is dominated by a few large generating units. That is not the case for TU Electric. Nevertheless, it is important to consider plant availability in this study because the annual output and capacity value of wind plants are likely to vary much more from year to year than those of fossil-fuel plants. The question we want to answer is, do the intermittence and variability of wind power offset its benefits in reducing fuel-price and environmental risks?

Data and Modeling Approach: Wind Plants. The variability in the annual output of wind power plants is easily modeled, although high-quality wind data records have not been collected for a sufficiently long period to provide a very accurate estimate. We relied on data collected in the DOE Candidate Wind Site program near Amarillo, Texas. The data consist of hourly average wind speeds measured at two anemometer heights, 9.1 meters and 45.7 meters, over a period of 4½ years starting in March 31, 1977, and ending September 30, 1981. While the data record contains some gaps, the recovery rate overall is quite high.[27] Table 4.4 below summarizes the data. The plant capacity factor assumes a 40 meter tower height, the Enercon E-40 wind turbine power curve, and a 5 percent

Table 4.4. Amarillo Wind Speeds and Predicted Plant Output.

Year/Period	March to March		October to October	
	Speed* (m/s)	Capacity Factor**	Speed* (m/s)	Capacity Factor**
1977/78	8.04	36.2%	7.99	35.8%
1978/79	8.14	33.9%	7.60	29.4%
1979/80	7.56	31.6%	8.84	43.8%
1980/81	8.89	42.4%	7.62	32.0%
Mean	8.16	36.0%	8.01	35.3%
Standard Deviation	6.7%	12.9%	7.0%	17.9%

*At 45.7 meter tower height. **At 40 meter tower height.

average wind speed reduction due to wake interference. For this study, we assume the annual average capacity factor of the wind plant is 36 percent and the standard deviation in the capacity factor is 18 percent.

The uncertainty in wind plant output is incorporated into the model by randomly drawing a new forced outage rate each year from a normal distribution centered on the mean of 64 percent. When the forced outage rate is higher than expected (i.e., the capacity factor is less than 36 percent), the model draws more generation than usual from fossil resources.

[27] The data recovery rate is approximately 90 percent on average. 1978 was the worst year with 85 percent recovery, 1979 the best with 95 percent recovery.

When the forced outage rate is lower than expected, the converse occurs. The wind output is assumed to be evenly distributed throughout the year.[28]

Data and Modeling Approach: Fossil Plants. Estimates of fluctuations in the availability of fossil-fuel and nuclear plants are more difficult to come by directly, but can be derived from data for large numbers of power plants provided in the National Electric Reliability Council *Generating Availability Report*. The table below summarizes the available data for different kinds of power plants.

These data are averages for units of varying age, design, size, maintenance history, and other pertinent characteristics. It can be expected that some units perform much worse than others. Charts provided in the report show, for example, that over the five-year period approximately 5 percent of all fossil-steam units had forced outage rates averaging more than 20 percent, whereas 40 percent of the units had forced outage rates of less than 5 percent.

The second-to-last column indicates the variability of forced outage rates for the different groups of units in different years. The values are in percentage points, i.e., a standard deviation of 1.02 percent on a mean of 11.29 percent indicates that the average forced outage rate for the group will fall between 10.27 and 12.31 percent approximately two-thirds of the time.

Table 4.5. Selected Outage Data for Conventional Power Plants (1988-1992)

Unit Type	Units	Average Forced Outage Rate (%)	Average Duration (Hrs)	Scheduled Outage Factor (%)	Group Standard Deviation in FOR (Percentage Points)	Implied Unit Std. Dev. in FOR (Percentage Points)
Coal Steam	887	5.49	39	11.35	0.70	20.8
Oil Steam	245	6.34	37	11.58	0.96	15.0
Gas Steam	440	6.46	58	12.10	0.74	15.5
Nuclear (all types)	129	11.29	212	18.32	1.02	11.6
Combined Cycle	25	5.13	23	10.98	4.70	23.5
Gas Turbine	231	55.52*	54	6.15	15.66	23.8

*The gas turbine forced outage rate may be high because these units are in service only a short period every year. Their true forced outage rate is likely to be comparable to, or slightly less than, that of combined cycle units.

[28] This is a simplification. In reality, the output of the wind plant will vary significantly by season and time of day, as will marginal fuel costs. These effects cannot be captured in the SRP model, which uses an annual dispatch function.

The last column shows the imputed standard deviation in the forced outage rates of individual power plants in each class. It is derived by multiplying the group standard deviation by the square root of the number of units in the group. The values are surprisingly large, indicating that individual units experience widely varying degrees of forced outages.

The unit standard deviations are used to estimate the standard deviation in forced outage rates for TU Electric plants as a group. The unit standard deviations for each plant type are divided by the square root of the number of units of that type on the TU system. It is important to recognize, however, that new units are likely to perform better than existing units. Moreover, it is likely that the implied unit standard deviations overstate the variation in the performance of individual units to some degree because the data include some units (perhaps the oldest or least efficient) that consistently perform worse than the others. Taking these factors into account, we have assumed the following forced outage rates and standard deviations (both unit and group) for the TU system:

Table 4.6. Assumed Outage Statistics for TU Electric Plants

Unit Type	Status	Total Capacity (MW)	Assumed Mean Unit Size (MW)	SOR (%)	Mean FOR (%)	Unit Std. Dev. in FOR (Percentage Points)	Group Std. Dev. in FOR (Percentage Points)
Lignite	Existing	5845	200	10	6	10	1.8
Gas CT	Existing	975	50	10	6	10	2.3
Purchase	Existing	1244	200	10	6	10	4.0
Gas/Oil Steam	Existing	11886	200	10	6	10	1.3
Nuclear	Existing	2300	750	18	11	10	5.8
Coal	New	NA	200	10	5	10	NA
Gas CT	New	NA	200	5	3	5	NA
Gas CC	New	NA	200	5	3	5	NA

The actual forced outage rate in each year for each group of plants is drawn from a normal distribution (negative values forced to zero) with the specified means and group standard deviations. For the new units, the group standard deviation is calculated by dividing the unit standard deviation by the square root of the number of units in operation in that year. It should be noted that, although the standard deviations appear higher for some groups than for others in the above table, what counts in the end is the total number of existing and new units on the TU system. The net standard deviation for all existing units on the system is about 1 percentage point. As the total number of units on the system increases over time, this value falls, thus illustrating the point that a larger system is generally more reliable than a smaller one.

4.5. Forecasting Errors

A final issue to be considered is how the SRP model forecasts certain variables given their uncertainties. This is a critical question, since it is forecasting errors that create risk, not changes in the variables themselves. If one could predict with certainty changes in the fuel prices over the next 10 years, then the changes themselves, no matter how extreme they might be, would not be a source of risk. How, then, should the model anticipate changes in the key variables?

One possible approach is to attempt to model the decision-making processes utilities use to select and build new power plants. For example, one could examine the record of load forecasts, measure the discrepancies between those forecasts and subsequent load behavior, and attempt to identify patterns relating the forecasts to conditions known at the time. Indeed, we have conducted such an analysis of TU's past load forecasts and discovered that the forecasted rate of load growth has been roughly equal to the average load growth observed in the five years or so preceding the forecast. This general rule could easily be applied in the SRP model.

This approach contains serious drawbacks, however. Although it may work reasonably well for load forecasts, it is difficult to apply to fuel prices, which are far more volatile than loads. Fuel price forecasts reflect the combined judgment of numerous analysts who consider many factors other than recent price history, such as known and suspected fuel reserves and trends in production capacity. The problem is not that these judgements are always right—they are not—but, rather, that it is virtually impossible to recreate them in a computer model.

More fundamentally, one needs to be wary of unnecessarily compounding the uncertainty in fuel prices and loads by introducing artificial or extreme forecast errors. A simple decision rule may look reasonable on the surface, but can seriously break down under unusual circumstances, leading to large errors in build decisions that might not occur in reality.

A more conservative (and certainly simpler) approach, in our view, is to assume that the decision makers know as much as the model does about possible future trajectories of key variables in any given year. Thus, if the mean rate of increase of fuel prices in the model is 1.9 percent, that is the rate the model assumes to make plant build decisions. Of course, the actual trajectory of fuel prices will vary from the expected 1.9 percent in any given Monte Carlo draw, but the *expected* forecast error will be minimized if the correct *expected* escalation rate is used.

The exception to this rule is environmental costs. Since, by their nature, they represent a potentially large and generally unexpected perturbation on the system, the model does not attempt to anticipate future increases in environmental regulatory costs. Only those costs already imposed at the time of the build decision are considered.

One source of forecast error that is retained in the model, however, is the time lag between the build decision—or more precisely, the first major commitment of construction funds—and the first year of plant operation. In general, we assume that this time lag is one year, which is appropriate for wind plants and gas-fired combined-cycle

and combustion turbine units. Thus, build decisions are made on the basis of fuel prices, loads, and environmental costs from the preceding year, with one-year price and load shocks removed.

5. RESULTS

The discussion of the results of the study is divided into two chapters. In this first chapter, we review the base plan and summarize the expected values and standard deviations (the raw data) from the various model runs; further details of these results are provided in the appendix. In the subsequent chapter, we consider how the observed changes in risk due to the addition of the wind plant should be valued. The results are described for three market scenarios: the regulated market, an unregulated power pool, and an unregulated market characterized by short- and medium-term fixed-price contracts.

5.1. Base and Alternate Plans

It is useful first to review the base (fossil) and alternate (wind) plan under expected conditions. Both plans cover the 20-year period from 2003 through 2022, and both involve primarily gas-fired combined cycle additions. The sole difference between them is that, in the base plan, a 400 MW gas-fired combined cycle unit is constructed in 2003, whereas in the alternate plan, a 1600 MW wind plant is constructed in its place.

Table 5.1 below compares some key outputs (from the regulated market scenario) for the base and alternate plans under expected conditions. The cost streams are discounted at two different discount rates, the utility's weighted average cost of capital (WACC), 9.64 percent, and the presumed risk-free discount rate, 7.5 percent, to illustrate the difference between them. Under both interpretations, the forced addition of the wind plant in 2003 increases revenues and net income for the utility and decreases costs. (Note that net income equals revenue minus cost.) The increased revenue requirements and net income are necessary to compensate company shareholders for the larger investment in the wind plant, as is evident from the fact that the return on equity (ROE) in both cases is the same.

Thus, if risk were ignored, the gas-fired combined cycle unit would clearly be the preferred choice. The following sections describe the effects of taking risk into account on the mean and variances of the key parameters under the various market scenarios.

Table 5.1 Comparison of Base and Alternate Plans*

Parameter	Discounted at WACC			Discounted at Risk-Free Rate		
	Base Plan	Alternate Plan	Change	Base Plan	Alternate Plan	Change
PV of Revenues	$69,737	$70,059	$322	$83,598	$83,906	$308
PV of Costs	$63,817	$63,685	-$132	$76,674	$76,469	-$205
PV of Net Income	$5,920	$6,374	$454	$6,924	$7,437	$513
Average ROE (%)	10.76%	10.76%	0.00%	10.76%	10.76%	0.00%
PV of Average Bill	$8,934	$8,983	$49	$10,580	$10,629	$48

*Figures are in millions of 1996 dollars, except average bills, which are in 1996 dollars. Average bills assume an average annual usage of 15,000 kWh.

5.2. Summary of Results and Statistical Errors

Table 5.2 compares the present-value means and standard deviations (discounted at the risk-free rate) of revenues, costs, and net income, as well as the average return on equity, calculated by the model for the gas and wind scenarios. In all cases high-risk probability profiles are assumed. No correlations are allowed among the different parameters. Additional results involving low-risk probability distributions and correlations are provided in the appendix.

Table 5.2. Summary of Results*

Scenario		Revenues		Costs		Net Income		ROE	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Regulated Market	Gas	$91,159	$17,503	$83,629	$16,337	$7,530	$1,843	10.70%	1.14%
	Wind	$91,180	$17,039	$83,154	$15,846	$8,026	$1,857	10.71%	1.11%
	Change	$21	-$464	-$474	-$492	$496	$14	0.00%	-0.03%
Unregulated Market Power Pool	Gas	$100,270	$23,705	$88,111	$17,973	$12,159	$7,379	21.80%	11.32%
	Wind	$100,053	$23,759	$87,595	$17,667	$12,459	$7,523	21.50%	11.01%
	Change	-$216	$55	-$516	-$306	$300	$144	-0.31%	-0.31%
Unregulated Market Fixed-Price Contracts	Gas	$91,902	$16,143	$84,079	$15,954	$7,823	$2,098	11.01%	2.68%
	Wind	$91,984	$15,755	$83,609	$15,474	$8,375	$2,085	11.14%	2.47%
	Change	$82	-$388	-$470	-$480	$552	-$13	0.13%	-0.21%

*All figures except ROE are present values over 20 years (2003-2022) discounted at 7.5 percent, converted to 1996 dollars Revenues, costs, and net income are in millions of dollars. High-risk probability profiles are assumed.

Before discussing the results, it is first important to say a word about errors. In general, for any particular run, the standard error in the mean and standard deviation is about 6 percent of the standard deviation for that run.[30] The standard error in the *change* in any parameter with the substitution of wind for gas is much smaller, however, because the model runs both cases simultaneously and tracks the differences between them. To a close approximation, the standard error in the change is given by,

$$(5.6) \quad \varepsilon_3 \cong \sqrt{\varepsilon_1^{\,2} + \varepsilon_2^{\,2} - 2\varepsilon_1\varepsilon_2} = \varepsilon_1 - \varepsilon_2,$$

where ε_1 and ε_2 are the standard errors of the results of the individual gas and wind runs. In other words, the standard error in the change of any variable roughly equals to 6 percent of the change itself. Of course, these estimates do not reflect possible systematic biases due to errors in the model but account only for statistical uncertainties resulting from the limited number of observations, or iterations, in any given run.

5.3. Regulated Market Scenario

The core scenario for the SRP model is the standard regulated utility system. The basic assumption driving this scenario is that electricity prices are not market-determined but set by the regulatory system to achieve a target rate of return on equity (ROE) for TU

[30] The standard error is the standard deviation divided by the square root of the number of observations. The typical run contains 300 observations, and $1/\sqrt{300} = .058$.

Electric's stockholders. Changes in fuel prices and environmental costs are passed on to customers through a fuel-price adjustment to the basic electricity rate. In practice, the fuel-price adjustment may occur after the fact in proceedings to correct for discrepancies in fuel charges; frequently, only a portion of the surplus or deficit is recovered. The SRP model, however, assumes that the fuel price adjustment works perfectly.

The total price charged equals a combination of a base price covering all non-fuel expenses and a fuel price,

(5.1) $p(t) = p_{base}(t) + p_{fuel}(t)$.

In this scenario, it can be expected that the major risks (i.e., source of standard deviation in net income) for the utility shareholders will arise from deviations between forecasted and actual loads. The base price is assumed to be set for the current year based on loads projected from the preceding year. (In reality, the base price is normally set for several years until the next rate hearing, which may be requested either by the utility or by a stakeholder group.) Any deviation in the loads will result in a departure from expected revenue, which, after payment of interest, taxes, fuel costs, and other expenses, will cause a change in net income and ROE.

Other risks will be passed on to utility customers. The fluctuations in fuel prices, changes in environmental costs, and changes in plant availability will be reflected in fuel costs and therefore captured through the fuel-price adjustment. The effect on ratepayers will be felt through changes in the total electricity price. It should be noted that a drop in revenue alone does not necessarily signal good news for customers, since it may merely reflect a drop in load, which could lead to an increase in electricity price to cover fixed costs. In this case, however, it is assumed that the variance in revenues accurately reflects the risks to consumers.

These qualitative considerations are clearly reflected in the results shown in the first block (three rows) of Table 5.2. Taking environmental regulatory risks into account has raised the mean present-value revenues for both wind and gas runs to about $91 billion from $70 billion, an increase of $21 billion. More significantly for our purposes, the change in mean revenues with the substitution of wind for gas has dropped from $308 million to $21 million, and the standard deviation of revenues in the wind case is $464 million less than the standard deviation in the gas case. These results show the substitution of wind for gas provides significant risk protection for the utility's captive customers, lowering both the expected effect of environmental regulation and the variances due to that and all other sources of risk.

In contrast, the substitution of wind for gas has virtually no impact on risk to shareholders' net income or return on equity. The change in net income drops from $513 million (Table 5.1, last column) to $496 million, a difference of $17 million, which is well within the standard error of $30 million for this parameter. There is a slight increase in the standard deviation of net income and virtually no change in the standard deviation of return on equity. Both results confirm that, as the present regulatory system is modeled, utility profits are insensitive to fuel price and environmental risks. Instead, the primary

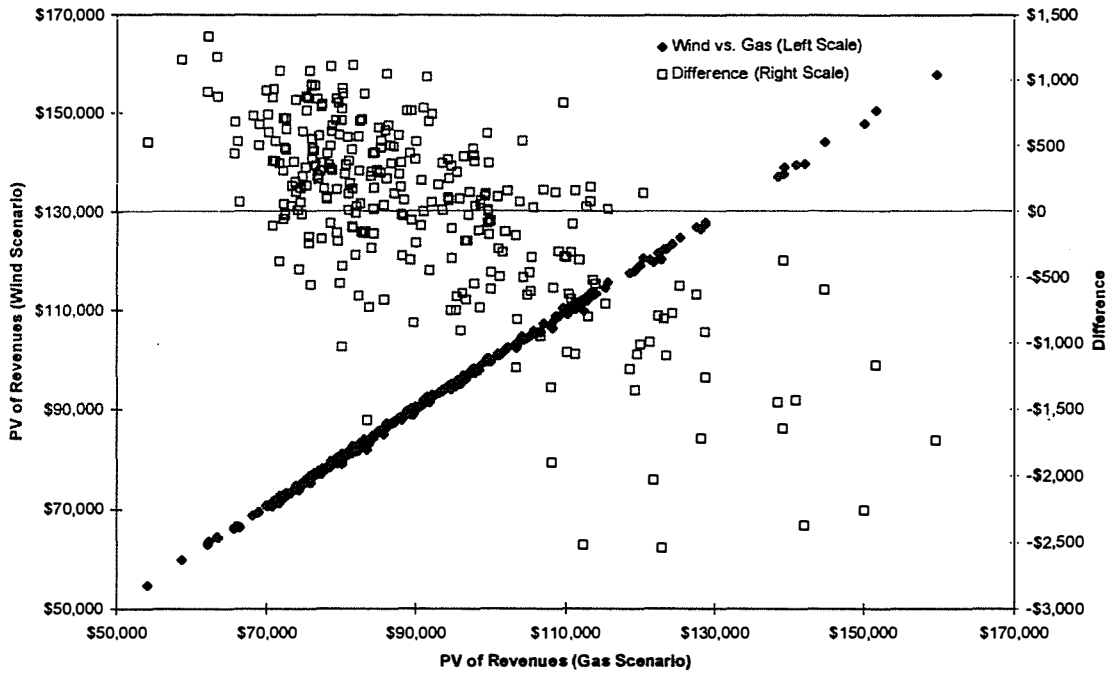


Figure 5.1. Scatter plot of present-value revenues of wind and gas cases and change in revenues with substitution of wind for gas (regulated market).

risk to profits lies in load growth uncertainty, for which wind offers no benefit (as modeled) over natural gas.[31]

Different slices of the data provide additional insights into the effects of replacing the gas-fired plant with the wind plant. Figure 5.1 shows a scatter plot of present-value revenues for several hundred iterations in a single run. The points in the closely spaced, upward sloping group show the intersection of revenues for the wind and gas cases, whereas the points in the larger, downward sloping group show the difference between the revenues for the wind and gas cases. The important thing to observe is that when the present value of revenues is high, the wind case tends to be less expensive than the gas case, whereas when the present value is low, the converse is true. This graphically illustrates the point that wind plants can act as an insurance policy or hedging strategy against fossil-fuel risks.

Yet another slice of the data is provided in Figure 5.2, which shows the annual mean revenues and their standard deviations of the gas case (top chart) as well as the differences between the mean revenues and standard deviations of the gas and wind cases (light and dark bars, bottom chart). Not surprisingly, the standard deviation of the revenues grows over time as fuel prices and environmental regulatory costs diverge from

[31] At this stage we are not modeling any benefits of modularity and short construction lead time.

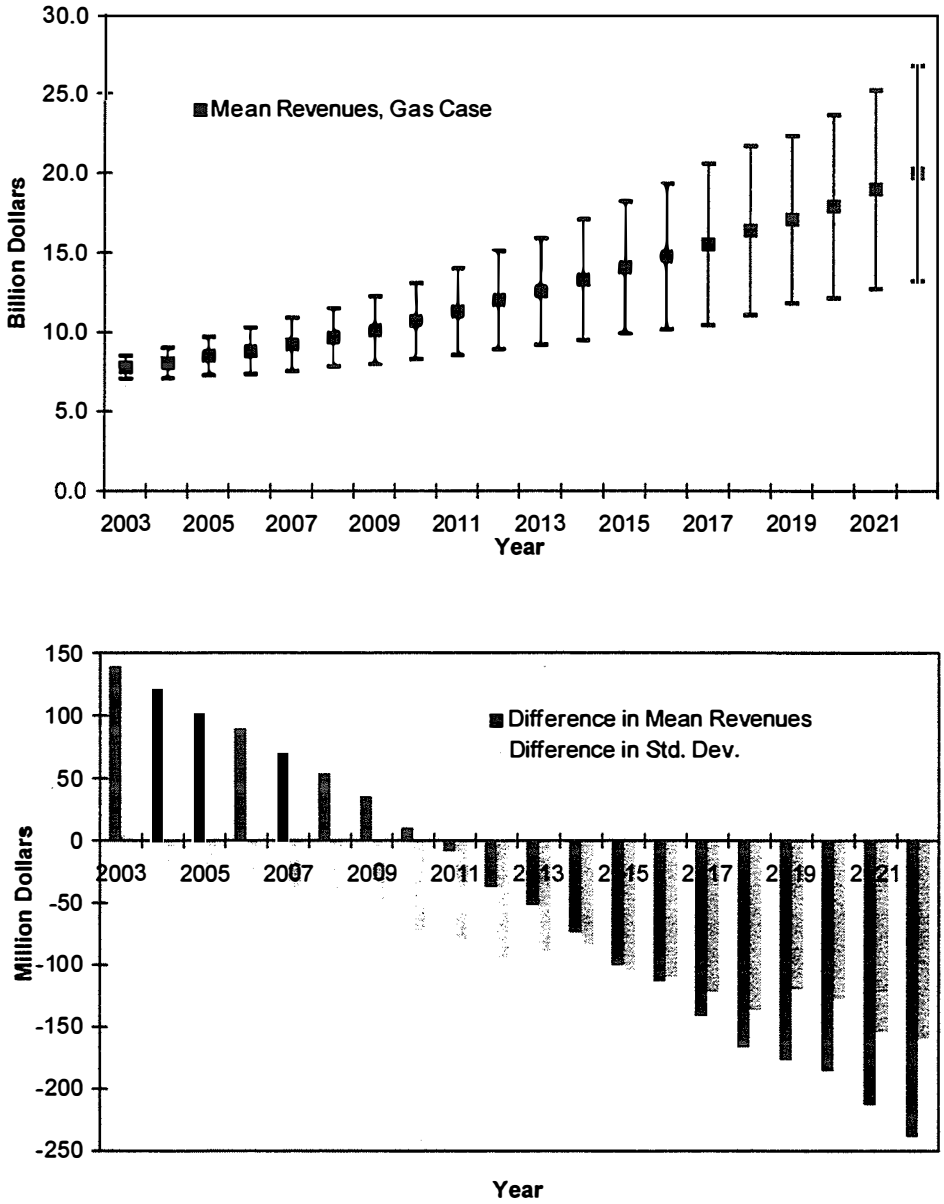


Figure 5.2. Annual mean revenues and standard deviations for the gas case (top chart) and differences between gas and wind cases (bottom chart), regulated market.

expectations. Also, as might be expected, the wind case starts out more expensive than the gas case on average, but after ten years or so it becomes less expensive as gas prices rise and the wind capital investment is paid off. The standard deviation for the wind case is lower than that of the gas case, by up to $150 million, in all but the first year.

We will return to these findings later when we calculate the certainty equivalents of annual revenue and net income. For now, we turn to the results for the unregulated market scenarios.

5.4. Unregulated Market Scenario

An unregulated market is more complicated to model than a regulated market. The risks seen by the utility and its customers depend on many factors, such as the nature and degree of competition, corporate structures, the role of regulation, the design and functioning of the power pool, and the contractual relationships between the utility company and its customers and fuel suppliers. We cannot incorporate all such factors into the model in a comprehensive way. Instead, we consider two cases that illustrate a plausible range of sensitivity to risk: a power pool case, and a fixed-price contract case.

The critical difference between the two is that, in the power pool case, the TU Electric plants compete against comparable fossil, nuclear, and renewable plants on a short-term basis, whereas in the fixed-price contract case, the price of power is to fixed for periods ranging from one to five years. In both cases, the capacity build decisions are assumed to be the same as in the regulated utility case. This is, of course, a simplification, since the criteria governing the decision to build a new plant could be much different in an unregulated setting than under traditional regulation.[32]

5.4.1. Power Pool

In this case it is assumed that the utility company sells all of its power into a power pool, which acts as a short-term spot market. The price paid to the utility by the pool has three elements: a variable cost rate (r_v), a capacity rate (r_c), and a transmission and distribution rate (r_t).

The *variable cost rate* is set in any given time period by the marginal variable cost of the highest-cost unit dispatched in the pool at the appropriate point along the load duration curve. It is based on the principle that, in a truly competitive pool, all plant owners will bid their units at their marginal variable costs to ensure that they are used to the maximum profitable extent. The price on the pool will be determined by the most expensive bid accepted in each time period, and should therefore equal the marginal variable cost of the last unit needed to meet demand. In practice, TU Electric would be competing against other utility companies for access to the pool, so the marginal variable cost would be determined by units belonging to all of the competing companies. In this study, however, we assume that the other companies own units of similar characteristics to TU Electric's units, so the marginal variable cost in each time period is determined by TU Electric's own plants.

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[32] Among other differences, a regulated utility is obliged to provide reliable service to the customers in its service territory, whereas an unregulated power company can make independent capacity build decisions based on its perceptions of market opportunities. In general, discount rates, time horizons, and other pertinent factors will also differ.

To calculate the variable rate, the computer first calculates the change in variable operating cost for the entire system resulting from a one-percent reduction in load across all time periods, then divides that number by the reduction in load:

$$(5.1) \quad r_v = \frac{\Delta(VariableCost)}{\Delta(Load)}.$$

The *capacity rate* is based on the capital and fixed operating cost of a gas-fired combustion turbine peaking unit. The model assumes, however, that the size of the payment will be proportional to the annual loss-of-load probability for the TU system. Consequently, when there is a surplus of capacity on the system the capacity rate will be low, thus reducing the incentive for power companies to build more capacity. When there is a deficit of capacity, the opposite will occur. The equation can be written as follows:

$$(5.2) \quad r_C = C_{peaker} \frac{Accredited\ Capacity}{Annual\ Energy} \frac{LOLP(RM)}{LOLP(RM = 15\%)}.$$

The first term to the right is the combined levelized capital and fixed operating and maintenance cost for a peaking unit. The next term represents the system load factor, which converts from dollars per kilowatt to dollars per kilowatt-hour. (Payments to generators are based on accredited capacity, not peak capacity.)

The last term is the ratio of the cumulative *LOLP* at reserve margin *RM* (the actual reserve margin in a given year) to the cumulative *LOLP* at an assumed equilibrium reserve margin of 15 percent. We constructed a model to estimate the LOLP for the TU Electric system as a function of reserve margin. This model calculates the probabilities of all possible combinations of forced outages on the TU Electric system, then constructs an output duration curve showing the probability that the system can meet a given maximum load. The equation that was fit to this curve is an exponential function of reserve margin:

$$(5.3) \quad \begin{aligned} \frac{LOLP(RM)}{LOLP(15\%)} &= e^{-39.9(RM-15\%)} && RM \geq 15\% \\ &= 5.08 \cdot e^{-32.5(RM-10\%)} && 10\% \leq RM < 15\% \\ &= 18 \cdot e^{-25.3(RM-5\%)} && 5\% \leq RM < 10\% \\ &= 42.7 \cdot e^{-17.3(RM)} && RM < 5\% \end{aligned}$$

The cumulative LOLP at 15% reserve margin is assumed to be equivalent to one day's outage in 10 years, or 2.74×10^{-4}. Thus, if the reserve margin is zero, the cumulative LOLP is 0.0117, indicating that there will be insufficient capacity to meet the load in 100 out of 8760 hours in a year.

This method of determining the capacity payment is conceptually similar to that used in the United Kingdom. It is intended to replicate the effect of demand-side bidding, which was originally planned in the UK but could not be implemented because of software constraints. In theory, demand-side bidding affects the price of power only when there is a shortage of capacity to cover the load. Pool customers (such as distribution companies or industries) submit bids for how much they are willing to pay to avoid an interruption in service. Supply to the lowest bidders is interrupted first, until the load is reduced to meet

available capacity. The greater the number of megawatt-hours of lost load, the higher the total demand payments. Thus, in theory, the average capacity rate should be proportional to the annual energy not served, which is approximated by the loss-of-load probability.

In practice, calculating the capacity rate in this manner introduces a high degree of volatility in the electricity price and the utility's revenues. LOLP varies exponentially with reserve margin, so that a relatively small change in reserve margin causes a large increase or decrease in the capacity rate. Indeed, the capacity payment can become large enough to provide a return on equity of over 100 percent if the reserve margin drops below about 9 percent. Of course, pool customers would be very unlikely to pay such a large amount for power. Consequently, the capacity rate is capped at twice the levelized capital and fixed operating cost of the peaking unit: $r_C \leq 2 \cdot C_{peaker}$.

The *transmission and distribution rate* covers the operating and capital costs of the transmission and distribution system. Regardless of whether the utility would own these assets in an unregulated market, their costs would have to be recovered somehow through rates. The T&D rate is set, as in the regulated market scenario, to yield a target ROE on T&D assets of 10.8 percent.

5.4.2. Fixed-Price Contracts

The second case assumes that all of the utility's power will be sold to customers under fixed-price contracts of varying duration. The initial price of each contract is determined by the revenue requirements for that year, calculated in the conventional way, and is allowed to rise with inflation each year thereafter. The model assumes that the terms of the contracts will range from one to five years, that any term is as likely to be chosen as any other, and that the current age of the contracts is randomly distributed between zero and five years. The average price charged in a given year is the weighted average of prices for contracts established in the preceding five years. The weights in the average are given by the following equation:

$$\begin{aligned} p(t) = {} & 0.29\,p_{RR}(t) + 0.29\,p_{RR}(t-1) + 0.19\,p_{RR}(t-2) \\ & + 0.12\,p_{RR}(t-3) + 0.07\,p_{RR}(t-4) + 0.04\,p_{RR}(t-5), \end{aligned} \tag{5.4}$$

where $p(t)$ is the average price charged to all contracts in year t, and $p_{RR}(t\text{-}n)$ is the price charged on new contracts established in year $t\text{-}n$, based on revenue requirements (i.e., the contract prices are the same as the prices established in those years in the regulated market scenario).

5.4.3. Unregulated Market Results

Table 5.2 shows the results of the two unregulated market scenarios. It is important to note, first, that the power pool scenario poses much greater risks for both customers and company shareholders than the mixed-term contract scenario, whether wind is present or not. The standard deviation in all parameters is considerably greater—four to six times greater in the case of return on equity. The main reason is the volatility of the capacity portion of the price due to its dependence on LOLP. Expected revenues and net income

are also much higher in the power pool scenario than in the contract scenario reflecting the way capacity payments were defined.

The effect of substituting wind for gas varies strikingly between the two scenarios. In the power pool case, the substitution of wind for gas appears to *increase* the standard deviation of both revenues and net income, although the risk to return on equity is substantially reduced. However, the expected revenues (and hence, the average price paid by consumers) is somewhat lower, as are expected net income and return on equity. The explanation is that the wind plant slightly reduces the amount of high-cost fossil

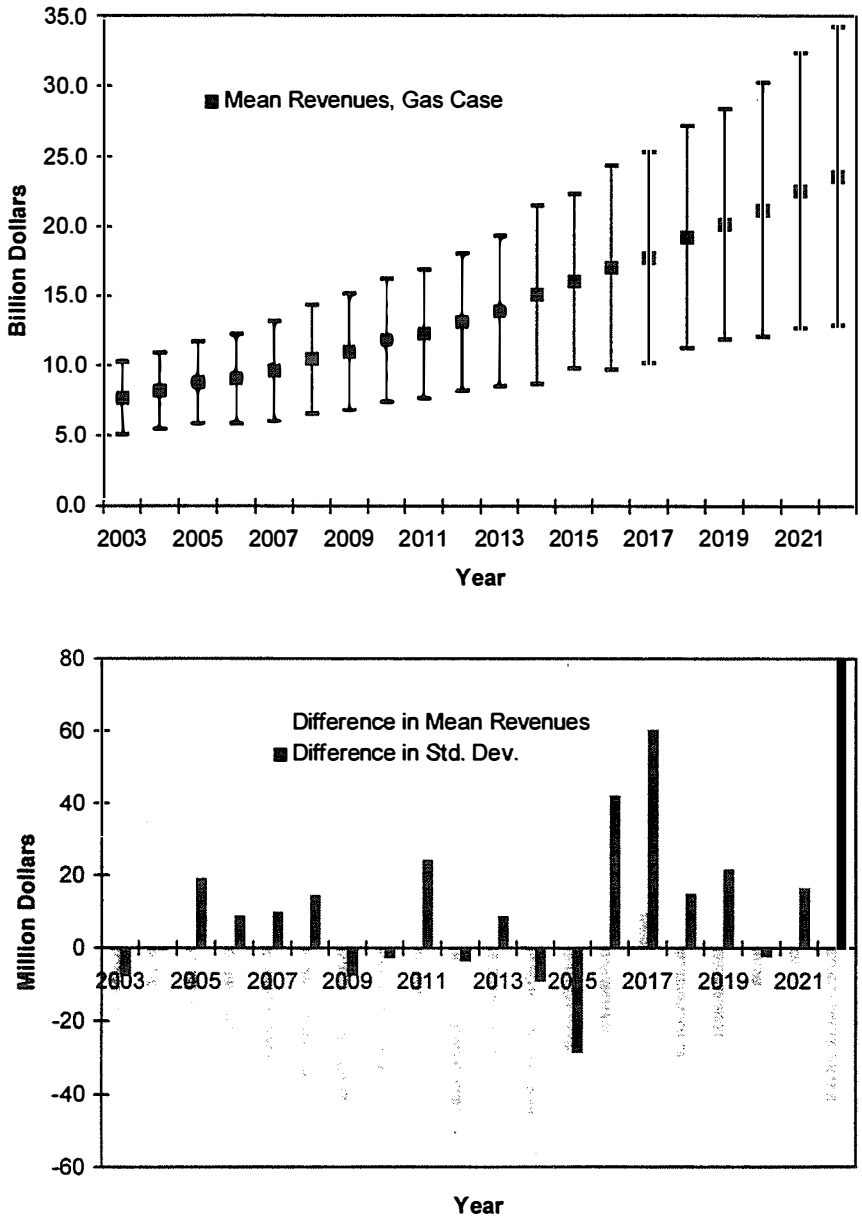

Figure 5.3. Same as previous figure but for the power pool scenario.

generation needed to supply loads at the margin and thereby reduces the variable portion of the electricity rate.

The results of the contract scenario, on the other hand, more closely resemble those of the regulated market scenario. There is a decrease in risk to revenues ($388 million) and a decrease in the risk to return on equity (0.21 percent).

Looking at the yearly data, one can see further confirmation of the extreme volatility in prices in the power pool scenario. Figure 5.3 shows yearly revenues in the power pool

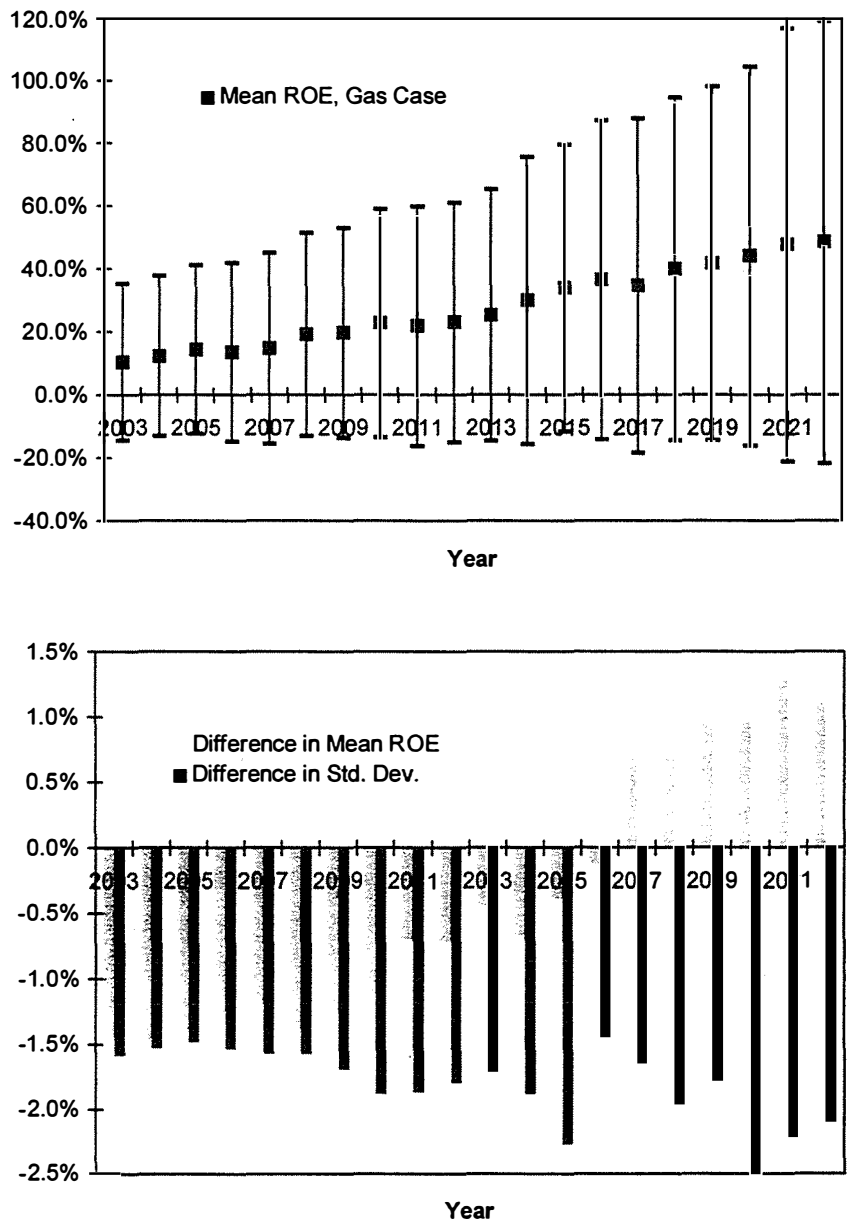

Figure 5.4. Same as previous figures but for return on equity, power pool scenario.

scenario have a large standard deviation, while the differences between the wind and gas cases fluctuate wildly between positive and negative. Figure 5.4 indicates huge fluctuations in return on equity, but wind reduces the standard deviation in ROE by about 1.5 to 2 percent relative to the gas case.

As Figures 5.5 and 5.6 illustrate, the yearly results of the contract scenario are less volatile, and there is a clear pattern of reduced standard deviation in both revenues and ROE with the addition of the wind plant. One difference between this scenario and the regulated market scenario is that the utility cannot begin recovering the entire cost of the

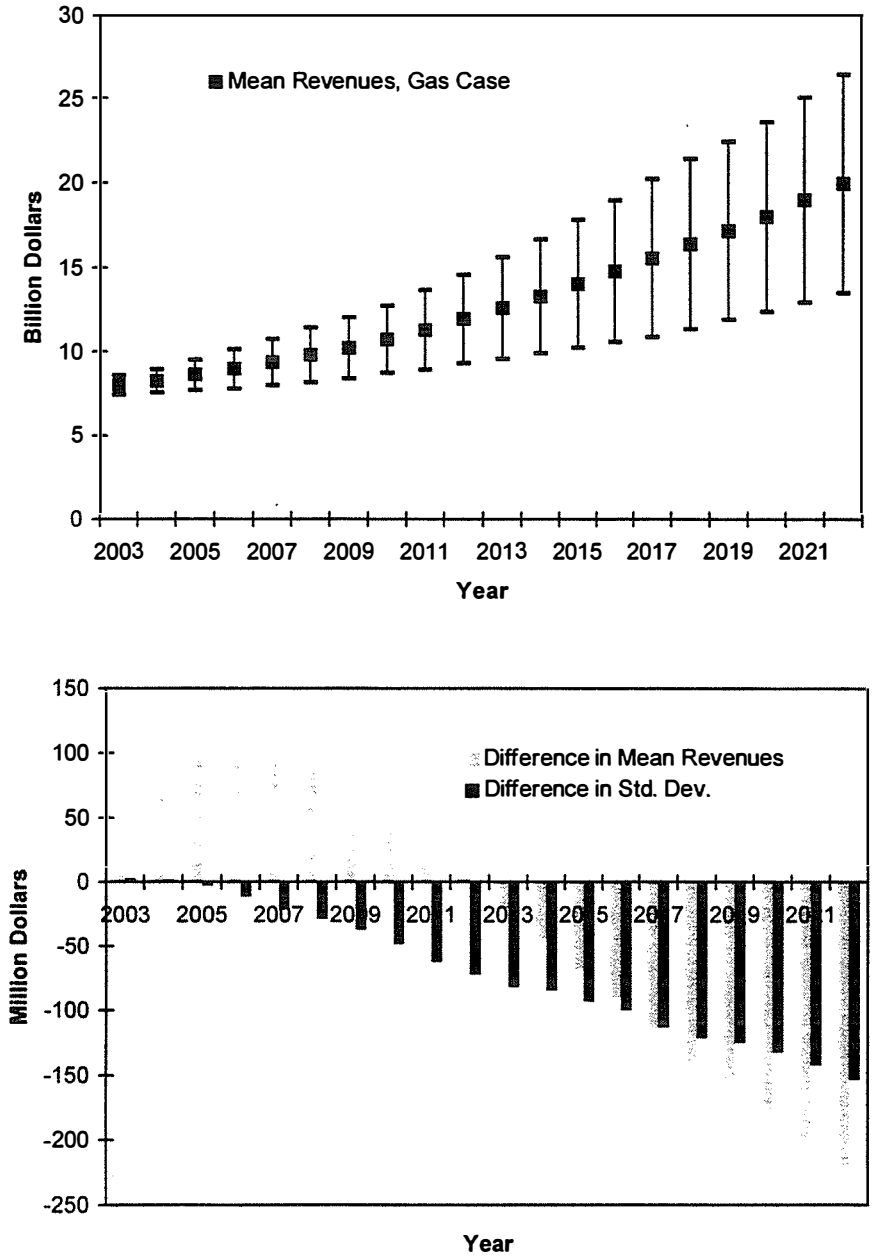

Figure 5.5. Same as previous figures but for revenues, fixed-price contract scenario.

wind plant until its existing contracts turn over. Thus, the return on equity is initially lower with the substitution of wind (Figure 5.6), although the deficit is recovered through higher returns in subsequent years.

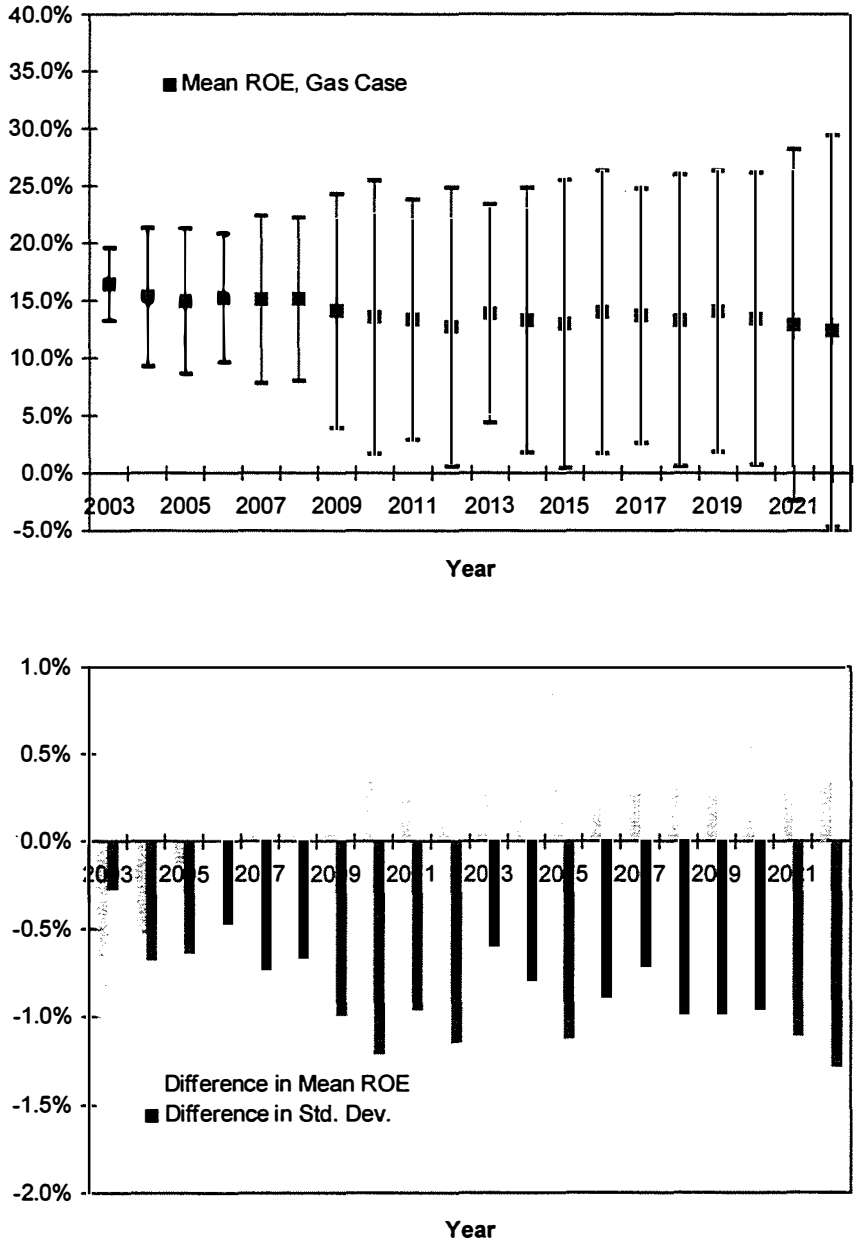

Figure 5.6. Same as previous figures but for return on equity, fixed-price contract scenario.

6. VALUING RISK REDUCTION

A critical issue in interpreting the results of a study such as this is estimating the economic value of changes in risk. If the costs and returns from different investments were known with certainty, then the choice between them would be easy: one would simply pick the one with the highest return. The introduction of risk to the equation complicates the decision considerably. There is, first, the possibility of a change in the expected, or mean, outcome, which would occur if probability distributions are skewed in some fashion. For example, since environmental regulatory costs are far more likely to increase than decrease, including such costs should raise expected revenue requirements. Such an effect is easy to estimate, once appropriate probability distributions are agreed upon.

More difficult is the problem of assigning value to the variance of outcomes, which may affect the present value of resource options. In this section, we discuss two different approaches to valuing risk and apply one of them—the mean-variance method—to estimating the risk-reduction benefits of wind energy.

6.1. The Capital-Asset Pricing Model

The standard method of valuing risk in financial theory is to estimate the appropriate risk-adjusted discount rate, r, with which to calculate the present value of the uncertain future cash flows associated with a particular investment or company.[33] The discount rate is equivalent to the return investors expect from an investment, whether it is a project, a government bond, or a company's stock. Ideally, r should be found by comparing the risk characteristics of the investment with those of other, similar investments whose discount rates are known. This is not always possible, however.

When suitable comparisons are not available, an alternative is to use the capital asset pricing model (CAPM). This model presumes that all investors can hold a diverse portfolio of investments through owning stocks and bonds. When considering the risk of a particular investment, the critical issue is how the addition of that investment will impact the risk of the entire portfolio. That impact is measured by the degree to which the risks of the investment and the portfolio move together, or in other words, by the covariance of their returns. The relative covariance is known as β (beta), and is given by the equation,

$$(6.1) \quad \beta = \frac{\sigma_{im}}{\sigma_m^{\ 2}},$$

where the numerator is the covariance of the investment and market returns and the denominator is the variance of the market returns. A beta much less than one indicates an investment that is not strongly exposed to risks shared by the entire portfolio, while a beta greater than one indicates the opposite is true.

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[33] See, e.g., Brealey and Myers, op. cit., chapters 7 and 8.

The most important conclusion of the CAPM is that the risk premium for an investment—the amount by which its return should exceed that of a risk-free security such as a government bond—varies in proportion to its beta. This simple relationship can be written as

$$(6.2) \quad r = r_f + \beta\left(r_m - r_f\right),$$

where r_f is the risk-free rate of return obtainable from safe investments such as federal government securities, and r_m is the return from the portfolio. This follows from the fact that, given the expected returns of the market and the risk-free security, any desired return can be obtained by a suitable mixture of the two types of investment.[34]

Once the discount rate is known, the present value of cash flows may be calculated as follows:

$$(6.3) \quad PV(CF) = \sum_{i=1}^{\infty} \frac{CF_i}{(1+r)^i},$$

where CF_i is the cash flow in year i, and the discount rate is assumed to be constant over time. When competing investments are being considered, the best choice is the one with the highest net present value, which is given by the equation,

$$(6.4) \quad NPV = C_0 + PV(CF) = C_0 + \sum_{i=1}^{\infty} \frac{CF_i}{(1+r)^i},$$

where C_0 is the initial investment (usually a negative number). Clearly, the investment choice can be greatly influenced by the value of r.

6.2. The Mean-Variance Model

It often arises in simulations that beta cannot be estimated either by comparison with similar investments or by use of the capital asset pricing model. Such is the case in our study. An alternative approach used in decision analysis is derived from expected utility theory, which states that the true value of money for an individual or corporation is generally different from its face value and depends on how much money one already has. For example, a relatively wealthy person usually places much less value, or utility, on $100 than a relatively poor person does. The precise relationship between utility and monetary value for a particular person or corporate entity is known as a utility function.

Once a utility function is postulated, then any future cash flow of known risk can be translated into a certainty equivalent, CE, which is the amount the cash flow is worth to the decision maker today. The utility of the certainty equivalent equals the expected utility of the cash flow:

$$(6.5) \quad U(CE) = \langle U(CF) \rangle$$

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[34] Different cash flows in an investment may pose different risks and hence have different betas and discount rates.

By expanding both sides of the equation in a Taylor series and rearranging the terms, one can express the certainty equivalent in the following equation:

$$(6.6) \quad CE \cong \langle CF \rangle - \frac{\alpha}{2}\sigma_{CF}{}^{2},$$

where α is referred to as the risk-aversion coefficient, an empirically derived parameter (usually assumed to be constant) related to the shape of the utility function. (The equation holds when the second term on the right is small compared to the first, or in other words, when the risk premium is much smaller than expected value.) This equation shows that the risk premium—the amount an investor will demand as compensation for risk—is proportional to the variance of the expected cash flow. The sign of the risk aversion coefficient reflects whether the decision maker is risk averse or risk seeking. A risk-averse person discounts the expected rewards from an investment depending on how risky it appears to be. Since most people are risk averse, the coefficient is usually positive.

The two approaches, the capital asset pricing model and mean-variance model, are of course related to one another. If the variance in Eq. 6.6 is taken to be that of a broad portfolio of investments, then the incremental addition of a new investment will change the certainty equivalent value of the portfolio by an amount equal to the risk-aversion coefficient times the covariance of the investment and portfolio returns. It is easy to see how this could lead to a relationship between the expected return from the investment and its beta. Indeed, the mean-variance model can be used to measure the risk aversion of the market itself, as shown below. A critical difference is that the mean-variance model does not assume that the investor is diversified, nor does it assume that the investor's risk aversion equals that of the market as a whole.

The two approaches can be related to one another in a different sense. Once the certainty equivalent of a future cash flow is known, then that value may be discounted to the present at the risk-free discount rate. The resulting present value must be equal to the present value calculated using a risk-adjusted discount rate, that is,

$$(6.7) \quad PV(CF) = \sum_{i=1}^{\infty} \frac{\langle CF_i \rangle - \frac{\alpha}{2}\sigma_{CF,i}{}^{2}}{(1+r_f)^i} = \sum_{i=1}^{\infty} \frac{\langle CF_i \rangle}{(1+r)^i}$$

If the variance and risk aversion coefficients are known, this equation can be rearranged to solve for the discount rate r.

In this study, we are comparing the outcome of two possible decisions, building a fossil plant or a wind plant; call them scenarios f and w, respectively. From Eq. 6.6, we derive the change in certainty equivalent of the net income of the company,

$$(6.8) \quad \Delta(CE) = \Delta(\langle I \rangle) - \frac{\alpha}{2}\Delta(\sigma^2) = \langle I_w \rangle - \langle I_f \rangle - \frac{\alpha}{2}\left(\sigma_w{}^2 - \sigma_f{}^2\right).$$

The first and second terms on the right represent the change in expected value of net income and are therefore independent of risk. The third term on the right is the certainty

equivalent of the change in risk. Note that the negative sign before α means that a decrease in standard deviation results in an increase in the certainty-equivalent of net income. If this equation were written from the perspective of ratepayers, than the variable of interest would be ratepayer bills, and the sign would be positive.

6.3. Risk Aversion Coefficients

The critical challenge of the mean-variance method is to determine an appropriate value of the risk-aversion coefficient. This is often done through interviews with key decision makers such as corporate managers. The classic question that is posed is how much money would a person be willing to gamble for a 50:50 chance of winning twice that amount or losing the entire sum. The answer is known as the risk tolerance, which is approximately the inverse of the risk-aversion coefficient:

$$(6.9) \qquad \tau \cong \frac{1}{\alpha}.$$

Surveys of corporate managers suggest a risk tolerance in the range of 1 to 2 times average annual net income, with a typical value of 1.25 times average annual income.[35]

Alternatively, one may analyze past investment patterns to determine the implied risk-aversion coefficient for particular investors or groups of investors. One researcher who analyzed stock market behavior concluded that the implied (non-dimensional) risk aversion coefficient for stock market returns is in the range of 6 to 8.[36] Since the return approximately equals the net income divided by the book asset value, and the average stock market return in recent years has been approximately 15 percent, the implied risk tolerance of the stock market is 0.8 to 1.1 times expected corporate net income. This range is at the low end of, but is reasonably consistent with, the survey results.

The above values are appropriate for companies acting on behalf of stockholders, who are sensitive primarily to risks to net income or cash flow. The risk tolerance of consumers (ratepayers) must be estimated somewhat differently. For one thing, they are sensitive not to the risk to corporate net income but to the risk to their cost of living. This implies that the important measure of risk should be the standard deviation of revenues or electricity bills. In addition, since consumers are a heterogeneous group, one must calculate an aggregate risk-aversion coefficient using some weighting function, such as one based on the proportion of sales for each customer class. To make the calculation manageable, individual customers may be aggregated into several more or less homogeneous customers classes, such as residential, commercial, and industrial customers.

A study of Pacific Gas and Electric Company postulated two conceptually different approaches to this problem, one based on the average income and proportion of sales for different customer classes, and the other based on total electricity bills, or equivalently,

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[35] Jonathan M. Jacobs and Thomas E. Huntley, Pacific Gas and Electric Company, "Valuation of Fuel Diversity," Submitted for Hearings before the California Energy Commission (February/March 1992).

[36] Robert S. Pindyck, "Risk Aversion and Determinants of Stock Market Behavior," *The Review of Economics and Statistics* **70** (May 1988), 183-190.

total utility company revenue. The resulting risk-aversion coefficients were quite similar, however. Assuming the same holds true for TU Electric, we assume a risk tolerance for TU Electric's customers as a whole to be 1.25 times expected annual revenues.

6.4. Regulated Market Scenario

We begin by applying Eq. 6.8 to the yearly means and standard deviations of revenues and net income in the regulated market scenario. Table 6.1 shows how the method works from the ratepayer perspective, that is, looking at revenues alone. The risk premium is given by the second term on the right-hand side of Eq. 6.6. The risk reduction due to wind power is the amount by which the gas-case risk premium exceeds the wind-case risk premium. In this scenario, the annual risk benefit ranges from zero to about $32 million, and has a present value in 1996 dollars of $98 million. This represents a benefit of $245 per kilowatt of firm capacity displaced by wind power, or, on a real levelized basis, $1.9/MWh of displaced fossil generation.

The results, of course, depend on the assumptions. Rather than present yearly figures for every scenario, Table 6.2 summarizes results of all the scenarios from both the ratepayer and shareholder perspectives. In addition to the change in risk premium, which is calculated exactly as in Table 6.1, Table 6.2 also shows the change in the *expected*

Table 6.1. Risk Benefits: Regulated Market, Ratepayer Perspective

	Gas Case			Wind Case			
Year	Mean Revenues	Standard Deviation	Risk Premium	Mean Revenues	Standard Deviation	Risk Premium	Risk Benefit
2003	7746	737	28	7886	742	28	0
2004	8054	964	46	8176	946	44	2
2005	8490	1208	69	8593	1186	66	3
2006	8801	1451	96	8890	1423	91	5
2007	9213	1683	123	9284	1641	116	7
2008	9652	1826	138	9706	1786	132	7
2009	10122	2142	181	10158	2086	171	10
2010	10688	2402	216	10699	2329	203	13
2011	11283	2732	265	11274	2652	249	15
2012	12005	3104	321	11967	3009	303	18
2013	12551	3353	358	12499	3264	341	17
2014	13296	3810	437	13223	3727	420	17
2015	14049	4135	487	13949	4031	466	21
2016	14737	4569	567	14624	4460	544	23
2017	15503	5051	658	15361	4929	633	26
2018	16372	5309	689	16205	5173	661	28
2019	17065	5260	649	16888	5141	626	23
2020	17904	5772	744	17719	5644	719	25
2021	18985	6263	826	18772	6109	795	31
2022	20015	6791	922	19776	6632	890	32
PV	**$91,159**		**$2,273**	**$91,180**		**$2,175**	**$98**

*Annual figures figures are in millions of nominal-year dollars. Present values are in millions of 1996 dollars, discounted at the risk-free rate of 7.5 percent. The risk aversion coefficient is the reciprocal of 1.25 times the mean revenue. The risk benefit is the amount by which the gas case risk premium exceeds the wind case risk premium.

Table 6.2 Summary of Wind Risk Benefits*

Scenario	Risk	Customer Perspective			Shareholder Perspective		
		Change in Mean Revenue	Change in Risk Premium	Total Wind Risk Benefit	Change in Mean ROE	Change in Risk Premium	Total Wind Risk Benefit
Regulated Market	High	($298)	($98)	$396	0.00%	-0.02%	0.02%
	Low	($113)	($27)	$140	0.00%	-0.02%	0.02%
Power Pool	High	$29	$36	($65)	0.52%	-0.97%	1.48%
	Low	$82	$35	($117)	0.27%	-0.89%	1.16%
Fixed-Price Contract	High	($260)	($78)	$338	0.12%	-0.38%	0.50%
	Low	($97)	($21)	$119	0.05%	-0.12%	0.17%

*Figures for the ratepayer perspective are in millions of 1996 dollars.

outcome resulting from the consideration of environmental regulatory risk. The total risk benefit combines the two numbers.[36] Under the high-risk assumption, environmental regulatory risks result in a reduction of $298 million in expected revenues for the wind scenario relative to the gas scenario.

The table shows that regardless of whether high or low risks are assumed, the substitution of wind for gas confers a substantial risk benefit on utility customers. With high-risk probability profiles for fuel prices and environmental costs, the total risk benefit is $396 million. The benefit is $140 million, or about a third as large, with low-risk probability profiles. This range corresponds to about $350 to $1000 per kilowatt of firm capacity or $2.8 to $7.8/MWh of displaced energy.

The general magnitude of the benefit is clearly large enough to merit its consideration in the utility's decision to build a wind or gas-fired power plant—*if* the customer's perspective is given weight, as it should be under monopoly regulation. As expected, however, there is no significant risk benefit to the shareholder from wind power, confirming that company managers have little incentive on their own to seek out opportunities for wind power investment.

6.5. Unregulated Market Results

Table 6.2 also shows the results of the power pool and fixed-price contract scenarios. In the power pool case, wind energy does not lower risks for utility customers, but actually raises them by $65 to $117 million. On the other hand, shareholders come out consistently ahead. The total wind risk benefit for this group ranges from 1.16 percent to 1.48 percent of return on equity.

To interpret these results one must reflect on how prices are established in the power pool scenario. (Recall that costs are the same in all scenarios since fuel prices and loads are assumed to be independent of the market type.) The variable component of the price at the margin is determined by the variable operating costs of the most expensive units needed to meet load. Since neither the wind plant nor the new gas-fired combined cycle

[36] Note that a negative change in risk premium with the substitution of wind for gas is counted as a benefit, as is a negative change in mean revenues; but a negative change in mean ROE is counted as a loss, since it will be seen as less attractive to shareholders.

facility operate at the margin, one might expect the price to be about the same in either case. However, the wind plant generates substantially more energy for the same firm capacity, with the result that it reduces the need for higher-cost units at the margin and thereby reduces the variable price component. When environmental costs are considered, however, the reduction is narrowed because the units operating at the margin with wind rely more on coal, which has a relatively high carbon intensity.

In the fixed-price contract scenario, the risk benefit for utility customers is slightly smaller than that observed in the regulated market scenario. The range is $145 to $338 million, which corresponds to a levelized benefit of $2.4 to $6.7/MWh of displaced energy. Unlike the regulated market scenario, however, shareholders also derive a risk benefit from the wind addition ranging from 0.17 to 0.5 percent ROE. In effect, the contract scenario splits the difference between the regulated market and power pool extremes.

7. DISCUSSION AND CONCLUSIONS

From the foregoing analysis we can draw the following conclusions. First and foremost, risk should be an important consideration in comparing wind and fossil-fuel resources. Although the exact methodology may be disputed, there is little question that risk factors can and should have a significant impact on utility resource decisions. The results so far suggest that the principle source of risk from fossil-fuel power plants is environmental regulatory costs. Fuel price fluctuations are also important to consider. However, our study did not account for any risks posed by long construction lead times, which could work to the benefit of modular, short-lead-time wind plants. The SRP model could be adapted quite easily to explore this issue.

The size of the risk benefit of wind energy and its allocation between shareholders and ratepayers depends strongly on the assumed risk distributions and market conditions. Traditional regulation shifts most risks to captive customers and hence creates little incentive for utility investments in risk-reduction strategies like wind. In states where utility industry restructuring is not under consideration, the case can be made that gas-fired power plants should be assigned a risk premium of perhaps $2.8/MWh to $7.8/MWh (see Table 7.1). Such a sizable premium could result in a decisive shift in the net present value equation in favor of wind plant investments.

As far as unregulated markets are concerned, a power pool appears to create the strongest incentive for shareholder investment in wind. Our calculations suggest that shareholders should see a risk benefit equivalent to an increase of 1.2 to 1.5 percent return on equity. But the extreme price volatility of this scenario makes firm conclusions difficult.

The most favorable market condition for wind power may well be one in which most power is traded through short- and medium-term fixed-price contracts. Both customers and sellers in that case are likely to see modest but significant risk reduction from wind energy investments. The customer benefit would be about $2.4/MWh to $6.7/MWh, while the shareholder benefit would be 0.2 to 0.5 percentage points in return on equity.

Table 7.1 Summary Results: Wind Risk Benefit

Market Scenario	Ratepayer Perspective ($/MWh)		Shareholder Perspective (% ROE)	
	Low	*High*	*Low*	*High*
Regulated	3.4	7.8	≈ 0	≈ 0
Power Pool	(2.3)	(1.3)	1.2	1.5
Fixed Contracts	2.9	6.7	0.2	0.5

Further study is needed in several areas:

1. The SRP model or similar tools should be applied to exploring the benefits of modularity and short construction lead times. Results from at least one other recent modeling effort suggest that these benefits could be substantial in the case of wind power.[38] Large conventional power plants have construction lead times (excluding licensing and permitting) ranging from two to five years or longer, compared to the one year typically required for wind power plants. Longer lead times increase the risk that the financial attractiveness of a power plant investment will diminish between the time substantial construction funds are first committed to the time the plant goes into operation. Factors that may affect the financial attractiveness include fluctuating loads, fuel prices, and environmental regulatory costs.

2. A related question is the need to consider the value of delaying a large capital investment such as a wind power plant until conditions are better known. As one reviewer of this report noted:

   > "Risk has everything to do with foreclosing alternatives. The discussion in the report emphazes 'variation' [in costs]...However, the flip side of this risk is capital commitment that works against capital intensive renewables such as wind...Especially with wind capital costs decreasing while fossil-fuel prices increase (or 'tend to increase') there is a benefit to waiting to invest."

   The 'option value' of wind energy can be measured using decision analysis and similar techniques and should be a subject of further study.

3. There needs to be more study of appropriate probability distributions for the uncertain input parameters, particularly environmental regulatory costs. One option would be to conduct a survey of energy and environmental experts, including managers of utility companies and independent power producers.

4. Further work should be done to define appropriate risk aversion factors for both utility managers and power consumers. A literature search would be useful. In addition, focus groups and similar polling techniques could be applied to measure risk aversion.

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[38] Hoff, *Integrating Renewable Energy Technologies in the Electric Utility Industry*, op. cit.

5. The pros and cons of various approaches to measuring risk should be evaluated in greater depth. In particular, the capital asset pricing model and the decision analysis approach used here should be systematically compared. Our results suggest that the very large risk premium estimated by Awerbuch for gas-fired power plants (upwards of 7 ¢/kWh) is unjustified. It is important to understand why the two approaches disagree.
6. Finally, it would be interesting and potentially useful to see if analytical short cuts could be developed that would yield good results without the degree of effort demanded by probabilistic simulations. An approach that is more easily grasped and applied by non-experts could help communicate the importance of risk issues to decision makers such as utility managers and investors.

APPENDIX

This appendix provides additional details on the results of the model runs.

Table A.1 shows a complete set of model runs (regulated market scenario) in which different variables are allowed to vary while others are held fixed. In the first four sets of runs (labeled Fuel Prices, Load Growth, Plant Availability, and Environmental Costs), the named parameter is allowed to vary while the others are set equal to their expected values. In the first combined run (Fuel, Load, Plant), fuel prices, load growth, and plant availability are allowed to fluctuate while environmental costs remain zero. In the second combined run (Fuel, Load, Plant, and Environmental), all parameters are allowed to vary independently. All cases involving variable fuel prices and environmental costs assume the high-risk probability profiles.

Focusing first on the runs in which only one input is allowed to vary, several observations can be made:

1. The long-term risks from fuel prices, load growth, and environmental costs are much greater than those from plant availability. Compare, for example, the standard deviation of revenue requirements for the environmental cost scenario ($12.075 billion) with that of the plant availability gas scenario ($60 million). This outcome is explained by the fact that fluctuations in average plant availability are relatively small and, unlike the random-walk process that governs load growth and fuel prices, do not tend to diverge with time.[39]
2. Allowing environmental costs to vary increases the expected costs of both the gas and wind cases by about $9 billion relative to the base. However, the increase is smaller when wind is added to the system, with the result that the wind case has very nearly the same mean present-value revenues as the gas case. This change occurs, of course, because the cost of operation of the wind plant is not affected by any CO_2 regulation. Overall, accounting for environmental regulatory risks reduces the expected cost of the wind case relative to the gas case by about $298 million,[40] or $745/kW of displaced gas-fired plant capacity.
3. The substitution of wind for gas substantially reduces the standard deviation of revenues in the environmental and fuel-price scenarios, but increases them slightly in the load growth and plant availability scenarios. The former occurs because the wind plant is not affected by fuel-price and CO_2 regulatory risks. The latter reflects mainly the higher capital cost of the wind plant, which, for the same relative variance, results in a greater absolute variance in revenues.

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[39] We have assumed no systematic changes in plant availability over time such as might be caused by plant aging or changes in average wind speeds due to regional or global climate change.

[40] If environmental costs are ignored, the wind addition increases expected revenues by $319 million over the gas-only scenario. When environmental costs are considered, the increase is reduced to $21 million. The net reduction is therefore $298 million.

Table 5.2 Regulated Market Results Summary*

Scenario		Revenues		Costs		Net Income		ROE	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Fuel Prices	Gas	$82,111	$7,118	$74,802	$6,664	$7,309	$659	10.76%	0.00%
High Risk	Wind	$82,463	$6,706	$74,650	$6,274	$7,814	$628	10.76%	0.00%
	Change	$352	-$412	-$153	-$390	$505	-$31	0.00%	0.00%
Load Growth	Gas	$84,656	$10,097	$77,433	$8,359	$7,223	$1,747	10.78%	1.20%
	Wind	$84,971	$10,151	$77,237	$8,392	$7,734	$1,769	10.78%	1.17%
	Change	$315	$54	-$196	$33	$511	$22	0.00%	-0.03%
Plant Availability	Gas	$83,608	$60	$76,684	$60	$6,924	$0	10.76%	0.00%
	Wind	$83,915	$80	$76,478	$80	$7,437	$0	10.76%	0.00%
	Change	$307	$20	-$206	$20	$513	$0	0.00%	0.00%
Environmental Costs	Gas	$92,446	$12,075	$85,383	$11,822	$7,063	$280	10.76%	0.00%
High Risk	Wind	$92,438	$11,628	$84,876	$11,397	$7,562	$256	10.76%	0.00%
	Change	-$8	-$448	-$507	-$426	$499	-$24	0.00%	0.00%
Fuel, Load, Plant	Gas	$83,397	$12,532	$75,793	$10,802	$7,604	$2,030	10.80%	1.02%
High Risk	Wind	$83,716	$12,291	$75,616	$10,537	$8,100	$2,034	10.80%	1.00%
	Change	$319	-$241	-$177	-$265	$496	$4	0.00%	-0.02%
F,L,P & Enviro	Gas	$91,159	$17,503	$83,629	$16,337	$7,530	$1,843	10.70%	1.14%
High Risk	Wind	$91,180	$17,039	$83,154	$15,846	$8,026	$1,857	10.71%	1.11%
	Change	$21	-$464	-$474	-$492	$496	$14	0.00%	-0.03%

*All figures are present values over 20 years (2003-2022) discounted at 7.5 percent, converted to 1996 dollars. Revenues, costs, and net income are in millions of dollars. Standard deviations reflect variations between iterations, not between years. No correlations are assumed among the parameters.

In addition to the runs summarized above, we conducted several runs to test the sensitivity of the results to changes in certain parameters. The results are summarized in Table A.2.

Two features should be noted. First, the assumption of low-risk probability profiles for fuel prices and environmental costs has a major affect on the outcome. This is shown in the first two sets of data, which indicate a relatively lower standard deviation for both gas and wind cases than previously seen, as well as a smaller change in mean revenues and standard deviation of revenues between the two cases. When environmental costs are ignored, there is only a slight decrease ($10 million) in the standard deviation due to the wind addition.

Second, correlations among the parameters also have a major impact on the results. The assumption of inter-temporal and inter-fuel correlations in fuel prices not only increases the variance of the results, but also causes a significant reduction in the expected revenues of the wind scenario relative to the gas scenario. Note, for example, that the change in mean revenues for the third run is $196 million, whereas for the same run without fuel-price correlations it is $319 million (fifth run, Table A.1); expected net income is largely unaffected. Assuming a negative correlation between loads and electricity prices (the last two runs in Table 5.5) tends to moderate any difference in expected revenues, whether positive or negative, between the wind and gas cases. Both types of correlation affect the standard deviation of revenues. The inter-temporal fuel-price correlation, which is positive, tends to increase the standard deviation, whereas the load-price correlation,

Table A.2 Sensitivity Summary, Regulated Market Scenario

Enviro		Load-Price	Fuel Price	Build	Revenues		Net Income		ROE	
Costs	Risk	Correlation	Correlations	Decision	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
No	Low	No	No	Gas	$84,101	$10,688	$7,198	$1,778	10.68%	1.13%
				Wind	$84,389	$10,679	$7,707	$1,796	10.68%	1.10%
				Change	$288	-$10	$509	$18	0.00%	-0.03%
Yes	Low	No	No	Gas	$87,567	$13,213	$7,316	$1,810	10.79%	1.08%
				Wind	$87,742	$13,060	$7,822	$1,833	10.79%	1.06%
				Change	$175	-$153	$506	$22	0.00%	-0.02%
No	High	No	Yes	Gas	$85,405	$16,745	$8,077	$2,298	10.80%	1.01%
				Wind	$85,619	$16,214	$8,538	$2,270	10.80%	0.99%
				Change	$214	-$530	$462	-$28	0.00%	-0.02%
Yes	High	No	Yes	Gas	$92,805	$19,220	$7,902	$2,038	10.80%	1.02%
				Wind	$92,732	$18,602	$8,373	$2,025	10.81%	1.00%
				Change	-$72	-$618	$471	-$13	0.00%	-0.02%
No	High	Yes	Yes	Gas	$85,125	$14,955	$7,911	$2,006	10.82%	0.94%
				Wind	$85,315	$14,543	$8,379	$1,994	10.83%	0.92%
				Change	$190	-$412	$468	-$12	0.01%	-0.03%
Yes	High	Yes	Yes	Gas	$87,626	$16,275	$7,362	$1,741	10.58%	1.13%
				Wind	$87,692	$15,808	$7,831	$1,745	10.61%	1.10%
				Change	$66	-$467	$470	$4	0.02%	-0.03%

*All figures are present values over 20 years (2003-2022) discounted at 7.5 percent, converted to 1996
Revenues, costs, and net income are in millions of dollars. Standard deviations reflect variations
iterations, not between years.

which is negative, tends to decrease it. These effects can be seen by comparing the last four runs in Table A.2 and the last two runs in Table A.1.

Given these findings, caution should be used in relying on the results of any single set of input assumptions. Rather, a plausible range of assumptions should be used, which may then lead to greater insight into the potential risks and risk benefits of different resource options.

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The question of uncertainty and risk in electric utility resource planning has received considerable attention in recent years. New risk management strategies are being considered. This study compares the costs and risks of two competing resource options, a gas-fired, combined-cycle plant and a wind plant, both utility-owned, through decision analysis. The case study is Texas Utilities Electric, a very large investor-owned company serving an area with substantial, high-quality wind resources. The initial findings of this study indicate that risk should be an important consideration in evaluating competing wind and gas-fired combined cycle plants.

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