Incorporating DSM Uncertainty and Flexibility into Integrated Resource Planning

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This paper presents an approach for incorporating DSM uncertainty and flexibility into the process of Integrated Resource Planning. Techniques of judgmental probability assessment are used to dimension DSM uncertainty on a program-by-program basis using the key inputs used in DSM planning models. Probabilistic DSM model inputs are then used in conjunction with Monte Carlo simulation to quantify the overall uncertainty surrounding the utility's DSM portfolio. Uncertainty propagation analysis is used to rank the relative importance of DSM model inputs in terms of overall DSM uncertainty. In the final stage of the analysis, Monte Carlo simulation results are converted into the decision tree inputs, which can be used to assess the impact of DSM in the overall context of Integrated Resource Planning. The paper discusses practical issues and findings of a case study conducted in conjunction with Colorado Public Service Company (PSC).

Introduction

Increasing reliance on DSM as a utility resource has added several new dimensions to the process of Integrated Resource Planning. The uncertainty surrounding future DSM impacts represents another major source of uncertainty that must be considered in the IRP process. For utilities relying on DSM to meet a significant portion of new resource needs, ignoring the uncertainty surrounding DSM impacts may increase the risk of future imbalances between loads and resources. At the same time, the short lead times, small unit sizes and flexibility associated with DSM represents a potential source of decision flexibility that may help to offset much of the risk associated with DSM and other planning uncertainties. To date, few utilities appear to have incorporated the uncertainty and flexibility of DSM into the IRP process.

Background

A variety of different approaches may be used to incorporate planning uncertainty and flexibility into the IRP process. However, accurately capturing the impacts of planning uncertainty and flexibility on planning outcomes requires three basic elements not currently incorporated into most IRP methodologies:

Use of probabilistic uncertainty analysis. The most common techniques used to assess planning uncertainties are sensitivity analysis and scenario analysis. Both these approaches identify the potential importance of planning uncertainties in terms of planning decisions and outcomes. However, neither technique provides an analytical framework of incorporating different sources of uncertainty in actual planning decisions. Probabilistic forms of uncertainty analysis such as Monte Carlo simulation and decision tree analysis provide a framework for assessing the performance of different planning decisions in a manner which accounts for the relative likelihood of different future scenarios and the combined effects of different sources of uncertainties.

The dynamics of decision-making under uncertainty. Many IRP methodologies treat utility planning as an *open-loop* process in which a resource plan is fixed for the entire planning horizon regardless of how uncertainties unfold. In other studies, capacity expansion models are allowed to re-optimize for different scenarios (such as low or high demand growth), simulating perfect foresight about the uncertainties being assessed. In practice, however, IRP is a *closed loop* process which allows resource plans to be modified sequentially over time as uncertainties unfold.

Lead times and flexibility of supply and demand-side resources. Realistic assessment of the impact of planning uncertainties on total system costs requires explicit representation of the lead times, flexibility, and relative fixed and variable costs of supply and demand-side resources.

One of the key goals of the methodology developed for this study is to help bridge the gap that currently exists between the tenets of decision analysis and the application of these principles in the IRP process. Therefore, this methodology was shaped by a several practical issues and realities of utility planning.

Building Upon Existing Utility Planning Models. A key challenge in applying more sophisticated techniques of uncertainty and decision analysis in the IRP process is developing practical approaches that can be used in conjunction with existing utility models. Specific models used by a utility often have substantial credibility and support among utility planning departments and management. Institutionally, these models often provide a structure around which much of a utility's past and future data collection and planning activities are based. Using these existing models as a framework helps to maximize the quality of data inputs and the likelihood that results can be feed back into the utility's planning process.

Developing Model Inputs. Several of the most widely used IRP planning models now have add-on features which facilitate the use of decision tree analysis. However, these features do not appear to be widely used in actual utility planning studies to date. In practice, use of more sophisticated techniques for incorporating uncertainty and flexibility in the IRP decisions appears to limited largely by the ability to develop meaningful inputs needed to apply these techniques. Ultimately, a substantial degree of judgment and simplification must be used to represent the dynamics of planning uncertainty and flexibility associated with different resource portfolios. However, existing demand forecasting and DSM planning models provide a framework that can be used in conjunction with well-established techniques of indirect probability assessment to develop inputs needed for probabilistic analysis of major IRP uncertainties.

Computational Tractability. Another major obstacle in using decision tree analysis in the IRP process stems from the *curse of dimensionality* which occurs as additional uncertainties, decision options and planning periods are included in the analysis. With the major existing IRP models, run times on state-of-the-art personal computers for each end node of a decision tree are about five minutes. For the relatively simple decision tree used in this case study, it would take approximately two weeks to compute a total of 3,856 end nodes with any of the major IRP models used by utilities. In this study, the time needed to solve a decision tree was reduced from almost 14 days to several hours using a *reduced form* model derived from a selected sample of runs with the utility's IRP capacity expansion planning model. In previous studies, supply costing results derived from similar reduced form models have been shown to be within 5 percent of the more detailed models from which they are derived. Thus, reduced form modeling techniques represent a valuable approach for utilizing existing planning models while reducing the computational barriers of performing more realistic forms of probabilistic uncertainty analysis.

Methodology and Findings

The methodology used in this case study combines the major advantages of the two most basic forms of probabilistic uncertainty analysis: Monte Carlo simulation and decision tree analysis. The methodology consists of four components:

- Techniques of judgmental probability assessment are used to dimension DSM uncertainty on a program-by-program basis using the same model inputs used in all DSM planning models.
- Monte Carlo simulation is performed using probabilistic DSM model inputs to the overall uncertainty surrounding the utility's DSM portfolio.
- Uncertainty propagation analysis is performed to quantify the relative importance the uncertainty surrounding each DSM model input in terms of overall DSM uncertainty.
- Monte Carlo simulation results representing different DSM portfolios and decision strategies are converted directly into decision tree inputs, which can be used to incorporate DSM uncertainty and flexibility into a decision tree of major IRP uncertainties and decision options.

On overview of this approach is shown in Figure 1. The following sections provide a more detailed description of this approach and its application in case study conducted in conjunction with Colorado Public Service Company (PSC).

DSM Probability Assessment

Two basic techniques can be used to dimension major uncertainties involved in the IRP process:

- *Direct Probability Assessment.* This approach requires that probability distributions or decision tree inputs be assigned directly to major planning uncertainties, such as DSM impacts or load growth.

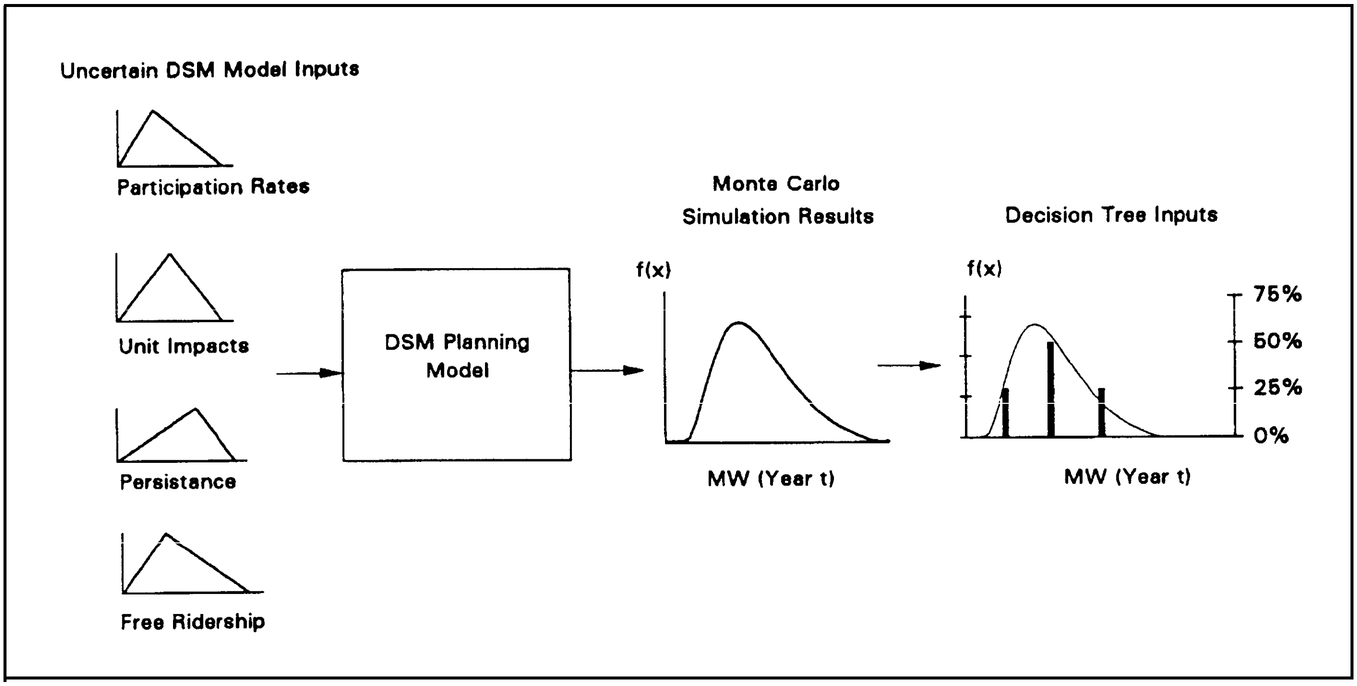

Figure 1. Overview of Methodology

- *Indirect Probability Assessment.* With this approach, major planning uncertainties are disaggregated into different underlying sources of uncertainty which may be represented as inputs to a computer model or variable in an equation. Probability distributions are assigned to each uncertainty model input or variable. Probabilistic modeling is then used to quantify major planning uncertainties (see Figure 1).

There is a widely accepted belief among the decision science community that techniques of indirect probability assessment can typically produce more reliable estimates of uncertainty than use of direct probability assessment. The potential benefits of indirect probability assessment stem largely from the fact that less tangible factors (such as net DSM impacts) are disaggregated into more specific tangible underlying sources of uncertainty (such as participation rates, unit impacts, etc.). In addition, indirect probability assessment allows interactions between many different source of uncertainty to be represented by a computer model, rather than requiring that these factors be incorporated into the analysis through human cognition (Morgan and Henrion 1990).

The detail contained in DSM planning models presents a major obstacle to using these models as a framework to assess DSM uncertainty. In this case study, probabilistic estimates were needed for almost 200 different model inputs. However, one of the key propositions of this study is that DSM planning models represent the most logical framework for dimensioning the uncertainty and flexibility of DSM resources. DSM model inputs represent the basic framework around which a large portion of data collection, market research and evaluation activities are based. Instead of requiring planners to select one single "best" estimate for each model input, the approach used in this study allows inputs to be represented in terms of a low, *medium* and *high* value. A probability distribution can then be selected which best represent the relative likelihood of different outcomes within this range of uncertainty. [1]

Correlation of DSM Model Inputs. One of the most difficult methodological issues involved in any form of probabilistic uncertainty analysis involves the correlation that may exist between model inputs. Currently, little or no empirical data exist for estimating the correlation that it apt to exist between different sources of DSM uncertainty. Assuming perfect correlation between model inputs (such as participation in different programs) may significantly *overestimate* total DSM uncertainty, while treating all DSM model inputs as being independent is apt to *underestimate* DSM uncertainty.

In this study, it was assumed that a relatively strong positive correlation (.50) is apt to exit across programs for each major category of model inputs. For instance, since participation rates in different programs are apt to be effected by many of the same behavioral, organizational and economic factors, the difference between actual and projected participation rates is likely to be positively correlated across programs. Similarly, errors in current estimates of unit impacts and measures lifetimes it apt to be positively correlated across programs due to systematic errors in techniques commonly used to estimate unit impacts and measure lifetimes. Assumptions about the correlation between uncertain model inputs were incorporated into this analysis using a special computer algorithm which generates sets of Monte Carlo inputs based on a pre-specified matrix of rank-order correlation coefficients (Iman and Conover 1980).

Overall DSM Uncertainty. Statistical confidence intervals derived from Monte Carlo simulation results are shown in Figure 2, which characterizes the overall uncertainty surrounding demand impacts of the utility's DSM programs. In Table 1, decision tree inputs derived from simulation results are compared to decision tree inputs used by PSC in a decision analysis conducted as part of the utility's 1993 IRP process. As shown in Table 1, results of this study show a range of uncertainty of +29 to -22 percent, well below the ±50 percent range assigned to represent DSM uncertainty in previous analyses by the utility.

Results of this case study reflect the basic principles of 'portfolio theory and risk diversification commonly applied in fields such as finance, insurance and risk management. The range of uncertainty assigned to most model inputs by utility planners approaches or exceeds ±50 percent of the *most likely* value. However, because these inputs are assumed to be either independent or not perfectly correlated, Monte Carlo simulation results show that overall DSM uncertainty is significantly lower than the range of uncertainty assigned most individual model inputs. Even under the assumption that inputs which are likely related across programs have a high positive correlation (.75), case study results suggest that overall DSM uncertainty is well below the ±50 percent level (at 90 percent confidence) over the utility's 10-year planning horizon. Thus, one of the key findings of this case study is that the diversification of different sources of DSM uncertainty may often be overlooked or difficult to estimate when planners directly assign ranges of uncertainty to DSM (or other factors in the IRP process) which depend on many underlying sources of uncertainty.

Uncertainty Propagation Analysis. Uncertainty propagation analysis examines how uncertainty underlying individual model inputs contributes to the overall uncertainty underlying model output (see Figure 3). By providing a means of measuring the relative importance of importance of different sources of DSM uncertainty, results of this analysis provide a framework for setting future DSM research and evaluation priorities.

To apply techniques of uncertainty propagation analysis with DSM planning models, specific model outputs must be selected as indicators of key planning criteria or goals. In this case study, relative importance of different sources of DSM uncertainty on immediate capacity planning decisions is assessed based on peak load impacts of DSM in the year 1999 (representing a five-year lead time to bring new plants on-line). Total energy impacts over the 40-year planning horizon was used as a proxy for assessing the importance of DSM uncertainties in terms of program cost-effectiveness, long-term DSM potential and environmental impacts. Detailed results of uncertainty propagation analysis show the percentage of total DSM uncertainty (as measured by specific model outputs) that may be attributed to each uncertain DSM model input. Selected case results of this analysis are shown in Figures 4 and 5, which present aggregated results for different model input categories and programs.

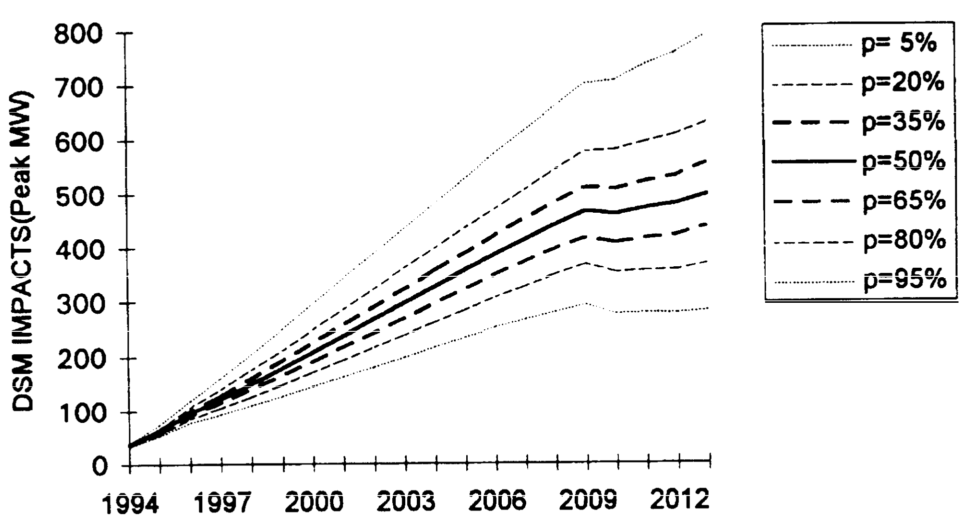

Figure 2. Probabilistic Estimate of Total DSM Impacts: Monte Carlo Simulation Results

Table 1. Results of Direct vs. Indirect Probability Assessment of DSM Impacts

Direct Probability Assessment of DSM Impacts (PSC 1993)		Indirect Probability Assessment of DSM Impacts (Case Study Results)			
Probability	**MW 1997**	**Probability[a]**	**MW 1997**	**Probability[b]**	**MW 1997**
5%	198 (+50%)	5%	177 (+29%)	25%	159 (+22%)
70%	132	70%	137	50%	130
25%	61 (-50%)	25%	107 (-22%)	25%	107 (-18%)

(a) Probabilities based on PSC estimates to allow direct comparison of results.
(b) Probabilities selected for this study for use in tree decision analysis.
NOTE: Percentages in parentheses represent variation from medium values.

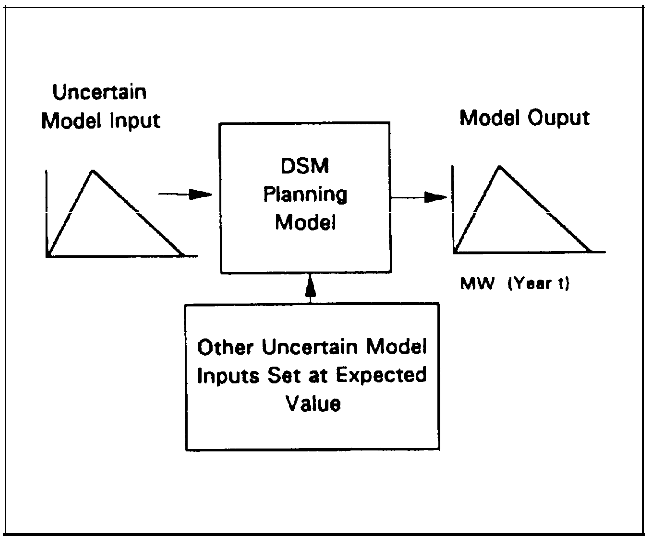

Figure 3. Uncertainty Propagation Analysis with DSM Planning Models

Uncertainty propagation analysis does not explicitly answer the question of whether the *value* of reducing different sources of uncertainty exceeds the cost of DSM research needed to reduce uncertainty. In practice, however, total evaluation budgets for a program or entire portfolio are often established in large part by rules-of-thumb involving criteria such as total program expenditures, expected impacts or previous budget commitments. Given a fixed overall budget for evaluation and research, results of uncertainty propagation may be used to allocate budgets more effectively towards reducing overall planning uncertainty. Figure 6 compares case study results of uncertainty propagation analysis to preliminary program evaluation budgets proposed in PSC's 1993 resource plan.

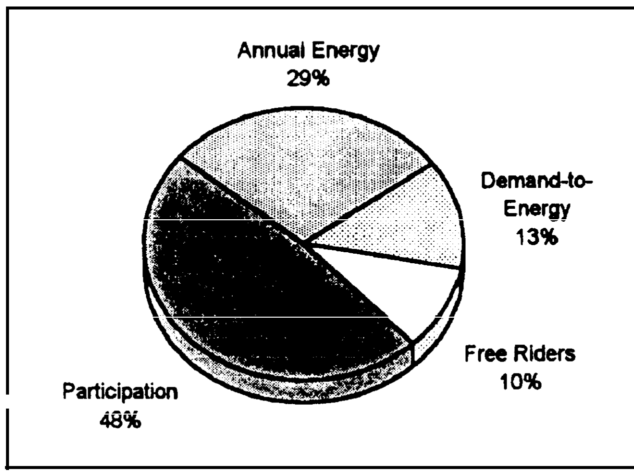

Figure 4. Contribution to Total DSM Uncertainty (MW by 1999)

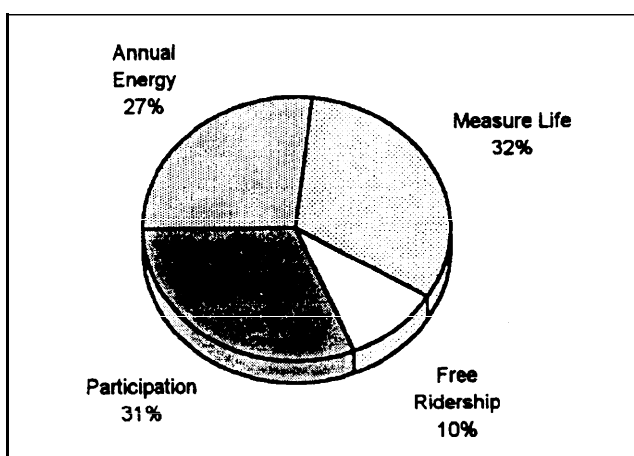

Figure 5. Contribution to Total DSM Uncertainty (GWH by 1994-2033)

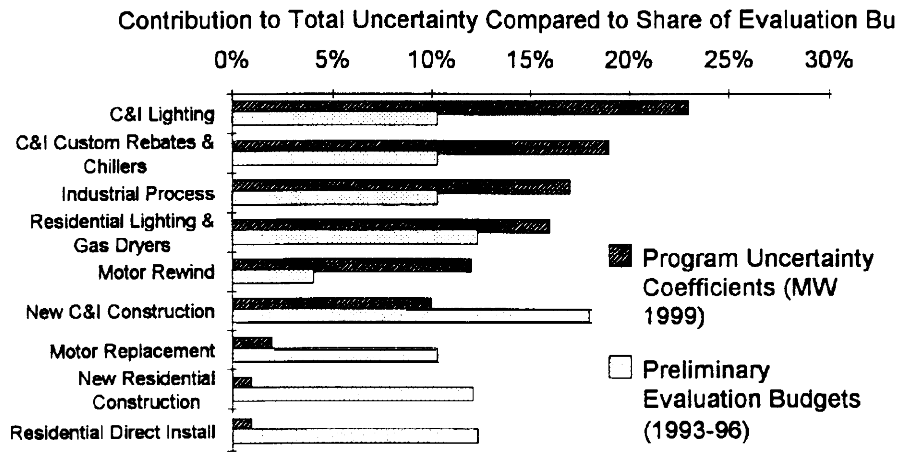

Figure 6. Comparison of Program Level Uncertainty and Evaluation Budgets

Currently, the bulk of program evaluation budgets are typically focused on quantifying unit energy and demand impacts the first year after program participation. Results shown in Figure 4 suggest that it may be cost effective to allocate more DSM research and evaluation resources towards market research, pilot programs and experimental program designs that may reduce uncertainty about participation rates over the medium range planning horizon. Similarly, results shown in Figure 5 suggest that reducing uncertainty about measure life is equally important as assessing first-year unit impacts in terms of program cost-effectiveness and long term DSM potential.

Within the last two years, one form uncertainty propagation analysis has been used to quantify the importance of different sources of uncertainty underlying total building energy consumption (Stern et. al. 1994) and program-level savings estimates (Keifer 1993), and to identify the most cost-effect means of reducing uncertainty about program impacts (Violette et al. 1993) The form of uncertainty propagation used in this study differs from the technique used these other studies in two ways:

- *Any type of probability distribution can be assigned to model inputs, including distributions which are skewed toward higher or lower values.* For inputs which have a linear effect on model output, as few as two or three model runs may be needed to analytically calculate the effect of model input uncertainty on model output. In other cases, standard techniques of Monte Carlo simulation may be used. In contrast, the basic equation typically used to perform uncertainty propagation analysis is based on the assumption that inputs *normally distributed* and requires that inputs be expressed in terms of a *mean* and *standard deviation.*
- *The correlation between different model inputs can be explicitly specified.* As discussed above, one of the key issues that must be addressed when assessing the net effect of different sources of uncertainty is the potential correlation between different model inputs. However, a key assumption of the analytical method more commonly used to apply the concept of uncertainty propagation to DSM planning and evaluation is that each input represents an independent or uncorrelated source of uncertainty.

Decision Tree Analysis

The final stage of this methodology involves the use of decision tree analysis to assess the overall impact of DSM uncertainty and flexibility in the context of other planning uncertainties and resource options. The decision tree used in this example includes three key sources of uncertainty identified during the utility's IRP process as being most important in terms of immediate capacity planning decisions:

- Baseline demand growth;
- Available capacity of non-utility supply options; and
- DSM impacts.

At the beginning of each 3-year planning cycle, decision options include major sources of supply and demand-side planning flexibility:

- Accelerate or defer the on-line date of plants in the utility's preferred resource plan;
- Modify DSM programs by increasing rebates and/or implementing a direct installation/retrofit program for C&I customers.

Decision tree inputs representing the uncertainty associated with DSM impacts can be calculated directly from Monte Carlo simulation results using standard techniques for converting continuous probability distributions into discrete distributions (Morgan and Henrion 1990). For this study, a special computer algorithm was developed to utilize Monte Carlo simulation results to calculate conditional probabilities for each consecutive three-year planning period in the decision tree.

Decision Tree Results

Decision tree inputs representing DSM and baseline demand uncertainty developed in this case study were examined in conjunction with scenarios representing typical supply options (with 3 to 6-year lead times) currently being implemented by many utilities. Results of these analyses indicate that within the framework of a decision tree, DSM uncertainty and flexibility typically has little or no effect incremental on the immediate planning decisions over the two to three year IRP cycle used by many utilities. Over the longer term planning horizon, the widening "jaws of uncertainty" surrounding DSM impacts may be offset by the flexibility to accelerate or defer the on-line new supply options. In large part, these results may be attributed to two elements of the scenarios and methodology used in this study:

- The small size, short lead times and flexibility of supply options being developed by many utilities, which allows these options to be used as "swing resources" in defending against IRP uncertainties. In most cases, for instance, final decisions on when to bring new supply options on-line may be made over just a three-year planning horizon.

- The tendency for decision tree results to be affected by major sources of uncertainty in and "all or nothing" manner.

Under most scenarios, baseline demand uncertainty was found to be the only source of uncertainty that affecting immediate planning decisions within the framework of decision tree analysis. In several scenarios, only the *combined* effect of uncertainty associated with DSM, baseline demand and/or non-utility supply capacity was significant enough to effect the "decision path" of the decision tree. Nevertheless, results emphasize the fact that while DSM may represent a major new resource of planning uncertainty, baseline demand growth remains the by far the most critical source of uncertainty that should be incorporated into the IRP process. Ultimately, the impact of uncertainty on short-term planning decisions must be assessed on a case-by-case basis, in manner which captures the combined effects of each major sources of uncertainty and flexibility.

Conclusions

The methodology developed and applied in this case study provides insights into the practicality and potential benefits of probabilistic uncertainty analysis in the IRP process:

Is probabilistic uncertainty analysis workable in the IRP process? DSM planning models provide a practical framework for dimensioning DSM uncertainty in conjunction with simple techniques of judgmental probability assessment. The type of Monte Carlo simulation techniques used in this analysis could be used in conjunction with virtually any existing planning model, including end-use demand forecasting models. Calculating inputs for decision tree analysis from these results is straightforward and represents a more empirical method of deriving inputs needed to represent planning uncertainties in the framework of a decision tree. However, solving more realistic decision trees may require use of reduced form modeling techniques which approximate results of detailed supply models.

What does probabilistic uncertainty analysis add to the IRP process? Any form of integrated probabilistic analysis will help decision makers focus on the net effect of the many uncertainties involved in the IRP process in terms of actual planning decisions and outcomes. Results provide basis for replacing qualitative judgmental of the risk associated with planning uncertainties with more quantitative assessments. Over the longer term, perhaps the greatest benefit of this approach is the framework it provides for targeting research and evaluation efforts more effectively, and responding to new developments or sources of uncertainty.

Under what conditions would it be most valuable to perform probabilistic uncertainty analysis? The value of incorporating more detailed treatment of uncertainty and flexibility into a utility's planning will vary on the nature of the utility's supply and demand-side options and resource needs, as well as the timing of the utility's planning cycle. In the short term, the approach is apt to be most valuable when utilities are faced with making specific supply-side planning commitments which involve significant lead times and fixed costs. For utilities beginning to implement an IRP process, different elements of probabilistic analysis may be more gradually be incorporated into the planning process. In this manner, the process of DSM probability assessment could be used to establish long term goals and evaluation priorities, while developing inputs that could be used in decision tree analyses as specific short-term planning decisions need to be made.

Acknowledgments

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Endnote

1. In this case study, a triangular distribution was used for all model inputs, using low, *medium* and *high* values developed by utility staff and consultants. The triangular approximates the central tendency of the normal distribution, but can also be used to represent distributions that are *skewed* toward lower or higher outcomes.

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