

APPLICATION OF STOCHASTIC DOMINANCE TESTS TO UTILITY RESOURCE PLANNING UNDER UNCERTAINTY

JONATHAN A. LESSER

Washington State Energy Office, 809 Legion Way S.E., Olympia, WA 98504-1211, U.S.A.

(Received 2 March 1990)

Abstract—Uncertainty and risk have become critical elements of electric-utility planning. Planning has become more complex because of uncertainties about future growth in electricity demand, cost and performance of new generating resources, performance of demand-side resources that increase end-use efficiencies, and overall structure and competition within electricity markets. Current methodologies for incorporating risk and uncertainty into planning are limited by their potential lack of consistency with economic theory, or the necessity to specify expected utility functions that are difficult to defend. In this paper, we describe these limitations and suggest a new approach to utility planning under uncertainty, called stochastic dominance, which can augment or, in some cases, replace existing methods to evaluate uncertainty. Stochastic dominance permits comparison of resource plans with uncertain performance in a theoretically consistent manner, without having to assess or justify individual expected utility functions. Stochastic dominance tests can also be implemented with little additional effort over current decision methodologies, especially those methodologies that rely on Monte-Carlo models as a planning tool. Stochastic dominance tests can incorporate alternative risk attitudes of decision makers more easily than existing empirical methods and therefore provide more robust solutions to decision making under uncertainty. The paper concludes with a demonstration of stochastic dominance applied to a resource-planning decision for a hypothetical utility.

1. INTRODUCTION

Uncertainty and risk have become critical elements of electric utility planning. Uncertainties about the future growth in electricity demand, the cost and the performance of new generating resources, the performance of demand-side resources that increase end-use efficiencies, and the overall structure and competition within energy markets have increased the complexity of utility planning.¹ Utility resource planning has also been difficult because many utility decisions are unique and irreversible.²

The importance of planning for uncertainty can be gauged by examining some of the legacies of past utility planning efforts, perhaps best exemplified by the numerous nuclear power plants that have been terminated or delayed, and which have contributed to rate shocks to consumers in many cases. The underlying causes of these impacts have been complex, but have included failures to account for uncertainty in load growth and responsiveness to electricity prices, volatility of fuel prices, and unexpected complexities in siting, licensing and constructing plants.

Planning for uncertainty, however, can complicate decision making for utilities and consumers. If uncertainty is ignored, adopted resource plans may be disastrous, in terms of much higher than anticipated costs, if the expected future fails to materialize. And, even if uncertainty is accounted for, resources may still be allocated inefficiently.³ Numerous methods have been developed to account for these uncertainties, and to assess their risks. Planners have used sensitivity analyses, scenario planning, and complex decision analysis models which generate and evaluate multiple future scenarios.^{2,4}

Many of the existing methods to incorporate uncertainty and measure its associated risks may be inadequate, however. Methodologies that emphasize comparisons of the expected future costs of alternative resource portfolios, for example, may not sufficiently account for the value of flexibility in planning,⁵ or may fail to compare alternative risks in a theoretically consistent manner.⁶ Direct comparisons of alternative resources, or portfolios of resources can also be difficult. Resources can possess multiple private cost characteristics, such as sensitivity

to changes in future fuel prices, as well as possess different levels of non-market costs, such as environmental impacts. Because of these complexities, existing methodologies may lead to decisions that are not optimal from an economic standpoint, and may not minimize the costs associated with uncertainty.⁷

We suggest a new approach to utility planning under uncertainty, called stochastic dominance, that may be used either in place of or to augment existing methods to incorporate uncertainty. Stochastic dominance tests are consistent with economic theory, and can be implemented with little additional effort over current decision methodologies. Stochastic dominance may also incorporate alternative risk attitudes (e.g., risk aversion vs risk neutrality) of decision makers more easily than existing methods, and provide more robust solutions. Section 2 deals with current decision methodologies and illustrates some of their deficiencies in more detail. Particular attention is paid to the lack of theoretical consistency of many existing methods with expected utility maximization, upon which stochastic dominance is based. Section 3 then defines stochastic dominance, and discusses its limitations. Section 4 illustrates how stochastic dominance tests can be used in utility planning decisions. Section 5 offers some concluding remarks.

2. LIMITATIONS OF CURRENTLY USED METHODOLOGIES

Several methodologies exist for incorporating uncertainty and risk into utility decision making. The most common methods include sensitivity analysis, scenario analysis, and decision trees. Risk has been incorporated by using several measures, including coefficients of variation, "safety-first" criteria, mean-variance frontiers and, much less commonly, specifications of specific utility functions that incorporate behavioral assumptions towards risk.[†]

Uncertainty can be incorporated into utility planning in several ways. The first and simplest way is to ignore uncertainty altogether. Suppose, for example, the utility wishes to choose between building a gas-fired combustion turbine (CT) or a coal plant.[‡] Each of these resources will have different capital and operating costs, depending on fuel prices, plant availability factors, lifetimes, and other factors. The utility predicts the most likely (or base case) values for all these factors, and then determines the cost of both resources using these predicted values. In that case, the utility determines.

$$C_{ct} = C_1[E(\mathbf{F}_1)], \quad (1)$$

$$C_{coal} = C_2[E(\mathbf{F}_2)], \quad (2)$$

where C_i refers to the cost function associated with the particular resource, and $E(\mathbf{F}_i)$ equals the expected values of the various input factors that determine the overall costs of the two resources. Under this decision criterion, the utility will choose the resource with the lowest cost.

If the actual values of those determining factors do not equal their expected values, however, the costs of the resources may change significantly. A utility decision to build a CT based on that resource's lower capital costs and in spite of a lower operating efficiency, for example, may prove to be disastrous if natural gas prices unexpectedly increase.

[†]There is some confusion about the difference between risk and uncertainty, especially in utility planning. A classic work on the difference between risk and uncertainty is Knight.⁸ In his view, risk refers to future events with known probabilities. Thus, gambling on the outcome of a flip of a coin entails risk, since the probability of heads or tails is known. Uncertainty, on the other hand, refers to events that cannot be assigned known probabilities, such as the probability that exposure to certain pollutants will cause cancer.

Rau et al⁹ use arguably different definitions for risk and uncertainty. They define uncertainty as being associated with unknown outcomes of future events that have been assigned subjective probabilities. Risk is defined as "a measure of the effect of outcomes of an event. It is the probability of an ensuing outcome multiplied by its consequences" (p. 2). Thus, using their definition, risk can be measured, say in dollars, and is not uncertain. A reasonable goal for a utility, therefore, would be to reduce the risk from uncertain future events.

[‡]There may be argument that such a comparison is inappropriate, since CTs are more likely to be used as peaking resources. However, in a hydroelectrically based system such as the United States Pacific Northwest, CTs are under consideration as a means of meeting baseload energy growth.¹⁰

One way of reducing the risk that values for the various input factors will vary from their expected values is to consider the probability distributions around their expected values. It is clearly impossible to analyze an infinite set of future outcomes. The set of future outcomes should, however, include a set of reasonable outliers, which will likely be determined by judgment. The assumption is also made here that the probability density functions for the cost factors are determined in some manner. From the probability distributions, expected costs for the two resources can be computed. In this case,

$$E(C_{ct}) = E[C_1(\mathbf{F}_1)], \quad (3)$$

$$E(C_{coal}) = E[C_2(\mathbf{F}_2)], \quad (4)$$

where $E(C)$ refers to the expected cost of the resources, based on the entire set of possible outcomes for the various input factors. In general, $E[C_i(\mathbf{F}_i)]$ will not equal $C_i[E(\mathbf{F}_i)]$. Thus, the overall expected costs of the two resources calculated using Eqs. (3) and (4) could lead utility decision makers to choose differently between the CT and the coal plant, if their decision criterion was to minimize expected cost.

Basing a resource acquisition policy on expected costs, however, can still fail to adequately account for the risk of making an incorrect decision. While $E(C_{ct})$ may be less than $E(C_{coal})$, for example, the actual cost of the CT will be highly sensitive to changes in the price of natural gas. Utility decision makers must then decide whether to incorporate this uncertainty into its choice of a new resource and, if so, how? If decision makers are not risk neutral, a method that can incorporate more of the information contained in the probability distributions of the resource costs in Eqs. (3) and (4), and not merely the expected values, will be required.

One technique often used by utilities is sensitivity analysis. The Bonneville Power Administration (BPA),¹¹ for example, used sensitivity analyses to assess the cost-effectiveness of completing the Washington Public Power Supply System's (WPPSS) nuclear plants WNP-1 and WNP-3. Another example of sensitivity analysis can be found in the Northwest Power Planning Council's (NPPC)⁴ least-cost planning process. For the two resources considered above, a sensitivity analysis might involve varying the fuel costs and assessing the effect on the overall costs of the resources. Thus, sensitivity analysis can be useful for identifying critical factors. Unfortunately, sensitivity analysis by itself does not consider the likelihood that those critical factors will actually occur, and may therefore leave utilities vulnerable. For example, in its study for the cost-effectiveness of the WPPSS nuclear plants, BPA¹¹ determined that a 15% increase in expected construction costs would reduce the net present value of completion to zero. The Bonneville Power Association did not assess the likelihood of that event, even though the completed portions of the plants had already experienced construction cost overruns on the order of 200%.

Another method that has been used by utilities is scenario planning.^{10,12} Scenario planning postulates a set of plausible futures which may or may not be realized. Each scenario contains a set of underlying characteristics and assumptions. An "environmental" scenario, for example, might postulate stringent air quality standards, restrictions on burning fossil fuels, and an emphasis on energy efficiency measures and non-polluting renewable energy sources like solar and wind power.

Sets of scenarios are developed and resource acquisition strategies are determined based on the impacts of specific resources in each of the scenarios. For example, developing energy efficiency measures may be identified as a preferred strategy because it results in lower costs regardless of the scenario. Reliance on coal-fired plants, on the other hand, may be the lowest cost alternative if coal prices are low and environmental restrictions few, but expensive otherwise.

While scenario planning may identify particular resource acquisition strategies under different assumptions, it does not necessarily provide a clear way of choosing between those strategies. And, while judgment remains important, regulatory bodies may require more objective criteria to serve as a basis for utility resource acquisition decisions. Lastly, scenario planning generally does not assign probabilities to the alternative scenarios, which may lead to the mistaken assumption that probabilities of occurrence for the alternative scenarios are equal.

As a result of the limitations of scenario planning, multi-objective decision models and decision trees are being increasingly used by utility planners. One such model, the Multiobjective Integrated Decision Analysis System (MIDAS), was developed by the Electric Power Research Institute (EPRI),¹³ and used by Rau et al.⁹ Hirst⁵ uses a decision tree analysis to investigate the benefits and costs of shorter lead-time generating plants when future demand is uncertain. These models can be quite complex, analyzing hundreds of alternative outcomes. They can be solved for a particular objective, often minimizing total expected costs, but can also be used to determine the costs of ignoring uncertainty, as was done by Hobbs and Maheshwari.¹⁴ Decision trees can also be used with a specific utility function to incorporate alternative attitudes towards risk.¹⁴ Thus, decision trees and scenario planning can begin to incorporate measures of risk into decisions between alternative resources.

Other simple tests have been proposed to incorporate risk and uncertainty in investment decisions. These include minimizing coefficients of variation, applying safety-first guidelines, and mean-variance (EV) frontiers.¹⁵ The major problem with these latter methods is their potential lack of consistency with expected utility maximization, which is often used as the theoretical basis for decision making under uncertainty. Decision criteria that are inconsistent with expected utility maximization can lead to counterintuitive outcomes such as consumers preferring less to more, or risk-averse consumers preferring greater uncertainty to less uncertainty.

Choosing a resource with the smallest coefficient of variation (i.e., the lowest amount of uncertainty relative to the magnitude of the expected outcome) may be inappropriate for projects whose probability distributions cannot be adequately characterized solely by their means and variances. This test, which is extremely simple, can be easily shown to be inconsistent with expected utility maximization.⁶

The objective under a safety-first decision criterion is to minimize the probability of an outcome that is below some desired level Θ . As an example, suppose that the probability that the CT will cost more than 120 mills/kWh has been estimated to equal 0.40, while the probability that the coal plant will exceed this cost is only 0.25. Using a safety-first criterion, the utility would choose to build the coal plant since it provided the lowest probability to exceeding the 120 mill/kWh threshold.

On the surface, this test appears reasonable. However, the safety-first approach suffers from several potential defects. While criteria based on expected costs focus only on mean values of probability distributions, safety-first tests focus on the extreme values of probability distributions. Thus, while the coal plant may have a lower probability of exceeding the chosen threshold value, there is no consideration of the rest of its probability distribution of costs. In other words, the coal plant might be less likely to exceed the chosen threshold value, but more likely to exceed some other threshold value.

This points to another criticism of safety-first: selection of critical value for comparing resources. The value chosen will be necessarily ad-hoc. Should it be that value that will be exceeded at most 5% of the time, or exceeded at most 25% of the time? The answer will depend on the utility's attitude toward risk.

A second decision analysis tool is the mean-variance (EV) frontier. Mean-variance frontiers have been commonly employed in portfolio analysis.^{16,17} With this approach, only the mean and the variance of outcomes are used to rank prospects. For certain probability distributions, such as a normal which can be completely characterized by its mean and variance, the EV approach is consistent with maximization of an exponential expected utility function. But, for other distributions, especially those with additional characteristics, the EV approach can break down.

Table 1. Costs for two representative power plants (cents/kWh).

Plant	Exp. Cost	Std. Dev.	Best-Case	Worst-Case
Coal	8.0	1.5	6.0	10.2
CT	12.0	1.2	10.0	15.0

As an example, we suppose that analysis by the utility has resulted in an updated set of costs for the CT and the coal plant, as shown in Table 1. The expected cost of the coal plant is lower than the expected cost of the CT. The standard deviation of the cost for the coal plant, however, is higher than that for the CT. In addition, we suppose that utility planners have estimated best- and worst-case values for the costs of the two plants, representing the upper and lower bounds on resource costs that could reasonably be expected to occur. A best-case value, for example, might incorporate reductions in the expected capital costs and no escalation in fuel prices. A worst-case estimate, on the other hand, might assume future fuel escalation rates equal to the highest escalation rate in the past, along with capital cost overruns.

The EV frontier approach cannot choose between the two resources since both resources lie on the EV efficient frontier, even though from an expected utility standpoint, the decision maker will almost always be better off building the coal plant. The EV approach breaks down in this example due to the truncation of the distributions of costs of the two plants.

In order to incorporate expected utility maximization¹⁸ and alternative attitudes towards risk, specific expected utility functions are sometimes incorporated into decision analyses. The advantage of this approach is the axiomatic consistency of expected utility theory. Hobbs and Maheshwari,¹⁴ for example, use an exponential utility function to represent the decision maker's preferences. Specifically, the functional form used is

$$\text{maximize } U(X) = a - b \exp(\lambda X), \quad (5)$$

where X equals the value of the objective (such as the net present value of total utility system costs), and a , b and λ are constants. If the objective is to minimize total system costs, then setting b , $\lambda > 0$ will result in a risk-averse utility function.†

The obvious problem with this approach is specification of the utility function to be maximized. Using the specification in Eq. (5), for example, the coefficient of absolute risk aversion¹⁸ equals λ . Empirical studies, however, show little agreement on likely values for this coefficient.²⁰ And, indeed, there is no reason to expect that utility functions for individuals should be identical. Small differences in values of λ may also result in large differences in expected utility and therefore different choices. And, lastly, while exponential specifications are often used in decision analyses, other specifications may be equally viable, while leading to different outcomes. As a result, the decision maker's ultimate choice of a resource may hinge on the chosen specification of a utility function, even though there is little empirical evidence to guide the choice of any particular functional form.

The conclusion from this discussion of currently used methods for incorporating uncertainty into utility planning is that they all suffer from certain flaws. Many of the existing methodologies are ad-hoc, in that they do not correspond to expected utility maximization, except under limited circumstances. By failing to consider the likelihoods of occurrence for alternative values, several of these methodologies, such as sensitivity analysis and scenario analysis, may fail to incorporate important information about the inherent probability distributions of the underlying factors that determine resource costs. And, while specification of utility functions ensures theoretical consistency, there will always be arguments over the chosen specifications.

The next section describes a new approach to utility planning under uncertainty. This method, called stochastic dominance, offers the advantage of always being consistent with expected utility maximization, while not requiring actual specification of any utility function. Consequently, the approach may offer benefits to utility planners who seek to identify the impacts of risk in a theoretically consistent and defensible manner, without having to assess a specific utility function.

†When X is to be maximized, a risk-averse utility function would require that $b > 0$ and $c < 0$. Two standard measures of risk aversion commonly used were developed independently by Pratt¹⁹ and Arrow. The coefficient of absolute risk aversion $R_a = -U''(X)/U'(X)$, and is affected by the choice of units with which to measure X . The coefficient of relative risk aversion $R_r = X * R_a$, R_r is unaffected by the choice of units for X .

3. STOCHASTIC DOMINANCE

Planning for uncertainty can be enhanced by utilizing as much information as possible from the probability distribution of a resource, or resource portfolio's expected costs. Such an approach can incorporate useful information about the likelihood of specific levels of benefits and costs, and provide utility decision makers with more information about the risks associated with different options. But, any distributional approach that looks beyond expected values may be limited if its decision criteria are ad-hoc, or consistent with expected utility maximization only under limited circumstances, as was discussed above. Stochastic dominance is a potential alternative that incorporates both the positive aspects of a distributional approach and theoretical rigor even when the underlying set of preferences is not known exactly.

The concept of stochastic dominance arose from decision theory. Specifically, stochastic dominance permits a partial preference ordering to be imposed on a set of possible decision outcomes *without knowing the underlying set of preferences*. Thus, an analysis consistent with expected utility maximization such as Hobbs and Maheshwari¹⁴ can be conducted without having to specify the underlying utility function. The disadvantages of stochastic dominance include the partial ordering not allowing comparisons to be made for some alternatives, and a somewhat greater computational effort required to test for stochastic dominance than with other methodologies.

Stochastic dominance can provide pairwise comparisons of risky prospects such that all individuals whose utility functions belong to some set U will prefer one prospect over another. Stochastic dominance, therefore, can provide theoretically correct comparisons of resources without the necessity of specifying or defending a particular utility functional form. Stochastic dominance can utilize the information contained in distributions of benefits and costs without resorting to ad-hoc decision criteria, or be limited to the mean-variance characterization of the EV approach.

Stochastic dominance can best be introduced by way of a simple example. Suppose that a consumer must choose between two *independent* gambles X and Y , with dollars as shown in Table 2.

Here, the outcomes are in terms of dollars that will be received. It is not immediately apparent which is the preferred gamble, since X is better for some outcomes, and Y is better for others. However, because the gambles are assumed to be independent (i.e., particular outcomes of X are not linked with particular outcomes of Y) the gambles can be reordered. This is shown in Table 3.

With this reordering, it is clear that X dominates Y , since X always returns at least as much as Y in every state of the world. In an EV (mean-variance) frontier context, however, neither gamble can be eliminated since $E(X) > E(Y)$, but $\sigma^2(X) > \sigma^2(Y)$. Formally, we define the set U_1 of monotonically increasing (in income) utility functions. Any investor with a utility function u_i in the class of utility functions U_1 will prefer X to Y , since investors are assumed to prefer more income to less income. Equivalently, the expected utility of gamble X , $EU(X)$, is greater than $EU(Y)$, the expected utility of gamble Y , for all u_i in U_1 , or X dominates Y in U_1 or, alternatively, that X dominates Y in the first degree.

Table 2. Returns from two independent gambles X and Y (\$).

Gamble	Probability					
	1/6	1/6	1/6	1/6	1/6	1/6
X	1	4	1	4	4	4
Y	3	4	3	1	1	4

Table 3. Re-ordering of returns from the two independent gambles X and Y (\$).

Gamble	Probability					
	1/6	1/6	1/6	1/6	1/6	1/6
X	1	1	4	4	4	4
Y	1	1	3	3	4	4

Table 4. Returns from two alternative gambles X' and Y' (\$).

Gamble	Probability					
	1/6	1/6	1/6	1/6	1/6	1/6
X'	1	1	4	4	4	4
Y'	0	2	3	3	4	4

In many cases, however, it may not be possible to reorder the gambles to establish clear dominance. We assume, for example, that the two gambles X' and Y' are as shown in Table 4.

There is no way to reorder the outcomes such that X' returns at least as much as Y' in every probability state. Thus, it is possible to construct utility functions in U_1 such that X' will be preferred to Y' , and alternative functions such that Y' will be preferred to X' . Therefore, neither X' nor Y' is dominant in U_1 . Suppose, however, that the decision maker is assumed to be risk-averse. Consider a subset U_2 of utility functions in U_1 that are also concave, implying risk aversion. For example, u_i is contained in U_2 if u_i is continuous and has a second derivative $u'' < 0$. By breaking the gamble into simpler gambles, it can be shown that, for all u_i in the class of utility functions U_2 , $EU(X')$ is greater than $EU(Y')$.† In this example, therefore, X' dominates Y' in U_2 or, alternatively, that X' dominates Y' in the second degree.

As an example, consider the probability density functions of the returns from two alternative investments A and B , as shown in Fig. 1. While the mean return of investment B is higher than the mean return of A , B is also more uncertain, with a greater probability of either small or large returns. The cumulative density functions (cdfs) for A and B are shown in Fig. 2. Because these density functions cross, first degree stochastic dominance cannot be established. The cdf for B is initially above the cdf for A , but then lies below the cdf for A for returns $\geq \$6.00$.

To test for second degree stochastic dominance, we consider the difference in the cumulative areas under the cdfs, as shown in Fig. 3. Because the difference in areas is always greater than or equal to zero over the entire range of possible returns, investment A dominates investment B in the second degree, and will therefore be preferred by any risk averse investor. Thus, the greater expected return from investment B cannot compensate sufficiently for its greater degree of uncertainty. Risk-averse investors, who seek to avoid uncertainty, will be willing to forego the greater expected return from B for the reduced risk from A .

One weakness of first and second degree stochastic dominance is sometimes called the "left-tail" problem. This occurs if, for some small threshold return, A no longer dominates B . In other words, A may lie to the right of B over 99% of the possible outcomes. But, for the

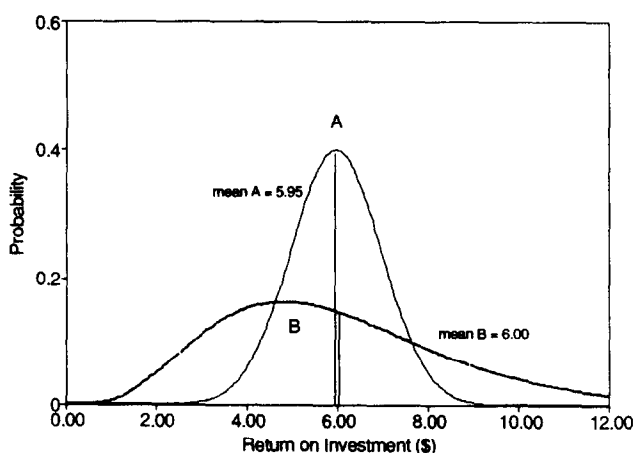


Fig. 1. Probability density functions for alternative investments A and B . B has the higher mean but also the higher variance.

†We redefine gamble X' as a one-third chance of receiving 1 dollar (X_1), and a two-thirds chance of receiving 4 dollars (X_2). Y' is equivalent to a one-third chance of an even gamble between 0 and 2 dollars (Y_1), and an even chance gamble between 3 and 4 dollars (Y_2). Because of the concavity assumption, $EU(Y_1) = 1/2 * u(0) + 1/2 * u(2) < u(1) = EU(X_1)$. Similarly, $EU(Y_2) = 1/2 * u(3) + 1/2 * u(4) < u(4) = EU(X_2)$. Therefore, $EU(Y') = 1/3 * EU(Y_1) + 2/3 * EU(Y_2) < 1/3 * EU(X_1) + 2/3 * EU(X_2) = EU(X')$.

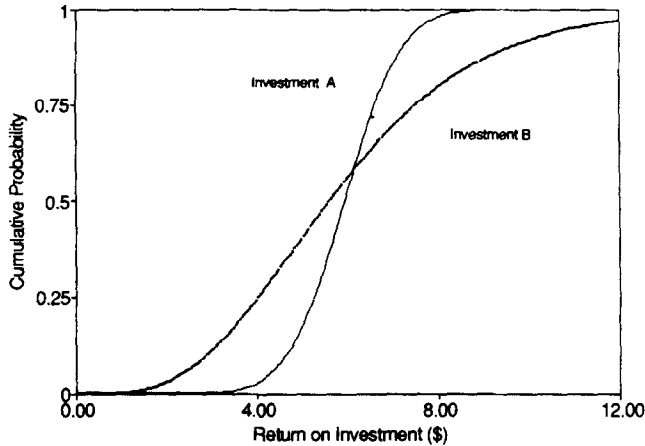


Fig. 2. Cumulative density functions for the two alternative investments *A* and *B*.

remaining 1%, *B* lies to the right of *A*. This implies that there exists a strictly increasing utility function (in either U_1 or U_2) that can be chosen so that *B* will be preferred to *A*. The left-tail problem makes it unable to determine dominance in certain cases. However, there may be ways around this problem using some form of approximation (e.g., if *A* dominates *B* 99% of the time then *A* is approximately dominant), or through more sophisticated methods that restrict the allowable expected utility functions in U_1 and U_2 . This method, called stochastic dominance with respect to a function, is fairly complex and will not be discussed here. The interested reader is referred to Cochran et al²¹ for a discussion and applications.

Another potential weakness is the necessity to compare resources on a pairwise basis. That is, if there are three resources *A*, *B*, and *C*, *A* cannot be simultaneously shown to dominate *B* and *C*, unless *B* has been previously shown to dominate *C*. This weakness may be overcome in certain cases through the use of convex set stochastic dominance.²¹ Rather than comparing alternatives in a pairwise fashion, convex set stochastic dominance (CSD) compares one alternative to a convex combination of several others.

Stochastic dominance, therefore, may be able to provide a theoretically consistent ranking of alternative prospects without having to specify the underlying utility functions. Other methods, while offering greater computational ease, may lead to decisions that are difficult to defend and which may not be theoretically consistent. In the next section of the paper, application of stochastic dominance is demonstrated for a hypothetical utility seeking to choose between two alternative resources.

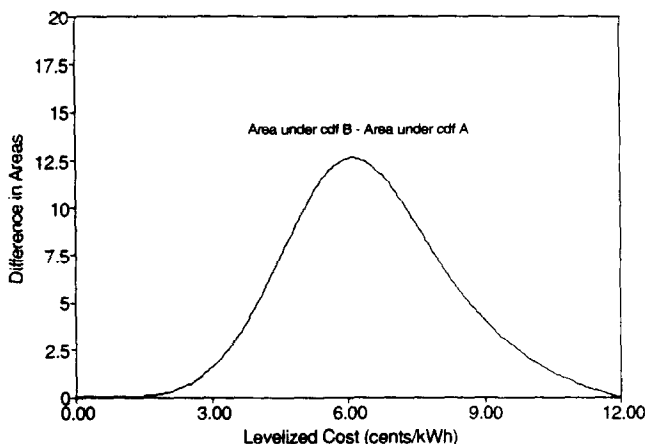


Fig. 3. Difference in areas under the cdfs for investments *A* and *B*. Since this difference is always greater than zero, investment *A* dominates investment *B* in the second degree.

4. APPLICATIONS

The application of stochastic dominance to utility planning under uncertainty can be better understood by considering a hypothetical example. A similar type of example can be found in Hirst and Schweitzer,² however, while they generated probability distributions of resource costs, they did not apply stochastic dominance techniques. We consider a utility that has identified two alternative resources that could be used to meet the growth in forecast demand in its service territory. We suppose that the utility is considering two alternative projects: a 500 MW combined-cycle CT and a 500 MW coal-fired plant. Utility planners have determined base case values for the important operating characteristics of these plants in order to determine their total costs of delivered power. These base case values are shown in Table 5.

Utility planners have also determined that the three critical factors that will determine the actual production costs of the plants are the overall capital cost to construct the plants, the delivered cost of natural gas and coal, and the plant availability factors (e.g., the percentage of time the plant will be actually running.) The planners have developed estimates of High, Medium High, base case, Medium Low, and Low values for each of the three factors, based on judgment. The planners have also determined that the factors are independent of one another. Thus, plant availability is uncorrelated with the price of natural gas or coal, which are also assumed to be uncorrelated with one another. The values for these three critical factors are shown in Table 5. To simplify the example, each value has been assigned an identical probability of 0.20. The objectives of the utility decision maker are to minimize the overall costs associated with the resource chosen, which will be assumed to maximize net benefits to consumers, and to minimize the risk that the utility will face.

While the capital cost to construct the coal plant is higher than the cost to build the CT, the fuel costs for the coal plant are lower than for the CT, and subject to less upside risk. Using the planning assumptions from Table 5, the base case levelized cost for the CT equals 4.6 cents/kWh, while the base case levelized cost of the coal plant equals 5.1 cents/kWh, where the levelized cost is analogous to an annual mortgage payment. A utility decision maker relying solely on base case values would, therefore, prefer the CT, since its cost of delivered power is less than the cost of delivered power from the coal plant.

By examining all of the 125 possible outcomes for each technology, however, a different preference ordering for the plant may result. Because the critical variables are skewed, with greater risk towards high cost values, the expected levelized costs of the plants are higher than the base case estimates. For the CT, the expected levelized cost equals 5.4 cents/kWh. The expected levelized cost of the coal plant equals 5.6 cents/kWh. Focusing solely on mean values, the decision maker would still prefer the CT, though the difference in levelized costs is less than half as large as the difference resulting from a comparison of the base case values.

While the CT has a lower expected cost, it also has a greater standard deviation of cost. The standard deviation of the levelized cost of the CT equals 1.54 cents/kWh, while the standard deviation of the levelized cost of the coal plant equals 0.91 cents/kWh. Thus, there seems to be

Table 5. Critical uncertainty factors for a coal plant and a CT.

Resource 1: CT					
Uncertain Variable	Scenario				
	High	Med. High	Base Case	Med. Low	Low
Capital Cost (\$/kW)	700.00	600.00	400.00	350.00	300.00
Fuel Cost (cents/kWh)	6.00	5.00	3.30	2.70	2.00
Plant Avail. (%)	45	55	65	70	85

Resource 2: Coal					
Uncertain Variable	Scenario				
	High	Med. High	Base Case	Med. Low	Low
Capital Cost (\$/kW)	1400.00	1300.00	1000.00	900.00	800.00
Fuel Cost (cents/kWh)	3.50	3.00	2.50	2.30	1.50
Plant Avail. (%)	45	55	65	70	85

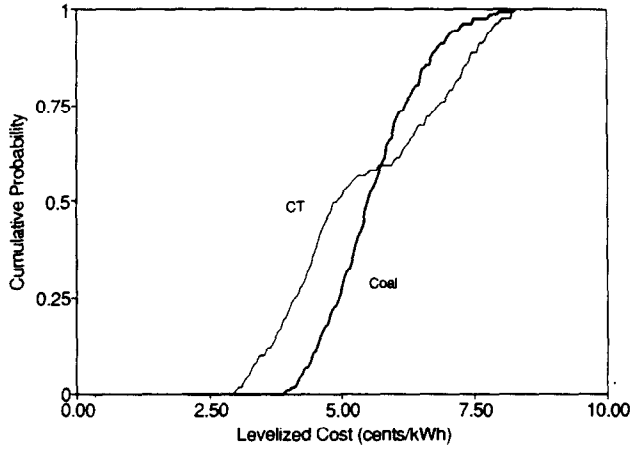


Fig. 4. Coal plant and CT cdfs based on the data in Table 5.

a clear tradeoff facing the decision maker—a higher expected cost for the coal plant vs a greater variance in cost for the CT.

If the decision maker relied on a simple coefficient of variation test to choose between the two plants, then the coal plant would be selected. The coefficient of variation for the coal plant equals 0.16, while the coefficient of variation for the CT equals 0.29. Applying a safety-first decision rule, however, could lead to a different conclusion. By calculating all of the possible levelized cost outcomes for each plant, cdfs for both plants can be determined. These are shown in Fig. 4. The shapes of these cdfs are a direct consequence of the underlying uncertainty factors listed in Table 4. As a result, the cdf for the CT, unlike that for the coal plant, appears to be somewhat kinked. If the decision maker wanted to minimize the risk that the plant selected would have a realized levelized cost >7.0 cents/kWh, for example, then the coal plant would again be preferred. However, if the safety-first threshold were lowered to approximately 5.7 cents/kWh, then the CT would be preferred.

Unlike the previous two tests, stochastic dominance can be applied to determine analytically if one plant is preferable to the other in an expected utility sense. Because the cdfs shown in Fig. 4 cross, first degree stochastic dominance cannot be shown. Thus, the decision maker must next test for second degree stochastic dominance by plotting the difference in the areas under the cdfs at all cost levels. This is shown in Fig. 5. In the example, the area between the cdfs of the CT and the coal plant is always greater than or equal to zero for all possible outcomes. Thus, the CT dominates the coal plant in the second degree. Any risk-averse decision maker will prefer the CT over the coal plant, even though the uncertainty associated with the CT is

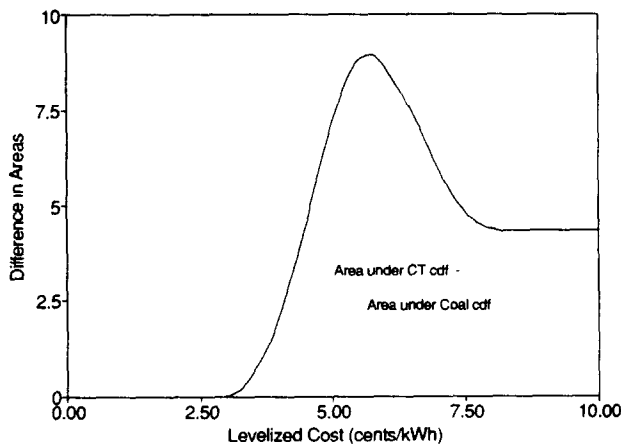


Fig. 5. Difference in the area under the CT and coal plant cdfs. Since this difference is always greater than zero, the CT dominates the coal plant in the second degree.

Table 6. Alternative critical uncertainty factors for the coal plant and the CT.

Resource 1: CT					
Uncertain Variable	Scenario				
	High	Med. High	Base Case	Med. Low	Low
Capital Cost (\$/kW)	700.00	600.00	400.00	350.00	325.00
Fuel Cost (cents/kWh)	7.00	5.00	3.30	3.00	2.50
Plant Avail. (%)	40	55	65	70	85

Resource 2: Coal					
Uncertain Variable	Scenario				
	High	Med. High	Base Case	Med. Low	Low
Capital Cost (\$/kW)	1300.00	1100.00	1000.00	900.00	800.00
Fuel Cost (cents/kWh)	3.30	2.80	2.50	2.30	2.00
Plant Avail. (%)	45	55	65	70	85

greater than the uncertainty associated with the coal plant. Risk-loving decision makers, on the other hand, will prefer the coal plant.

The stochastic dominance results are critically dependent on the assumed probability distributions for the critical input factors. Suppose, for example, that the utility planners used an alternative set of values for the critical input factors, shown in Table 6, while leaving the base case assumptions constant. In this case, the capital cost estimates have been refined slightly. The low case capital cost for the CT has increased, while the high case capital cost for the coal plant has decreased. The uncertainty of the estimated fuel costs for the coal plant has decreased. The low and high case fuel cost estimates for the CT have both increased. Lastly, plant availability has decreased in the high case for the CT.

For this example, the expected cost of the coal plant equals 5.3 cents/kWh, while the expected cost of the CT equals 5.8 cents/kWh. The standard deviations of the costs are 0.72 cents/kWh for the coal plant and 1.73 cents/kWh for the CT. As a consequence, a decision maker using the EV rule would prefer the coal plant over the CT. This preference ordering is not surprising, and indeed might be intuitively expected. Nevertheless, in this example, neither first nor second degree stochastic dominance can be shown, and the coal plant would not necessarily be preferred in an expected utility sense by all risk-averse decision makers. To see this more clearly, we consider the cdfs of the plants as illustrated in Fig. 6.

In this example, stochastic dominance cannot be found due to a left-tail problem. While the coal plant has a much smaller risk of very high costs, there is still over a 50% probability that the CT will have lower costs than the coal plant. As a consequence, the difference in the areas underneath the cdfs will not be greater than zero over the entire range of costs, and stochastic

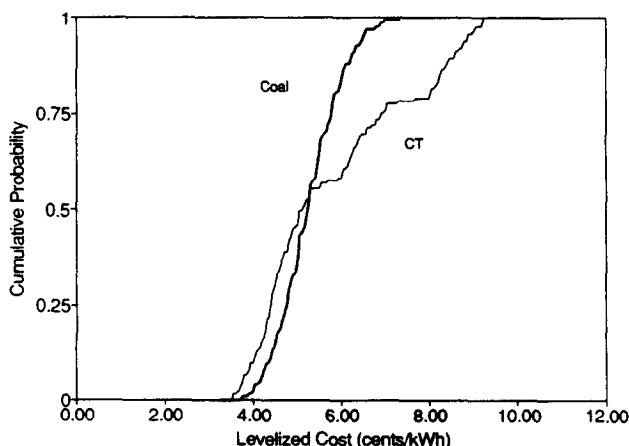


Fig. 6. Coal plant and CT cdfs based on the data in Table 6. In this case, the CT no longer dominates the coal plant in the second degree.

dominance cannot be demonstrated. As a consequence, either higher order stochastic tests would have to be performed, or a utility function specified to establish preference of one resource over the other. Clearly, assumptions about the probabilities of the critical factors in each case are important in ranking resources. (Further discussion of estimating individual scenario probabilities may be found in Plummer et al²².)

While the previous examples have illustrated stochastic dominance tests between individual resources, the relative rankings of portfolios of resources may also be tested. The Northwest Power Planning Council (NPPC), for example, selects a preferred portfolio of resources as the basis for its regional power plan.⁴ Using a Monte-Carlo model to generate alternative future outcomes incorporating uncertainty in load growth, resource costs, and plant availability, the portfolio which minimizes the expected present value of costs is selected as the preferred portfolio. Alternative attitudes towards risk, as well as the costs of risk for different portfolios, however, were not incorporated by the NPPC in this least-cost plan. There is no reason that stochastic dominance tests could not be applied to the cdfs associated with alternative pairs of resource portfolios to help eliminate inferior portfolios and identify preferred strategies based on costs. Indeed, since overall integrated system costs are important, comparisons of alternative portfolios of resources may be preferable to comparisons of individual resources. A variant of this type of analysis has already been attempted by Lesser⁶ in regards to inclusion of the Columbia River Treaty Downstream Benefits in the NPPC resource portfolio.

Limitations

Stochastic dominance tests are not a panacea for utility planners. They may only be able to provide a partial ordering of the available resource alternatives, and are computationally more intensive than existing methodologies. Stochastic dominance tests (and other evaluation methods) depend critically on the underlying probability distributions of the major factors that contribute to the uncertainty in resource costs. In practice, utility planners will likely wish to use more sophisticated analytical tools to generate and sample from probability distributions to subsequently generate distributions of overall resource and resource portfolio costs. Puget Sound Power & Light Co. (PSPL),¹² for example, has been mandated by the Washington Utilities and Transportation Commission to develop a least-cost electric plan. As part of this plan, PSPL utilized a specific software application called @RISK which samples the underlying probability distributions of input variables to generate an overall distribution of costs for a resource-portfolio. However, judgment will be required at some point to determine both the critical input factors subject to uncertainty, and their associated probability distributions. As a result, the robustness of stochastic dominance tests, as with other criteria, will depend on the underlying modeling assumptions.

While stochastic dominance tests may fail to determine uniquely dominant resources or portfolio of resources, planners may still benefit by determining dollar bounds to establish dominance. Suppose, continuing the earlier example, that the CT was not found to dominate the coal plant in the second degree. It would still be possible to determine the overall dollar reduction in levelized costs needed so that the CT would dominate, by shifting the CT cdf to the left until it was dominant. This dollar premium could, in principle, be used to help determine cost reductions in construction costs necessary for the CT to be a clearly superior choice or, if there was a concern about potential construction costs overruns with the coal plant, cutoff values to determine dominance. In this sense, stochastic dominance tests could supplement some of the more ad-hoc decision criteria. Lastly, stochastic dominance tests may prove difficult to apply when critical input variables that determine resource costs include non-market factors such as environmental costs. However, similar limitations will arise from existing criteria as well.

5. CONCLUSIONS

As uncertainty in utility planning takes on greater importance, the need for improved decision criteria will continue to increase. Many of the existing decision criteria used by utility

planners can be ad-hoc, and inconsistent with the basic principles of rational decision making which underly the axioms of expected utility maximization.

The increasing use of decision models which can generate probability distributions of costs to examine the uncertainty inherent in the estimated costs of both individual resource and portfolios of resources present the opportunity to apply stochastic dominance tests. Stochastic dominance tests can provide a theoretically consistent method for evaluating utility resource acquisition decisions, and incorporate alternative attitudes towards risk without resorting to ad-hoc methodologies. In many cases, stochastic dominance may provide rankings consistent with expected utility maximization without requiring specifications of individual functional forms.

Many utility resource decisions will undoubtedly rely on criteria that cannot be easily quantified. Considerations of environmental externalities, utility competitiveness, and customer service may not be sufficiently quantifiable to lend themselves solely to analytical criteria. Stochastic dominance should, therefore, be viewed as an additional tool for the utility planner that may be able to clarify the options available. Because of its clear benefits and straightforward application, stochastic dominance can contribute to the tool kit of utility planners and decision makers.

Acknowledgements—The helpful comments and suggestions of E. Hirst, B. Hobbs, and R. Byers are gratefully acknowledged. Remaining errors are, of course, solely my responsibility. The views expressed here are those of the author, and do not necessarily reflect those of the Washington State Energy Office.

REFERENCES

1. M. Hayes and R. Scheer, *Publ. Utilities Fortnightly* **119**, 13 (1987).
2. E. Hirst and M. Schweitzer, "Uncertainty in Long-Term Resource Planning for Electric Utilities," Oak Ridge National Laboratory, Report ORNL/CON-272, Oak Ridge, TN (1988).
3. D. Duann, *Publ. Utilities Fortnightly* **124**, 21 (1989).
4. Northwest Power Planning Council (NPPC), "1986 Northwest Conservation and Electric Power Plan," Portland, OR (1986).
5. E. Hirst, "Benefits and Costs of Small, Short Lead-Time Power Plants and Demand-Side Programs in an Era of Load-Growth Uncertainty," Oak Ridge National Laboratory, Report ORNL/CON-278, Oak Ridge, TN (1989).
6. J. Lesser, "Renegotiating the Downstream Benefits of the Columbia River Treaty: an Application of Benefit-Cost Analysis Under Uncertainty," Ph.D. Dissertation, University of Washington, Seattle, WA (1989).
7. A. Briehpohl and F. Lee, *Publ. Utilities Fortnightly* **116**, 21 (1985).
8. F. Knight, *Risk, Uncertainty, and Profit*, Houghton-Mifflin, Boston, MA (1933).
9. N. Rau, M. Harunazzaman, D. Duann, B. Hobbs, and P. Maheshwari, "Uncertainties and Risks in Electric Utility Resource Planning," Columbus: The National Regulatory Research Institute, NRRI 89-9 (February 1989).
10. Puget Sound Power & Light Co. (PSPL), "Securing Future Opportunities 1990-1991," Bellevue, WA (1989).
11. United States Department of Energy, Bonneville Power Administration, "Draft Resource Analysis Documentation, 1987 Resource Strategy," Portland, OR (1986).
12. G. Bjorklund, *Publ. Utilities Fortnightly* **120**, 15 (1987).
13. Electric Power Research Institute (EPRI), Multiobjective Integrated Decision Analysis System (MIDAS), Report No. P-5402, Palo Alto, CA (1987).
14. B. Hobbs and P. Maheshwari, *Energy* **15**, 785 (1990).
15. B. Taylor and R. North, *Am. J. Agric. Econ.* **58**, 636 (1976).
16. T. Copeland and J. Weston, *Financial Theory and Corporate Policy*, Addison-Wesley, Reading, MA (1983).
17. H. Markowitz, *J. Finance* **7**, 77 (1952).
18. J. Hey, *Uncertainty in Microeconomics*, New York University Press, New York, NY (1979).
19. J. Pratt, *Econometrica* **32**, 122 (1964).
20. S. Wheatley, *J. Monet. Econ.* **22**, 193 (1988).
21. M. Cochran, L. Robison, and W. Lodwick, *Am. J. Agric. Econ.* **67**, 289 (1985).
22. J. Plummer, E. Oatman, and P. Gupta, *Strategic Management and Planning for Electric Utilities*, Prentice-Hall, Englewood Cliffs, NJ (1985).