NRRI 89-9

UNCERTAINTIES AND RISKS IN ELECTRIC UTILITY RESOURCE PLANNING

by

Narayan S. Rau
Research Scientist

Mohammad Harunuzzaman
Research Associate in Engineering

Daniel J. Duann
Senior Institute Economist

The National Regulatory Research Institute

and

Benjamin Hobbs
Associate Professor

Pravin Maheshwari
Graduate Student

Department of Systems Engineering
Case Western Reserve University

February 1989

This report was prepared by The National Regulatory Research Institute (NRRI) with funding provided by participating member commissions of the National Association of Regulatory Utility Commissioners (NARUC). The views and opinions of the authors do not necessarily state or reflect the views, opinions or policies of the NRRI, the NARUC, or NARUC member commissions.

EXECUTIVE SUMMARY

Decisions regarding electric utility resource expansion take into account uncertainties associated with several parameters. Examples of the parameters are the demand projection, fuel prices, interest rate, penetration and effectiveness of demand-side management programs, and the price or availability of purchased energy. The analysts are aided by several computer models to analyze the effect of uncertainties. One popular method of analysis uses decision trees.

In decision tree analysis and several other variants of it, one associates a subjectively chosen probability for the parameters that form the input to resource expansion models. For instance, one may associate a probability of 0.5 for the demand growth at an average rate of 2.5 percent per year while the probabilities associated with growths of 3 percent and 2 percent might be 0.3 and 0.2. The probabilities reflect the user's assessment of the uncertainty associated with the input parameters to the model.

The solution obtained from such models (the output) is the probability distribution of financial, economic, and technical aspects. Examples of some output quantities are rates, total costs, number of decisions, and cost of DSM programs. In contrast with the subjectively chosen probabilities that represent the uncertainties regarding the <u>input</u>, the probability distribution of the <u>outcome</u> of a chosen objective is used to quantify risk. The goal would be to minimize the expectation (mean) or the standard deviation of a chosen objective. Therefore, a comparison of risks of various alternative plans aids in the selection of a preferred plan. For instance, if the chosen objective is total cost, the mean total cost and its standard deviation are used to measure risk. For normal distributions, this means that there is a 50 percent probability that the cost will be above or below its mean value, an 84 percent probability that the cost will be higher than the mean minus one standard deviation, and a 16 percent probability that it will be higher than the mean plus one standard deviation. One might choose an option that has the lowest mean cost or, alternatively, a plan with a higher mean but with a larger standard deviation. The risks of the two choices, would, of course, be different. Other objectives such as excess capacity, disallowed costs, rates, and borrowing requirements can be used as a measure of risk towards the selection of a preferred plan.

The work performed covers three major areas. The first identifies some misconceptions in the literature on the subject of least cost planning. Misconceptions regarding the definition of a "least cost plan", the existence of a global optimum solution, the ability to identify all feasible alternatives versus local optimal solutions, and the specification of the resource plan in a static context are elaborated upon. Certain difficulties and complexities in the planning process are discussed and suggestions to resolve them are proposed. Another concern in this area of analysis arises from the fact that the modelers have developed increasingly complex models to account for the uncertainties associated with the large number of input parameters.

Such models, lucid as they may seem to their creators, have become more and more opaque to regulators and decision makers. Therefore, our attempt is made to identify the more important parameters that influence the outcome. Also with a view to reduce the burden of examination of all the parameters in the input data of such models, certain internal consistency checks for the data have been suggested. Consistency checks, certainly, are utility-specific. Establishment of such checks would simplify the task of a particular utility and its regulators during a rate hearing.

The goal of the second area of investigation was that of establishing a sensitivity ranking of different uncertainties as they impinge on risk. A decision tree analysis model called MIDAS (Multi-Objective Integrated Decision Analysis System) developed for the Electric Power Research Institute (EPRI) was used to perform some of the studies. To minimize the computational effort, a simplified model based on the principles of MIDAS, called SMARTS (Simple Multi-Attribute Risk Tradeoff System), was developed by the authors to perform several studies. This simplification allowed the consideration of more input parameters without an increase in computation time or data preparation burden.

Three illustrative utilities resembling the utilities in the northeast, midwest, and western regions of the country, are used in the analysis. The study addressed three aspects of planning in this area of investigation. The first is the impact of different objectives on the choice of plans. The second is an analysis of risk attitudes on planning. The third is the ranking of uncertainties by their importance.

Three objectives are used in the decision tree analysis: minimize expected present worth of cost ("cost"), minimize expected levelized rates ("rates"), and minimize expected disallowed capacity cost ("dis. cost"). The objectives are compared two at a time. To clarify this further, the minimized total costs objective ("cost") was compared with the "rates" objective. It was found that the latter objective could increase the total cost. Similarly, the comparison of "cost" objective with "dis. cost" objective indicated that the latter could increase total costs. In essence, the objectives of "cost" and "rates" was found to be incompatible. Another conflict was that the policy of disallowing the recovery of "excess" capacity costs might in certain circumstances increase the total costs and actually encourage inefficiency.

The report outlines a sensitivity analysis of the major parameters. The variations of purchased power costs, fuel cost, and demand as they impinge on rates and total cost are shown. The effect of the variations of the above parameters on the number of decisions that change is shown. The effect of risk-neutral and risk-averse attitudes on the objective are also shown. For the three utilities studied, it was found that risk attitudes do not influence the decisions to a great degree.

Ranking uncertainties based on their relative importance depends on whether the concern is with financial ratemaking problems or with resource planning. The former concern addresses the variance of system costs and rates that result from a variance in the values of input parameters. From this point of view, fuel price uncertainties were found to influence the rates more than the demand uncertainties. But from the perspective of long-range planning, it was found that the demand uncertainties mattered the most regarding decisions in capacity planning and DSM programs. In other words, for the utilities studied, only demand uncertainties influenced decision strategies while fuel price uncertainties influenced the rates.

Strictly speaking, the above conclusions are applicable only to the utilities studied. However, since the utilities resemble a cross-section of the nation, it is believed that the results will have general applicability but with certain confirmatory checks for specific utilities.

The third area of investigation addresses the relative risks of consumer classes. In planning activity, the risk to investors and consumers is generally examined with the consumers viewed as a whole. In this third area, the risks (in terms of the objective of revenue requirement) to industrial, residential, and commercial classes are examined separately. For example, the risks of higher incurred costs by the residential and commercial classes were shown to increase with increasing uncertainty for industrial demand. A simple ratemaking procedure along with the MIDAS model is used. The shape of the probability distribution of revenue requirement for each class of customer is compared.

The study found some anomalies in the relative risks of consumer classes. The anomalies were more pronounced when the demand growth projections for each customer class were represented separately with more uncertainty in the projection of one class. It is not our intent to suggest that the risks of the classes be the same or similar. Rather, the risks to each class should be examined to address the question of equity in the distribution of risk to classes of customers. Therefore, the examination of ratemaking alternatives is intertwined with the planning process. The results of our study indicate that it is preferable to model the loads of each customer class individually (rather than the total system load) and to evaluate and compare the risks of the customer classes separately.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF FIGURES (Cont'd)

LIST OF TABLES

FOREWORD

Electric utility capacity expansion plans take into account several factors--engineering, economic, financial, and social. Demand projections, fuel prices, interest rates, technologies, and penetration of demand-side management are a few of the vast number of parameters considered in such plans. There are, of course, uncertainties associated with the parameters, e.g., volatility of fuel prices, variability of interest rates, and the realized demand growth. The uncertainties associated with the input parameters to a plan result in uncertain outcomes.

One method of analyzing uncertainties is to associate a subjectively chosen probability value to the different values of input parameters. Then a tree or a path depicting the various decisions to be taken and the various chance events can be constructed. Such a procedure is termed "decision tree analysis." Three illustrative utilities, each resembling utilities in the northeast, midwest and western region of the country have been used in the analysis.

In order to do the analysis in the limited time available, a simplified model called Simple Multi-Attribute Risk Tradeoff System (SMARTS) was developed by the authors. This model was based on the MIDAS model which was readily available from the Electric Power Research Institute. This simplification allowed the consideration of more input parameters without an increase in computation time or data preparation burden.

Douglas N. Jones
Director, NRRI
Columbus, Ohio
February 13, 1989

ACKNOWLEDGEMENTS

The authors are grateful to Mr. Youssef Hegazy and Mr. Govindarajan Iyyuni of NRRI for their help in performing computations during this project. Our thanks are due to Mr. Dave Wagman of NRRI for his editorial comments. We thank Marilyn Reiss and Joan Marino for their painstaking effort in preparing the manuscript.

CHAPTER 1

INTRODUCTION

There is a considerable amount of interest in the principles of planning electric utility resources. Of late, least-cost planning (LCP), value-based planning (VBP), and integrated resource based-planning (IRP) are proposed for resource planning of electric utility systems. LCP, VBP and IRP have been defined by several authors accentuating different aspects of the planning process.

In each of the above planning philosophies, the utilities take into account demand-side management (DSM) options along with resource expansion evenhandedly in planning for future resources and loads. Copious literature exists on planning philosophies addressing issues of economics, engineering, risks, conservation, and demand-side management. This report addresses the issues of uncertainties and risks in electrical utility planning. Methods of accounting for them in planning practice are identified and examined.

Uncertainties cannot be made to disappear. As an example of a major uncertainty, consider the demand projection based on a load forecast. No forecast can assert with certainty that a specific demand will occur at a given future date. In that sense, all forecasts are wrong. Despite this, there is a need for a forecast arising from the necessity to agree on a scenario for which the utility should plan. In other words, forecasts by their very nature are tools to seek a consensus among parties regarding a future course of action.

The reaction of planners and modelers in the complex environment of uncertainty has been to develop larger and more complex models to account for various uncertainties. One way of using such models is to make a sensitivity analysis by running the model several times under different assumed conditions. Another variant is to make a scenario analysis in which some selected scenarios are studied. Yet another type of approach is where one assigns subjective probabilities for the outcome of a set of uncertainties. We call this last category "probabilistic models."

In probabilistic models, subjectively chosen probabilities are associated with the outcomes of events. For instance, one can associate a probability of 50 percent for the price of oil at $25 a barrel in 1992 and a 25 percent probability for the price to be at $15 or $35 a barrel. Consensus should be sought among the parties (the utility and its regulators) regarding the probability values chosen.

In an idealized situation, no uncertainty exists and the analysis can be made by selecting single values for the parameters to be accounted for in the planning process. When the values of the parameters are unclear or uncertain in engineering economic analysis, a probability measure is usually associated with the representation of the different possible values of the parameters. In associating probabilities for outcomes, they are implicitly assumed to be Bayesian. That is, the parameters are looked upon as random variables having prior distributions obeying certain laws. The prior distributions are used to reflect one's belief about the possible values they can assume in the future by assuming a posterior or future distribution. However, it would be incorrect to extrapolate the previous trends and behaviors of certain parameters in the planning process into a posterior probability distribution since the prior outcomes may not obey any physical laws. In probabilistic models, such subjective projection of prior probability distributions into the future is a common recourse due to the lack of better techniques. Therefore, the subjective selection of probabilities must have the consensus of all the parties involved.

Another important matter is the distinction between uncertainty and risk. Often, these terms are used interchangeably. Uncertainty is associated with the unknown outcome of events when one ascribes subjectively chosen probabilities to the outcomes in an event. Risk is a measure of the effect of outcomes in an event. It is the probability of an ensuing outcome multiplied by its consequence. One may choose any objective for the measure of outcome. Examples of objectives are total cost, reliability, and capital disallowed from rate base. In that sense, the above definition of risk represents the expected value of a chosen objective. A more sophisticated measure of risk could be the variance of the objective. This distinction between the uncertainty associated with the input parameters in an analysis and the consequences of the ensuing result (risk) is important.

To continue the clarification of the difference between uncertainty and risk, consider an expansion plan which results in a certain total revenue requirement (RR) (if certain events happen) with a probability of 0.15. If other events were to occur, the total RR may be higher. In utility resource plans, RR and rates are frequently used as objectives. Therefore, in the following discussion on uncertainties, these two objectives are considered. The risk associated with the other events is now measured in dollars, namely the increase or decrease in RR. Therefore, it is clear that the risk or the penalty is measured in dollars and is not uncertain. However, the probability associated with the outcome of higher RRs compared with the lower RR represents the uncertainty associated with a high RR.

In our analysis, the probability distribution of a certain objective--for example, total or class revenue requirements--is used as a proxy to risk. A comparison of the distribution over different ranges of RR or a comparison of the variances is used to represent risk.

Returning to the subject of models, the use of complex models in seeking consensus has spawned lengthy debates. Considerable time could be spent arguing about the validity of the input data, be it the probabilities, price, or any other parameter. Moreover, with the increasing complexity of the models and the amount of information that can be produced by digital computers, the models and their workings have become increasingly opaque to regulators.

This report, therefore, does not attempt to proffer any new mathematical methods. Furthermore, it was not our intent to undertake an exercise in least cost planning to identify the optimal decision. Instead, we restricted our purpose to the examination of certain concepts to show the types of studies that could be conducted by the utilities and regulatory commissions. We have chosen the model, Multiobjective Integrated Decision Analysis System (MIDAS)[30], to examine certain aspects. There is more than one piece of computer software which accepts input probability values for chance variables and produces a probability distribution of selected objectives or outputs. MIDAS is one such software and was available from Electric Power Research Institute (EPRI) with relative ease: hence, our choice of MIDAS.

MIDAS is a software program that uses multi-objective decision analysis, with the user selecting the input of subjective probabilities for the outcomes of different chance variables. The program also considers decision variables in addition to chance variables. The details of MIDAS can be found in the user's manual obtainable from EPRI.

The logic of examination is the following. Believing that the state commissions' time would be better spent in examining the more critical input parameters to the planning models rather than all the parameters, our intent was to examine the impact of more important sources of uncertainty upon planning decisions and the resulting uncertainties and risks in rates and revenue requirements. Such a study enables us to rank the major input variables in terms of their impact on rates and revenue requirements. The advantages of establishing such a ranking are obvious. Certainly, such a ranking could vary from state to state.

Most of the above analysis was conducted using a simplified program called Simple Multi-Attribute Risk Tradeoff System (SMARTS) based on the principles of MIDAS which we developed for this study. In spite of demand-side management and conservation measures there could be a need for new capacity in the future. Therefore, any proposed method of planning should be defensible under circumstances of high load growth as well as under low load growth, not just under the low load growth being experienced now. The object, therefore, is to examine a general and comprehensive framework for discussion and decision making in the presence of uncertainties. The examination of MIDAS in this light was to propose certain sensitivity analysis and consistency checks for data.

In addition to the above, the data input to planning models should be internally consistent. For example, one might argue that the cost of capital and rate of inflation should have a positive correlation. One might also hold that interest rates have a positive correlation to the escalation of oil prices. Therefore, it was recognized that some form of internal consistency checks for the data should be examined.

Additionally, the relative risks to the consumer classes were examined. The questions that were addressed were: Is the risk associated with a certain planning process the same for industrial, commercial, and residential customers? Should the risk for the three parties be the same?

How should the risk be measured? The succeeding chapters outline the investigations.*

Scope of Report

The report is organized in the following manner. Chapter 2 examines several issues and misconceptions in electric utility resource planning. In addition, certain checks for the internal consistency of input data also have been suggested. Chapter 3 outlines the decision tree analysis framework for three illustrative utilities using the MIDAS model. A simplified version of the model, (SMARTS) was developed to facilitate this study. Chapter 4 shows the results of the study of the three utility systems. Chapter 5 draws upon the results of chapter 4 in examining the ranking of certain major uncertainties. Chapter 6 addresses the issue of relative risks of consumer classes.

---

*The above areas of investigations were identified by the project leader, Dr. Narayan S. Rau and were carried out under his general direction. The decision tree analysis to study the effect of objectives and the relative importance of objectives was carried out by Dr. Benjamin Hobbs and Mr. Pravin Maheshwari of Case Western Reserve University (Chapters 3-5). The development of SMARTS, a simplified computer model for analyzing decision trees, was a contribution of Dr. Hobbs. The discussion regarding the search for optimal solutions was contributed by Dr. Daniel Duann of NRRI (Chapter 2). Mr. Mahashwari and Dr. Duann collaborated on the examination of internal consistency checks. The investigation of risk evaluation among classes of customers using the MIDAS model and decision trees was undertaken by Mr. Mohammad Harunuzzaman with the assistance of Mr. Youssef Hegazy, both of NRRI (Chapter 6).

CHAPTER 2

SEARCH, OPTIMALITY, AND CONSISTENCY IN UTILITY RESOURCE PLANNING

This chapter examines several issues that have been generally ignored in the discussion of utility resource planning. Specifically, the proper roles of alternatives-searching, flexibility, and internal consistency in utility resource planning are explored. Some solutions to overcome the difficulties associated with these issues are suggested.

In discussions of utility resource planning, especially "least-cost planning," substantial efforts have been devoted to the definition of an optimal plan, the objective and content of such a plan, and the regulatory framework for implementing the planning process. These are important issues. However, these issues do not constitute the whole sphere of utility resource planning (or least-cost planning). Other important issues are involved and tend to be taken for granted. For example, the practical and conceptual difficulties in searching for and identifying all available options in utility resource planning are rarely discussed. The search for an optimal plan is often viewed as a routine planning exercise; that is, once the meaning of an optimal plan is found, the preparation and identification of the optimal plan can be assured. In the following sections, it is suggested that the search and preparation of an optimal plan are not trivial exercises. The difficulty and cost associated with the search for alternatives can significantly change the meaning of an "optimal" plan and the approach taken to prepare a utility resource plan.

This chapter first outlines some common misconceptions about planning. Second, it presents the difficulties of traditional utility resource planning in the framework of these misconceptions. Third, additional complexities of implementing least-cost planning are identified. In view of the difficulties and misconceptions identified, suggestions for their resolution in a complex planning exercise are put forth. Finally, we discuss the general approach of assuring internal consistency in utility resource planning.

Some Misconceptions of Planning

A plan can be defined as a summary of proposed future actions. An electric utility resource plan can be defined as the actions expected to be taken by a utility in meeting its customers' future demand with reasonable costs and acceptable service reliability. A "least-cost plan" may be viewed as a variation of the traditional utility resource plan that places special emphasis on serving its customers at "least-cost".[1]

There are considerable debates on the meaning of "least-cost".[2,3] Some argue that "least-cost" means minimizing electricity rates facing ratepayers. Others advocate minimizing the customers' monthly electricity bills. Still others assert that the utility's total revenue requirement needs to be minimized to achieve "least-cost". Some also argue that the entire social cost of providing energy service, including some externalities associated with energy production and consumption, should be minimized. There is some validity for each of these arguments.

Another point of contention is the regulatory framework or institutional arrangement in implementing utility least-cost planning.[1,4,5] Should the utility alone be responsible for preparing the least-cost plan or should regulators actively participate? What degree of detail should a least-cost plan have? Who bears the responsibility for any adverse consequences of a "least-cost" plan? Debates on the meaning of least-cost planning and the regulatory framework for its implementation are important. A concern now may be that these two issues can dominate the discussion on utility resource planning, or least-cost planning, and result in certain misconceptions being created or left unchallenged.

The emphasis of the current debates on least-cost planning illustrates hidden assumptions or misconceptions about the planning process. Some regulators and utility planners may be aware of these planning misconceptions, but they are not being given the attention they deserve. The first misconception is that a well-defined and clearly-stated planning problem can always be specified as an optimization problem to be solved. In using least-cost planning as an example, it is perceived that knowing the objective of a least-cost plan means the search for a least-cost plan can be defined and analyzed. However, no matter how precise or comprehensive the objective of a planning problem may be, it may not always be specifiable in a clearly defined optimality-seeking form.[6] Planners still need to specify the constraints to be met, to identify all alternatives available, and to project the effects of chosen alternatives on the objective function.

The second misconception about planning is that the solution to a well-defined planning problem can always be characterized and identified.[6] For example, even though a utility resource problem is sometimes defined as a mathematical programming problem where objective functions, decision variables, and constraints are clearly spelled out, there is no assurance that an optimal solution always exists and is identifiable. In other words, there may be no feasible solution.

The third misconception is that the activities of identifying all feasible alternatives, finding the solutions, and verifying them can always be accomplished within a reasonable time and at a reasonable cost.[6] Studies indicate that the human cognition process and the computational capability of decision support systems constrain the size and complexity of a planning, system operation, or contracting problem that can be solved.[7,42] Specifically, even some relatively "simple" problems can be extremely time-consuming to solve, or prove unsolvable despite the advanced computer systems and planning tools currently available. For example, in considering a broad-brush new-town planning problem where the planners need to locate ten activities in one of ten possible zones and connect them with fifteen out of thirty possible highway links, a total of 5×10^{14} plans might be considered.[6]

The fourth misconception is the assumption that there are no local optimal solutions in addition to the overall optimum. The existence of local optimums is primarily due to the specific nature of a utility resource planning problem such as economies of scale or externalities. As discussed before, there are limitations to the identification and search for all possible alternatives. The existence of a local optimum can be a serious problem. A solution that is optimal over only a narrow range of alternatives can be mistakenly identified as the overall optimal solution.

The fifth misconception is the assumption of the validity of specifying a resource plan in a static context. This is an especially acute problem when we consider that most utility resource plans cover a long timeframe. As a result, a plan that is optimal initially may have only a limited usefulness in guiding a utility's future actions in a constantly changing environment. In other words, an "optimal" plan lacking the possibility of flexible future actions may be less useful than an initially "suboptimal" plan with considerable flexibility. While there is general agreement that flexibility should be built into plans, its value is difficult to quantify, leaving it ignored in many planning exercises.

It should be noted that the preceding discussion of the misconceptions regarding planning is not a repudiation of existing planning methods, current utility resource planning activities, or the significant advances that have been achieved in the past. It merely points out that the implementation of planning activities can sometimes be more difficult than just the conceptual formulation of a planning problem. Although it may be attractive to expand the sphere of a planning problem to make it more comprehensive conceptually, there is no guarantee that this approach is always feasible or that a better plan can always be developed. Therefore, in applying the above arguments to utility resource planning, regulators, utilities, and ratepayers need to recognize that utility resource planning is a costly and time-consuming process. The benefits of expanding such activities must be weighed against the costs of doing so. Recognizing and addressing these misconceptions can enhance the validity and usefulness of utility resource planning in general, and least-cost planning in particular.

Some Difficulties in Traditional Utility Resource Planning

In this section, we discuss three issues in traditional utility resource planning in terms of these planning misconceptions. The first example is the economic dispatch of generating units in a utility system. The order of economic dispatch is generally determined in terms of operating cost. It is also assumed that the marginal operating costs for all generating units are increasing or remain constant over the whole range of electricity generation. Under this specification, the economic dispatch of generating units becomes a routine exercise: generating units are dispatched in the order of increasing marginal operating cost. The overall system optimum is reached when the marginal operating cost is equalized across all generating units.[8,9] Several techniques have been developed to implement this optimization principle.

It is possible that the heat rate (fuel used/electricity generated) of specific generating units may not be constant or increasing continuously. This consideration as well as the possibility of scale economies in fuel purchases may entail a decreasing marginal operating cost for certain generating units over a certain range of electricity generation. Under this circumstance, the solution to the economic dispatch problem becomes more complicated; even unattainable, in some cases. The equalization of marginal costs across different generating units does not lead to overall optimization. The issue of suboptimization arises, and an optimal rule in guiding the economic dispatch of generating units might not be available. Even though some decomposition techniques have been suggested to solve the suboptimization problem in general, some additional concerns need to be addressed in using these techniques.[10]

The second example is the joint production problem associated with electricity generation. If the monetary values of the joint products (such as electricity and steam) are independently determined and remain constant over the whole range of electricity generation, joint production does not change the formulation and solution of the resource planning problem. The monetary value of the secondary product can be added directly to the primary product. The problem of finding the optimal amount of electricity generation can be solved readily. However, some secondary products do not necessarily have constant market values, so their values cannot be added directly to the primary product. It appears that, up to now, no systematic way exists of finding and assuring the optimal solution under this circumstance.

The third example is that the mere use of a typical utility resource planning models currently available does not assure the search for, and identification of, all possible alternatives. The planning models--such as the MIDAS discussed in this report--usually only indicate the financial and engineering consequences of specific alternatives deterministically or probabilistically. It is still up to the utility planners to search for, identify, and specify all feasible alternatives. This may not be a serious problem if only a small number of alternatives is available. With limited alternatives, the utility planner can devise a system to identify or examine the more obvious alternatives. Examination of those more obvious alternatives, even without a systematic reduction of infeasible alternatives, may do a reasonably good job of identifying an optimal plan, provided that all alternatives are of similar natures. However, this approach can be risky and haphazard if a large number of alternatives with quite distinct natures exists (such as building a new power plant and retrofitting lighting fixtures).

These three examples indicate that searching for alternatives and finding optimal solutions are not routine exercises. Actually, substantial efforts are needed, and there is no assurance that all planning problems, no matter how well defined, can be solved or bear useful results. Nevertheless, these inadequacies, as identified above, in traditional utility resource planning, in most instances, do not severely compromise the process of identifying the best alternative available. The resulting utility resource plan may not always be optimal in the strictest sense. Often, however, it can be characterized as a "satisfactory" solution when the costs and benefits of further refining the resource planning process are considered.

Additional Complexities in Least-Cost Planning

Least-cost planning, as currently envisioned, appears to be much more complex than traditional utility resource planning. The additional complexity of least-cost planning is fundamentally different from the planning inadequacies encountered in traditional utility resource planning. These complexities, if left unaddressed, can materially affect the utility resource plan.

The Sources of Complexity

The additional complexities of least-cost planning are derived from two factors. First, least-cost planning emphasizes the inclusion of non-traditional alternatives such as conservation and load management programs. The development of demand-side options has gone hand-in-hand with the emergence of the concept of least-cost planning. Demand-side options include, among other things, the implementation of time-of-use electricity rates, utility control of customer appliances, promotion of energy-efficient appliances and lighting, and building weatherization. Demand-side options can be usefully included in utility resource planning and play a role in meeting future electricity demand. Utility involvement in the development of demand-side options is justified in certain circumstances. However, additional refinements in the methodologies and practices of incorporating demand-side options into the utility planning process are still needed. Complex issues are involved in evaluating the cost-effectiveness of demand-side options, in formulating the proper role of the utility, and in treating the cost of demand-side options. Additionally, the inclusion of demand-side options can significantly increase the scope of utility resource planning.

Second, there is a strong tendency to expand the role of a utility resource plan by having a wider sphere of objectives. For instance, a least-cost plan is evaluated not only in terms of its effects on ratepayers within the utility's service territory, but in terms of regional or national impacts such as employment, economic development, and environmental concerns.[5] A least-cost plan is required to incorporate not only ratepayers' decisions on electricity usage, but their use of other forms of energy and possibly their non-energy related decisions.[1,5]

These are admirable goals of utility resource planning, but they may also induce some undesirable effects. The uninhibited expansion of the objectives of a least-cost plan may be self-defeating. The consideration of other social goals may inhibit the performance of the utility in meeting its primary objective--supplying electric energy with reasonable quality at reasonable costs. An electric utility is primarily a business entity rather than a social institution. The issues of economic development and promoting employment, for example, are probably better dealt with by state departments of development or local chambers of commerce.

The Complexities

The combination of incorporating many nontraditional alternatives and expanding its objective has greatly changed the nature of utility resource planning. The complexity of a utility least-cost plan as compared to traditional utility resource planning is reflected in three areas. First, a broad range of new demand and supply options is incorporated into the planning process. Under the least-cost planning paradigm, an electric utility can no longer be content with just building power plants or purchasing power from outside sources to meet future electricity demand. Alternative power supplied by nonutility power producers also need to be considered. Conservation and load management programs sponsored by the utility or nonutility entities cannot be ignored.

Second, an electric utility may be required to coordinate with neighboring utilities in preparing and implementing statewide or regionwide least-cost plans. This is in sharp contrast with traditional utility resource planning that is generally confined to a utility system or to a loosely cooperative effort among utilities. The degree of coordination and integration is much higher in the least-cost planning process--at least in terms of statutory requirements--than in traditional resource planning. Unfortunately, the implementation of least-cost planning itself typically does not provide additional incentives or political mechanisms to promote closer coordination among neighboring utilities. Electric utilities have different objectives, different supply and demand characteristics, and may be subject to regulation from different regulatory agencies. Even though statutory requirements on coordination and cooperation can be specific and monitoring mechanisms can be instituted, it still would be difficult to achieve closer cooperation without providing economic incentives to the utilities.

Third, the definition of "cost" is broadened so that it not only includes the cost incurred by the utility, but also the cost incurred by the ratepayers. Specifically, the utility's least-cost plan as currently contemplated requires the utility to consider not only ratepayers' total electricity bills but also the total cost of ratepayers' energy usage. The inclusion of the total cost of energy usage presents great challenges to the utilities. A utility either has no reliable information about ratepayers' energy consumption patterns and no means to control them, or can do so only with substantial efforts and expenses.

The Consequences

Two undesirable side-effects are associated with the increasing complexity and scope of a utility least-cost plan. First, the plan may become too complex and too comprehensive so that the costs of preparing and searching for alternatives become prohibitively expensive or the planning problem becomes unsolvable. Then, even though the utility may have a more elegant and ambitious resource planning process, it may not necessarily produce a better resource plan to serve its customers.

Second, the regulators, the utility, and the ratepayers may have a hard time understanding a highly complex resource planning problem and communicating with one another about its merits and weaknesses. The development of sophisticated mathematical models to include a larger number of variables, while making the planning process lucid to the modeler, has, perhaps, made the process more opaque to regulators and ratepayers. It is becoming increasingly difficult to resolve disputes among different parties and to reach a consensus about a utility resource plan. The cost and time delay experienced in planning and building new generation capacity under existing regulations are likely to be substantial.

Suggestions for Resolving Complexities

This discussion of the additional complexities and consequences of a utility least-cost plan is not intended to question or verify the validity of least-cost planning. It merely points out the difficulties and complexities in the development and implementation of a utility least-cost plan. A least-cost plan process, as currently envisioned, simply may be unworkable. In this section, several suggestions are provided which represent necessary refinements for a utility least-cost planning process.

The definition of "cost" in least-cost planning should be narrowed rather than broadened. As indicated before, broadening the definition, though attractive in theory, has undesirable side-effects that can impede the primary function of an electric utility--providing electric service with reasonable quality at reasonable cost. Least-cost planning is not a panacea for all the problems facing electric utilities; it is but a new approach to utility resource planning. A poorly prepared least-cost plan, no matter how broadly it defines the concept of least-cost or how many policy goals it includes, does not lead to least-cost electric service for the ratepayers. The key in least-cost planning is not, therefore, how comprehensive the plan is, but if the concept of cost is appropriate to the purpose of the utility resource plan, and if the specification of the planning problem is clearly defined and solvable.

The difficulty and cost of preparing and searching for alternatives needs to be explicitly recognized in least-cost planning. Considerable amounts of time and effort are usually expended in presenting feasible alternatives and in identifying the "optimal solution." The effort needed in preparing and searching for all feasible alternatives generally is positively related to the size and complexity of the planning problem. If the task of searching for an alternative is given proper attention, utility planners and regulators will recognize that they need to reach a balance between a complex, though more realistic, resource planning process and a simplified, but more tractable one. Some decisions have to be made concerning the degrees of detail and comprehensiveness in the planning process. After all, the resources that can be devoted to utility least-cost planning are not unlimited.

The value of flexibility in a least-cost plan needs to be considered. Since a utility least-cost plan typically covers a long period of time, substantial changes in the outside environment are likely. As a result, an initial optimal plan may bear little resemblance to the actual plan that evolves. Consequently, value is associated with flexibility in planning. But its quantification is difficult because utility planners rarely know in advance the range of future events and their likelihood of materialization.

For example, utility planners do not know how many unexpected load changes will occur or the availability of outside power. Without this knowledge, it is difficult to assign a value to preserving the option of future outside power purchase. Nevertheless, maintaining flexibility with respect to future action does have value, and it needs to be considered. In this chapter, we do not propose specific evaluation mechanisms to measure the benefit of flexibility. We only emphasize that to view a least-cost plan as a unique action plan over an extended period of time without giving proper consideration to preserving flexibility may be unrealistic.

Finally, internal consistency checks can be applied in a least-cost plan to reduce the size and complexity of a planning problem. Such checks can reduce the numbers of objectives, constraints, decision instruments, or assumptions used in least-cost planning. Through internal consistency checks, regulators and ratepayers would examine only the more important variables and the internal consistency in the values attributed to them, rather than examining the details of all of them. (The issue of the more important variables in terms of their sensitivities is addressed in chapter 5.) The following section is a discussion of the general approach of considering internal consistency in a typical electric utility planning process.

Internal Consistency in Least-Cost Planning

The primary reason for considering the issue of internal consistency is to make a better utility resource plan within cost and time constraints. The use of internal consistency may reduce the size and complexity of the planning problem and make it manageable. Internal consistency of the data also reduces the efforts and costs associated with searching for all feasible alternatives. More importantly, checks for the internal consistency of data improve communication between regulators, ratepayers, and the utility. The task of preparing a utility resource plan becomes more accessible to all parties involved if the size and complexity of the resource planning problem can be reduced. Improved communication among the parties can enhance the formation of a common understanding about the best alternative in meeting future electricity demand. But there is a downside to the use of internal consistency checks. To reduce the complexity and size of the planning problem, some simplification is needed. If improperly done, the planning problem may be unrealistically simplified to meet internal consistency requirements. The solution derived may become irrelevant to the least-cost planning problem.

The importance of certain types of data varies from utility to utility based on their historical configurations and location. Therefore, it would be unwise to suggest a universal set of data and an internal consistency check between them. However, as an example, a list of some primary factors that may be considered in a typical utility resource is provided in table 2-1. The relative importance of these factor, based on our judgments, is also indicated. Such ranking of the important factors of utility planning helps to set the priority of analyses conducted in following chapters. Understandably, some utilities may view different factors in the table as more or less important.

The correlations among the factors listed in table 2-1 are presented in a correlation matrix in figure 2-1. The rows and columns correspond to the

TABLE 2-1

FACTORS OF UTILITY RESOURCE PLANNING

Factors	Importance[1]
Supply-side factors	
1. Fuel availability	*
2. Fuel cost	***
3. Capital cost	**
4. Power plant lead time	*
5. Technological developments in generation technology	*
6. Cogeneration	**
7. Power sales to other markets	*
8. Power cost and availability from other utilities	**
9. Cost of power from other sources	**
Demand-side factors	
10. Annual rate of load growth	***
11. Number of customers by class	*
12. Customer response to demand-side management programs (DSMs)	**
13. Cost of DSMs	***
14. Effectiveness of DSMs	**
15. Conservation investment life	**
16. "Free rider" issue[2]	*
17. Price elasticity	*
Regulatory factors	
18. Policies regarding bearing of risks	***
19. Environmental regulations	**
20. Rate-setting policies	*
21. Cost-recovery policies for demand-side programs	*
General economic factors	
22. Inflation rate	*

[1]* less important
** important
*** very important

[2]This refers to the case that certain customers will adopt demand-side options even without utility promotion and subsidy. So the effects of these customer actions need to be excluded in measuring the benefits of DSMs.

	Supply-side Uncertainties									Demand-side Uncertainties								Regulatory/planning Uncertainties					
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	
1		--				++	+/-	++	++	-									+			--	1
2				-		--	+/-		--										--			++	2
3				++					+	-												++	3
4									++									++					4
5																							5
6							++			--	+						++						6
7										++				+									7
8									--	--	++												8
9										++	++												9
10											++	--	++	--	--								10
11												+	++			+							11
12													--										12
13																						++	13
14															++	++							14
15																						+/-	15
16																							16
17																							17
18																				+/-	+/-	+/-	18
19																							19
20																					+/-	+/-	20
21																						+/-	21
22																							22
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	

KEY: + = a positive correlation (++ signifies a strong correlation).
- = a negative correlation (-- signifies a strong negative correlation).
+/- = negative or positive correlation, depending on utility's circumstances, or one or more qualitative variables involved (which are not measured).

Fig. 2-1. Correlation matrix for uncertainties in least-cost planning factors listed in table 2-1. The correlation matrix for just the "important" and "very important" factors is given in figure 2-2.

Clearly, the factors of utility resource planning and the correlations among them identified here are highly simplified and subjective. They probably reflect the general condition facing a typical electric utility. Individual utilities may exhibit unique correlations among the different factors of utility resource planning. Once the correlation matrix is identified, the next step is to specify the quantitative relationship among the various factors. A range of the possible values of each factor may be established.

Here we use the annual rate of load growth as an example to illustrate the procedure of an internal consistency check. According to the correlation matrix representing very important factors (figure 2-2), the annual load growth is positively correlated to the cost of demand-side management options, and negatively correlated with a customer's acceptance of demand-side programs and the effectiveness of such programs. It should be noted that the correlation matrix only reflects the important relationship among factors. It does not necessarily reflect any causal relationship among factors. For example, it is inappropriate to interpret from the correlation matrix that higher annual load growth can cause higher cost of demand-side management. In this instance, the internal consistency check shows that the probability of a higher load growth associated with an extremely low cost of demand-side management option is low. The utility planners can choose not to consider such a scenario, or to restrict the values assigned to the cost of demand-side management. In either instance, the complexity and size of the utility resource planning problem can be reduced. In the general move toward simplifying the planning process, commissions and utilities may want to consider establishing internal consistency matrices and agree on certain parameters for investigation during the planning process.

Sources of Uncertainty

	Supply side					Demand side					Regulatory		
	2	3	6	8	9	10	12	13	14	15	18	19	
2			--		--							--	2
3					+	-							3
6						--							6
8					--	--							8
9						++							9
10							--	++	--	--			10
12								--		++			12
13													13
14										++			14
15													15
18													18
19													19
	2	3	6	8	9	10	12	13	14	15	18	19	

Fig. 2-2. Correlation matrix, "important" and "very important" uncertainties

CHAPTER 3

DECISION TREE ANALYSIS OF RISKS: MODELS AND ASSUMPTIONS

Risk and uncertainty are important in utility planning for several reasons. Uncertainties mean that a unique "least-cost" plan cannot be defined, since a plan which results in the lowest costs under some circumstances is likely to perform poorly under others.[16] We saw in chapter 2 that the existence of a truly optimal plan is doubtful. The search is instead for a "robust plan" that will do well under a range of possible outcomes, although is not necessarily the best under any of them. A planning process that ignores or underestimates uncertainty may yield "brittle" plans that perform disappointingly under circumstances other than the narrow ones considered during its development.

Another reason that risk is important is because it makes financial planning difficult and may prevent utilities from recovering all of their costs. Third, uncertainties in the price of electricity are costly to consumers who must make capital investments based on a forecast of electric rates.

In this and the following chapters, the importance of risk in utility planning is studied for three hypothetical utilities. In particular, the following questions are addressed:

* What is the impact upon costs and rates of risk-averse decision making by utilities?
* What is the effect of demand and supply uncertainties upon optimal utility plans, the worth of information, and the variance of rates and total electricity production costs?
* What is the cost of disregarding these uncertainties?

These questions are answered by applying the methodology of decision analysis to three hypothetical utilities.

In the next section, a brief review of the methodology of decision tree analysis is given. In the remainder of this chapter, the MIDAS and SMARTS models are summarized, along with the data assumptions used in the analysis. Three "base cases" are defined: one for a model utility that depends upon oil-fired generation and power imports, one for a utility with generation capacity that is primarily coal fired, and one for a utility experiencing high growth rates and uses both coal and natural gas. The first utility resembles the conditions in the northeastern United States. The second model is typical of midwestern utilities. The third case is based on conditions in the southwestern United States. Assumptions concerning supply costs, demand, and uncertainties are described for each. Three different objectives are considered in each case: minimize revenue requirements, minimize electric rates, and minimize disallowed capacity costs. The effect of different levels of risk aversion is modeled using utility functions to show how risks can be lowered at the expense of expected performance. The analysis answering the questions posed above is presented in chapters 4 and 5.

Solving Decision Trees

In decision analysis, decision trees are created to explicitly lay out the options available and the uncertainties faced. Such trees can be used to (1) determine an optimal strategy which optimizes the expected value of some objective, (2) calculate the value of obtaining information which reduces uncertainties, and (3) assess the effects of different sources of uncertainties upon decisions.[17]

As an example, figure 3-1 represents the decision tree which is used in the analysis of chapters 4 and 5. Uncertainties are portrayed using "chance nodes" (round nodes), with possible events shown as distinct paths, each having a subjectively chosen probability associated with it. Decision options are represented as paths from a "decision node" (a rectangle in figure 3-1). When solving a tree, the decision maker must choose one of those paths for each decision node. As an example of a decision node, figure 3-1 shows that in year four (stage 6) the decision maker can choose to start construction of a new plant with one or two units, to delay a plant whose construction was started in year zero, or to continue construction of a plant. In the same year, there is a chance node which shows that demand growth for years four to thirty can be low (with probability 0.25), medium

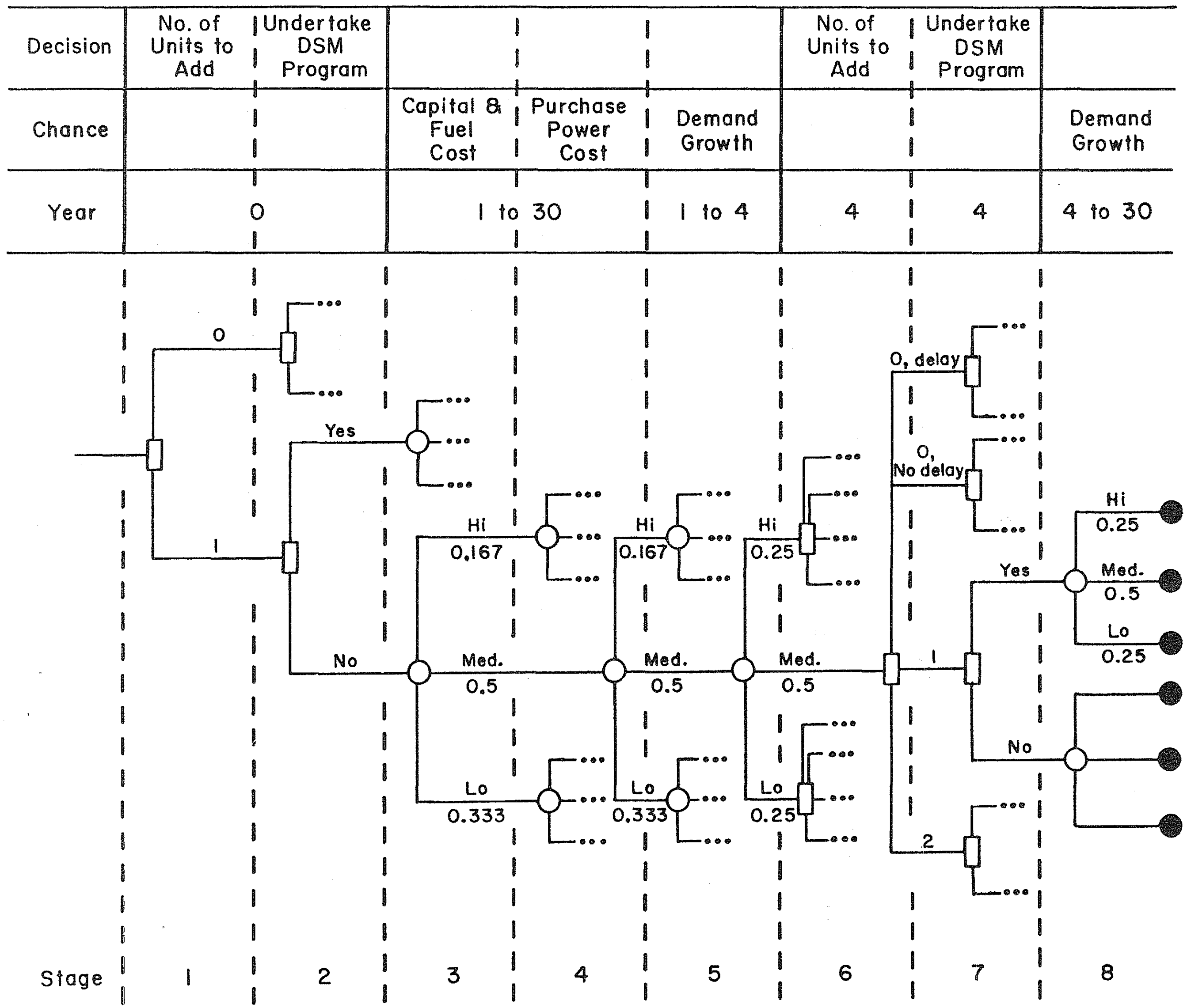


Figure 3-1 Schematic of decision tree used in SMARTS analysis

(with probability 0.5), or high (with probability 0.25). A particular path from the starting node on the left to a terminal node on the right represents one possible sequence of decisions and outcomes. The terminal nodes are represented by filled circles. There are 2,598 terminal nodes. Hence, only a portion of the tree can be shown in figure 3-1. Other paths to the terminal nodes would be obtained by completing the decision tree along the dotted line paths shown.

A solution to a decision tree consists of identifying an optimal strategy and its expected performance. Such a strategy defines the optimal decision for each decision node that can be reached. For example, a simple strategy of choice in decision nodes might be:

> Start construction of a coal-fired unit in year zero, implement a demand management program in years one to four. If the demand growth in years one to four is over 1 percent per year, delay construction in year four. If, instead, demand growth is over 3 percent per year, then start construction of a second unit in year four. Continue the DSM program in years five to thirty only if demand growth exceeds 1 percent per year.

Decision tree-based models have been recommended as an appropriate means of analyzing uncertainties in utility planning.[18,19,20] Below, two such models are used to evaluate risks in utility planning. The first is MIDAS, a utility planning tool developed under sponsorship of the Electric Power Research Institute. The second is SMARTS, which is a simplified version of MIDAS developed specifically for this project by the team. Most of the analyses are performed using SMARTS because of its flexibility. MIDAS, which requires more effort to calibrate and run, is applied to a few cases to check the results of SMARTS.

Ford and Geinzer[15,20] published two comprehensive analyses of risks in utility planning using what may be viewed as a simple decision-tree approach. They focused on the Bonneville Power Authority system. In one study, they defined a simple tree in which the first node was a decision node in which the utility chose either to make a high level of investment in demand-side programs or no additional investment.[20] Four sets of chance nodes were then defined, which modeled uncertainties in demand growth, cancellation of nuclear units under construction, the market for aluminum, and the market for secondary power. This tree can be viewed as an "open loop" planning process in which all decisions must be made before any of the uncertainties can be resolved. A more realistic analysis, such as that represented in figure 3-1, allows for "closed loop" decision making in which utilities can modify their initial decisions as time passes and uncertainties are resolved.

Before presenting models used in the analysis, the choice of optimal plans in decision tree analysis is explained using an illustration.

An Example

We can introduce the fundamentals of decision tree analysis with the help of a simple example. Figure 3-2 is a decision tree representation of a capacity expansion problem in which the decision maker must first pick option A or option B (which might represent alternative generation technologies). Proceeding from left to right, we see that after the choice is made, that the demand growth can either be low, medium, or high. The probability of each growth rate is shown in parentheses. The outcomes (present worth of power supply cost) are shown next to the terminal nodes. For example, if option A is chosen and demand growth is high, the present worth of costs will be two billion dollars.

To determine the optimal strategy, the decision tree is "folded back." This procedure starts at the terminal nodes and moves backwards through the stages of the decision tree. It assumes that the decision maker is trying to optimize the expected value of the outcome of a desired objective. The desired objective in this example is the present worth of costs. The expected value of a variable X--designated E(X)--is defined as the sum of the possible outcomes, each weighted by its probability. Hence, E(X) is the probability weighted average. In the illustration of figure 3-2, the expected value of costs for the upper chance node is 0.25 x 0.9 + 0.5 x 1.6 + 0.25 x 2 billion or 1.525 billion dollars. For the lower chance node, the corresponding value is 1.575 billion dollars.

Folding back proceeds as follows. At each chance node, the expected value (mean) of the outcomes is calculated. At each decision node, the best option is chosen. The procedure works its way backwards through the tree until the calculations for the first node on the left are completed. The result is an optimal strategy (defined by the decisions made at each decision node) and an expected value for the performance of that strategy.

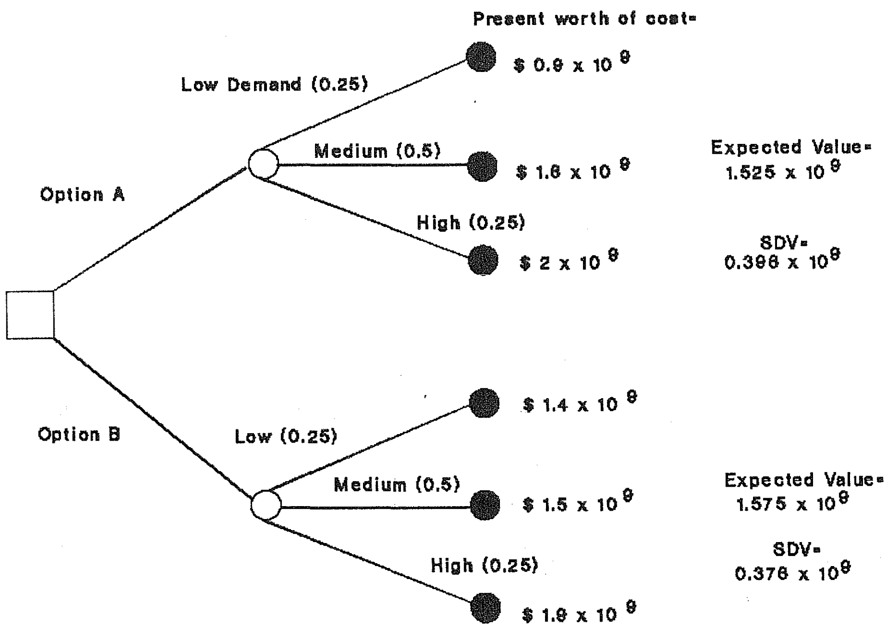


Figure 3-2. Example of decision tree for choosing optimal strategy under risk (Option A is chosen).

Applying this procedure to figure 3-2, the calculations are as follows. First, the expected outcomes are calculated for the chance nodes in the last stage of the tree. Recall that the performance of option A is $\$1.525 \times 10^9$ and of option B $\$1.575 \times 10^9$. Having finished the calculations for that stage, the procedure moves back to the previous stage, which is the decision node. At this point, option A is chosen because its expected cost is better (lower). Since the first node on the left has been encountered, the procedure is finished and the optimal strategy (choose A) and its expected performance ($\$1.525 \times 10^9$) has been determined.

Model Overview

In both MIDAS and SMARTS, uncertainties are represented as chance nodes in a decision tree and decision alternatives are portrayed as decision nodes. In addition, both models can automatically add generation capacity as needed after a specified year without having to represent explicitly those decisions with decision nodes.

It is not possible to include a realistic amount of detail about all aspects of utility planning in a single model. MIDAS treats technical aspects such as pricing and production costing in a detailed and rigorous manner. But because of the model's relative size and slow execution time, it can only include a limited number of uncertainties and decision options. It includes submodels which perform load analysis, capacity planning, production costing, financial projections, and rate calculations. As an example of the detail incorporated in MIDAS, production costing can be accomplished using probabilistic simulation while accounting for unit maintenance schedules, monthly load duration curves, energy-limited plants, and pumped storage. MIDAS output includes detailed reports on the results of all these submodels. It also calculates and provides several useful pieces of information, including (1) the optimal strategy and the expected value of the objective function, (2) the expected value of perfect information, and (3) probability distributions for the objective under alternative strategies.

MIDAS requires many hours for data preparation and program execution. For example, a 144-terminal-node problem took forty hours to execute on a

IBM PC-XT with a math-coprocessor, while data preparation took several man-weeks. Therefore, for practical purposes, the number of terminal nodes on a MIDAS decision tree is limited to one or two hundred. For this reason, SMARTS was developed so that more extensive analyses could be undertaken.

SMARTS uses a number of simplifications to reduce model size and computational time. The simplifications permit the modelling of many more uncertainties and options. To make this possible, SMARTS must use simple production costing, financial, and demand models, while still capturing the essential elements of the planning process. These two models complement each other. MIDAS yields realistic and very detailed solutions for a few cases. They provide a benchmark for the SMARTS simulations. Meanwhile, SMARTS flexibility allows analysis of a wider range of options and uncertainties. The important simplifications in SMARTS are:

* The production costing submodel uses a trapezoidal annual load duration curve whose dimensions are based on the peak and average demand values provided by the user.

* The production costing submodel uses a derating procedure to include forced outages and maintenance.

* Only one aggregate customer class is considered.

* Revenue requirements are calculated as the sum of capital charges, fixed operating costs, and variable production costs ignoring the detailed structures of these.

* Capital charges are of two types: a fixed fraction of capital investment in distribution, transmission, general, and pre year-zero generation plant; and a capital recovery factor multiplied by the post year-zero investment in power plants.

* The total capital investment in distribution, transmission, general, and pre year-zero generation plant is assumed to grow by a fixed percentage each year.

* The fixed fraction by which that investment is multiplied accounts for depreciation, income taxes, interest, and return to stockholders.

* Fixed operating costs, excluding those associated with post year-zero plants, are assumed to grow by a fixed percentage each year.

* All calculations are performed in constant dollars.

* Unlike MIDAS, loads cannot be adjusted based on calculated prices and assumed price elasticities.

These simplifications enable SMARTS to solve much larger decision trees with up to several thousand terminal nodes. Data preparation for SMARTS is simpler than for MIDAS because there are far fewer parameters. The model's quick run times makes it possible to perform a wider range of sensitivity analyses.

Despite these simplifications, SMARTS can incorporate many essential features of the utility planning process:

* Up to two types of capacity additions (for instance, baseload coal and peaking combustion turbines).

* Costs of demand-side programs, which may be uncertain.

* Differential growth rates for peak and average demands.

* Escalation in fuel prices.

* Bulk power sales and purchases.

* Regulatory disallowance of costs for "excess" capacity.

* A variety of objectives, including minimization of revenue requirements, minimization of electric rates, and minimization of disallowed capacity costs.

* A variety of risk attitudes, from risk neutral to risk averse.

SMARTS solves a decision tree, such as that in figure 3-1, by following three steps:

1. Data bases on costs, demands, decision options, and uncertainties are prepared within an electronic spreadsheet, such as LOTUS 1-2-3.[33]

2. For each terminal node on the decision tree, three quantities are calculated by a program written in TURBO-BASIC: the present worth of total utility costs, the discounted sum of power demands (used in step 3 to calculate levelized rates), and the present worth of disallowed capacity costs. Each terminal node represents one possible sequence of decisions and resolution of the uncertainties. These calculations are accomplished by performing production costing and financial analyses for each year in the planning period. Prior to stage 8, construction starts for new plants are dictated by the

choices made at the tree's decision nodes (see figure 3-1). However, subsequent starts are automatically made by SMARTS to satisfy reserve margin requirements, just as in MIDAS. It is accomplished as follows: the user specifies a target reserve margin; if demand in any year after year fifteen is such that there would be inadequate capacity, the model adds additional generation units of a size and type defined by the user. It is assumed that eight years are required to build a plant, so that to satisfy a reserve margin constraint in year sixteen, construction would have to commence in year eight. Shortfalls in capacity prior to year sixteen are assumed to be made up by purchasing power at a very high price ($200 a megawatt-hour).[45]

3. Given the values of costs, demands, and disallowed costs at each terminal node, the decision tree is then solved by the standard "folding back" method, analogous to backwards dynamic programming. The objective used can be to minimize expected present worth of costs, expected levelized rates, expected disallowed capacity costs, or a weighted sum of the three.

Objectives Used to Select Optimal Plans

General Objectives

Three general objectives are considered for the selection of optimal plans, discussed in the next chapter. The first two are frequently-stated objectives of integrated resource planning: minimizing the present value of total utility costs (in dollars) and minimizing of electric retail rates (in dollars per kilowatt-hour).[23] Both objectives are used in the applications of MIDAS and SMARTS. The definition of the present value of total utility costs is obvious. The retail rate objective, P^*, the price charged per kilowatt-hour levelized over the planning horizon, is defined as[37]:

$$P^* = \frac{\Sigma_t \, P_t E_t/(1+i)^t}{\Sigma_t \, E_t/(1+i)^t} \tag{3-1}$$

where P_t is the actual price per kilowatt-hour in year t and E_t is the total energy sales in kilowatt-hours during year t. In other words, if a price of P^* was charged for every kilowatt-hour sold over the time horizon, the present worth of utility revenue would equal the present worth of revenue under the actual time series of prices. Thus, P^* can be viewed as a kind of average price. P^* is referred to here as the "levelized rate."[46]

The third general objective is minimizing the present worth of disallowed capacity costs. The costs consist of the sum of the discounted costs of plant construction that are assumed to be disallowed by a regulatory commission because the system's reserve margin exceeds a specified threshold. Because of the difficulty of calculating it in MIDAS, this objective is used only in SMARTS.

Other objectives have been suggested for utility planning. One is the maximization of net consumer value, which can be operationalized as consumer surplus.[24] However, use of that objective would require that the models allow demand to depend on price. SMARTS currently lacks that capability, so this objective is not considered here. Future work could include this criterion.

These objectives do not necessarily lead to the same solutions.[23] For example, consider a utility whose marginal (or avoided) cost of providing power is less than its average cost. In that case, minimizing total utility costs would justify subsidizing a conservation program whose cost per kilowatt-hour-saved is less than marginal cost. However, electric rates would have to increase as a result of that program, because the utility's fixed costs would have to spread over fewer sales. Therefore, minimizing the costs might not minimize the rates. As another example, a utility which attempts to minimize disallowed capacity costs may avoid adding new capacity, even if the cost of such capacity were less than the expense of the additional power it would have to purchase from other utilities. In this instance, one observes a contradiction between minimizing disallowed cost and minimizing total costs. Finally, minimization of total costs may justify certain demand management programs that would not be economical under a maximization-of-consumer-surplus objective. These conflicts are examined in chapters 4 and 5.

Incorporating Risk Attitudes in the Objectives

As Hirst has stated, the presence of risk makes it impossible to identify a plan that is "least cost" under all circumstances.[16] Rather, decision makers must somehow weigh the possible outcomes when choosing an optimal plan. One approach as explained earlier, is simply to minimize the expected value of the objective, defined as the sum of its possible values, each multiplied by its probability. Decision analysts call this type of behavior "risk neutrality." It is also possible to behave in a risk-averse or risk-seeking manner by giving greater weight to poor or good outcomes.

One way of modeling these different types of behavior is to describe a decision maker's preferences by a utility function whose expected value the decision maker attempts to maximize. The following general utility function is one frequently used by decision analysts:

$$\text{Maximize } U(X) = a - be^{cX} \tag{3-2}$$

where X is the value of the objective (such as the present worth of utility costs) and a, b, and c are constants. Assuming that X is to be minimized, setting $b>0$ and $c>0$ will yield a risk-averse utility function.

To illustrate the application of utility functions in decision making, consider again the simple example of figure 3-2. Imagine that the decision maker is risk averse, so that it is inappropriate merely to minimize expected costs. Risk here is the chance of having the cost stream too high. Instead, the values of a and b in (3-2) are chosen to result in the following utility function to model the decision maker's preferences:

$$U(X) = 1.0556 - 0.005e^{2.6762X} \tag{3-3}$$

where X is the cost in billions of dollars. This function is risk averse because the expected value of U(X)--designated E[U(X]--for a risky alternative will have a lower utility than a riskless alternative which has the same value of E(X). That is, when choosing between two alternatives with the same E(X), the function results in a higher E[U(X)] for the less risky alternative.

If X is the cost in equation (3-3), a cost of $\$0.9 \times 10^9$, which is the best value in figure 3-2, has a utility of one, while the worst value ($\$2 \times 10^9$) has a utility of zero. To apply this utility function, the value of equation (3-3) is substituted for cost at each terminal node in figure 3-1, and then the tree is solved in the normal fashion. Considering figure

3-2 as an example, the utility of option B under medium demand growth is 0.779, which is calculated by substituting $\$1.5 \times 10^9$ in (3-3). E(u(x)), the expected utility of option A, which is the sum of the utilities of each level of demand growth weighted by the probabilities, is 0.597. The expected utility of option B is 0.662, which is higher, implying that B is preferred under this utility function although its expected cost is higher than that of option A. Option B is preferred because it is less risky compared to A, having a smaller chance of bad outcomes and a lesser standard deviation of cost.

To what extent would a risk-averse attitude change the optimal strategy for an electric utility? In general, there are tradeoffs between risk and expected value; if a utility planner is willing to accept, say, a poorer expected value of total cost, then it may be possible to choose a strategy which is less risky. As shown in the above example, in figure 3-2, a planner could choose option B, which is less risky than A but has a higher expected cost.

Note that risk-seeking functions can be simulated by using $b<0$ and $c<0$ in equation (3-2). This study is confined to risk-averse functions. Therefore, by inserting a risk-averse utility function in the MIDAS and SMARTS models, the strategies that maximize expected utility were found. Risk aversion is simulated by choosing high values of the parameter c. (The a and b parameters do not affect the ranking of alternatives and can both be set equal to one.) The effects of risk-averse decision making are studied in the next chapter by plotting the standard deviation of the objective (a measure of "risk") for each solution versus the objective's expected value. The results will indicate whether it is possible to significantly lower risks in utility costs and rates and what it would cost (in terms of expected performance) to do so.

Data Assumptions

To illustrate the importance of uncertainty in utility planning, three planning problems are modeled, utilities A, B and C. Because this analysis considers only three specific cases, the results cannot be generalized for all utilities. But, because the utilities span a range of supply and demand conditions, the results can be considered indicative of the importance of uncertainty for many utilities. Nevertheless, the reader is cautioned that before specific conclusions can be made for a particular utility, it is necessary to study that utility's special circumstances by using models similar to MIDAS or SMARTS.

This section summarizes the data assumptions used in the analyses. The appendix provides additional detail for the MIDAS models. For each utility, a thirty-year planning horizon is considered in SMARTS. However, only a twenty-year horizon is modeled in MIDAS, due to its required computational time.

Figure 3-1 displays the structure of the planning problems as modeled in SMARTS. There are four sets of decision nodes, representing capacity and demand-side management program decisions at years zero and four, and five sets of chance nodes, representing various supply and demand uncertainties. The MIDAS model is the same, except that it omits the supply uncertainties and has fewer alternatives at each decision node. Table 3-1 lists these details for the MIDAS and SMARTS decision trees in relation to figure 3-1.

For utilities A and B, expected growth rates are 1.8 percent a year (peak) and 2.0 percent a year (energy) in the absence of demand-side management programs. These growth rates are consistent with those forecast by utilities in the northeast and midwest. Utility C, however, expects peak and energy growth rates of 2.6 percent and 2.8 percent a year respectively. These rates are the averages used in chapters 4 and 5. Sensitivity analyses are conducted using a range of variances of the rates of demand growth around these expected values.

Both the MIDAS and SMARTS models include decision nodes in years zero and four representing decisions about whether to pursue a demand-side program. Initial impact on demand growth of DSM programs was derived from an EPRI[28] survey of fifty-nine rebate programs. An analysis of seventeen of those programs, which reported both peak reduction and cost data, reveals that the average program costs approximately $200-per-kilowatt-per-year of reduction in peak demand, with a range of $100-to $600-per peak kilowatt-per year (see the appendix). Typical programs reduce peak demands by between 0.2 percent and 0.6 percent a year, with an average of 0.35 percent a year. Another EPRI report[27] presents subjective probability distributions for the nationwide impacts of DSM programs by the year 2000. DSM programs were forecast to reduce the total demand of 715 gigawatts in the year 2000 by 45 gigawatts on the average. The uncertainty band was that there is a 90 percent chance that at least 19 gigawatts would be cut, and a 10 percent chance of more than 170 gigawatts. If this decrease takes place over an eight-year period, as is assumed in the MIDAS and SMARTS models, this implies that DSM programs are expected to lower the demand peak by an expected value of 0.8 percent a year, with an 80 percent confidence interval of 0.34 percent to 3.3 percent. The EPRI report also forecasts that the DSM programs would have even a greater impact on energy consumption, although individual utility DSM programs are often designed to address peaks rather than energy.

Based on these results, it is assumed here that a DSM program is available to the three utilities which could lower peak and energy growth rates by 0.7 percent a year and 0.5 percent a year, respectively. These impacts are greater than have been experienced by most programs thus far, but are slightly less than the long-run impact that is expected by EPRI. The cost of these programs is assumed to be $200 per kilowatt-a-year.

It is assumed that if the DSM programs are kept in place indefinitely, these decreases in growth rates would be maintained for eight years, at which time the higher (1.8 percent a year and 2.0 percent a year) growth rates would resume. On the other hand, if a DSM program is started and then later dropped, it is assumed that by eight years after the end of the program, the demands would be the same as they would have been without the program. The presumption behind these growth rates is that a DSM program targets energy-using equipment having a lifetime of eight years and that consumers replace one-eighth of that equipment every year. In the presence of a DSM program, it is assumed that consumers buy more efficient equipment, but that if the program was absent, then less efficient equipment would be purchased. Based on an eight-year effective life for DSM investments and a real interest rate of 6.1 percent, the $200 per kilowatt-a-year program cost translates into a cost per kilowatt-hour saved of about $0.008. The effect of higher values of this cost upon the optimal solutions is examined in the next chapter.

It is assumed that each utility can build coal-fired generation capacity in increments of 400 MW. In addition, for every 400 MW coal unit,

TABLE 3-1

MIDAS AND SMARTS DECISION TREE SUMMARIES

Stage No.	Node Type	Year	Description
MIDAS Model:			
1	Decision	0	Capacity expansion. Options: -Start construction of 0 units. -Start construction of 1 coal unit and associated combustion turbines. Unit will be on line in year 8.
2	Decision	0	Demand-side program. Options: -Base case: no additional programs over those assumed in base case growth rate. -Additional program for years 1-4, expected to decrease peak growth rate by 0.7 percent/yr.
3	Chance	0	Demand growth rate, years 1-4. Possible outcomes: -Growth rate 1% less than expected value. -Expected growth rate, given demand-side program. -Growth rate 1% more than expected value.
4	Decision	4	Capacity expansion. Options: same as stage 1, except that the choice is between 0 or 2 coal units. Coal units started in this year come on line in year 12.
5	Decision	4	Demand-side program. Options: -Base case: no additional programs over those assumed in base case growth rate. -Additional program for years 5-20, expected to decrease peak growth rate by 0.7% until saturation.
6	Chance	4	Demand growth rate, years 5-20. Possible outcomes, same as Stage 3. Expected growth rate accounts for demand-side programs and saturation of such programs.

TABLE 3-1 (Cont'd)

Stage No.	Node Type	Year	Description
SMARTS Model:			
1	Decision	0	Capacity expansion. Options: same as MIDAS, plus: -Start construction of two coal units and associated combustion turbines. (If not delayed, units will be on line in year 8).
2	Decision	0	Demand-side program. Options: same as MIDAS.
3	Chance	0	Demand growth rate, years 1-4. Possible outcomes: same as MIDAS.
4	Chance	0	Supply cost, years 1-30. In base case, possible outcomes include: -low capital and fuel costs. -expected capital and fuel costs. -high capital and fuel costs. In sensitivity analysis for utilities A and C, fuel costs are considered in stage 4 so that fuel and capital costs are independent.
5	Chance	0	Supply costs, years 1-30. For utility B, base case, possible outcomes include: -high purchased power cost. -purchased power at expected cost. -low purchased power cost. In sensitivity analysis for utilities A and C, three outcomes (low, expected value, and high) are defined for fuel cost.
6	Decision	4	Capacity expansion. Options: same as Stage 1, plus: -Delay construction of units started in year zero for four years.
7	Decision	4	Demand-side program. Options: same as MIDAS, except any implemented programs are extended through year 30.
8	Chance	4	Demand growth rate, years 5-30. Possible outcomes, same as MIDAS.

100 MW of combustion turbine capacity is also added. The costs and technical performance of these units are based on EPRI analyses, with the exception of the construction lead time and cost of construction delay. Table 3-2 summarizes these data. In the decision trees, decisions to start or delay construction in years zero and four are modeled using decision nodes. Recall that the decisions to start construction in year eight and afterwards are made automatically by the models. The automatic additions are made by adding enough capacity in each year, starting with year sixteen (allowing for eight years of construction after year eight), so that the utility's reserve margin is at least 20 percent. Perfect foresight regarding future demand levels is assumed for the automatic capacity additions; however, commitments to construction in years zero and four must be made without the benefit of knowing what demand will be realized. For example, if the reserve margin falls below 20% in year seventeen, (perfect foresight assumed), the model starts the construction of a 400 MW coal plant and a 100 MW combustion turbine in year nine to come on-line in the sixteenth year.

TABLE 3-2

GENERATION CAPACITY ADDITIONS COST AND PERFORMANCE DATA

Parameter	Baseload Unit	Peaking Unit
Fuel type	Coal	Distillate
Capacity	500 MW(e)	2x50 MW(e)
Construction lead time	8 years	1 year
Capital Cost:		
-if no construction delay	$1806 /kW	$337 /kW
-if construction delayed four years	$2004 /kW	$337 /kW
Heat rate	10,060 Btu/kWh	13,800 Btu/kWh
Nonfuel variable operating cost	$2.3 /MWh	$4.0 /MWh
Fixed operating cost	$24 /kW/yr	$0.4 /kW/yr
Forced outage rate	0.11	0.043
Planned outage rate	0.09	0.05

Source: EPRI, Reference 28. Capital costs inflated to 1988 dollars.

Capacity costs are assumed to escalate at the general rate of inflation. In cases where excess capacity costs are assumed to be disallowed by the public service commission, "excess" is defined as the capacity in excess of a 25 percent reserve margin. Once the reserve margin falls below 25 percent, enough capacity to bring the margin up to 25 percent is allowed into the rate base.

Note from table 3-1 that the year-zero supply decision node for each MIDAS decision tree presents two options: start construction of either zero or one coal-fired unit, plus associated turbines. In year four, the options are to start building two additional units or none. The SMARTS tree contains more options. In year zero, the utility can start construction of zero or one coal unit plus combustion turbines. In year four, the utility can delay construction of the unit that is underway or continue its construction. If a unit is delayed, its capital costs are increased to account for the additional interest. Alternatively, each utility can decide to start building one, two, or no more coal units.

Below, additional information is given on the characteristics and data assumptions for the three representative utilities studied.

Assumptions Regarding Utilities Studied

Utility A

This hypothetical utility is typical of utilities in the Northeastern United States. At present it serves a peak demand of 2,200 MW with a load factor of 56 percent. The DSM program would cost $3,500,000 a year.

The utility has 2,950 MW of capacity, of which 25 percent is nuclear fueled, 66 percent oil-fired steam, and the remainder combustion turbines. Fuel costs are based on those actually experienced in 1987 for northeastern utilities (approximately $1 per 10^6Btu for nuclear, $2.5 per 10^6Btu for heavy oil, and $4 per 10^6Btu for distillate). These costs are assumed to escalate at the general rate of inflation.

The utility has contracted for 400 MW of firm power purchases from other utilities at an average cost of $42 a megawatt-hour. The utility has $2,100,000,000 in undepreciated assets and $450,000,000 a year in fixed operating expenses. In the near term, this utility's marginal cost of providing power is less than its average cost, but because of its slim reserve margins, its marginal costs will soon rise to levels close to its average cost.

Utility B

This utility, which is representative of those in the Midwest, serves a peak demand of 4,600 MW. The load factor is 74 percent. A demand-side management program costing \$6,400,000 a year is possible.

The utility has 6,250 MW of capacity. Of this amount, the majority (77 percent) is coal-fired. The heat rates of those units range from 10,300 Btu per kilowatt-hour for large units without scrubbers to 14,200 Btu per kilowatt-hour for smaller, older plants. An additional 19 percent of the total capacity is nuclear fueled, and the remainder consists of combustion turbines. Based on actual costs in the region, fuel costs are assumed to average \$1.4 per \$$10^6$Btu for the coal fired units, \$1 per \$$10^6$Btu for the nuclear capacity, and \$6 per \$$10^6$Btu for the combustion turbines.[40]

The utility has \$7,240,000,000 in undepreciated assets and \$620,000,000 per year in fixed operating expenses. Because of the large fixed expenses and low operating costs for the fossil fueled plants, this utility's marginal cost will be well below its average cost for the next few years.

Utility C

This utility is typical of Southwestern utilities. It serves a peak demand of 3,100 MW. The load factor is 59 percent. A \$4,400,000 demand-side program is an option.

The total capacity is approximately 4,450 MW. Just over half (51 percent) is coal-fired, with a fuel cost of about \$1.2 per \$$10^6$Btu.[40] Natural gas-fueled steam plants and combustion turbines provide 20 percent and 12 percent of the capacity, respectively. The cost of natural gas averages \$3 per \$$10^6$Btu. The combustion turbines are expensive to run because of their relatively high heat rates (over 18,000 Btu per kilowatt-hour). The remaining capacity, 17 percent, is nuclear.

The utility has approximately \$3,500,000,000 in undepreciated assets. Because of these large fixed costs, ample reserve margin, and low operating expenses for most of these plants, utility C's marginal cost will be significantly below its average cost for several years to come.

This utility was analyzed using SMARTS. MIDAS was not run for this utility, due to time and data constraints.

Uncertainties Modeled as Chance Nodes

Chapter 2 of this report reviewed sources of risk and uncertainty in least-cost planning. Table 2-1 in that chapter presented a preliminary screening of twenty-two causes of uncertainty. In the SMARTS analyses, only those rated in table 2-1 as important (**) or very important (***) are included. A comparison of table 2-1 and figure 3-1 shows how the uncertainties are captured as chance nodes in SMARTS. On the supply side, uncertainties 6, 8, and 9 (cogeneration, power from other utilities, and power from other sources) are modeled using a single chance node for the cost and availability of purchased power in figure 3-1. Fuel and capital cost uncertainties (numbers 2 and 3) are modeled explicitly as chance nodes. On the demand side, uncertainties 10, 13, and 14 (load growth rate, customer response to DSMs, effectiveness of DSMs) are combined into a single uncertainty: load growth. Uncertainty 12, cost of DSMs, is not modeled as a chance node, due to constraints on model size. Instead, a sensitivity analysis is performed to determine at what cost DSM programs are no longer justified under the objective to minimize the present worth of total cost. The third group discussed in chapter 2, regulatory uncertainties, is not modeled probabilistically. Instead, it is assumed that the utility knows exactly what fraction of "excess" capacity costs will be disallowed by its utility commission.

Due to limits on model size, only demand uncertainties are modeled (using chance nodes) in the MIDAS decision trees. The supply uncertainties were not considered.

The base-case probability distributions are summarized next. These distributions are modified extensively in the sensitivity analysis described subsequently.

Base Case Probability Assumptions

The probabilities associated with the base case are displayed in figure 3-1 and are discussed below. These are the probabilities against which the sensitivity analysis is compared.

Demand Uncertainties

An EPRI report states, "because of uncertainty in GNP, in relative fuel prices, and in other factors, future electricity demand is highly uncertain."[27] It reports that the expected value of annual growth of the nation's peak demand between 1984 and the year 2000 is 2.5 percent, with an 80 percent confidence interval of 0 percent to 4 percent. This probability distribution was based on interviews with experts on power demands.

With regard to the load growth under base cases for utilities A and B, it is assumed that, in the absence of DSM programs, peak demand grows at an expected rate of 1.8 percent a year, with a standard deviation of 0.7 percent a year. Energy demand grows at the slightly higher rate of 2 percent a year, with the same standard deviation. If a DSM program is in place, lower growth rates apply, as discussed earlier in this chapter. In those cases, too, a standard deviation of 0.7 percent a year is used. These standard deviations are smaller than those discussed in the EPRI report: the former assume a given level of DSM effort while the latter result from a variety of assumptions about the extent of DSM programs.

Utility C has mean growth rates that are higher than the above by 0.8 percent a year. However, the standard deviations are the same.

Ford and Geinzer present an analysis of the impact of energy performance standards for new homes and buildings upon demand uncertainties in the Pacific Northwest.[15] They conclude, contrary to the above assumption, that such standards would significantly reduce the standard deviation of demand. If true, such an effect would mean that all DSM programs would lower risks to utilities, the benefits of which could be estimated using a decision tree analysis. However, on the other extreme, it can be argued that uncertainties regarding participation rates, efficiencies, governmental subsidies, and other factors mean that DSM programs could increase the uncertainty in demand. In the analysis here, it is assumed that neither occurs and that DSM programs do not affect the standard deviation of demand growth rates. Future analyses should investigate this issue and its implications.

The demand probability distributions are modeled by chance nodes at years zero and four with the following three-point distribution around the expected value:

- A 25 percent chance of a growth rate 1 percent more than the expected value.
- A 50 percent chance of a growth rate equal to the expected value.
- A 25 percent chance of a growth rate 1 percent less than the expected value.

(See figure 3-1.) The chance node for year zero refers only to growth rates for years one through four, while the node for year four refers to the growth rates for years five through the planning horizon (twenty years for MIDAS and thirty years for SMARTS). For simplicity, probabilities for the two time periods are assumed to be independent. The above probabilities are changed in the sensitivity analysis to simulate cases with lesser or greater amounts of demand growth variance.

Supply Uncertainties

Three major groups of supply uncertainties are modeled in SMARTS: (1) fossil-fuel-price uncertainties, (2) capital-cost uncertainties, and (3) purchased-power uncertainties. Fossil-fuel-price and capital-cost uncertainties are modeled as a chance node at year zero of the model with the following three-point distribution (figure 3-1):

- A 33 percent chance of a fossil fuel cost equal to 70 percent of its expected value and a capital cost equal to 85 percent of its expected value.

- A 50 percent chance of the fossil fuel and capital costs equaling their expected values.

- A 17 percent chance of a fossil fuel cost equal to 160 percent of the expected value and a capital cost equal to 130 percent of its expected value.

The expected capital costs for capacity additions are given in table 3-2. The expected fossil fuel costs are assumed to equal the actual unit-by-unit costs in 1987 for the simulated utilities. Nuclear fuel costs are assumed to be known with certainty. The above cost levels are assumed to be maintained in real terms throughout the planning time horizon. An inflation rate of 6.1% per year is assumed in the studies. In the base case, fossil fuel and capital costs are assumed to be perfectly correlated, as indicated above. This assumption is relaxed in a sensitivity analysis, in which it is assumed instead that the two cost categories are statistically independent.

For the uncertainties associated with the cost and availability of purchased power, only utility A is assumed to have the opportunity to purchase significant amounts of power. The following three-point distribution is included in utility A's decision tree using a chance node:

- A 33 percent chance of one-half the expected power supply being available at seven-sixths the expected price.
- A 50 percent chance of the expected amount being available at the expected price.
- A 17 percent chance of two-times the expected amount being available at two-thirds the expected price.

Sensitivity Studies

The above data associated with the probabilities of outcome at chance nodes were used for the studies termed the "base case" analysis. In addition, sensitivity analyses were made to examine the effect of higher and lower variance in the demand. The following are the details of the data used for the sensitivity studies:

* "High demand variance," in which probabilities of 0.5, zero, and 0.5 are assigned to growth rates of 1 percent a year above, 0 percent a year above, and 1 percent a year below the expected annual growth, respectively. This yields a standard deviation for demand of 1 percent a year.
* "Zero demand variance," in which a probability of one is assigned to the expected growth rate. A standard deviation of zero results.

In contrast, note that the base case distribution has a standard deviation of 0.7 percent a year.

In the sensitivity analyses, the standard deviations of fuel and capital costs are altered by changing the probabilities of the extreme outcomes. For the "high fuel cost variance" case, the standard deviation is 42.4 percent, resulting from a probability assignment of 0.67 for 70 percent of the expected value, 0.33 for 160 percent, and a zero probability for the expected value. The "zero fuel cost variance" case results from giving a probability of one to the expected value. The high-and zero-variance scenarios for construction costs are obtained similarly, yielding standard deviations of 21.2 percent and zero percent, respectively.

For the sensitivity analysis, changes in purchased power supply and cost uncertainties are modeled in the same manner. A standard deviation of 0 results from assigning a chance of one to the expected value. A standard deviation of 70.7 percent of the expected availability and 23.6 percent of the expected price results from giving a probability of 0.67 to the least favorable outcome (one-half of the expected power availability at seven-sixths of the expected price) and 0.33 to the most favorable outcome (twice the expected power at two-thirds of the expected price).

CHAPTER 4

RESULTS OF DECISION TREE ANALYSIS OF RISKS UNDER DIFFERENT OBJECTIVES

This chapter describes the base case decision tree analysis of uncertainties for the utilities studied. Three general categories of results are presented. First, the effects of different planning objectives (minimization of total costs, rates, or disallowed capacity costs) upon optimal strategies are discussed. Then, the effect of risk attitudes is examined. Chapter 5 compares the impact of the uncertainties in supply and demand upon planning with a view to establish a ranking of uncertainties in order of their importance.

Results

Table 4-1 shows the results obtained from SMARTS. (All cost figures in this chapter are given in real 1988 dollars.) The table shows the present worth (PW) of expectations of cost, its standard deviation (SD), levelized value of expected rate and its SD of the optimal strategy for different objectives. The expected value of perfect information (EVPI) is also shown in table 4-1. The details of solving the decision tree to attain the different objectives have been shown in chapter 3.

In table 4-1, the results for three main categories of objectives as shown. They are:

* Minimize expected present worth of cost ("cost")

* Minimize expected levelized rates ("rate")

* Minimize expected disallowed capacity costs ("dis. cost")

Table 4-1 displays three different types of solutions. In the first type, it is assumed that all costs are recovered. In the second type, it is

TABLE 4-1

SMARTS BASE CASE RESULTS: SOLUTION PERFORMANCE

Case	Utility	Objective[1]	PW Total Costs $[10^6\$]$	PW Total Costs SD[2] $[10^6\$]$	Levelized Rate [$/kWh]	Levelized Rate SD[2] [$/kWh]	Disallowed Costs PW $[10^6\$]$	EVPI[3]
1	A	Cost[4]	12860	1023	0.06953	0.00517	2	4
2	A	Cost,Risk[4]	12860	1022	0.06951	0.00515	6	-
3	A	Rate[4]	13191	1081	0.06833	0.00507	135	0.000127
4	A	Rate,Risk[4]	13180	1067	0.06834	0.00508	122	-
5	A	Rate[5]	13084	1086	0.06849	0.00523	0	0.000043
6	A	Rate,Risk[5]	13091	1098	0.06852	0.00522	0	-
7	A	Dis. Cost[4]	12861	1027	0.06954	0.00518	0	0
8	B	Cost[4]	25416	2479	0.05045	0.00416	64	74
9	B	Cost,Risk[4]	25512	2383	0.05022	0.00411	287	-
10	B	Rate[4]	25994	2404	0.04986	0.00421	211	0.000109
11	B	Rate,Risk[4]	25967	2428	0.04988	0.00419	166	-
12	B	Rate[5]	25025	2550	0.05021	0.00433	0	0.000135
13	B	Rate,Risk[5]	26045	2572	0.05024	0.00430	0	-
14	B	Dis. Cost[4]	25555	2650	0.05084	0.00430	0	0
15	C	Cost[4]	17265	1595	0.05632	0.00435	23	19
16	C	Cost,Risk[4]	17342	1579	0.05666	0.00447	136	-
17	C	Rate[4]	17727	1546	0.05566	0.00438	184	0.000057
18	C	Rate,Risk[4]	17699	1561	0.05567	0.00437	153	-
19	C	Rate[5]	17634	1603	0.05595	0.00453	0	0.000085
20	C	Rate,Risk[5]	17698	1690	0.05601	0.00450	0	-
21	C	Dis. Cost[4]	17308	1548	0.05652	0.00443	0	0

Key:
Cost = Minimize Present Worth of Total Cost
Cost, Risk = Maximize Risk Averse Utility Function for Cost
Rate = Minimize Levelized Price of Electricity
Rate, Risk = Maximize Risk Averse Utility Function for Rate
Dis. Cost = Minimize Present Worth of Disallowed Capacity Costs
SD = Standard Deviation.

[1]Based on assumption that all costs, including "excess" capital costs are recovered in rates.

[2]Based on assumption that capital costs of new generation capacity in excess of 25% reserve margin are not recovered in rates.

[3]EVPI = Expected Value of Perfect Information, in units of the objective.

assumed that "excess" capacity costs are disallowed and are not recovered. The third category shows the objective of minimization or rates. In addition to the above, two sub-categories involving risk attitudes are also shown in table 4-1. They are:

* Risk neutrality, modeled using a linear utility function ($U(X) = -X$).

* High-risk aversion ("risk"), modeled using a risk-averse-utility function ($c > 1000$, $b = 1.0$ and $a = 0$ in equation 3-2).

Table 4-2 shows the decisions made at each node concerning capacity addition and demand-side management programs resulting from the choice of a particular objective.

Comparison of MIDAS and SMARTS Solutions

MIDAS solutions for utilities A and B only under the total cost and levelized rate objectives were obtained. The MIDAS solutions are not shown, but are similar to the SMARTS results. The objective of minimizing disallowed capacity costs was not simulated in MIDAS. The MIDAS decisions, variable production costs, and differences between performance of different solutions are nearly identical to the SMARTS results. This confirms the usefulness and validity of SMARTS. However, the two models yield levelized rates that differ by about 10 percent. This occurs for several reasons:

1. SMARTS employed a thirty-year time horizon, rather than the twenty years used in MIDAS.

2. SMARTS has twice as many plant construction options in year four as MIDAS.

3. SMARTS and MIDAS treat fixed costs, assets, and taxes differently. SMARTS was calibrated to fit the first year's fixed costs of the utility being modeled, but the MIDAS data base was not calibrated. As a result, MIDAS fixed costs did not exactly correspond to the utility's because of differences in specific assumptions about

TABLE 4-2

SMARTS BASE CASE RESULTS: DECISIONS

Utility	Objective	Decisions[1] Stage 1	Stage 2	Stage 6	Stage 7
A	Cost[2]	0	DSM	0 (1)	DSM
A	Cost,Risk[2]	0	DSM	0 (1)	DSM
A	Rate[2]	1	No DSM	0 (1)	No DSM
A	Rate,Risk[2]	1	No DSM	0	No DSM
A	Rate[3]	0	No DSM	0 (1)	No DSM
A	Rate, Risk[3]	0	No DSM	0 (1)	No DSM
A	Dis. Cost[2]	0	DSM	0	DSM
B	Cost[2]	0	DSM	1 (2)	DSM
B	Cost,Risk[2]	1	DSM	1 (2,Delay)	DSM
B	Rate[2]	1	No DSM	1 (2)	No DSM (DSM)
B	Rate,Risk[2]	1	No DSM	1 (0)	No DSM (DSM)
B	Rate[3]	1	No DSM	1 (0)	No DSM (DSM)
B	Rate,Risk[3]	1	No DSM	0 (1,Delay)	No DSM (DSM)
B	Dis. Cost[2]	0	DSM	0	DSM
C	Cost[2]	0	DSM	1 (0)	DSM
C	Cost,Risk[2]	1	DSM	Delay (0,1)	DSM
C	Rate[2]	1	No DSM	1 (2)	No DSM (DSM)
C	Rate,Risk[2]	1	No DSM	1 (0)	No DSM (DSM)
C	Rate[3]	0	No DSM	1 (2)	No DSM (DSM)
C	Rate,Risk[3]	0	No DSM	0 (1)	No DSM (DSM)
C	Dis. Cost[2]	0	DSM	0	DSM

Key:

[1]Stage 1 and 6 are the plant construction decisions; the number of coal units that are started is shown. (See table 4-2 for definitions of the stages.) "Delay" indicates that completion of a unit started previously is delayed 4 years. Stages 2 and 7 are demand side measure (DSM) decisions; whether or not such a program is undertaken is shown. For stages 6 and 7, the decision taken in most of the decision nodes of those stages is shown without parentheses; decisions made in a minority of the nodes are shown in parentheses.

[2]Based on assumption that capital costs of new generation capacity in excess of 25% reserve margin are not recovered in rates.

[3]Based on assumption that all costs, including "excess" capital costs, are recovered in rates.

taxes, interest, depreciation, treatment of work-in-progress, and other fixed cost parameters. (Fixed costs associated with new plants were treated in the same way by the two models.)

The difference in fixed costs are unimportant from a strategic standpoint, since such differences will not change decisions under the minimize-total-cost objective. Similarities and differences between the MIDAS and SMARTS solutions are discussed elsewhere in the report. The purpose of such comparisons is to create a benchmark for comparing the results from the simplified SMARTS model to those from the more complex model.

Effect of Choice of Objective

A variety of objectives has been proposed for utility planning, including minimization of total utility costs, minimization of electric rates, minimization of total customer and utility costs, and maximization of consumer surplus. The purpose of this section is to determine whether the first two objectives make a practical difference when risk is accounted for explicitly. In addition, the effect of a regulatory policy that disallows "excess" capacity costs is also examined by simulating a utility which tries to minimize such penalties.

"Minimize Total Costs" Versus "Minimize Levelized Rates" Objectives

The most striking difference among the solutions in tables 4-1 and 4-2 is between solutions that minimize the present worth of cost and those that minimize levelized rates. In terms of decisions that ensue due to the two objectives, the demand-side management programs are always implemented in the former case and are rarely used in the latter. The reason is that a DSM program whose cost per kilowatt-hour-saved is less than a utility's marginal cost is always justified under the cost objective, but causes electric rates to increase if marginal cost is less than average cost. The reason for the higher rates is that costs will decrease by a smaller percentage than will demand under a DSM program, which means that the average cost per kilowatt-hour will increase.

The only situation in which DSM programs are attractive under the levelized rate objective is in year four if demand growth is high in years one to four and the expense of new capacity is also high. In that case, the capacity additions required by high demand growth rates cause levelized rates for utilities B and C to increase, which makes DSM programs easier to justify.[47]

Effect of the Cost of DSM Programs on Decisions

As explained in chapter 4, the costs and lifetimes assumed for DSM programs imply an average cost of $0.008 per kilowatt-hour saved. A sensitivity analysis was performed (by varying the cost of the DSM program around this value) for utilities A and B to determine at what cost DSM programs would no longer be justified under the total cost objective. In general for that objective, DSM programs are economical if their costs are less than the capacity and production costs they save.

For utility B, DSMs with incurred costs up to $0.04 for every kilowatt-hour saved, are justified in stage 2 (DSM decisions in year zero), while even more costly DSM programs are attractive[48] in stage 7 (DSM decisions in year four). The same figures result from the MIDAS analyses. The $0.04 a kilowatt-hour figure is slightly lower than the long-run cost of energy from new coal and combustion turbine capacity. Such a high cost is justified because utility B requires new capacity in the near future, and DSM programs help to delay the need for that capacity.

By contrast, for utility A, the highest DSM cost that can be tolerated under the cost objective in stage 2 is $0.024 a kilowatt-hour saved. This is because utility A does not need capacity for many more years and, as a result, DSM programs only help to avoid fuel and purchased power costs. However, in stage 7, DSM programs costing up to $0.05 a kilowatt-hour saved become justified under higher growth rates and higher fuel costs.

It should be noted that if maximization of the present value of consumer surplus is the objective rather than minimization of cost, then DSM programs would be more difficult to justify than is indicated above, particularly in stage 2.[24] The reason is that when marginal costs are less than average costs, rates increase as a result of DSM programs, which causes a loss in consumer surplus. To be economic, the DSM programs must be correspondingly less expensive to make up for this loss.

Figure 4-1 portrays the tradeoffs between the rate and total cost for each utility based upon the SMARTS results. The MIDAS results, which are not shown, are nearly identical.

The axes are the two objectives, costs and rates. As in all the figures of this chapter, the axes are "normalized" by dividing the actual value of the objective for the solution in question by the best value that could be achieved for that utility. For example, considering utility C, the point labeled "C (Min Dis. Cost)" represents the solution for that utility in which a strategy is chosen that minimizes the expected value of disallowed capacity costs. Its value on the X axis (1.0025) is the ratio of that solution's expected present worth of total cost ($17,308 million, table 4-1) to the best achievable total cost ($17,265 million, which is the minimum cost solution in table 4-1). Its value on the Y axis (1.0102) likewise is the ratio of that solution's expected levelized rate ($0.05652 a kilowatt-hour) to the minimum achievable levelized rate ($0.05595 a kilowatt-hour), assuming that no capital costs are disallowed. Normalizing the results in this fashion allows us to make comparisons between different utilities.

The points labeled "Min Cost" optimize the total cost objective, while those designated "Min Rate" optimize the levelized rate objective. The two points labeled "Min Dis. Cost" are discussed in the next subsection.

This figure demonstrates that the choice of objective in utility planning can make an important difference; minimizing rates can increase total costs by one or two percentage points. Although such a difference seems small, it translates into hundreds of millions of dollars in terms of present value.

In addition to the above, a sensitivity analysis was performed to examine the dependence of the cost-rate tradeoffs in figure 4-1 upon assumptions concerning demand variance. Three levels of the standard deviation of demand, discussed in chapter 3, were simulated for each utility: 1 percent, 0.7 percent, and 0 percent. The results of this analysis (not shown) reveal that a greater variance increases the spread of the tradeoffs between total costs and levelized rates.

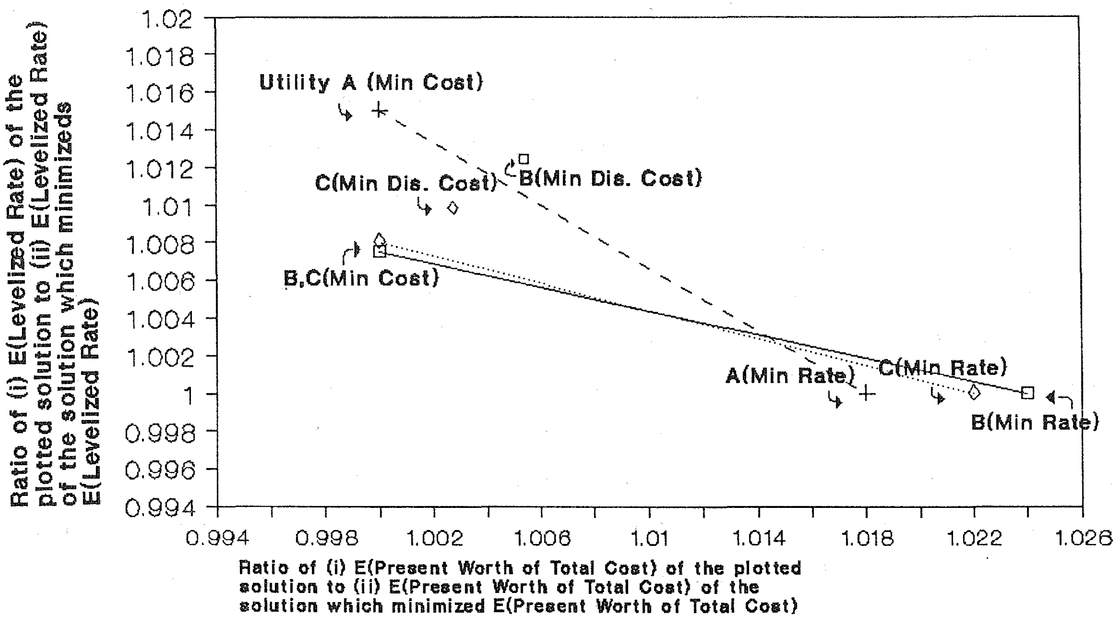


Fig. 4-1. Tradeoffs between total cost and levelized rates, base cases

Effect of the Minimize-Disallowed-Capacity-Costs Objective

If a utility's regulatory commission has a policy of not allowing consumers to be charged for the capital costs associated with surplus capacity, the utility's optimal strategy may change. This subsection examines the impact of a minimize-disallowed-capacity-costs objective on the SMARTS model.

Figure 4-1 also displays the solutions that minimize disallowed capacity costs for utilities B and C. These points are labeled "Min Dis. Cost". (For utility A, that solution is the same as the "Min Cost" strategy and hence not shown separately.) These solutions are less preferable than the "Min Cost" points, as they perform worse on both the total cost and levelized rates objectives. They also result in higher rates than the "Min Rate" objective and in higher total cost than the "Min Cost" objective. This occurs because a utility which minimizes disallowed capacity costs will make no capacity additions in either years zero or four, even if this results in increases in total costs or rates.

To elaborate this aspect further, the disallowed cost objective motivates the utilities to be conservative. The models assume that if there is inadequate capacity, peaking power is available from other utilities at a price of $200 a megawatt-hour.[49] The utilities prefer to purchase this expensive power rather than build a new generating unit and run the risk that demand will be lower than anticipated, which could result in disallowed capacity costs. This is in contrast with the fact that, on an expected total cost basis, such a capacity addition would be justified. Hence, a possible result of a policy of disallowing "excess" capacity costs associated with surplus capacity could actually be increased rates and total costs for the consumer.

Figure 4-2 shows tradeoffs between the present worth of total costs and the present worth of capacity costs that would be disallowed. It shows that if utilities B and C minimize their expected disallowed costs, they can force them to zero. However, this is done at the expense of a significantly higher total cost than the minimum cost solutions. Note that this cost increase is about double the disallowed cost, which implies that revenue requirements will go up if utilities try to minimize disallowed costs. For utility B, the indicated increase in cost in figure 4-2 translates to about

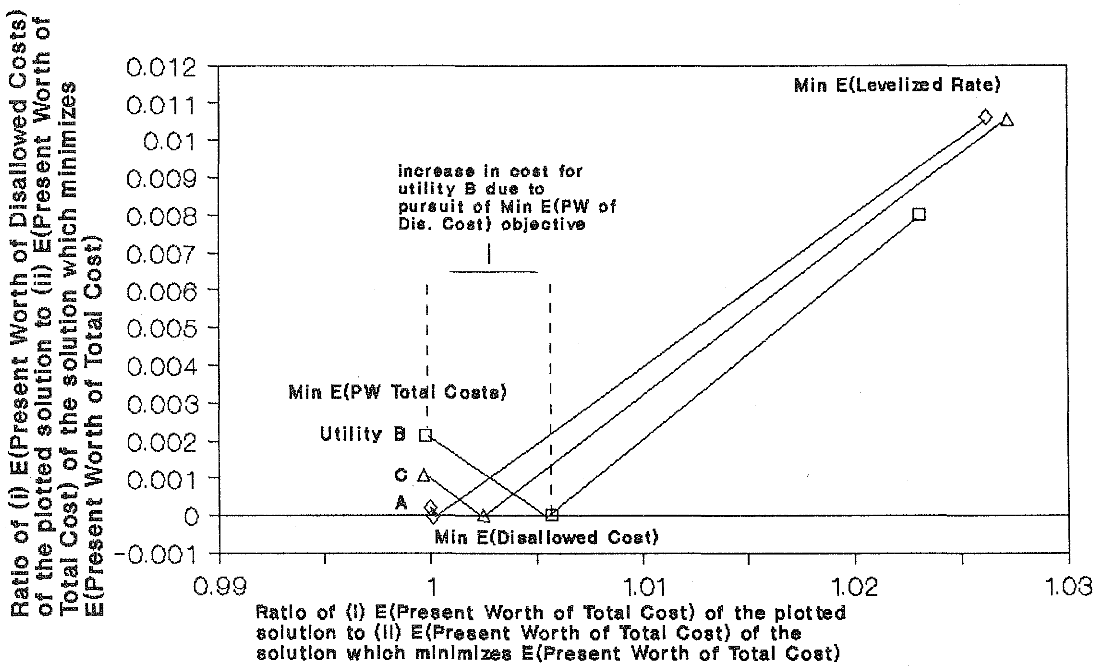


Fig. 4-2. Total Costs versus disallowed costs under three objectives, base cases

$70 million (table 3.1). These results indicate that disallowance of excess capacity costs can motivate inefficiency rather than efficiency.[50] The assumption behind this conclusion is that utilities would actually minimize costs if "excess" capacity costs are excluded from rates. Utilities, however, might pursue other objectives instead.[29]

Figure 4-2 also shows the effects of pursuing a minimization of levelized rates objective, assuming that capacity costs are disallowed. (These points are not the same as the minimize-rates points in figure 4-1, the latter assumes that all costs are recovered in rates.) The results imply that a policy of minimizing rates would result in even greater cost increases than if instead the utility strives to minimize disallowed costs.

Sensitivity analyses were performed to evaluate the effect of different demand variances upon the results of figure 4-2. It was found that the different variances made little difference to the results with one exception. The exception was that the disallowed costs in the minimize total cost solution increase with higher demand variances. That is, a utility faces a greater risk of not recovering its investments as demand uncertainty increases.

Effect of Risk Attitudes

In a risky environment, utilities may be like other businesses in that they are risk-averse: they might be willing to accept a strategy which performs worse in terms of expected value to avoid the risks of bad outcomes. This section explores this aspect further.

An increasing aversion to risk is equivalent to a heavier weighting of bad outcomes in a decision tree. As explained in chapter 3, risk-averse preferences are simulated here by maximizing the expected value of the utility function $-e^{cX}$ (a simplification of equation 3-2), with $c>0$ and X being either present worth of costs or levelized rates.

Tables 4-1 and 4-2 show solutions resulting from two extreme risk attitudes: risk neutrality (c very small, equivalent to minimizing the expected cost or rate), and large risk aversion (c very large, equivalent to minimizing the worst possible outcome under the chosen strategy). Figures 4-3 and 4-4 expand on those results by showing tradeoffs between risk (measured by the normalized standard deviation of the objective indicated as

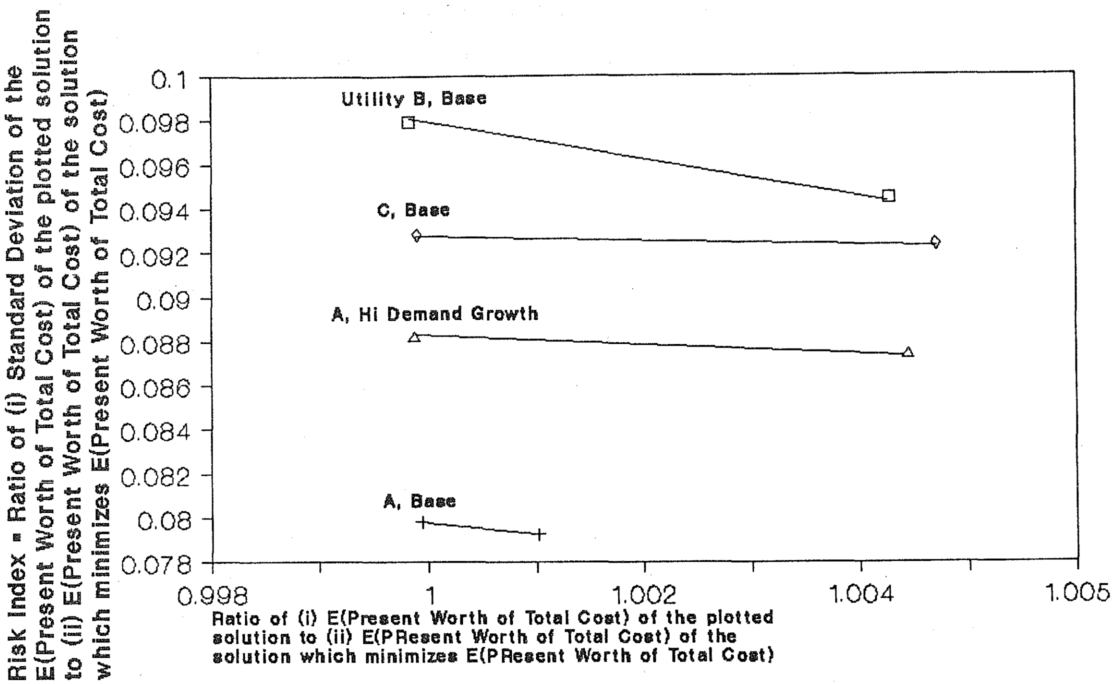


Fig. 4-3. Tradeoffs between total cost and its standard deviation, base cases and sensitivity analyses

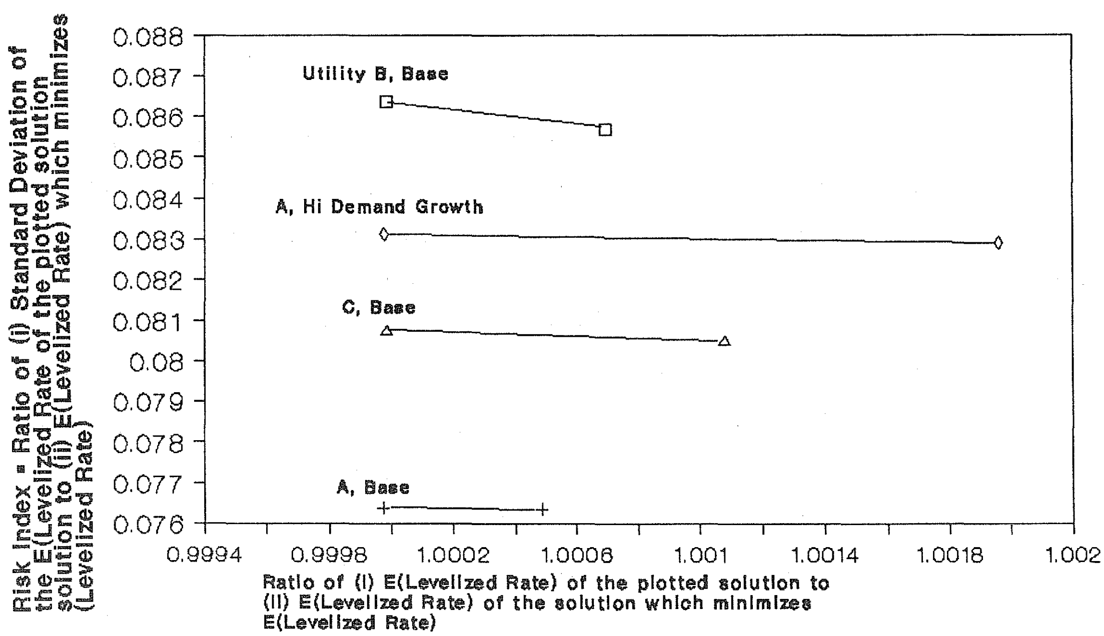


Fig. 4-4. Tradeoffs between levelized rate and its stan deviation, base cases

the ordinate) and the normalized expected value of the objective for each utility under the base case assumptions. These tradeoffs are generated by solving the decision trees for these two extreme values of c. Points lying to the left of the figure correspond to risk neutrality and points to the right represent risk aversion. Figure 4-3 displays the results for the present-worth-of-costs objective, and figure 4-4 portrays those for the levelized-rates objective. Figures 4-3 and 4-4 demonstrate that, in general, a small (and probably insignificant) decrease in risk can be obtained, but at a price of worsening the expected performance. As an example, consider utility B in figure 4-3. The standard deviation of total costs can be lowered from 9.8 percent of the mean costs to 9.4 percent if one is willing to accept an increase of 0.4 percent in the mean cost.

Table 4-2 shows how DSM and capacity addition decisions are affected by different risk attitudes. Under the minimize-total-cost objective, risk aversion motivates earlier capacity additions. The reason is that the utility, averse to the risk of high cost, prefers to avoid the very high cost situations of having insufficient capacity and having to purchase power during peak times at a high price (assumed to be $200 a megawatt-hour). Additional capacity may increase the expected cost, but lowers the risk because fuel and purchased costs are lower and, as a result, will not respond to changes in demand or fuel costs to such a great degree.

On the other hand, risk aversion under the minimize-rate objective motivates fewer capacity additions, in the case where "excess" capacity costs are not deducted from rates. This occurs because of the utility's desire to avoid spreading a new plant's fixed cost over too small of a demand, resulting in higher rates.

Figures 4-3 and 4-4 also show the effect of changing some of the base case demand assumptions for utility A. For utility A, the effect of 10 percent higher electricity demands is shown. Under the base case demand for that utility, capacity additions are rarely justified under the minimize-total-cost objective. With the higher demand shown, new plants become attractive. Therefore, there is a greater tradeoff between risk and cost. This is indicated by a larger difference in risk (ordinate) between the points in the extreme left and the right for utility A.

Figure 4-5 displays the effect of different variances for demand, fuel and capital cost, and purchased power for utility A. Some observations can

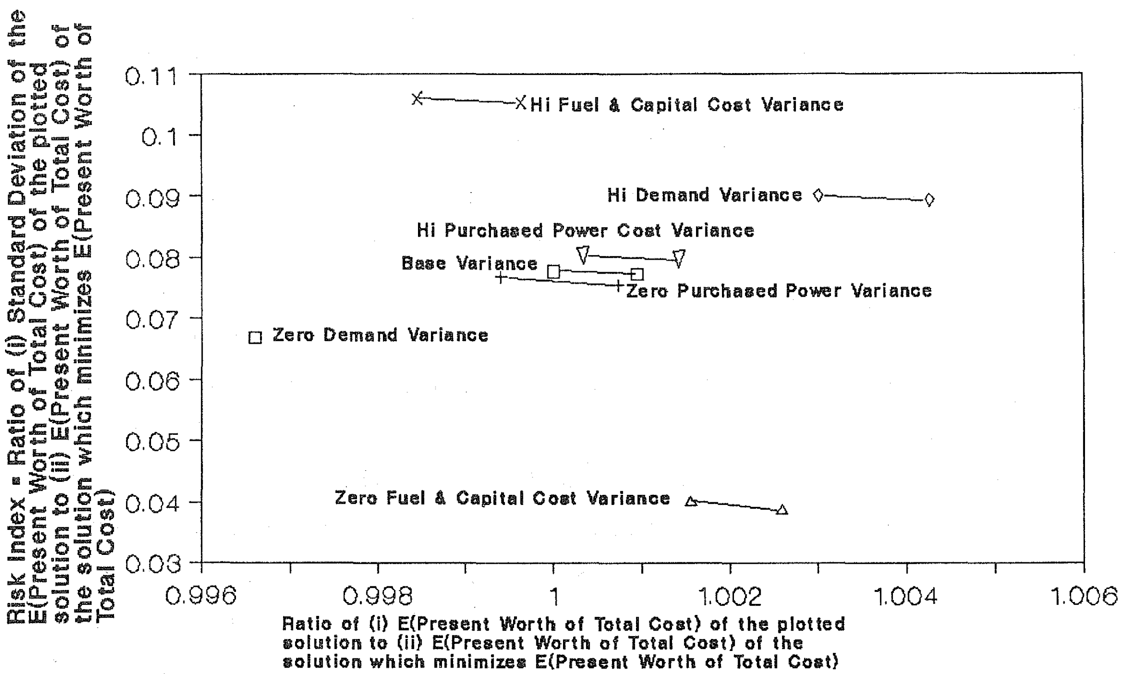


Fig. 4-5. Tradeoffs between total cost and its standard deviation under different demand and supply variances, utility A

be made from these results. The fuel and capital cost variance makes the most difference in the standard deviation of total cost, as indicated by the uppermost and the lowermost pairs of points. Differences in the variance of purchased power cost make the least difference. The latter result is not surprising, since purchased power supplies much less than half of utility A's energy. Note also that the variance of fuel and capital costs does not significantly affect the amount of the decrease in the standard deviation that can be obtained by increasing total cost. This is indicated by the almost identical slopes of the uppermost and the lowermost line segments.

The demand variance, by contrast, makes the largest difference in the slope of the segments. The case of zero demand variance is indicated by a single point in the left of the figure. There, the risk-averse strategy is the same as the risk-neutral strategy. However, the tradeoff between risk and expected value grows as the demand variance grows. This is indicated by an increasing slope and length of the line marked "high demand variance."

In sum, the above results show that only variance in demand ought to make a difference to a decision maker who is risk-averse. Risks in fuel, capital, and purchased power costs cannot be hedged against in these planning problems. The results demonstrate that a risk averse decision maker can hedge against demand risks to a small extent.

CHAPTER 5

RANKING UNCERTAINTIES USING DECISION TREE ANALYSIS

Uncertainties are of concern because they make financial projections (costs, revenues, and rates) uncertain, they make capacity expansion and DSM program decisions more difficult because of the possibility that those decisions will be suboptimal a posteriori, and consumers will be forced to make investments in conservation and plant expansion without knowing what electricity will cost. As a result, (1) financing becomes more difficult; (2) rates may not recover costs due to "regulatory lag"; (3) resources, such as generating capacity or conservation investments, may be wasted; and (4) opportunities for cost savings may be missed. This chapter compares various supply and demand uncertainties in terms of their influence upon the variance of total costs and rates, their effect upon optimal decision strategies, the expected loss resulting from ignoring uncertainty, and the expected value of perfect information. A discussion of the implications of the results of chapters 4 and 5 concludes the chapter.

Measures of Effects of Uncertainty

Some uncertainties have a greater effect upon financial projections, wasted resource, and utility decisions than others. This section compares supply and demand uncertainties in terms of four measures of these effects:

1. Variation in the Objective. Which sources of uncertainty contribute the most to uncertainty in utility costs and rates? In particular, how do the standard deviations of utility costs and levelized rates depend upon the standard deviations of the various sources of uncertainty?

2. Changes in Decisions. How do optimal capacity expansion and DSM program decisions depend upon the standard deviations of the various uncertainties?

3. The Cost of Disregarding Uncertainty. How does the expected value of the objective decrease if decisions are made as if there were no uncertainties? This cost is the difference between:

   * the expected value of the objective, given that an optimal strategy is chosen that takes into account the possible uncertainties, and

   * the expected value of the objective, if, instead, a strategy is chosen which ignores the uncertainties and assumes that the expected values of the demand and supply parameters will be realized.

   This difference measures the importance of explicitly considering probability distributions of uncertain parameters.

4. Value of Perfect Information. How does the expected value of perfect information (EVPI) depend upon the standard deviation of the various uncertainties? EVPI is the difference between:

   * the expected value of the objective, given that one knows the future exactly (with the expectation taken over all the possible outcomes), and

   * the expected value of the objective, given the imperfect knowledge actually available at the time that decisions must be made.

   EVPI quantifies the resource loss that results from making decisions under uncertainty. EVPI also indicates the maximum possible worth of studies which consider those uncertainties. If EVPI is small, then the uncertainties are unimportant to decision making and such studies would be unjustified. EVPI has been recommended as an appropriate measure of the cost of uncertainty in utility studies, and has even been suggested as a useful objective to be minimized in utility planning.[19]

In the following, with the aid of the simple decision problem portrayed in figure 3-2, the above four criteria are illustrated and elaborated upon.

Variation in the Objective. Under the base case probability distribution for option A in figure 3-2 (0.25 for low demand growth, 0.5 for medium, and 0.25 for high), the standard deviation of total cost is $\$0.396 \times 10^9$. If the variance of demand is increased by substituting probabilities of 0.5, zero, and 0.5 for low, medium, and high growth, respectively, option A is still optimal (now with an expected cost of $\$1.45 \times 10^9$, compared to B's $\$1.65 \times 10^9$) as shown in figure 5-1. The standard deviation of total cost for these probabilities associated with the load growths increases to $\$0.55 \times 10^9$. This shows that the variance of the objective depends upon the variance of demand.

Changes in Decisions. As just noted, increasing the variance of demand does not change the decision; option A is still best. But if the variance is decreased to zero by assigning a probability of one to medium demand growth and zero to the other growth rates, then option B is chosen instead (since its cost under medium growth is less than A's). Therefore, uncertainties in demand can affect decisions.

The Cost of Disregarding Uncertainty. Figure 5-2a shows a decision tree that results if demand uncertainties are ignored and it is naively assumed that the medium growth rate has a probability of one. The optimal strategy under certainty is then found to be option B. How does this naive strategy actually perform? This is calculated through use of the tree in figure 5-2b. There, the actual expected performance of B, considering the uncertainties, is found to be $\$1.575 \times 10^9$. If, instead, a choice is made which explicitly takes into account the uncertainties, option A would be picked and an expected cost of $\$1.525 \times 10^9$ would result (figure 5-1). Thus, the expected cost of disregarding uncertainty is $\$500 \times 10^6$, the difference between the two figures.

Value of Perfect Information. The value of perfect information for the problem shown in figure 5-1 is calculated by setting up the tree in figure 5-2c. First, through perfect foresight, it is learned whether demand will

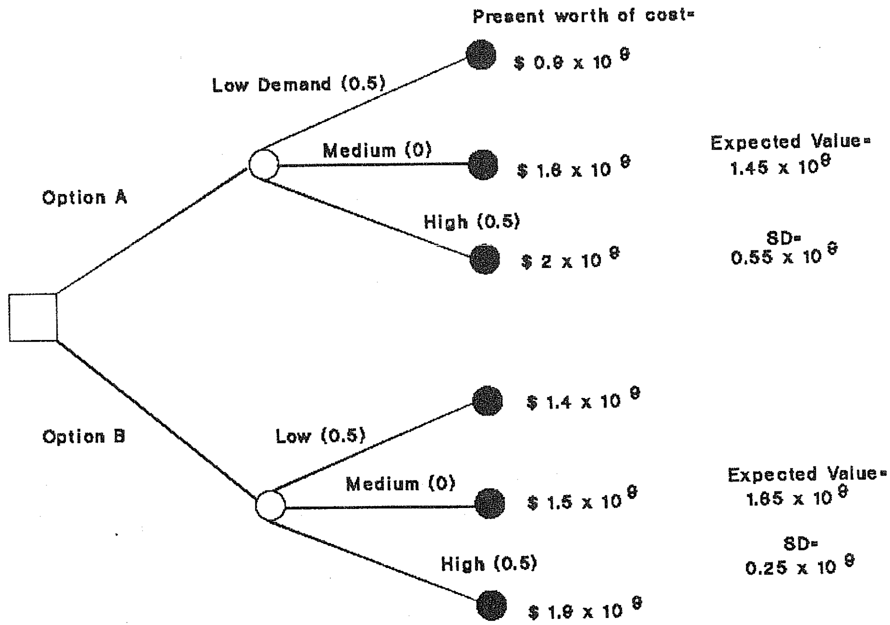
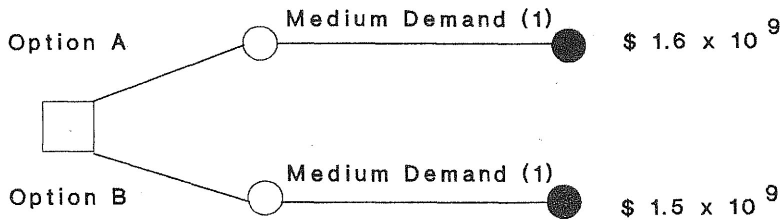
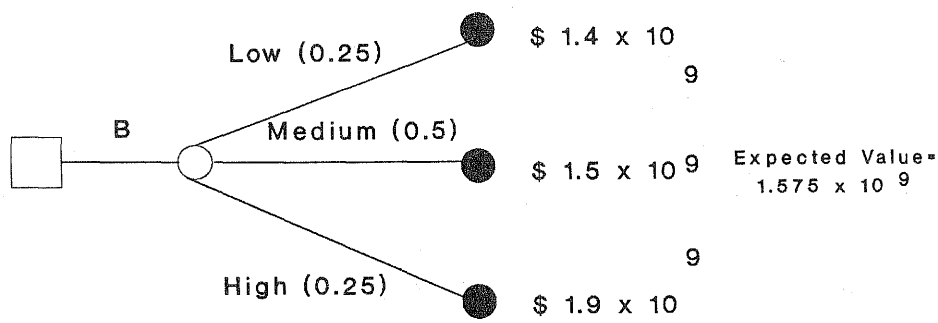


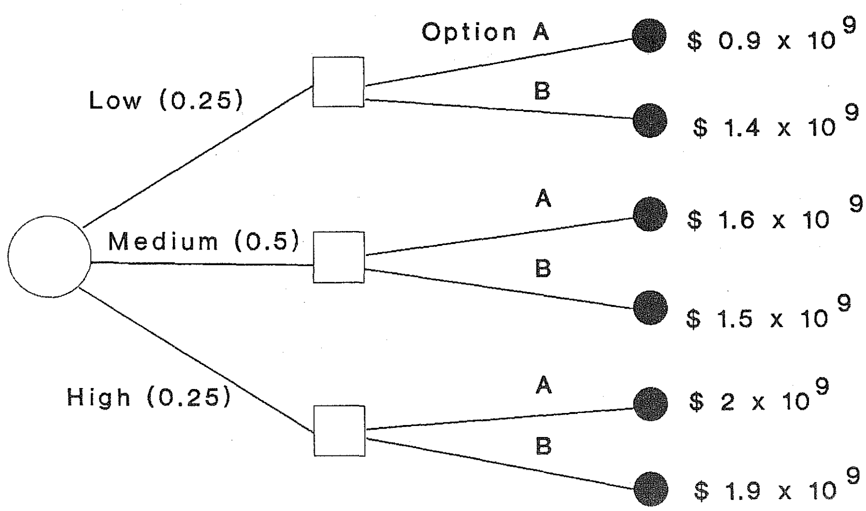
Figure 5-1. Example illustrating the effect of variance of demand on the variance of objective.



a) Decision tree for choosing optimal strategy, assuming incorrectly that demand growth will be "medium" (Option B is chosen).



b) Decision tree for evaluating correct expected performance of option chosen in figure 5-2a



c) Decision tree under perfect information about demand growth (Option A chosen if growth is low; Option B chosen if growth is medium or high).

Figure 5-2. Decision trees for calculating the cost of ignoring uncertainty and the value of perfect information be low, medium, or high. Each of these perfect forecasts has the probability shown in the figure. If demand is projected to be low, then option A would be chosen; otherwise, for medium and high demands, B would be the best. The expected cost of this optimal strategy under perfect information is $\$1.45\text{x}10^9$ (=$0.25\$0.9\text{x}10^9 + 0.5\$1.5\text{x}10^9 + 0.25\$1.9\text{x}10^9$). This is better than the expected performance of the optimal strategy under uncertainty (figure 5-1, $\$1.525\text{x}10^9$). The expected worth of this perfect foresight is the difference in the two costs, or $\$0.75\text{x}10^9$.

These four measures of the effects of uncertainty are chosen to measure their effect on consumers, financial analysts, and utility planners. To consumers, financial analysts in utilities, and public service commissions, the first measure is most meaningful, since they are directly concerned with the risks in costs and rates. By contrast, utility planners (and the regulators who oversee their planning decisions) would find the last three measures most useful, since they show how the uncertainties affect planning decisions. Each of the latter indices illuminates a different aspect of the effect of uncertainty upon planning.

As discussed in chapter 4, four types of uncertainties are modeled as probability distributions in the decision trees: (1) demand growth rates, (2) fuel costs, (3) plant construction costs, and (4) costs and availability of purchased power. Only the demand uncertainties are included in the MIDAS runs, while all four are incorporated in the SMARTS solutions.

For utility A, three categories of uncertainty are compared: "demand", "supply" (fuel and capital cost together), and "purchased power". Fuel and capital cost are considered as one because they are assumed to be perfectly correlated. For utilities B and C, four sources of uncertainty are contrasted: demand, supply, capital costs separately, and fuel costs separately. The effects of the fuel and capital cost uncertainties are distinguished by modeling them as being independent. Their total impact, under the alternative assumption that they are perfectly correlated, is shown under "supply".

Comparisons of Uncertainties: Results

The results of the analysis are compared in this section to obtain a ranking of the importance of different uncertainties. The comparison, at first, is that of the variance of the objective. Subsequently, we shall compare the number of planning decisions that change due to the uncertainties regarding the input parameters.

Variance of Objectives

Utilities, regulators, and customers are concerned about uncertainties in total costs and rates. In this subsection, the relative contributions of demand and various supply risks to the standard deviations of costs and rates are assessed.

Figures 5-3 through 5-6 summarize the effect of various sources of uncertainties on the standard deviations of the present worth of total costs and levelized rates. Figures 5-3 and 5-4 address utility A and figures 5-5 and 5-6 show the corresponding results for utility B. The results for utility C are nearly identical to those for utility B and are not shown separately. The standard deviations of the objective are expressed as coefficients of variation (standard deviation divided by the mean). The three sets of points in each figure show the standard deviations of the objective under "high", "base case", and "zero" variances for each of the uncertainties. Each point in the "high" and "zero" sets is obtained by setting the variance of the indicated source of uncertainty at its "high" or "zero" value, respectively (see chapter 3), while using the base case distributions for the other sources. To clarify this further, consider points a, b, and c in figures 5-5 and 5-6. Point a is obtained by assuming high variance for fuel and the base case variances for capacity costs and demand. Point b results from using base variances for all three sources. Assuming a low variance for fuel and base variances for capacity cost and demand yields point c.

The points labeled "base variance" in these figures are those that result from the base case probability distributions (described in chapter 3) for all the variables. It should be noted that the capacity cost and fuel cost uncertainties were assumed to be perfectly correlated for utility A (figures 5-3 and 5-4). However, for utility B, two different sets of assumptions were modeled: (1) where fuel and capacity cost are perfectly correlated, and (2) where fuel capacity costs are statistically independent. Figures 5-5 and 5-6 present the results of both sets of assumptions.

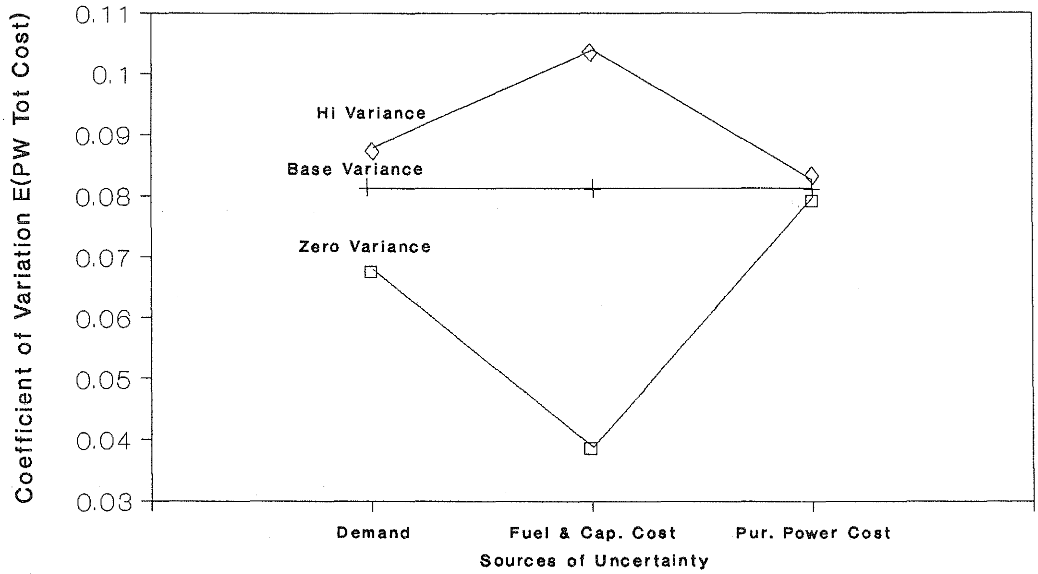


Fig. 5-3. Coefficient of variation of total cost as function of variance of different sources of uncertainty, utility A

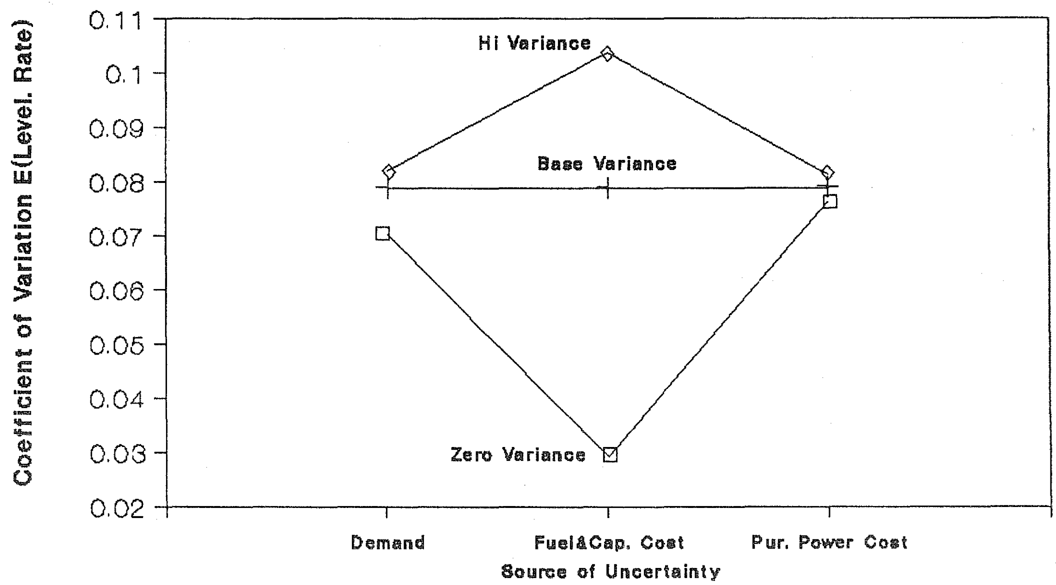


Fig. 5-4. Coefficient of variation of levelized rates as function of variance of different sources of uncertainty, utility A

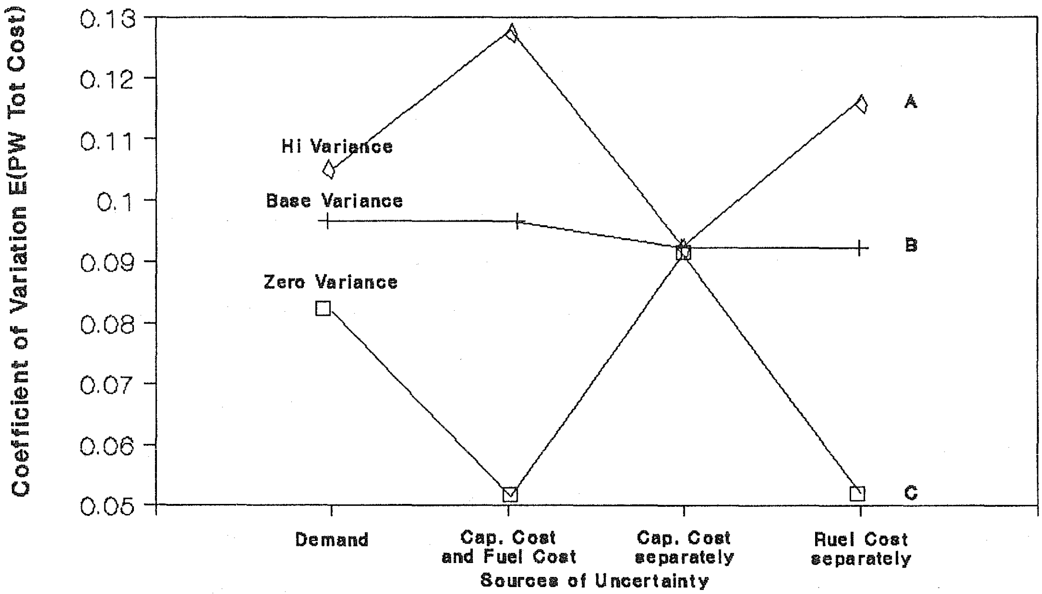


Fig. 5-5. Coefficient of variation of total cost as function of variance of different sources of uncertainty, utility B

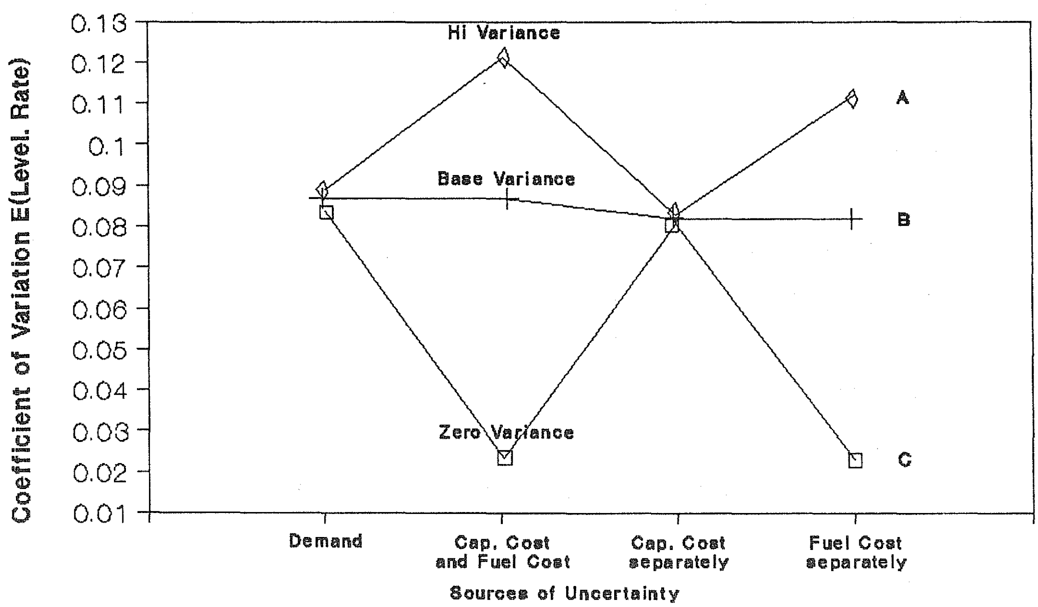


Fig. 5-6. Coefficient of variation of levelized rates as function of variance of different sources of uncertainty, utility B

These figures show that supply costs--in particular, fossil fuel costs--have the greatest impact upon uncertainty in total costs and rates. That is, eliminating the variation in fuel costs would lower the uncertainty in system costs and rates the most. For the systems studied, uncertainties due to purchased power and capital costs are negligible. Demand uncertainties have some impact, although it is very small in terms of rates.

The reasons for the relative importance of fuel costs compared to demand include: (1) its high variance (30 percent of the expected value in the base case), (2) its immediate impact, and (3) its effect on the cost of production for all the utility's output. Uncertainty in demand growth, by contrast, translates into a relatively small uncertainty in total demand (a standard deviation of 8.5 percent of the expected value after ten years), has its greatest impact many years into the future (when the cost impacts will be heavily discounted by the present worth calculations), and affects production costs for only the increment of demand. Uncertainties in capital costs are relatively unimportant for similar reasons.

The MIDAS model, which was only used to examine demand uncertainties, produced a change in the objective's variance due to a change in the demand variance was less than that in the SMARTS solutions. One reason for this is the longer time horizon used in SMARTS; it is in the later years when the variance in total demand is the greatest.

Changes in Decisions

From a utility planner's perspective, it can be argued that risks are unimportant unless they change the decision strategy. Variance in the objective means little by itself if the same decision is made no matter how much uncertainty exists. Two indices can be used to quantify this impact for each of the sources of uncertainty: (1) the fraction of generation expansion and DSM decisions that change as a result of increasing the standard deviation of the uncertainty in question from zero to the base case value, and (2) the fraction of generation expansion and DSM decisions that change as a result of increasing the standard deviation of the uncertainty in question from zero to the maximum value.

The two subsections that follow focus on the economic consequences of these decision impacts.

The above fractions are defined for the SMARTS models as:

$$F = \sum_{i=1,2,6,7} 0.25 I_i / N_i \qquad (5\text{-}1)$$

where I_i is the number of decision nodes in stage i that change and N_i is the total number of decision nodes in stage i. For SMARTS, the four stages are: supply decisions, year zero (i=1); DSM decisions, year zero (i=2); supply decisions, year four (i=6); DSM decisions, year four (i=7) (see figure 3-1 or table 4-1).

The fraction is defined as in equation (5-1) so that each stage is given equal weight; an unweighted index would allocate heavier weight to later stages because the number of decision nodes in the stages are unequal. Note that utility A must make a single capacity expansion and DSM decision in year one ($N_1=N_2=1$). However, there are twenty-seven different combinations of outcomes for fuel and capacity costs, purchased power, and demand in year four of utility A's decision tree (table 4-1). A capacity expansion and DSM decision must be made for each combination; hence $N_6=N_7=27$. Thus, the above definition of the fraction would normalize the changes in decisions by expressing them as a ratio to the total number of decisions in that particular stage.

Figures 5-7 and 5-8 show, for each utility, the value of the indices defined above for the demand uncertainties. For utility B, a significant fraction of decisions change: 11 percent under the cost objective and 45 percent under the rate objective. But for the other utilities, the fractions are 3 percent or less.

For the supply uncertainties (fuel, capital cost, and purchased power), a value of zero resulted for equation (5-1) in every case, even when comparing the "high" and "zero" variance cases. Therefore, these results are not plotted. This indicates that demand uncertainties matter more in decision making than supply uncertainties.

As a sensitivity analysis, two levels of demands in year zero are considered for utility A: the base level, and a high demand corresponding

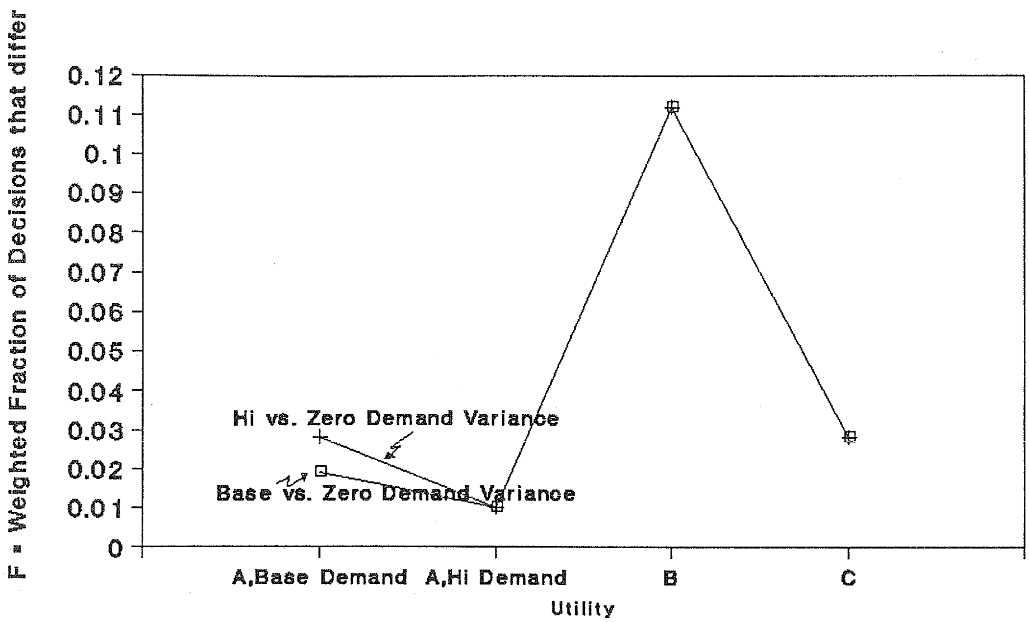


Fig. 5-7. Fraction of decisions that differ compared to zero demand variance solution, minimize total cost objective

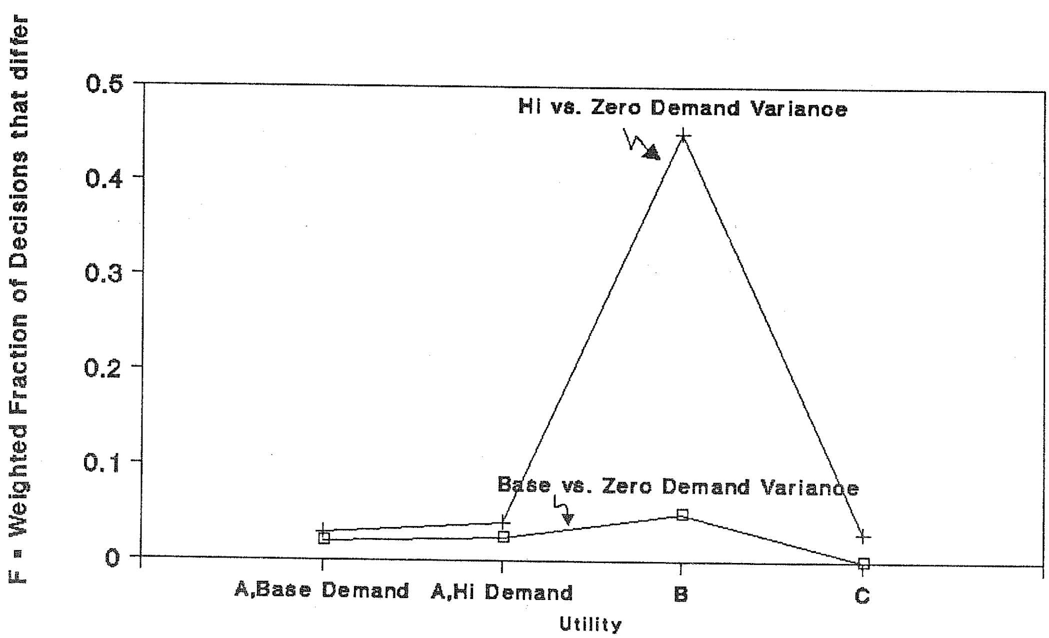


Fig. 5-8. Fraction of decisions that differ compared to demand variance solution, minimize levelized rate objective

to 10 percent above the base level (figures 5-7 and 5-8). Perhaps surprisingly, a high demand case results in fewer decisions in figure 5-7 (min. cost objective). The reason is that in the base case, a low variance results in no additions of plants while a high variance causes construction of plants in some cases in year four. Conversely, in the high demand case, plants are added in year four irrespective of the variance of demand.

However, under the rates objective (figure 5-8) more decisions change in the high demand case. This is because under the high demand variance and high demand level, utility A sometimes adds two units in year four rather than the one it adds under the smaller variance. This does not occur in the base demand case. Recall from chapter 4 that the rate objective justifies more plant construction than the cost objective.

On the matter of imminent decisions, decisions in year zero are of immediate concern to utility planners. Only one instance of the decision changing in year zero was observed. Utility B finds it worthwhile to start constructing a coal plant in year zero if demand variance is high, whereas in the base case it chooses to wait until year four.

MIDAS decisions show somewhat less sensitivity to demand. The major reason for this was that the MIDAS tree included fewer decision options. In particular, in year four, the MIDAS model simulation allowed the utility to choose between building zero and two units, while SMARTS model allows one, two or no units to be started. Therefore, it is easier for demand uncertainties to cause a change in the decisions in SMARTS due to the possibility of allowing single unit additions which are not permitted in the MIDAS simulation.

The Cost of Disregarding Uncertainty

Before 1973, in the era of stable prices and constant 7 percent a year demand growth, utility planners made capacity expansion decisions under the assumption that the future was known. To measure the cost of ignoring uncertainty, an index is suggested.

The index is quantified for each source of uncertainty as follows:

1. Obtain the optimal strategy assuming that the standard deviation of the source of uncertainty in question is zero, keeping

the standard deviations of the other sources of uncertainty at their base levels (figure 5-2a). These are the solutions associated with the lower points in figure 5-3 through 5-6.

2. Take those naive strategies and calculate their expected performance under the base case standard deviation for the uncertainty in question (figure 5-2b).

3. Compare the expected performance of the naive strategies (figure 5-2b) with that of the optimal strategy under the base case. The optimal strategy for each utility is that associated with the "base variance" points in figures 5-3 through 5-7. In general, the naive strategies perform poorly.

As shown in the previous section, of all the sources of uncertainty, only demand uncertainties affect planning decisions. Since only demand uncertainty matters, ignoring the uncertainties in fuel, capital costs, and purchased power would make no difference to the DSM and capacity decisions. Thus, the cost of ignoring the above supply uncertainties in planning is negligible compared to the cost of ignoring uncertainties in demand. By contrast, if the variance in demand is ignored, different decisions would be taken, especially in year four for capacity additions.

The cost of ignoring uncertainties in demand is shown in figure 5-9 for the SMARTS minimization of cost solutions. The ordinate shows the ratio of the expected cost of uncertainty to expected present worth of total costs. The ordinates in figure 5-9 are less than 0.2 percent of the total cost for each utility, being highest for utility A under a 10 percent higher demand. These numbers appear small, but on a present-worth basis can still amount to hundreds of millions of dollars. The results under the levelized rate objective were similar.

The MIDAS model shows a somewhat smaller cost of ignoring uncertainty for reasons discussed earlier.

Expected Value of Perfect Information (EVPI)

Unlike the cost of ignoring uncertainty, the value of perfect information measures the difference in performance between the optimal strategy under uncertainty and the optimal strategy if the future were known. This measures the maximum worth of studies which would reduce the uncertainty. It is calculated in the following manner:

1. Obtain the optimal strategy under uncertainty in the usual manner (figure 5-1).

2. Obtain the expected performance under perfect information by solving a decision tree that has been rearranged so that all the chance nodes are encountered first (revealing the future), after which the decisions are made (figure 5-2c). For example, in the SMARTS model, the stages are rearranged into the following order: 3,4,5,8,1,2,6,7. Note that stages 3,4,5, and 8 contain chance nodes and the rest contain decision nodes. In each of the chance nodes, different outcomes are taken as known and the performance (total expected cost or rates, etc.) of the system under perfect information is obtained as explained in connection with figure 5-2c. The system's expected performance under perfect information is generally better than that calculated in step 1.

3. Compare the performance of the optimal strategies under uncertainty and under perfect information. The difference between the expectation of the objective is the value of perfect information.

This analysis is performed separately for each demand and supply uncertainty, assuming the base case probability distributions for the other sources. The steps are repeated for three values of the standard deviation of each uncertainty: zero, the base case value, and the highest value.

As in the last two subsections, it was found that only demand uncertainties made any difference in planning decisions. The situation is the same here. Only demand uncertainties make a significant difference in decisions and, therefore, only information about demand has value. The value of information for the various supply uncertainties is zero because different decisions would not be taken even if future supply costs and availability could be perfectly predicted.

Figure 5-9 displays the effects of different levels of uncertainty in demand upon EVPI alongside the results of the previous subsection. The graph shows that as the standard deviation of the uncertainties increases, the value of perfect information increases in proportion. The figure shows that the most that a utility should pay for information which would eliminate uncertainties in demand is less than a fraction of 1 percent of the total cost of providing energy. However, this can, of course, amount to many millions of dollars.

Discussion

Uncertainties in utility planning are important because they increase the complexity of resource and financial decisions for utilities, and energy-using investment decisions for consumers. Even if uncertainty is considered in such decisions, there is a significant risk that resources will be wasted or opportunities for cost savings missed. If uncertainty is ignored, the danger is that plans will be adopted that are ideal for the narrow supply and demand projections upon which they are based, but disastrous under other, equally likely conditions.

This and the previous chapter have addressed the following three questions: What are the impacts of alternative objectives in utility planning under uncertainty? What are the impacts of risk-averse decision making in planning? Which long-run sources of uncertainty are the most important to electric utilities: demand, fossil fuel costs, capital costs of new plants, or costs of purchased power? Short run uncertainties, such as weather or plant availabilities, are ignored in this analysis.

These questions cannot be definitively answered for all utilities, since every planning problem is different. Nonetheless, the analysis presented is the first to have considered the implication of uncertainty in planning for a cross-section of electric utilities. The methodology used--decision analysis--is both a conceptually correct and a practical means of quantifying the impacts of uncertainty upon system costs, rates, and planning decisions.

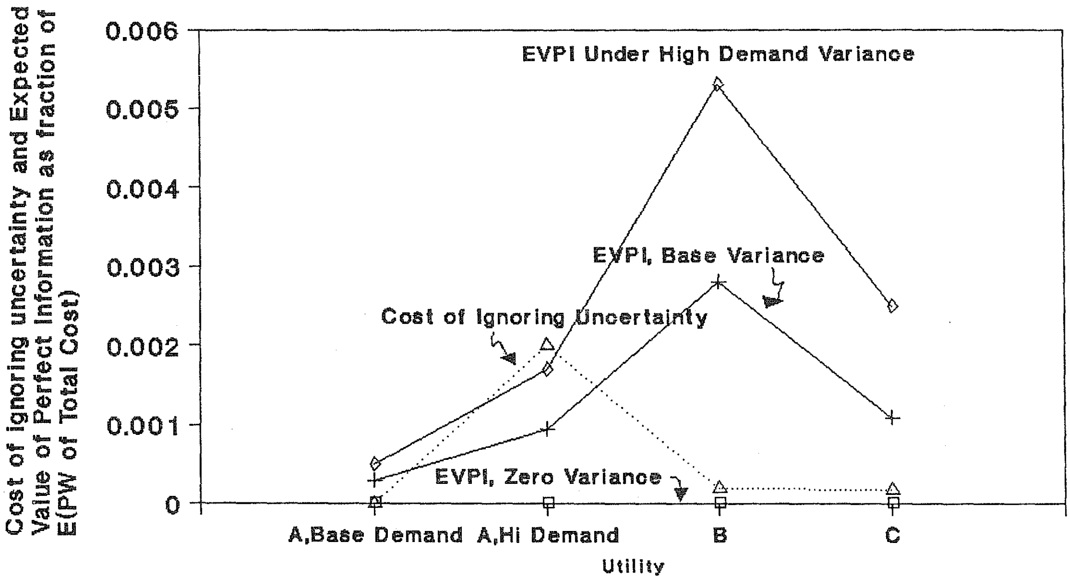


Fig. 5-9. Expected value of perfect information under base and high demand variance and expected cost of ignoring uncertainty

With regard to the first question, decision-tree models are solved under different objectives for three planning problems typical of utility conditions across the United States. It is found that two objectives, minimizing electric rates and minimizing system cost, may be incompatible in that they imply different capacity expansion and demand management decisions. Minimization of rates increases system costs. Another conflict between objectives occurs if a regulatory commission adopts a policy of disallowing recovery of "excess" capacity costs (or even if a utility just believes that such a policy is possible). The impact might be higher rates and higher system costs if the utility chooses to minimize the expected present worth of disallowed costs. As a result, it would avoid making capacity additions, even when they are economic. As pointed out earlier, this conclusion presupposes that the utility would otherwise attempt to minimize the present worth of system costs.

As for the second question concerning risk attitudes, it was found that the attitudes did not matter much for the three utilities studied. It appears to be impossible to lower the risk (as measured by the standard deviation of system costs or rates) significantly by making capacity or demand management decisions that are different from those made under a risk-neutral strategy. That is, in the models considered here, large decreases in risk cannot be purchased at the price of an increased expected value of total cost or rates.

The answer to the final question, however, is dependent on whether the concern is with financial and rate-making problems or with resource planning. From the financial and rate point of view, the importance of an uncertainty is related to its impact on the overall uncertainty in system costs and rates. From the perspective of planning, importance is best measured in terms of its potential impact on decisions, the consequences of ignoring the uncertainty, and the benefits of obtaining information. For this reason, several measures of "importance" are defined by which the sources of uncertainty can be compared.

The first measure of the severity of an uncertainty is the change in the variance of system costs and rates that results from a change in the variance of the source uncertainty. By this measure, fossil fuel price uncertainties are the most important for the three utilities studied, more so even than demand uncertainties. Uncertainties in capital cost and purchased power have even less of an impact than demand. Under the base case assumptions of this analysis, fuel uncertainties account for two-thirds to three-quarters of the variance in the present worth of total costs, and an even greater fraction of the variance of rates.

The reason for this is that fuel price uncertainties can affect the total cost of production dramatically in the near-term. Demand uncertainties, by contrast, affect costs farther in the future. In practice, however, demand uncertainties may still be crucial to financial planners because of the presence of fuel adjustment clauses and the need to raise capital for new facilities. Nevertheless, from a customer's point of view, the price of fossil fuels makes the cost of electric power most difficult to predict.

From a long-range planning perspective, however, demand uncertainties appear to matter the most in capacity planning and demand-side management. For each of the three utilities studied, only demand uncertainties make any difference in the decision strategies. No matter what variances were assumed for the various supply uncertainties, the optimal decisions remain unchanged. The cost of ignoring supply uncertainties is found to be zero for all utilities, as is the value of acquiring information about those uncertainties. In contrast, capacity expansion decisions depend upon the assumed variance of demand. Further, the expected penalty of ignoring demand uncertainties ranges from one million dollars up to thirty million dollars, in present worth terms for the cases studied. The value of a perfect forecast of demand over the next thirty years is as high as 140 million dollars.

Strictly speaking, these conclusions apply only to the particular utility systems and assumptions tested here. Supply uncertainties could still impact planning decisions under several circumstances. For instance, if the cost of intensive demand-side management programs turns out to be two or three times higher than assumed here, then whether or not such programs are justified could depend on the variance of supply costs. As another example, if a greater range of fuels for new power plants were considered and if it were not assumed that the costs of natural gas, oil, and coal were perfectly correlated, alternative assumptions about uncertainties in fuel prices could alter the choice of generation technology. Nevertheless, demand would probably remain the crucial source of uncertainty.

The implication of the paramount importance of demand risks in decision making is that utilities and regulators should emphasize that source of uncertainty in any planning study. However, because supply uncertainties could affect some decisions, it is inadvisable to ignore other sources of uncertainty entirely.[19] But this poses a problem for the planner: it is difficult to incorporate several sources of uncertainty in a rigorous manner while at the same time considering a realistic number of alternatives. The reason is that most utility planning models do not incorporate uncertainties explicitly, and MIDAS, one widely-used model that does, has the disadvantage of long run times and intensive data preparation.

The solution adopted here is one that might be useful to utility planners and regulators: apply a simple model such as SMARTS to examine a wide range of uncertainties and options and then use a more complex model to explore the critical uncertainties and choices in detail. A simple model can act as a screen, revealing which alternatives are unlikely to be chosen under what circumstances, and which uncertainties actually affect the decisions. Once those are known, a MIDAS scenario can be constructed which includes only the most attractive options at each decision node and the critical uncertainties. This modeling strategy will help planners and regulators be confident that all important uncertainties have been considered and that a good, "robust" decision has been reached.

CHAPTER 6

SHARING OF RISKS AMONG CUSTOMER CLASSES

Overview

Several objectives used in utility planning have already been examined. The objectives can be divided into two broad categories, those that minimize the risk to the utility, and those that minimize the risk to the ratepayer. The objective of minimizing disallowed capacity costs is an example of the former, while minimizing rates or costs exemplifies the latter category.

In terms of risks to the consumer, all the consumers have been viewed so far in the report as a single group. The industrial, commercial, and residential customers, however, are represented as separate interest groups during rate hearings. Some groups are more organized than others. In any event, it is the responsibility of state commissions to examine the effect of a particular plan on each class of customer. This chapter reports on an examination of the relative risks among the customer classes.

Long-term utility planning requires the projection of revenue requirements over a future period. However, such projections are subject to significant uncertainties caused by the uncertainties in the primary inputs used to estimate revenue requirements. These inputs include, among others, load growth rates, fuel prices, construction expenditures, interest and tax rates, and allowed rates of return. Uncertainty in any of these inputs produces a corresponding uncertainty in the revenue projections. To account for these uncertainties, one can assign subjective probabilities for various scenarios and produce a probability distribution of projected revenue requirements, or, for that matter, the distribution of any chosen objective. In addition to the probability distribution of total revenue requirements from all customers viewed as one class, one can also find the probability distribution associated with revenue requirements for each customer class. These probability distributions can be used as proxies for risks to different customer classes associated with various utility decisions. A comparative study of these risk profiles[30] may provide valuable insights about sharing of risks among customer classes. For example, if the risk profiles of two customer classes are significantly different, then it is pertinent to reexamine the basic rate-making principles that led to this outcome.

In terms of uncertainties from financial and cost considerations, the preceding chapters show that the fuel price uncertainty is the most important one followed by load growth uncertainties. In terms of relative risks among customer classes, however, fuel price uncertainties have the least effect. The risk of having a higher or a lower fuel price affects all the customer classes similarly because the fuel cost recovered from each class is roughly proportional to its electricity consumption. Load growth uncertainties, especially when there are differences in load growth rates among different classes of consumers, may affect the classes differently.

Besides this, utility decisions may affect the classes of consumers differently. For instance, the decision to build a new plant or not may influence the risk profiles of customer classes differently. The same is true for other decisions such as the purchase of power by a utility.

In view of the above, MIDAS is used to examine the relative risk profiles of consumer classes. Because of large computational times and data preparation efforts to run MIDAS, we restrict our examination to illustrative small problems. Therefore, the effect of decisions on the risk profiles is not undertaken. The effect of chance causes--in particular load growth uncertainty--on risks to customer classes is examined.

We consider two objectives, the revenue requirement (RR) and the levelized rate for each class. Here, the total revenue requirement represents total utility cost (assuming there are no disallowed costs) discussed elsewhere in the report. Then a class RR represents the allocation of the total utility cost to an individual customer class. The use of the rates objective would give an indication of the average price of electricity to each consumer class. We have chosen to examine the class RR objective.

One might argue that the class RR itself does not portray risk and that the rates are of importance. While this may arguably be true, we point out that the two objectives become identical in the absence of a demand-side management (DSM) program. The role of demand-side management programs in least cost utility planning has been examined in earlier chapters. In this chapter, we focus on the impact of load growth uncertainties on customer class risks. Demand-side management programs can indeed be a source of load growth uncertainties. Our analysis in this chapter, however, is limited to the examination of the effect of load growth uncertainties, irrespective of their sources. As such, we have chosen to ignore the role of demand-side management programs in our analysis of customer class risks. In view of the above, both the rates and the RR are equally valid objectives for the analysis. In the interest of minimizing the computational effort, we have opted for the latter.

Analysis of Load-Growth Uncertainties Using a Decision-Tree Framework

The use of decision trees to analyze utility risks has been described in the earlier chapters. In this chapter, we are concerned with the comparison of probability distributions of revenue requirements. Therefore, a simple decision tree and the method of obtaining the probability distribution of a chosen objective is described.

Figure 6-1 shows a decision tree. There are two possible decisions. One is to build a coal plant and the other is not to build it. There are three postulated chance events. These events are shown as high, medium and low load growth rates with probabilities of 0.2, 0.5 and 0.3 respectively. Each combination of decisions and events can be defined as a scenario. In figure 6-1, there are a total of six scenarios with three scenarios for each decision. In general, the probability of each scenario of a decision tree is given by the combined probability of events contained in the scenario. In figure 6-1, there is only one set of chance events and therefore, the probability of each scenario is simply that associated with corresponding chance event. For each scenario, one can also calculate an objective such as the revenue requirement. The set of values of the objective together with the corresponding set of probabilities constitutes a probability distribution. There is a probability distribution associated with each decision. For the decision tree in figure 6-1, there are two such probability distributions, one for each decision. The probability

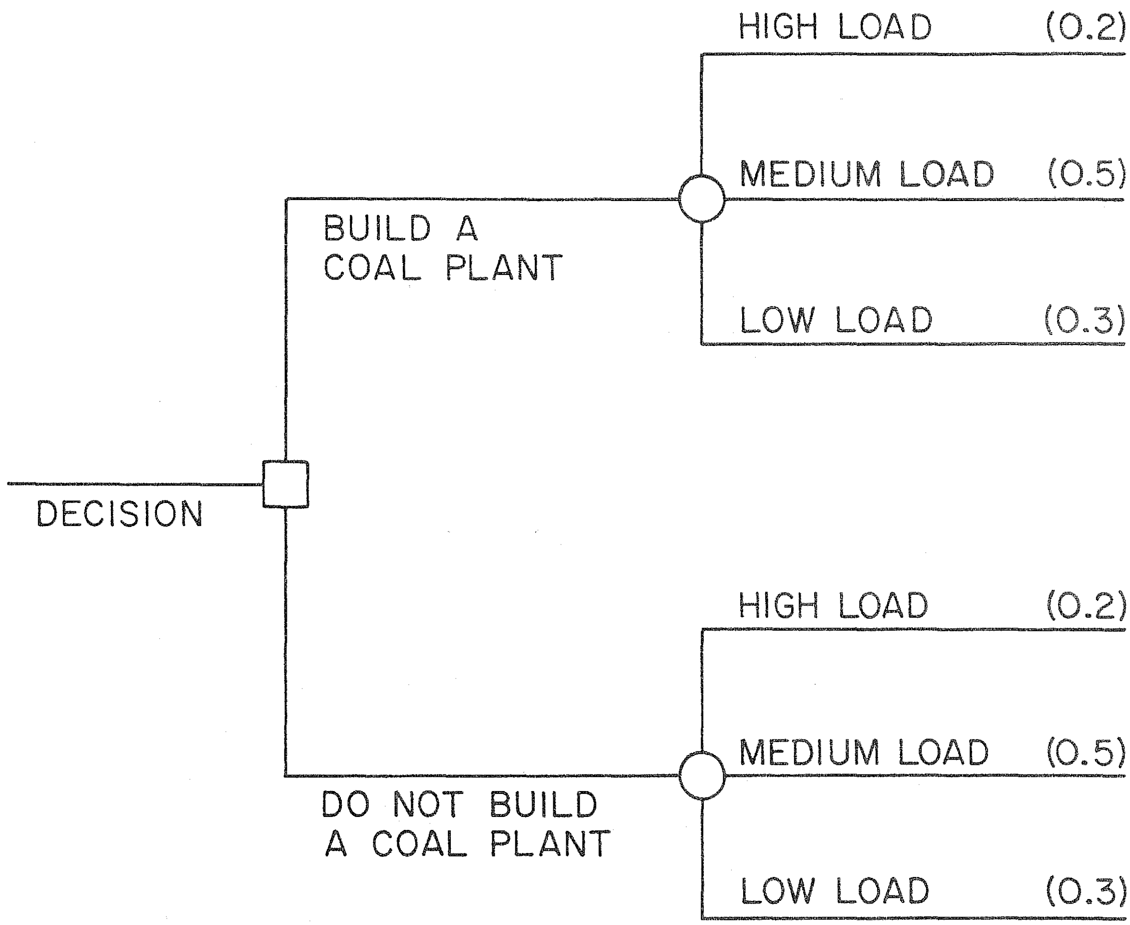


Fig. 6-1. A decision tree

distribution of the total revenue requirement (RR) obtained above is associated with the entire customer population viewed as a single group. One can find the probability distribution of class RR in the following way.

For a given scenario, the total RR is allocated to each customer class using a chosen cost-of-service method. The class RR thus obtained has the same probability as that of the total RR from which it has been derived. For example, let the total RR be $100 for scenario 1 with a probability of 0.2. Assume that $30 of this $100 is allocated to the residential class of customers according to a chosen cost-of-service method. Then the probability of residential customers having a class RR of $30 is also 0.2, because it corresponds to the same scenario. Similar cost allocation calculations are repeated for other scenarios. The set of class RR together with corresponding sets of probabilities constitutes a probability distribution of class RR.

As mentioned earlier, one can interpret the probability distributions of revenue requirements as risk profiles. Then the decision-tree framework allows the evaluation of utility decisions from a risk perspective. In normal utility planning practice, one examines risks to the utility as well as the ratepayers viewed as a whole. In this chapter, we examine how risk is distributed among customer classes by comparing their risk profiles. We also discuss how rate-making principles and related cost-of-service methods may effect the distribution of uncertainties and risks among customer classes.

Using MIDAS to Analyze Customer Class Risks

To analyze different scenarios in our study, we use the decision tree capability of MIDAS. An overview of MIDAS is given in chapter 3. In this section we provide a more detailed view of MIDAS with particular emphasis on its rate-making method.

MIDAS has a simulation module embedded in a decision-tree framework. The simulation module performs load analysis, capacity planning, production costing, financial projections, and rate calculations. The simulation is done for each scenario in the decision tree. The inputs for MIDAS consist of the data for the decision tree, historical load data as well as future load projections, plant operating data and financial parameters. The outputs are proforma financial statements such as the balance sheet, the income statement, and the sources-and-uses-of-funds summary. MIDAS also produces reports on production costs and cost-of-service analysis.

The simulations performed in MIDAS can be broadly divided into two major submodules. The first consists of production costing calculations. The second includes revenue requirements and cost-allocation analyses.

The production costing calculations in MIDAS proceed as follows. First, MIDAS uses historical load data and user-supplied forecasts for future load growth rates to create hourly load profiles for every year in the study period. Next, it uses "load duration curves" (LDC)[31], cost and operating data for generating plants, and probabilistic simulation[43] to find the total energy production. Finally, MIDAS calculates the cost of energy production.

Once the production cost has been determined, other expenses and return on capital investment are added to find total revenue requirements. Other expenses include fixed operating costs, depreciation charges and taxes. The return on investment is based on either an allowed rate of return on regulated rate base or an allowed return on equity.

Next, a cost allocation analysis is performed on the revenue requirements. Cost allocation assigns the total cost of service which is in this case, the total revenue requirement (assuming no disallowed costs) to causal factors, and finally to customer classes. Figure 6-2 illustrates a hypothetical cost-allocation process. Initially, each cost item contributing to the revenue requirements is classified according to three causal factors: demand, energy, and customer. Demand-related costs are costs such as investments in generation and transmission facilities. Energy costs include costs such as fuel expenses, purchased power, and part of operating expenses. Customer costs are expenses for customer-related services. They include some distribution expenses and costs of metering and billing. Finally, each category of cost is allocated to individual customer classes. In MIDAS these allocations are performed in the following way. Demand-related costs are allocated to each customer class in proportion to class peak demand. Energy-related costs are allocated in proportion to each class's energy consumption. Customer-related costs are allocated in proportion to the weighted number of customers in each class.

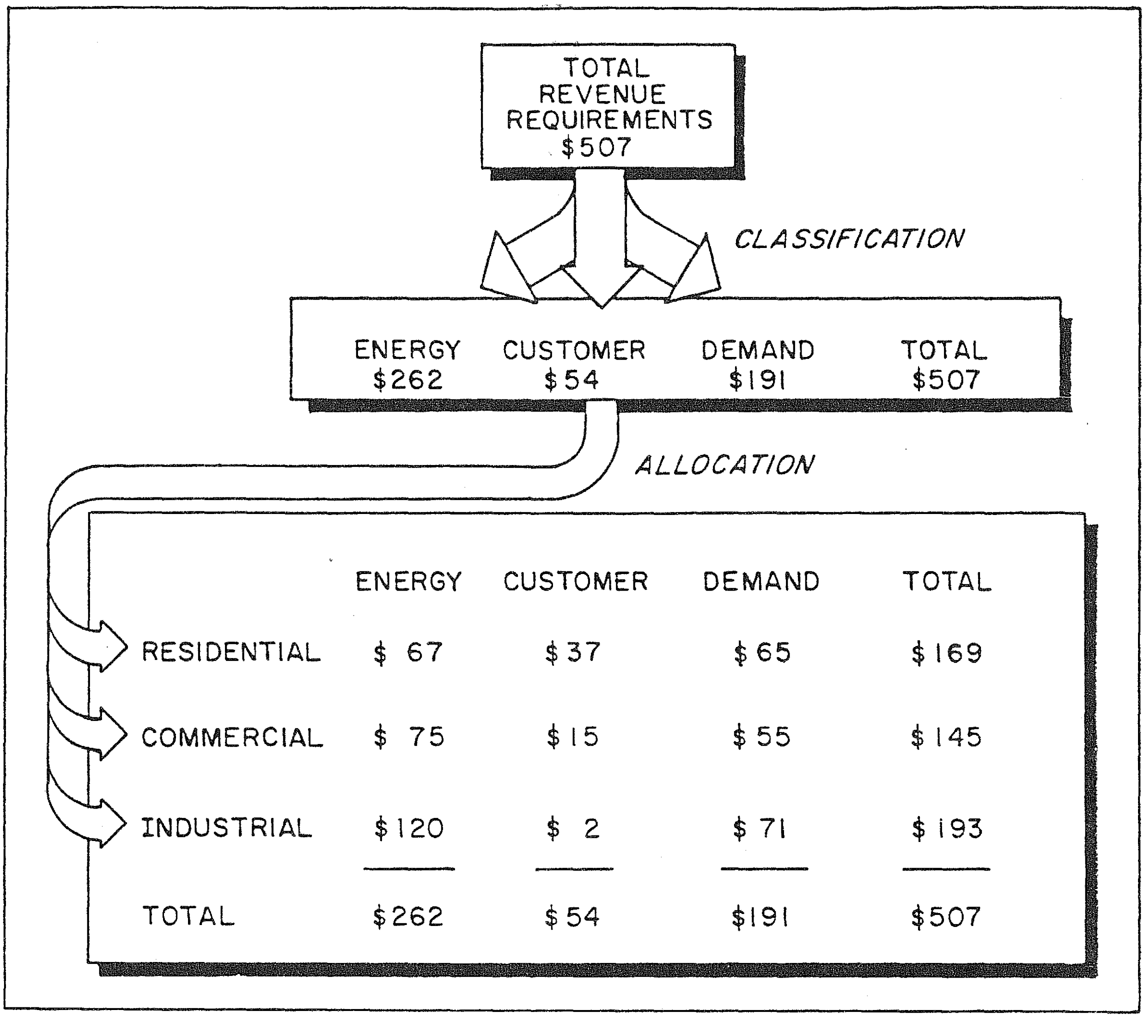


Fig. 6-2. A hypothetical cost allocation process

(Source: Electric Power Research Institute, *MIDAS*, Palo Alto, California, 1988)

In MIDAS, the first step (that is, cost classification, see figure 6-2) requires user inputs of cost allocation factors for demand, energy, and customer categories. These factors then are applied to the total revenue requirements to find the total demand, energy and customer costs. Thus in MIDAS the cost classifications are done on the total cost (that is, total revenue requirements) and not on individual cost items (such as fuel costs, operating expenses, depreciation charge, etc). This procedure is less rigorous than one where each cost item is classified into cost categories (i.e., demand, energy and customer). In our analysis, we have used a method which is intermediate between the above two in computational rigor. The details of our method are discussed in a later section.

Sample Study

A representative midwestern utility was chosen for our study. In 1987, the total system capacity for the utility was 5,827 MW and the reserve margin was 27.3 percent corresponding to a peak load of 4,579 MW. The system is identical to utility B described in the appendix. An 833 MW coal plant comes on line in 1988 and a 500 MW coal plant is added in 1998. The decision tree for this system is shown in figure 6-3. We do not consider alternative planning decisions in this example study but rather focus on the impact of load growth uncertainties on customer class risk. Therefore, there are no decision nodes in the decision tree shown in figure 6-3. The system is assumed to continue with a load growth rate of 2 percent until 1990. Beginning in 1990, three possible load growth scenarios are postulated. It is assumed that there is a 50 percent probability that the system load continues to grow at an annual rate of 2 percent, a 30 percent probability that the load growth rate is 1 percent and a 20 percent probability that it is 3 percent. Beginning in 1994, another set of scenarios are postulated with a broader band of uncertainty. It is assumed that there is a 50 percent probability that the load grows at a rate of 3 percent, a 30 percent probability that the growth rate is 1 percent and a 20 percent probability that the growth rate is 5 percent. A complete simulation of energy production, costs, and total revenue requirements is done for each scenario of the decision tree (figure 6-3) for the period

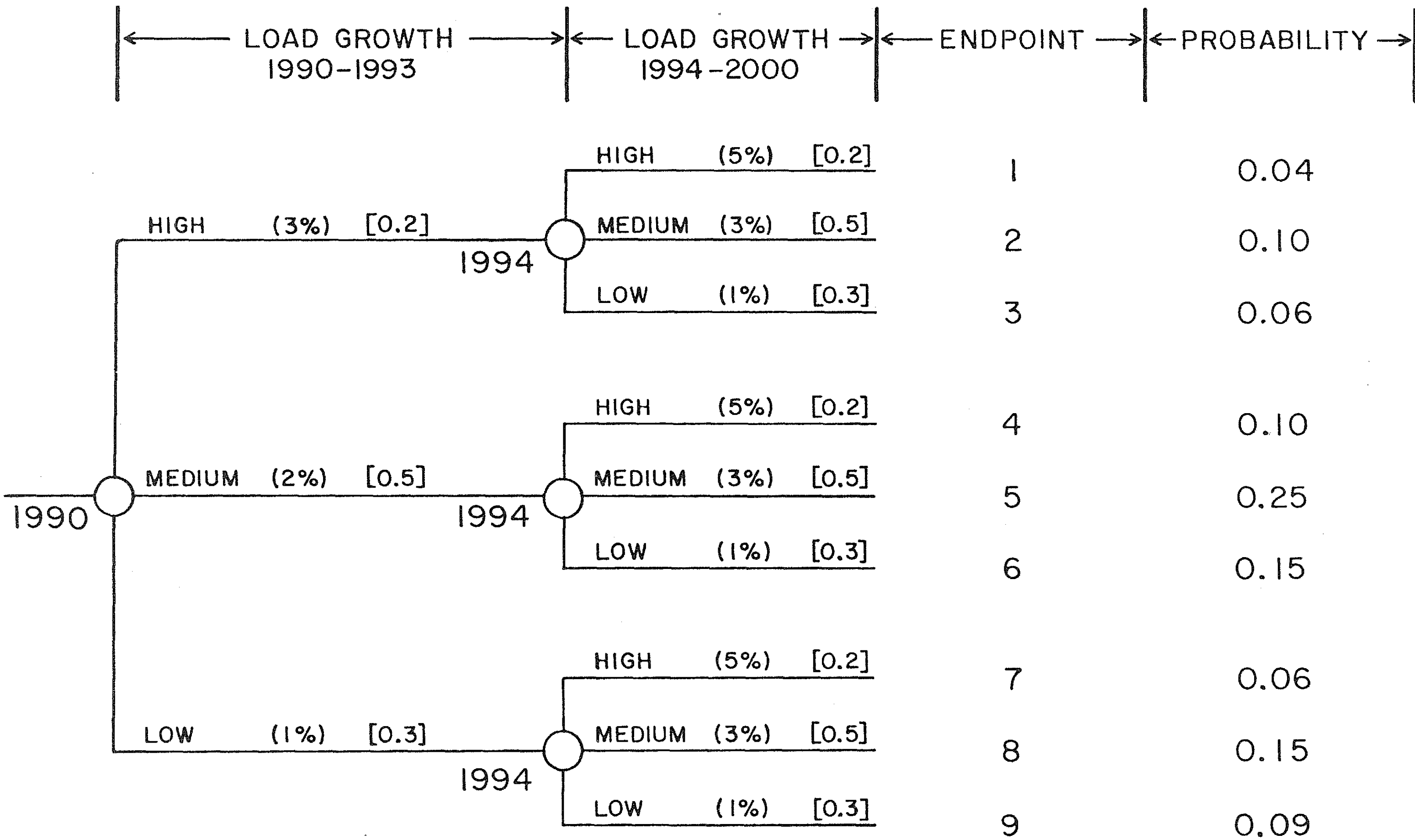


Fig. 6-3. Decision tree for sample study

1988-2000. The revenue requirement is assigned a present worth (PW) using a 6 percent escalation and a 5 percent discount factor. Each scenario in the tree is identified by an endpoint. Associated with each endpoint is a probability. For example, endpoint 1 represents the scenario in which a 3 percent load growth is followed by a 5 percent load growth. The corresponding probability is 0.2 times 0.2 or 0.04.

Two cases are considered in this sample study. In case one, all classes are assumed to have the same load growth rates as that of the system in each stage. In case two, differential growth rates in class demands are simulated. In this case, classes 1 and 2 (commercial and residential) are always assumed to have the medium load growth rate at each stage while class 3 (industrial) load growth rates are adjusted such that, the composite load growth rate for the whole system remain the same as in case one.

To illustrate the difference between the two cases, let us consider the load growth rates in stage 1 (years 1990-1993 in figure 6-3). It should be noted that the load growth rates shown in figure 6-3 are those for the whole system. In case one, for the high growth scenario, the load growth rates for all classes are all equal to 3 percent, the same as the system load growth rate. In case two, for the same high growth scenario, the load growth rates for classes 1 and 2 are assumed to be 2 percent, the same as the medium load growth rate. The load growth rate for class 3 is then adjusted such that the system load growth rate is still 3 percent, the same as in case one. A similar adjustment for class 3 load growth rate is made the low growth scenario. For the medium growth scenario, the load growth rates are all 2 percent for all classes in both cases. Therefore, in case two, the class 3 load growth rate is higher than 3 percent for the high growth scenario and less than 1 percent for the low growth scenario. The above examples assume that the industrial customer class is more volatile with respect to load growth rates than the other classes. This assumption is hypothetical and is made for illustrative purposes.

The set of revenue requirements for all end points and corresponding probability values constitute a probability distribution of total revenue requirements. To examine the sharing of the risks of load growth uncertainties among different customer classes, one also needs to construct probability distributions of revenue requirements for each customer class.

This requires an allocation of total revenue requirements among customer classes. The cost allocation routine available in MIDAS is not used for this analysis[44]. Instead, the following cost allocation procedure is used.

Cost Allocation Procedure

The data required for this procedure are the total revenue requirements, fuel and other variable operating costs, peak demand and energy consumption of each customer class, and the number of customers in each customer class. These are obtained as MIDAS outputs. The cost-allocation procedure, which is based on the standard embedded cost-of service method and similar to that used in MIDAS (except for the changes in input assumptions explained in endnote 44), is carried out in two steps.

Step 1

This is called the classification step. In this step, the total costs (that is, revenue requirements) are classified into energy, demand, and customer costs. Fuel and other variable operating costs are classified as energy costs. Purchased power is ignored in these calculations because it is not a part of the capacity mix used in this study. This leads to an energy allocation factor defined as follows:

$$\text{Energy Allocation Factor (EAF)} = \frac{\text{Fuel Cost + Other Variable Operating Costs}}{\text{Total Revenue Requirements (RR)}} \tag{6-1}$$

The customer allocation factor (CAF) is given a value of 0.1. This is based on a rough estimate of historical customer-related costs. Therefore,

$$\text{Customer Allocation Factor (CAF)} = 0.1 \tag{6-2}$$

The demand allocation factor (DAF) is given by,

$$\text{Demand Allocation Factor (DAF)} = 1 - \text{EAF} - \text{CAF} \tag{6-3}$$

The above allocation factors can now be used to assign costs to each category by the following method:

$$\text{Energy Expenses (EE)} = RR * EAF \tag{6-4}$$

$$\text{Demand Expenses (DE)} = RR * DAF \tag{6-5}$$

$$\text{Customer Expenses (CE)} = RR * CAF \tag{6-6}$$

Step 2

In this step, costs of each category are allocated to each customer class. Let E_n, D_n, and C_n be the energy consumption, the peak demand, and the number of customers, respectively for customer class n. Then the corresponding customer allocation factors FE_n, FD_n, and FC_n are given by

$$FE_n = E_n / \sum_n E_n \tag{6-7}$$

$$FD_n = D_n / \sum_n D_n \tag{6-8}$$

$$FC_n = C_n / \sum_n C_n \tag{6-9}$$

In (6-9), all classes of customers are assigned equal weights for simplicity although they may be different in a more rigorous calculation. Since customer costs are assumed to be only 10 percent of all costs, this simplification is unlikely to have any significant effect on the final results of this analysis.

The energy cost EC_n, the demand cost DC_n and the customer cost CC_n for customer class n are given by

$$EC_n = EE * FE_n \tag{6-10}$$

$$DC_n = DE * FD_n \tag{6-11}$$

$$CC_n = CE * FC_n \tag{6-12}$$

Finally, the total cost, RR_n (i.e., revenue requirements for customer class n), is given by,

$$RR_n = EC_n + DC_n + CC_n \qquad (6\text{-}13)$$

The RR_n for a complete set of scenarios and corresponding probabilities constitute the probability distribution for the customer class n.

Case One

In this case, the load growth rates for class 1 (commercial), class 2 (residential), and class 3 (industrial) are assumed to be equal to each other and to the total system load growth rate for different scenarios shown in figure 6-3.

Discussion of Results

The revenue requirements (RR) for the whole system and each customer class, and corresponding probabilities for each end point (scenario) are shown in table 6-1. Each horizontal line in the table shows values for a single scenario in the decision tree in figure 6-3. For example, endpoint 4 represents the scenario where a 2 percent load growth rate in 1990-1993 is followed by a 5 percent load growth rate in 1994-2000. For this scenario, the system RR is 48,623 million dollars. The RR of class 1, class 2 and class 3, for the same scenario, are 12,536, 18,943, and 17,144 million dollars respectively. The probability that the above scenario occurs is 0.10. This probability, therefore, is assigned to both the system RR and each class RR for endpoint 4. Table 6-1 also shows the mean and standard deviation of each RR. The mean is obtained as a probability-weighted sum of RR for all endpoints. The standard deviation is similarly derived using standard statistical techniques.

It is observed from table 6-1 that the variation in system RR as well as class RR is small relative to the mean. This fact is also reflected in the relatively small values of standard deviation, varying between 1.4 percent and 1.8 percent of the mean. In spite of this small variation, it may be useful to study how the class RR vary with each other and with the system RR. For example, let the total system RR by higher for scenario X than that for scenario Y. Then one also expects the RR of each class to be higher for scenario X than that for scenario Y. Any deviation from this

TABLE 6-1

REVENUE REQUIREMENTS (RR) FOR CASE ONE

Endpoint	System RR (M$)	Class 1 RR (M$)	Class 2 RR (M$)	Class 3 RR (M$)	Probability
1	49,358	12,718	19,224	17,416	0.04
2	47,141	12,139	18,361	16,441	0.10
3	47,657	12,209	18,456	16,993	0.06
4	48,623	12,536	18,943	17,144	0.10
5	47,751	12,326	18,606	16,819	0.25
6	47,014	12,124	18,007	16,883	0.15
7	47,907	12,364	18,666	16,877	0.06
8	47,086	12,166	18,350	16,571	0.15
9	46,447	11,920	17,993	16,533	0.09
Mean	47,518	12,248	18,451	16,798	
Standard Deviation	682	184	328	240	

Source: Authors' calculations.

behavior indicates an uneven sharing of revenue risks. In particular, if a change of scenarios results in a higher RR for one class and a lower RR for another class, it is clear that the revenue risk is not shared evenly by the two classes. We also compare the probability distributions of class RR, which may be interpreted as risk profiles[30] or measures of relative risk.

In figures 6-4 through 6-6, revenue requirements of two of the customer classes are shown against system revenue requirements. In comparing RR to assess risks, it is the variation from their means that is of interest and not their absolute values. Therefore, the RR of each class as well as of the whole system is shown as a percentage of its own mean to obtain dimensionless plots. Each point in the plots represents an endpoint and, therefore, shows revenue values that have equal probability for each

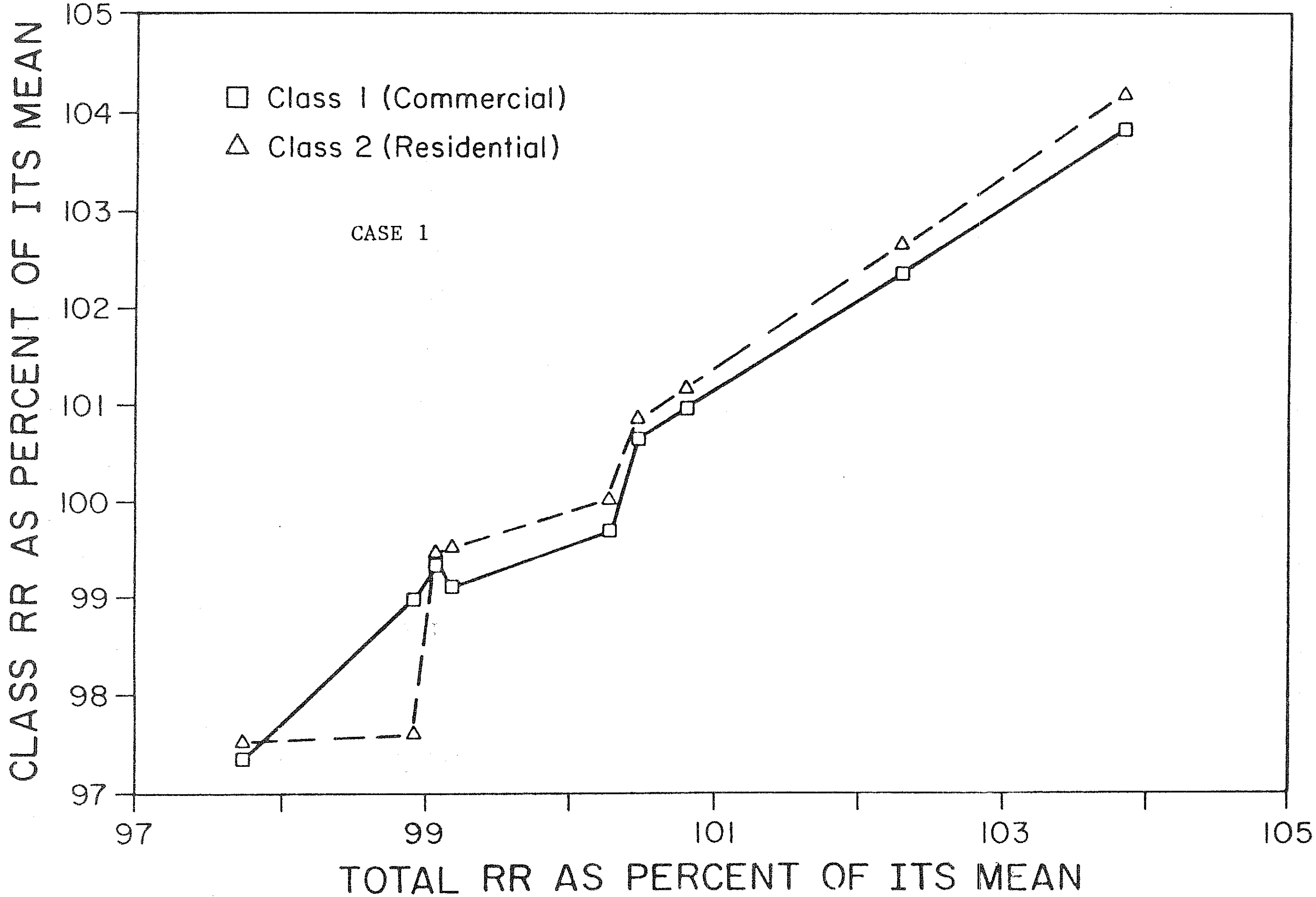


Fig. 6-4. Class 1 and Class 2 revenue requirements (RR) vs total system revenue requirements for case one

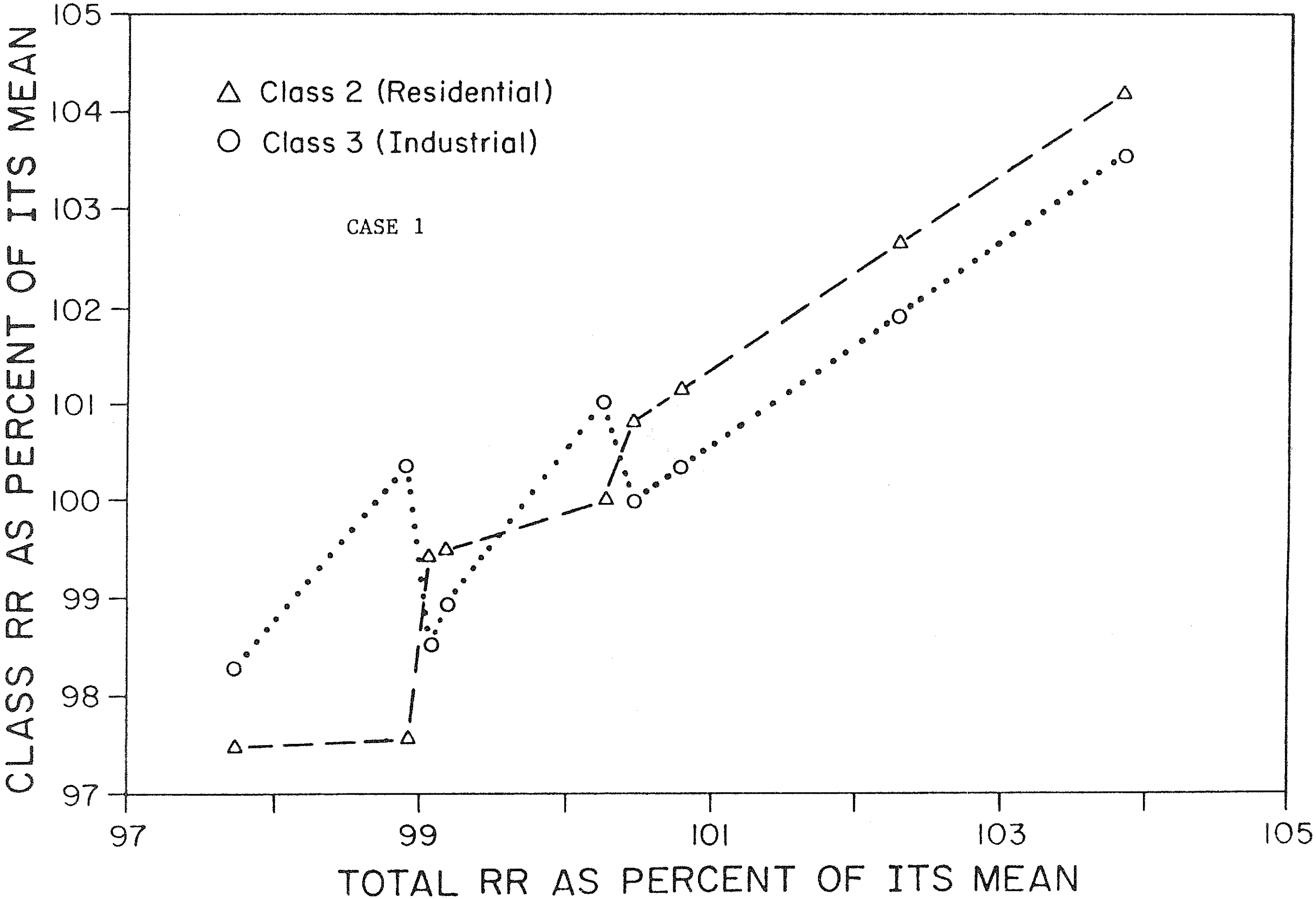


Fig. 6-5. Class 2 and Class 3 revenue requirements (RR) vs total system revenue requirements for case one

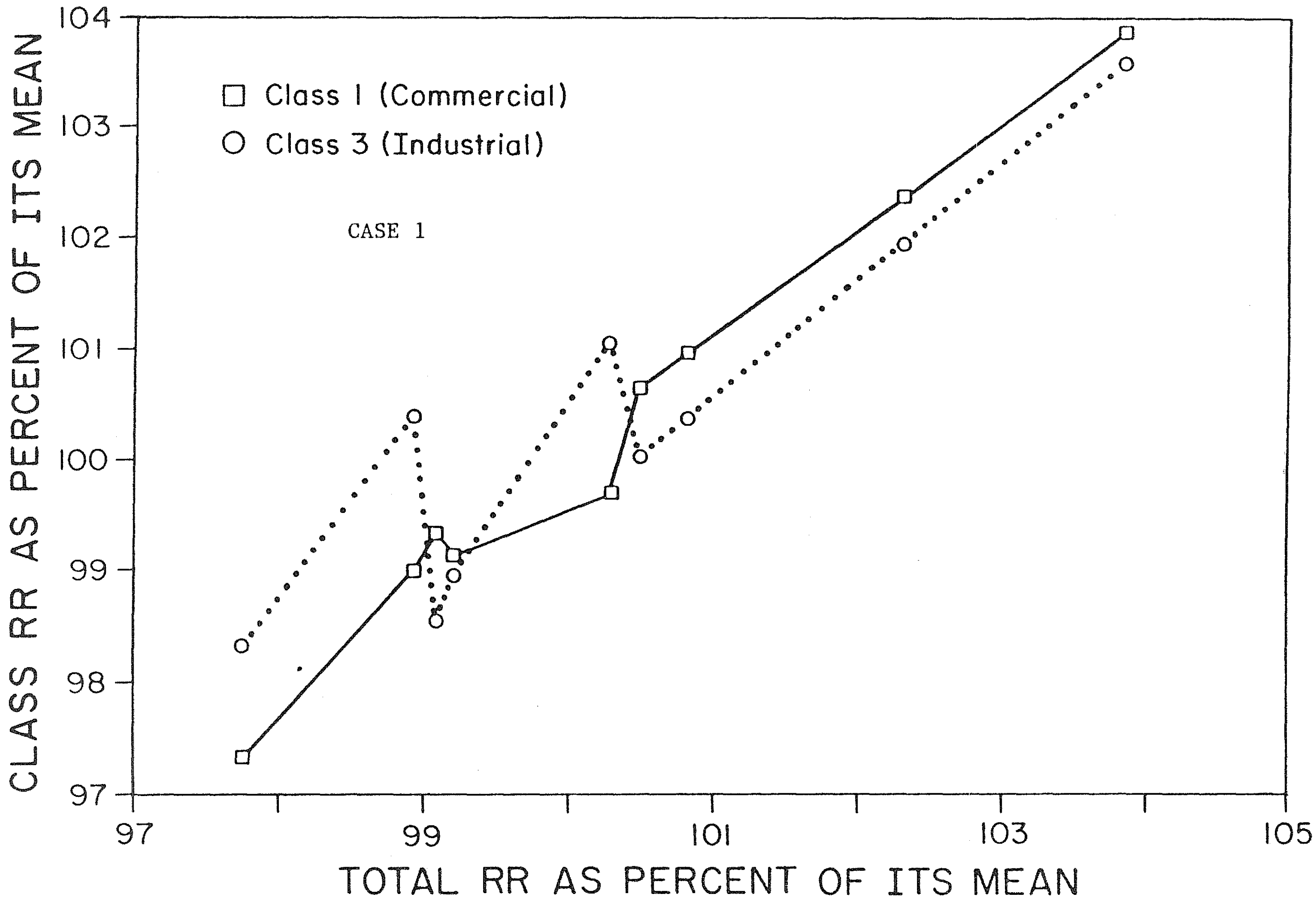


Fig. 6-6. Class 1 and Class 3 revenue requirements (RR) vs total system revenue requirements for case one

customer class. Figure 6-4 shows that class 1 (commercial) and class 2 (residential) revenue requirements generally show an increasing trend with increasing system revenue requirements. There is, however, a deviation from this behavior for system revenue requirements around 99.2 percent. The class 1 revenue requirement shows a slight drop around 99 percent of system revenue requirements. Class 2 RR shows a corresponding rise about the same point. At values above 99.2 percent of system RR, the two class RR track each other with class 2 RR staying slightly higher than class 1 RR. Figure 6-4 shows that at least at one point (around 99.2 percent) a rise in system RR is not evenly shared for the two customer classes. A similar effect is even more clearly shown in figures 6-5 and 6-6. In both of these figures, there are several points where a rise in system RR is accompanied by a drop in RR of one class and by a corresponding rise for another class. In figure 6-5 such an effect can be obtained around 99 percent and 100.5 percent of system RR. In addition, while class 1 and class 2 RR generally increase with increasing system RR (except for a slight drop in class 1 RR at about 99 percent of system RR), class 3 RR declines sharply at both 99 percent and 100.5 percent of system RR. The same observations are true for figure 6-6. From the above observations, it is clear that an increase in system RR may not always evenly distributed among all customer classes. While the above results may be specific to input data assumptions, the possibility of their occurrence is clearly demonstrated. We limited our analysis in this case to a single source of uncertainty, namely that of load growth. We also assume that the load growth rates and related uncertainties are the same for all classes. In a more complex case in which other sources of uncertainty are included and customer classes are considered to have different load growth rates, the above effect (the uneven sharing of RR among classes) may become even more accentuated.

Figures 6-7 through 6-9 show the cumulative probability distribution (CDF) of each class RR. Each ordinate in these figures represents the probability that the RR is equal to or lower than the corresponding abscissa. If one draws a vertical line through any abscissa, (figures 6-7 through 6-9), its intersection with the curve represents the probability that the RR is the indicated value or less. These probabilities can be interpreted as comparative measures of risk as they correspond to the same level of revenues. This is consistent with our earlier interpretation of

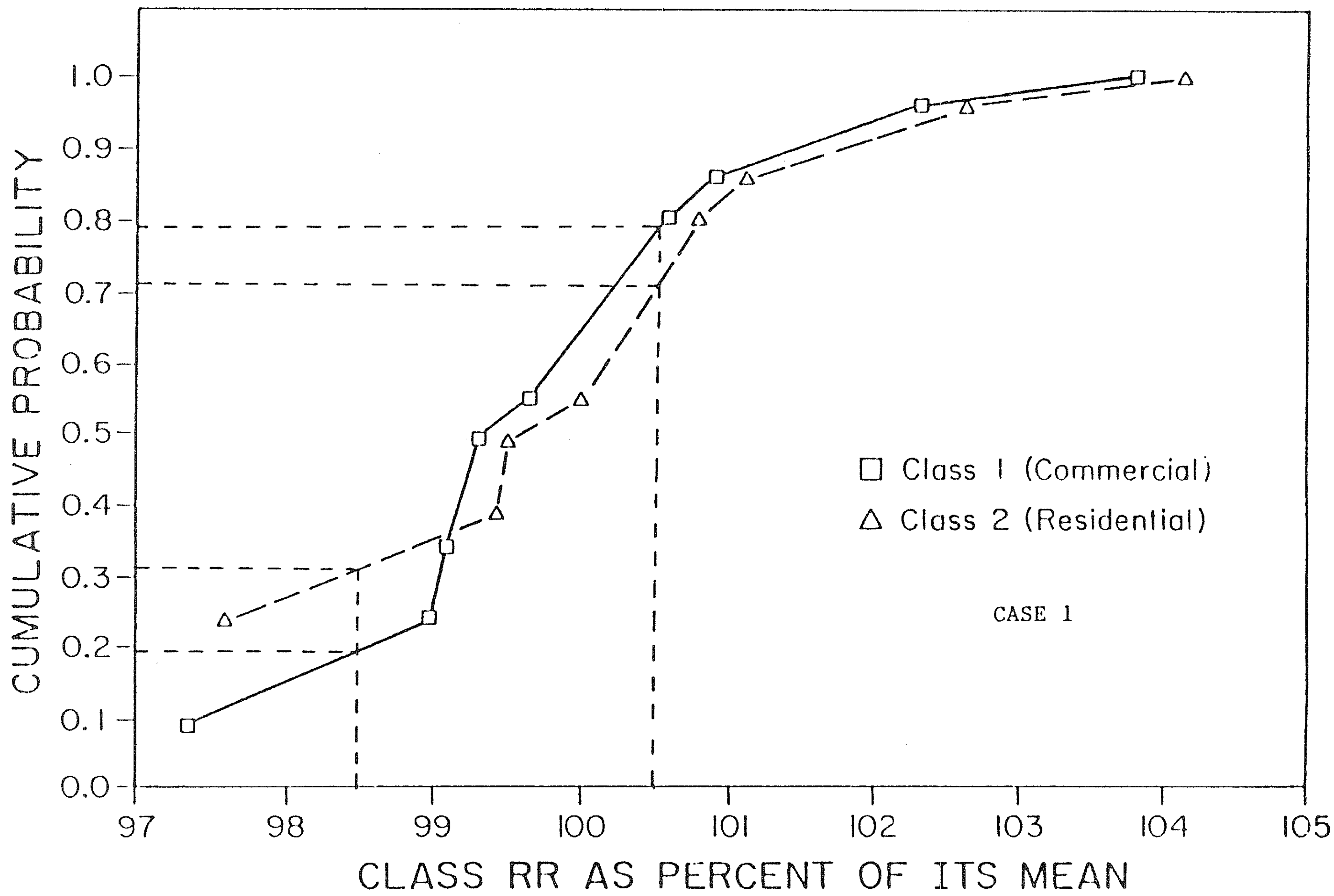


Fig. 6-7. Cumulative probability distribution function (cdf) of class 1 and class 2 revenue requirements (RR) for case one

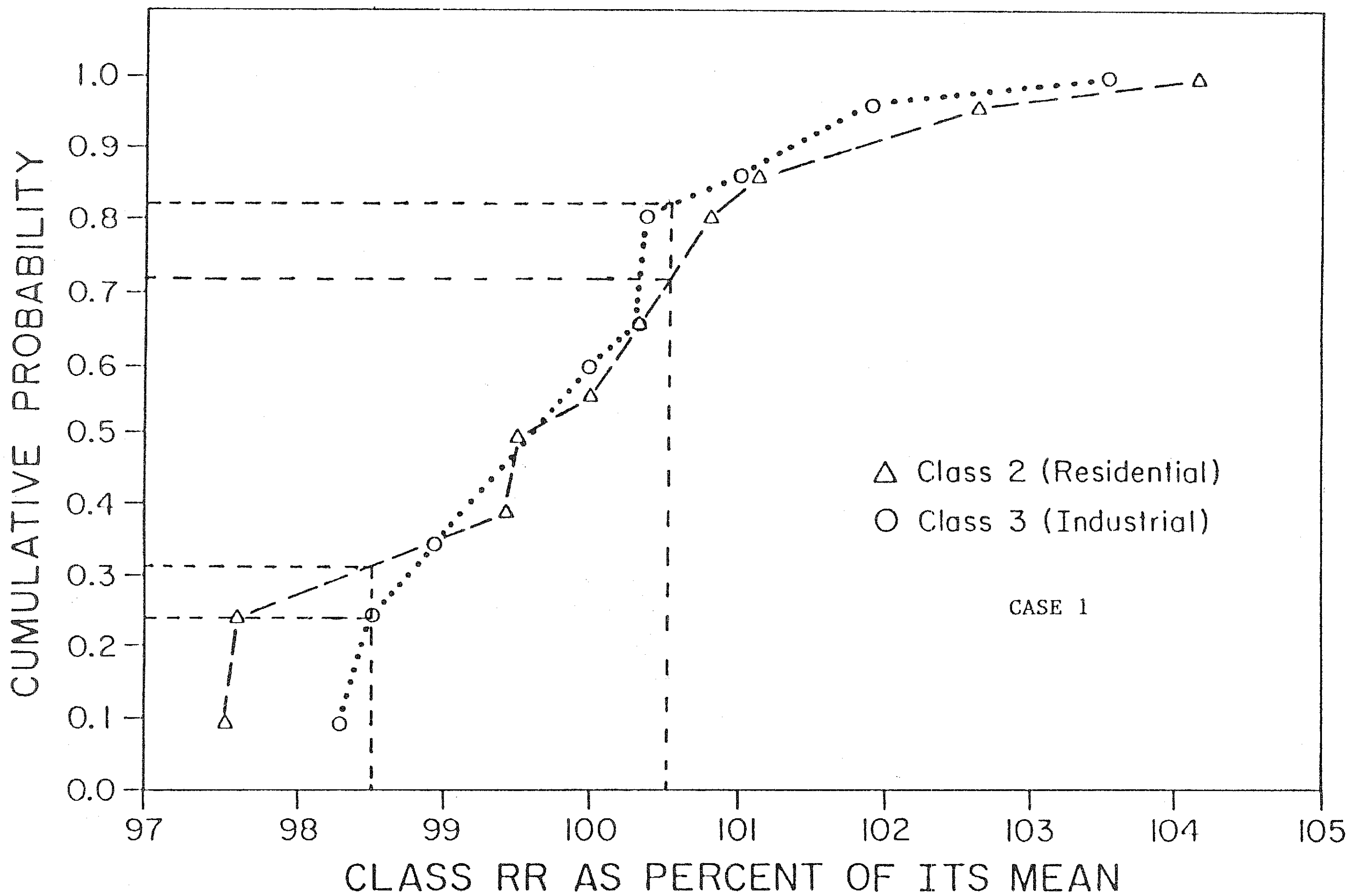


Fig. 6-8. Cumulative probability distribution function (cdf) of class 2 and class 3 revenue requirements (RR) for case one

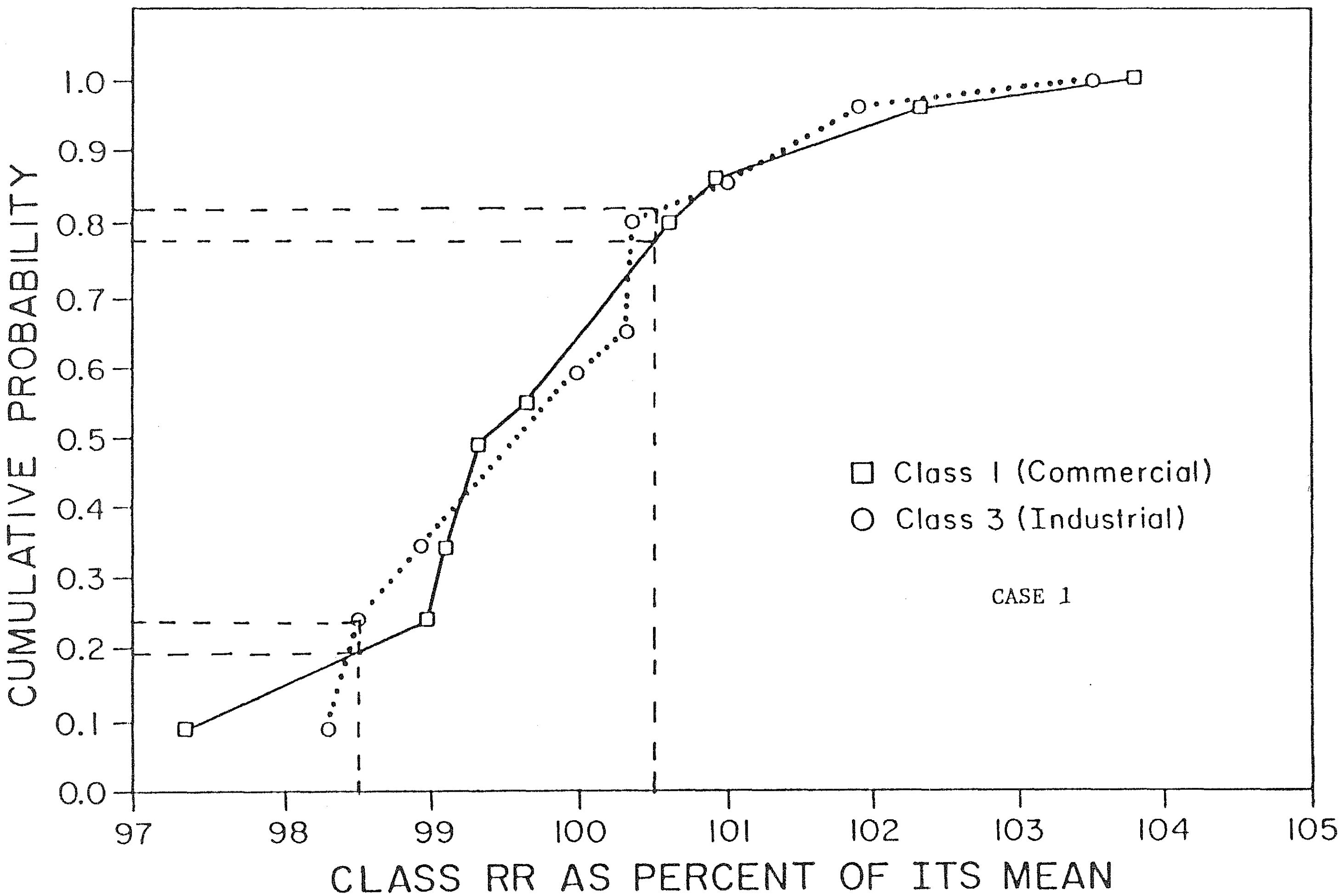


Fig. 6-9. Cumulative probability distribution function (cdf) of class 1 and class 3 revenue requirements (RR) for case one

probability distributions as risk profiles. It can be observed, from figures 6-7 through 6-9, that the risk is not evenly shared by all customer classes at all levels of RR[51], confirming our earlier observations.

The earlier analysis brings out two interesting conclusions. First, the increases in system revenue requirements may not be evenly shared among customer classes in some cases. In the illustrative example, the differences in risks may not be deemed very high. But in a general case, particularly when the effect of certain decisions on the customer classes is considered, these differences could be large. In particular, if the differences in the growth rates among the classes of customers were large, and if the anticipated growth rate for a particular class did not materialize, the other classes have to bear the risks associated with the plant construction justified on the basis of total system load growth. It is evident that if the relative share of revenue requirements decreases for one class, some other class has to take up the increased revenue burden. Also, the effect of a DSM program on different customer classes cannot be predicted with certainty. The introduction of a DSM program may lead to different load growth for different customer classes. A utility plan, based on the aggregate system load growth may not account for this effect, and may not distribute the revenue burden evenly among customer classes. This indicates a need to model the load growth rate of each customer class separately in least cost utility plans.

Second, relative risks, defined as the probability of equal levels of RR (when a level is defined as a percent of the mean), may not be shared evenly by all customer classes. We have considered only one source of uncertainty (load growth rates) and a relatively small time period (thirteen years) primarily to reduce the computational effort in using MIDAS. This has resulted in a narrow band of variation in RR. Therefore the PDFs of revenue requirements are relatively "peaky" and somewhat similar, and the total variation in RR as observed from figures 6-4 through 6-9 is only about 7 percent. The observed results, being dependent on the utility system studied and the subjective probabilities used in performing the analysis, could be different for other utilities and probability assumptions. Nevertheless, the results show that one can construct plausible scenarios where the risk associated with uncertain revenue burdens may not be shared evenly by all customer classes, given a particular cost-allocation method.

The above indicates that there may be a need to address the issue of equitable risk sharing for classes of consumers rather than viewing customers as one entity. One could possibly argue for a regulatory position that favors unequal risk-sharing among customer classes. Regardless of what regulatory position one favors on this issue, an investigation of risks to different classes of customer in the least-cost planning process merits consideration.

Case Two

In this case, customer classes 1 and 2 (commercial and residential) are assumed to have medium-load growth rates in the period 1990-2000 (see figure 6-3). They are 2 percent in 1990-93, and 3 percent in 1994-2000. It is assumed that the high (3 percent in 1990-1993 and 5 percent in 1994-2000) and the low (1 percent in 1990-2000) system load growth rates are caused entirely by class 3 (industrial). In other words, class 3 is considered relatively more volatile and entirely responsible for possible uncertainties in system load growth rates. This might be an extreme assumption, but our objective is to see how the volatility in the load growth of a particular class affected the sharing of the revenue burden. This is also a simple demonstration of the effect of modelling the load growth rate of each class separately in utility planning.

Discussion of Results

The results for this case are shown in table 6-2. The table shows that the RR values for each endpoint as well as the mean RR are not significantly different from those of case one. The variation in RR for the whole system as well as class 1 is small and is comparable to that observed in case one. There is, however, a much larger variation observed in class 3 RR, presumably caused by assigning the entire responsibility in load growth variation to this class. Also, class 2 RR appears to have an even smaller variation than observed earlier. The last two observations are also consistent with a larger standard deviation (870 million dollars) for class 3 and a smaller standard deviation for class 2 (167 million dollars) than those observed for case one (240 million dollars for class 3 and 328 million

TABLE 6-2

REVENUE REQUIREMENTS (RR) FOR CASE TWO

Endpoint	System RR (M$)	Class 1 RR (M$)	Class 2 RR (M$)	Class 3 RR (M$)	Probability
1	49,358	12,162	18,506	18,690	0.04
2	47,141	12,023	18,223	16,894	0.10
3	47,657	12,586	18,915	16,156	0.06
4	48,623	12,110	18,422	18,090	0.10
5	47,751	12,326	18,606	16,819	0.25
6	47,014	12,594	18,578	15,841	0.15
7	47,907	12,052	18,282	17,573	0.06
8	47,086	12,301	18,512	16,273	0.15
9	46,447	12,517	18,713	15,216	0.09
Mean	47,518	12,320	18,536	16,661	
Standard Deviation	681	194	167	870	

Source: Authors' calculations.

dollars for class 2, see table 6-1). Ideally, there should have been no variation (zero standard deviation) in class 1 and class 2 RR as these classes are assumed to experience no uncertainty in load growth rates. Yet, these classes experience uncertainties in RR due to uncertainties associated with total RR. It appears that even when a single class is responsible for uncertainties in load growth, other classes still have to bear a part of the resulting risk. As in case one, we study the correlation among class RR and the probability distributions of class RR to evaluate relative risks among customer classes.

Figure 6-10 shows the class RR as a function of system RR. Figure 6-10 shows that class 1 (commercial) and class 2 (residential) generally follow each other as in the previous case (figure 6-4). However, while there was a

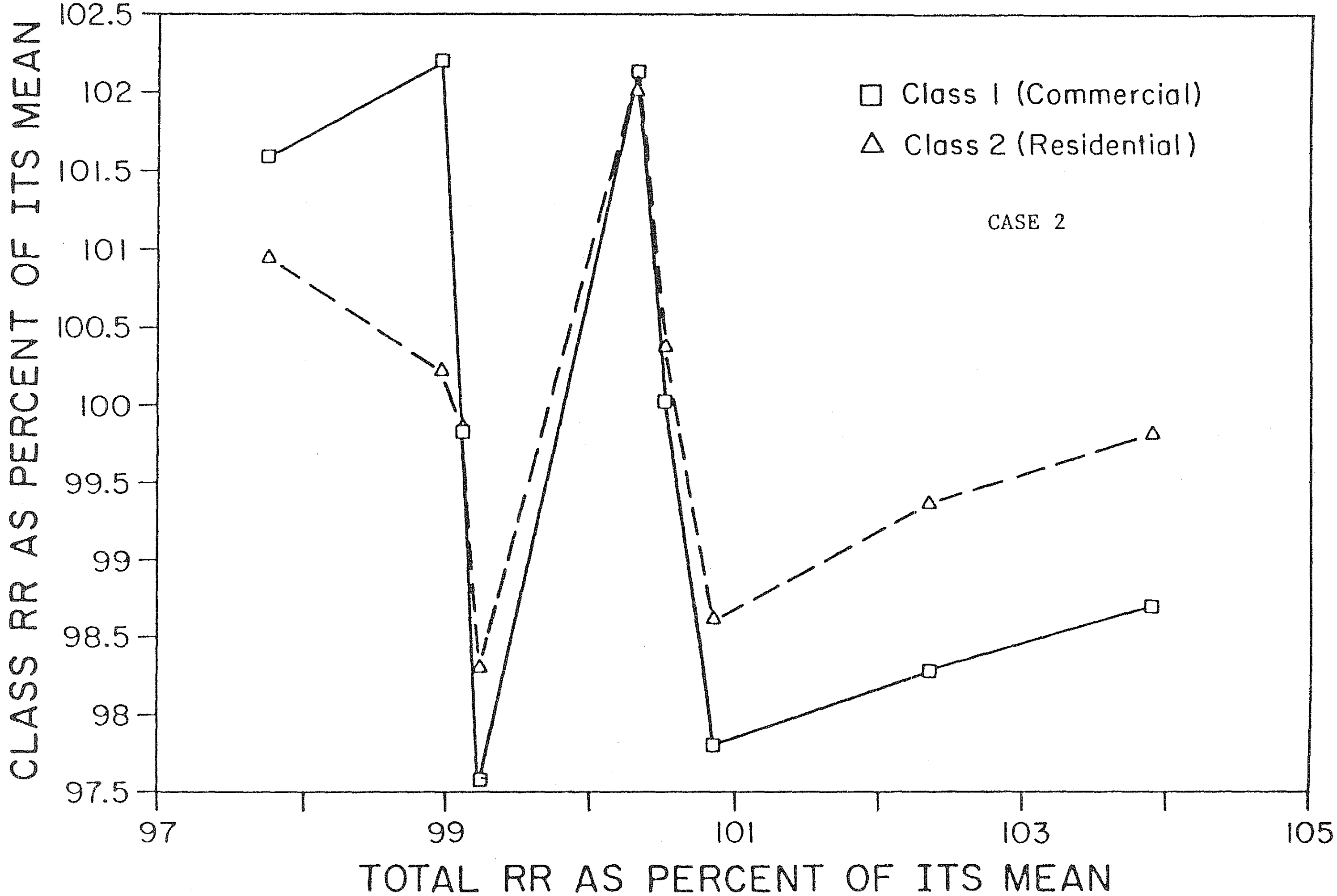


Fig. 6-10. Class 1 and class 2 revenue requirements (RR) vs total system revenue requirements for case two

general increase in class RR with increasing system RR in figure 6-4, a much wider fluctuation is observed in figure 6-10. An explanation can be found by observing figures 6-11 and 6-12. In both of these figures, there are sharp increases and decreases in class 3 (industrial) revenue requirements, which causes the opposite effect in either class 1 or class 2 RR. It can also be seen that class 3 RR does not follow either class 1 or class 2 RR. In other words, a decrease in class 3 RR is accompanied by an increase in either class 1 or class 2 RR and vice versa. These observations are similar to what we observed in the previous case as anomalies with respect to the sharing of revenue burden among customer classes. In case one, we observe this uneven sharing of the revenue burden among customer classes when their load growth rates are assumed to be equal. We conclude that this anomaly may be caused primarily by the use of a particular cost-allocation method. The introduction of differential load growth rates among customer classes is expected to exaggerate this anomaly. We intended to identify and quantify the magnitude of this effect. In the present case, the assumption of one particular class being entirely responsible for the uncertainty in load growth rates appears to exaggerate this anomaly. Observe that the uncertainty band for class 3 RR has been broadened from about 7 percent to about 21 percent, as seen by comparing the ordinates of figures 6-5 and 6-11. This fact and the shifting of the uncertainty in RR from class 3 to the other two classes (as discussed in an earlier part of this section) may have contributed toward sharpening this anomaly.

Finally, figures 6-13 through 6-15 show the cumulative probabilities for class 3 RR. It shows the same effects that were observed in figures 6-7 through 6-9. However, the variation in class 3 RR (caused by assigning the shifts in load growth rates entirely to this class) is wider. While the RR shown in figures 6-7 through 6-9 varied between 97 percent and 105 percent, it varies between 91 percent and 113 percent for class 3 (compare ordinates of figures 6-5 and 6-11). The variation in RR for classes 1 and 2 remains roughly the same in both cases. Because of the wider variation in RR of class 3 than in the previous case, the sharing of risk (interpreted as comparative probabilities for the same level of RR) between this and the other two classes is less evenly distributed (figures 6-14 and 6-15). For example, the probability that the RR is 100.5 percent of mean or less is 0.92 for class 2, while it is 0.66 for class 3. Note that the difference in

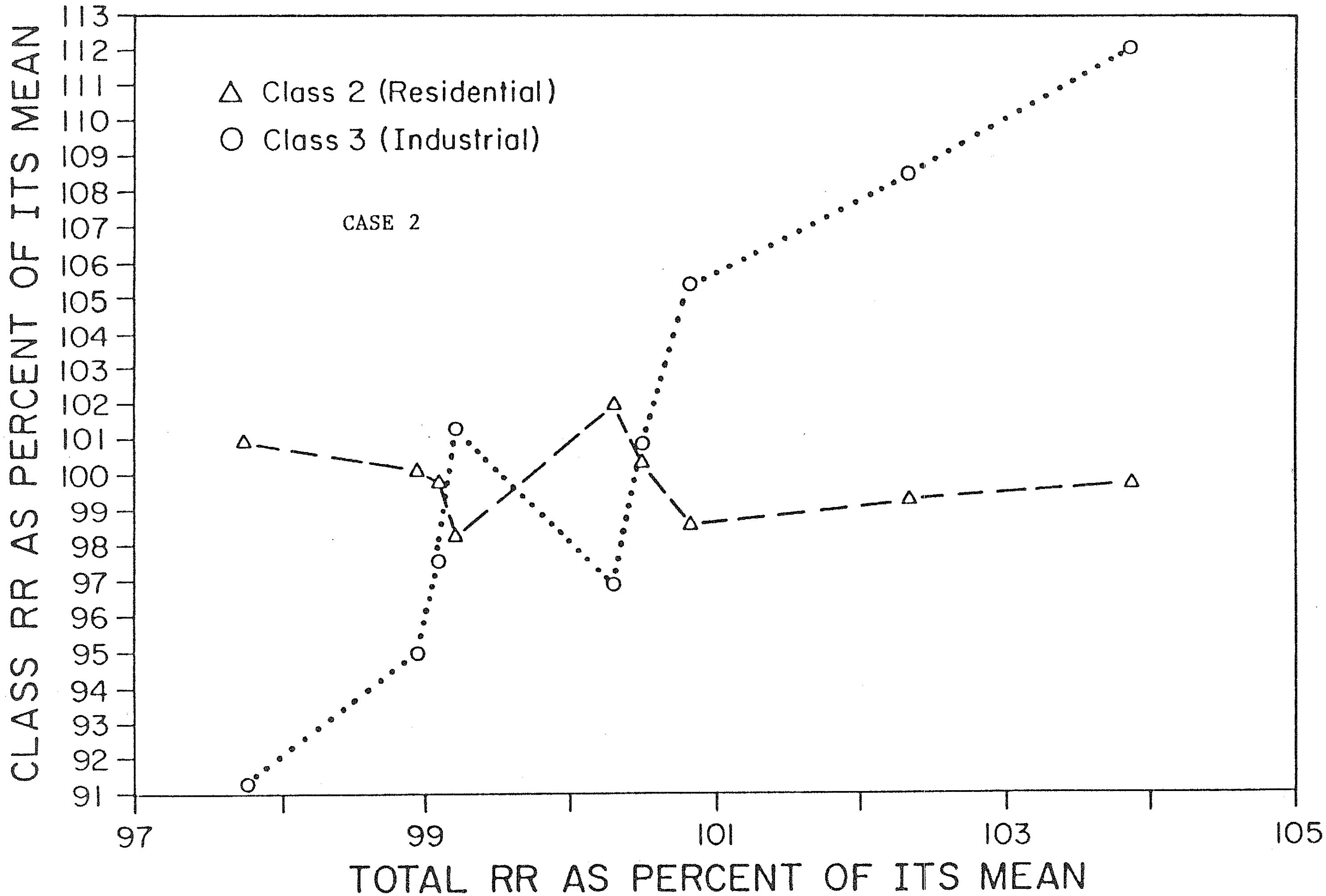


Fig. 6-11. Class 2 and class 3 revenue requirements (RR) vs total system revenue requirements for case two

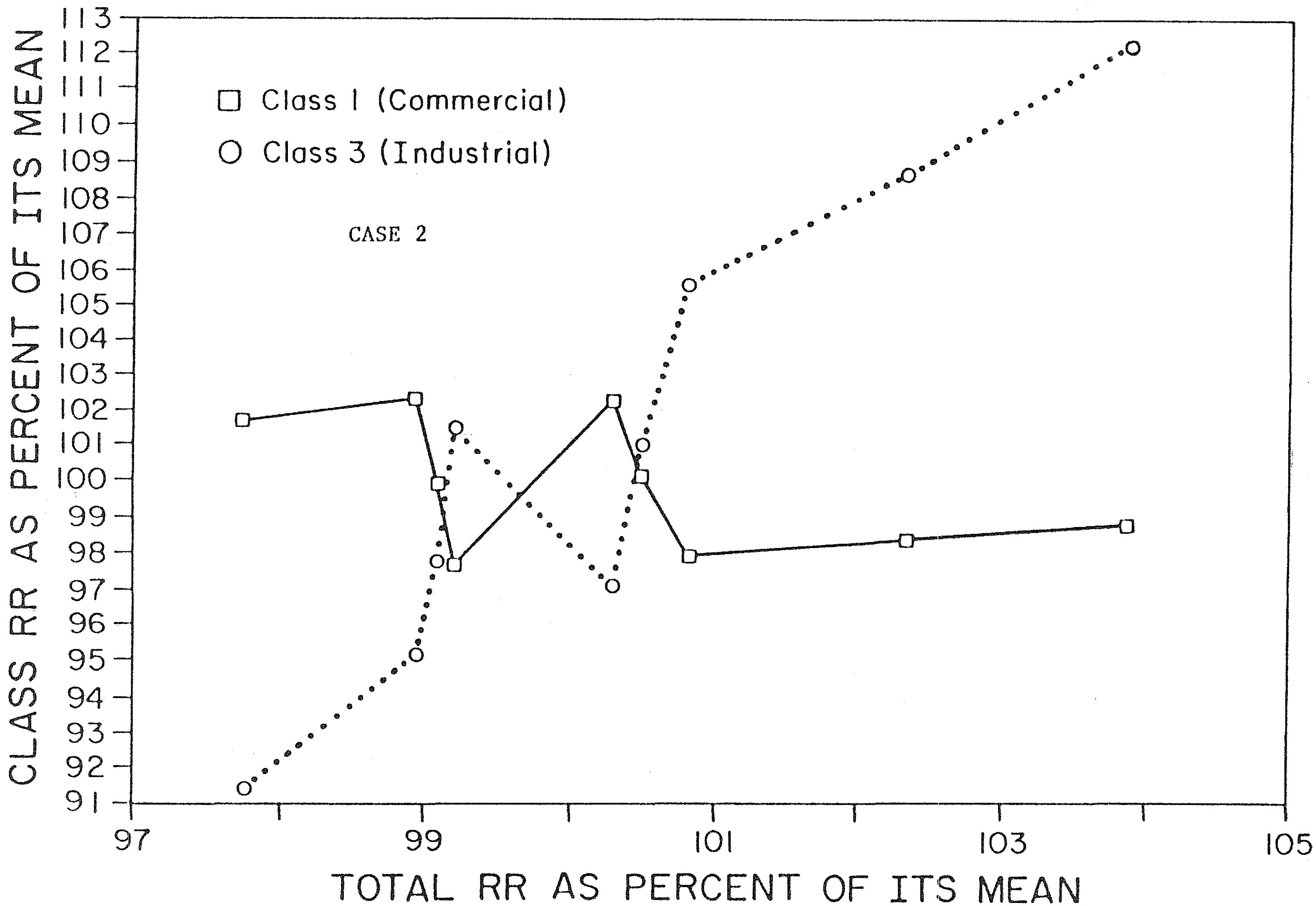


Fig. 6-12. Class 1 and class 3 revenue requirements (RR) vs total system revenue requirements for case two

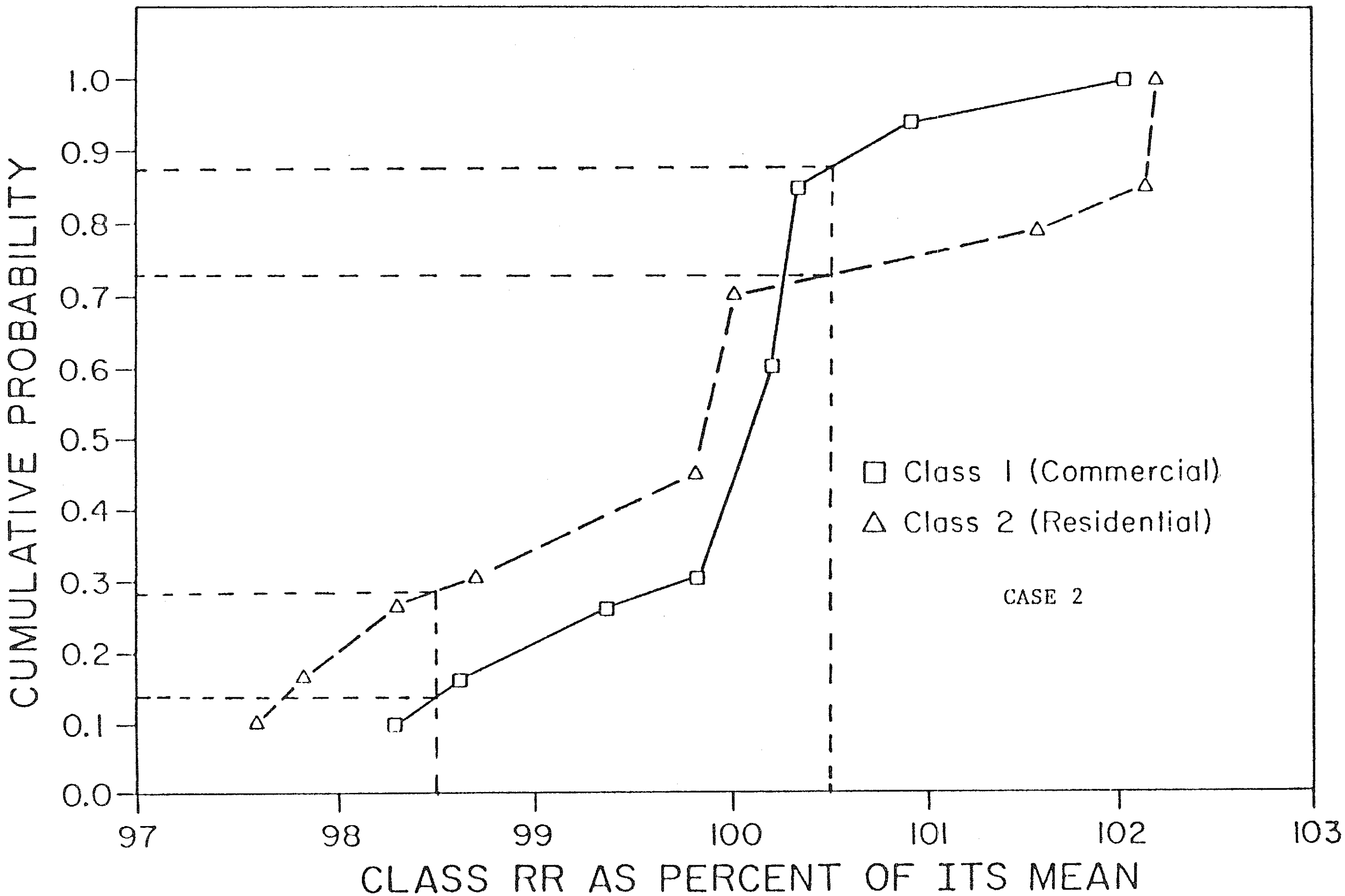


Fig. 6-13. Cumulative probability distribution function (cdf) of class 1 and class 2 revenue requirements (RR) for case two

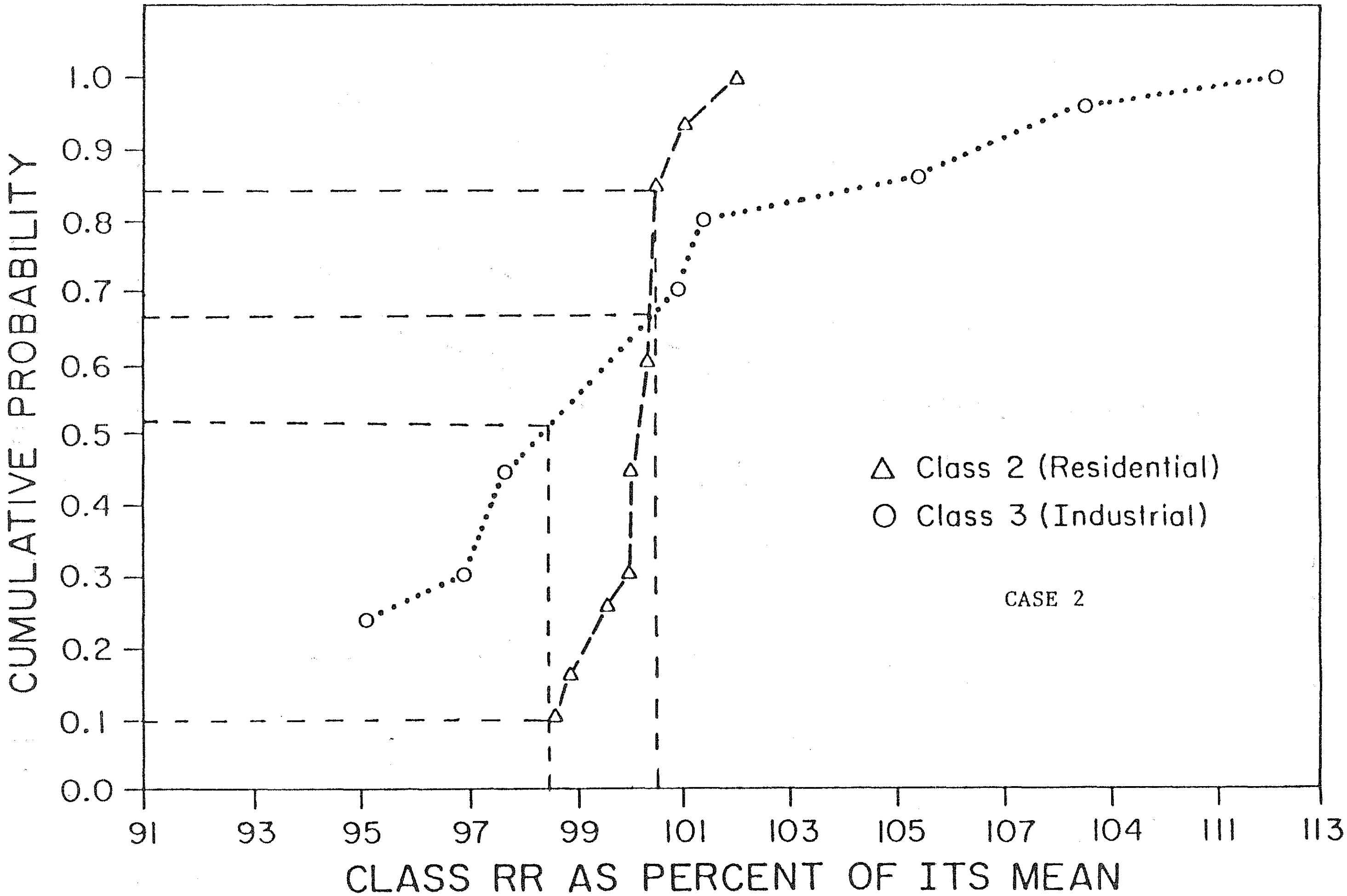


Fig. 6-14. Cumulative probability distribution function (cdf) of class 2 and class 3 revenue requirements (RR) for case two

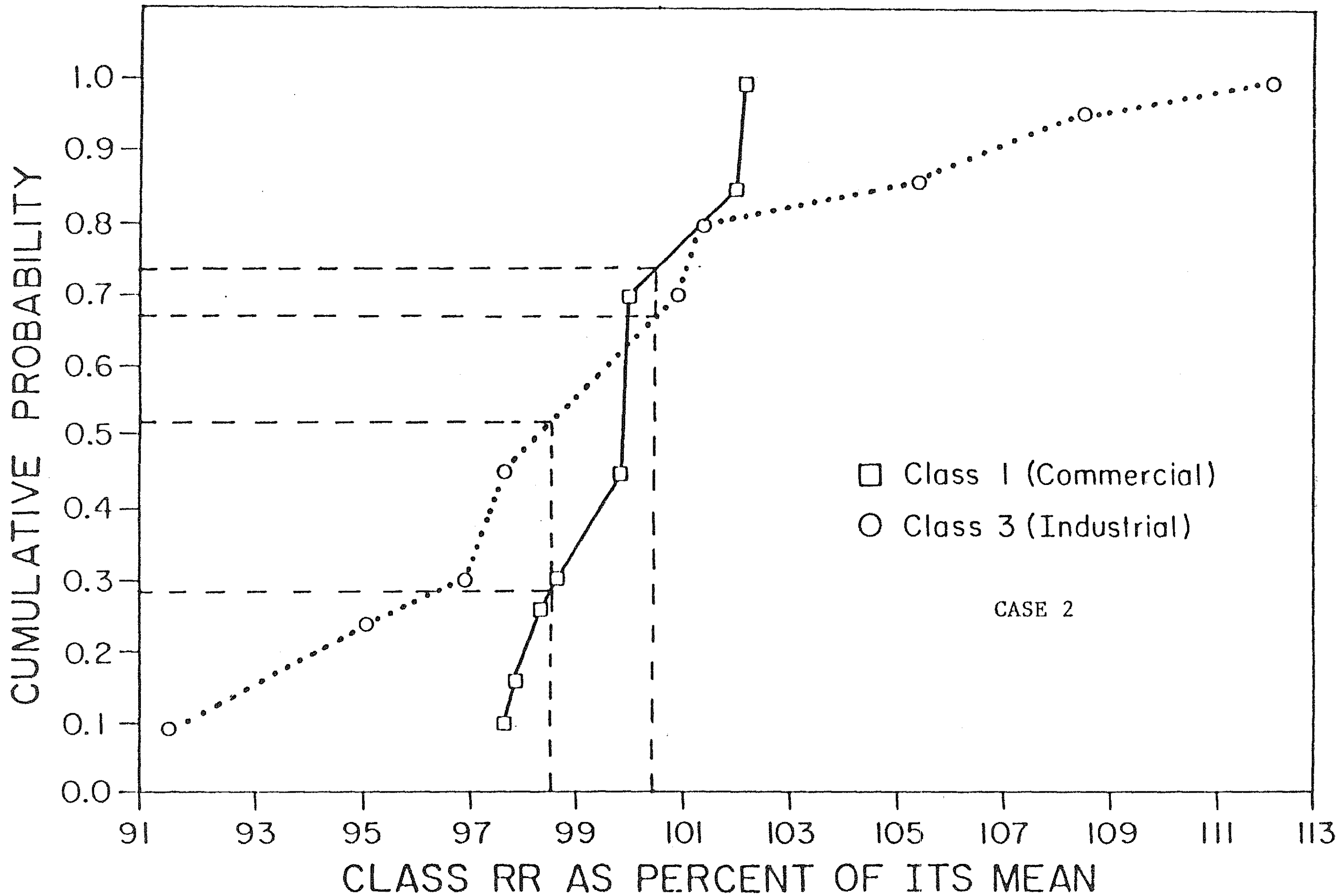


Fig. 6-15. Cumulative probability distribution function (cdf) of class 1 and class 3 revenue requirements (RR) for case two

probabilities varies with the class RR. At a RR of about 100 percent of the mean, this difference (figure 6-15) is zero. Analysis of case two strengthens our conclusions based on analysis of case one. When one class is responsible for uncertainties in load growth, the other classes would still share this risk if traditional cost allocation methods are followed. This is borne out more clearly by the analysis in case two. We also observe that there is uneven sharing of the revenue burden among classes at different levels of total system RR. This anomaly is further exaggerated in case two.

Summary

In this chapter, we examined the sharing of risks among customer classes and how it is affected by the use of traditional ratemaking principles. We presented two cases. Case one examines how the use of a particular cost allocation method affects the sharing of the revenue burden and related risks among customer classes. In case two, we analyze how the sharing of risks is affected by differences in load growth rates among customer classes. The analysis is for a simple illustrative scenario and considered only one uncertainty, that of load growth. As a result, we observe uncertainties in RR that are relatively small. Had other sources of uncertainties been considered, we would have expected significantly larger uncertainties in RR. In spite of these relatively small uncertainties in observed RR, we were able to analyze the distribution of relative risks among customer classes by comparing their probability distributions. We find that the revenue burden and the relative risks may not always be shared evenly among customer classes.

We also observed that the uneven sharing of risk might be a consequence of the use of a particular cost-allocation method. If a utility plan is designed to achieve a given objective for the entire customer population viewed as a single group, and the allocation of costs among customer classes is treated as a completely separate task, this may lead to uneven and perhaps inequitable sharing of risks among customer classes. Further, traditional cost-allocation methods ignore differences in load growth rates among customer classes and base their analyses on the system load growth rate. Such differences in load growth rates may be caused not only by inherent differences in consumption behavior among customer classes but also by the potentially different responses to DSM programs. The cost and related risk of either a construction program or a DSM program may not be evenly distributed among customer classes if the utility plan and the ratemaking method are based on the aggregate system load. There is, therefore, a need to model the load growth rates of different customer classes separately and build this into the utility planning and the ratemaking processes.

Based on the above, it is our opinion that the planning process cannot exclude the ratemaking process. The relative risks of different customer classes have to be examined in addition to the risk to the investors or the risk to customers viewed as a whole. Some might argue that the risks of different classes need not be the same. Irrespective of what interpretation of equity one favors in regard to sharing of ratepayer risks, different ratemaking methods must be examined along with the planning process to obtain equitable risks. Therefore, the planning process and the ratemaking process should be considered inexorably intertwined if one wishes to address the issue of equitable risk sharing among customer classes. This suggests that the utility planning models should not be run in isolation from the ratemaking models. This may require that sophisticated ratemaking models be built into planning models to examine the risk profiles of different customer classes. Further, the load growths of different customer classes may have to be modelled separately and integrated with planning and ratemaking models. Most of the currently available load forecasting models produce separate forecasts for each customer class and utilization of this resource merits consideration in building integrated least cost plans.

In our study, we have considered only one source of uncertainty (that of load growth) and a particular cost-allocation method (a simplified embedded cost-of-service method). A more comprehensive examination of ratemaking principles in regard to how they effect sharing of ratepayer risks requires analyses of different cost-allocation methods, other sources of uncertainty, and the impact of different utility decisions. Such analyses constitute potential directions for future research to address issues raised in this chapter.

CHAPTER 7

CONCLUSIONS

Utility resource expansion planning entails decision making under uncertainties. Several mathematical models to aid the decision maker are available. Models employing decision tree analysis are popular among utility planners and state commissions.

The planning process should include four major aspects: demand side options, coordination with neighboring utilities, cost incurred by ratepayers, and the inclusion of non-energy related goals. Chapter 2 shows that these considerations introduce certain complexities. Chapter 2 also discusses certain common misconceptions about least cost planning and suggestions to resolve these complexities. In addition, a way of establishing internal consistency in the data input to these complex planning models is also suggested. Internal consistency checks are site specific and may, therefore, vary from one utility to another.

The work reported in the subsequent chapters examines some major objectives in utility resource expansion plans using models based on decision tree analysis. Uncertainties regarding the outcome of future events are measured by a properly chosen objective. There is no general agreement on the choice of an appropriate objective. The choice is guided by one's perception of risks and the conditions prevailing in the power system. Therefore, there could be a considerable amount of discussion regarding the pros and cons of choosing a particular objective.

It was not the intent of the analyses to identify the optimum (or the least cost) resource plan for any utility for any given set of data and uncertainties. Rather, the intent was to examine the choice of different objectives in respect of the decisions to which they lead. In addition, our goal was to establish a ranking of uncertainties in regard to their degree of importance.

Certain objectives had to be chosen for the establishment of such a ranking. It is evident that the objectives of minimizing total cost and that of minimizing rates would be identical if there were to be no load management. The analyses of chapters 3 to 5 quantify the difference between these two objectives in the light of DSM programs. An additional objective used was that of minimizing disallowed capacity costs.

In order to conduct the analyses, certain assumptions were made. One might assert that other assumptions might have led to different results. While we agree with such assertions, we point out that the assumptions made in the study are not critical to the concepts that the report intends to examine. For instance, the addition of a 400 MW coal plant and a 100 MW combustion turbine when the reserve margin falls below 20% has been modelled in the studies. One could make different assumptions or set up more complex decisions for the capacity additions. Then, one might obtain results different from these. The objective of the minimization of cost may not conflict with that of minimizing disallowed capacity costs. Nevertheless, the conclusion that planners have to examine resource expansion alternatives obtained by the objectives of minimizing disallowed capacity costs, rates, number of decisions that change, and total costs is substantiated by our study.

In terms of the sensitivity of the objectives to uncertainties, it is found that the variance of the cost and rates objectives are most affected by the uncertainties in fuel prices. However, from the perspective of long range planning measured in terms of the number of decisions that change, demand uncertainties matter the most. In regard to the concerns of the investor, the minimization of disallowed capacity cost was used as an objective.

The report has examined one other aspect, the risks to customer classes. In a planning exercise, the system load is generally viewed as a whole. The analysis in chapter 6 shows that by representing the loads of individual classes (commercial, industrial and residential), the risk profiles for each class can be obtained. One could then examine the cost allocation procedure and the ratemaking principles vis a vis the risk profiles. Ratemaking principles could be examined to fairly distribute the risk among the three classes. This indicates that the ratemaking procedure is intertwined with that of resource planning.

In the examples shown in chapter 6, we were constrained by the fact that the spread in the revenue requirement (RR) for the various scenarios dictated by the chance causes was not large. In a more realistic situation, one would have a large decision tree with different load growth scenarios and with different penetration of DSM programs for the customer classes. In such a situation, the spread in the RR would be larger than those obtained in our simple and expedient examples. Nevertheless, our theses that the relative risks to the classes have to be compared by modelling them separately and that the cost allocation methods may need to be adjusted to obtain equitable risks, are well supported by our examples.

APPENDIX

MIDAS DATA BASE DESCRIPTION

This appendix describes briefly the two sets of data bases used in running MIDAS and the assumptions taken to arrive at them. It also explains the decision tree used to analyze the two systems described.

The decision tree created for the MIDAS test run has six nodes--four of them being decision nodes and two chance nodes. The first decision node is EFFORT put in promoting the DSMs with two branches--high effort and low effort. The second decision node is the supply side option selected in 1987--to build a new coal plant and a combustion turbine or not. The third node is a chance node concerning load growth. It has three branches--high load (or low response to DSMs, expected load (or expected response) and low load (or high response). The same three nodes are repeated for decisions four years later (1991), yielding 144 endpoints for the decision tree. The remainder of this appendix details the assumptions behind the construction of this tree.

The model is run for twenty years. Capacity expansion decisions in 1987 and 1991 are represented as explicit decision nodes. For capacity decision in the period 2003-2006, MIDAS does automatic capacity expansion to maintain a reserve margin of 20 percent over the peak demand. The units used for this capacity expansion are 500 megawatt coal, 50 megawatt Combustion Turbine units. Also there is option for MIDAS to automatically buy purchased power from other utilities at the rate of $200 a megawatt-hour (20 cents a kilowatt-hour).

Two systems, representative of a Northeastern and a Midwestern United States utility, have been modeled. They are known as utility A and utility B.

Generating Capacity Data

The total system capacity in 1987 is 3,362 megawatts for utility A and 5,827 megawatts for utility B, with a reserve margin of 38.24 percent and

27.25 percent respectively. The peak load for the two utilities is 2,432 and 4,579 megawatts, the annual demand being 11,925.3 and 29,710.1 gigawatt-hour. The capacities already available in the systems are listed below in table A-1.[34,35,36] The financial data for these plants and for the utilities as a whole has been taken from EIA documents.[34,35] The net plant value is 2,108.029 and 7,239.741 million dollars respectively.

TABLE A-1

LIST OF EXISTING CAPACITY INCLUDED IN THE MODEL

Type	Capacity, MW	
	Utility A	Utility B
nuclear	745	850
steam[1]	1,972	4,813
gas/oil	245	164
purchased power	400	-

[1]The steam capacity is oil/gas fired in case of Utility A and coal fired for Utility B.

The coal plant additions being modeled as explicit decision nodes are a 500 megawatt plant in 1987 and two 500 megawatt plants in 1991. For each 500 megawatt coal plant, a 100 megawatt unit of Combustion Turbine is also installed. The data for these plants has been taken from the EPRI Technical Assessment Guide[37] and utility reports. The parameters considered for the plants are given below in table A-2.

TABLE A-2

NEW COAL PLANT PARAMETERS

Type of Plant	Coal Steam	Combustion Turbine
Capacity, MW	500	100
Number of Units	1	1
Forced outage rate	11%	4.3%
Maintenance rate	9%	5%
Heat rate, Btu/KWh	10060	13800
Fixed Cost, $/KW/year	24	0.4
Variable costs, $K/MWh	2.3	3
Capital cost, $mm	660	29.5

Load Data

The three energy (KWh) load growth rates considered after 1987 are 3 percent for high, 2 percent for expected and 1 percent for low load growth rates under a low DSM effort. For high DSM effort, these rates become 2.5 percent, 1.5 percent and 0.5 percent respectively. The peak load (MWh) growths are 0.2 percent lower than the corresponding energy growth rates for low DSM effort and 0.4 percent lower for high DSM effort. These rates are summarized in table A-3. After 1991, the three rates depend upon decisions taken in 1991 as well as 1987. The load growth rates after 1991 are detailed in tables A-4 to A-6. below.

TABLE A-3

LOAD GROWTH RATES FOR 1988-1991 IN PERCENT

DSM Effort	Load growth Rates for energy (peak), High	Expected	Low
High	2.5(2.1)	1.5(1.1)	1.5(0.1)
Low	3.0(2.8)	2.0(1.8)	1.0(0.8)

TABLE A-4

LOAD GROWTH RATES FOR 1992-1995 IN PERCENT

Load Growth	Energy (peak) growth rates for different DSM decisions, Decision for DSM promotional effort taken in 1987/1991 High/High	High/Low	Low/High	Low/Low
High	2.5((2.1)	3.0(2.8)	2.5(2.1)	3.0(2.8)
Expected	1.5(1.1)	2.0(1.8)	1.5(1.1)	2.0(1.8)
Low	0.5(0.1)	1.0(0.8)	0.5(0.1)	1.0(0.8)

TABLE A-5

LOAD GROWTH RATES FOR 1996-1999 IN PERCENT

Load Growth	Energy (peak) growth rates for different DSM decisions, Decision for DSM promotional effort taken in 1987/1991 High/High	High/low	Low High	Low/Low
High	3.0(2.8)	3.5(3.5)	2.5(2.1)	3.0(2.8)
Expected	2.0(1.8)	2.5(2.5)	1.5(1.1)	2.0(1.8)
Low	1.0(0.8)	1.5(1.5)	0.5(0.1)	1.0(0.8)

TABLE A-6

LOAD GROWTH RATES FOR 2000 ONWARDS IN PERCENT

Load Growth	Energy(Peak) Growth Rates
High	3.0(2.8)
Expected	2.0(1.8)
Low	1.0(0.8)

The probability of high load growth is 0.25, for expected load growth it is 0.50, and for low 0.25. These probabilities are same for both the stages. The mean growth rates and variances for energy and peak growth rates are given in table A-7 below.

TABLE A-7

MEANS AND VARIANCES FOR DIFFERENT DSM DECISIONS

	Percent Energy Growth Rate		Percent Growth Rate of Peak	
	Mean	Variance	Mean	Variance
High DSM Effort	1.5	0.707	1.1	0.707
Low DSM Effort	2.0	0.707	1.8	0.707

The demand growth rate for ECAR (East Central Area Reliability) region is projected to be about 1.7 percent, and for NPCC (Northeast Power Coordinating Council) about 2.0 percent.[38] With higher effort for promoting DSM's this growth rate can be reduced by up to 0.7 percent (this figure is based on the various results of utility programs reported in the EPRI Compendium of Utility Sponsored Rebate Programs).[39] The peak reductions and the rebates to achieve this are detailed in figure A-1.

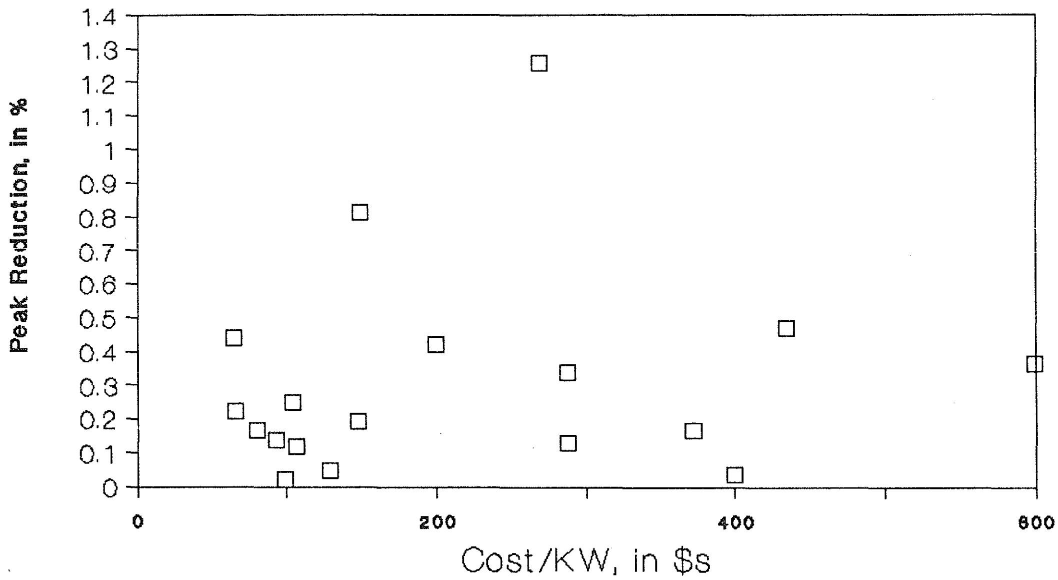


Figure A-1. Peak Reduction vs. Cost of Rebates reported by different utilities

The DSM costs in the MIDAS expenses file have been estimated based on the data given in the EPRI Compendium of Utility Sponsored Rebate Programs,[39] also shown in table A-8 and figure A-2. The cost of DSMs per kilowatt of peak reduction is taken as about $200 a kilowatt.

TABLE A-8

PEAK REDUCTION AND REBATE PROGRAM COSTS

Utilities	Cost/KW,$	Percent Peak Reduction
Arizona PSC	190	0.43
Aust TX Resource Mgmt Group	260	1.38
City Wl, L&P, Springfield IL	130	0.06
Gulf Power Co	100	0.01
Gulf States Util	400	0.02
Jersey Cent P&L	375	0.24
Metro Edison	100	0.18
Nevada Power	275	0.38
Okla Gas & Elec	140	0.19
Otter Tail Power	90	0.22
Pacific Gas & Elec	600	0.4
Penn Elec Co	115	0.25
Penn Power & Light	110	0.13
S Cal Edison	420	0.53
Texas Util Elec Co	125	0.88
Verdigris Valley Elec Co	280	0.14
W Texas Util Co	84	0.49

Source: Electric Power Research Institute, A Compendium of Utility-Sponsored Energy Efficiency Rebate Programs (Palo Alto, California: EPRI, December 1987).

ENDNOTES

1. National Association of Regulatory Utility Commissioners, *Least-Cost Utility Planning Handbook for Public Utility Commissioners* (Washington, D.C.: National Association of Regulatory Utility Commissioners, October 1988).

2. Illinois Commerce Commission, *Least Cost Energy Planning*, 86-NOI-2 Final Report, May 1987.

3. Eric C. Woychik, "Toward a Standard Practice Approach to Integrated Least-Cost Utility Planning," *Public Utilities Fortnightly*, Volume 117, No. 5, 3 March 1986.

4. Arizona Corporation Commission, *Regulatory Institutions for Least Cost Energy Planning*, July 1987.

5. Lisa Shapiro, Paul Markowitz, and Nancy Hirsh, *A Brighter Future: State Actions in Least-Cost Electrical Planning* (Washington, D.C.: The Energy Conservation Coalition, December 1987).

6. Briton Harris, *Theory of Planning*, mimeo, 1980.

7. Oliver E. Williamson, *Markets and Hierarchies, Analysis and Antitrust Implication* (New York: The Free Press, 1975).

8. Ralph Turvey, *Optimal Pricing and Investment in Electricity Supply* (Cambridge: The MIT Press, 1968).

9. Allen J. Wood and Bruce F. Wollenberg, *Power Generation, Operation, and Control* (New York: John Wiley & Sons, 1984).

10. Donald P. Gaver and Gerald L. Thompson, *Programming and Probability Models in Operations Research* (Monterey, California: Brooks/Cole Publishing Company, 1973).

11. Mary S. Hayes and Richard M. Scheer, "Least-Cost Planning: A National Perspective," *Public Utilities Fortnightly* Volume 119, No. 6, March 19, 1987.

12. ICF, Inc., *Least-Cost Utility Planning* (Washington, D.C.: ICF, Inc., October 1986).

13. Michigan Department of Commerce, *Michigan Electricity Options Study, Study Guide* (Lansing: Michigan Department of Commerce, January 1985).

14. J. P. Harper and C. W. Gellings, "Energy Conservation: Shaping Energy Use," Forum for Applied Research and Public Policy (Spring 1987): pp. 64-76.

15. Andrew Ford and Jay Geinzer, *The Impact of Performance Standards on the Uncertainty of the Pacific Northwest Electric System* (Portland, Oregon: Bonneville Power Administration, Office of Conservation, February 1988).

16. Eric Hurst, *Regulatory Responsibility for Integrated Resource Planning* (Oak Ridge, Tennessee: Oak Ridge National Laboratory, 1988).

17. J. T. Buchanan, *Discrete and Dynamic Decision Analysis* (New York: John Wiley, 1982).

18. H. P. Chao, et al., "Analyzing Complex Decisions for Electric Utilities," *Long Range Planning* 18(2) (April 1985): pp. 46-55.

19. Arthur M. Breipolh and Fred N. Lee, "Reducing the Expected Cost of Uncertainty for Electric Utilities," *Public Utilities Fortnightly* Volume 116(5) (September 5, 1985): pp. 21-24.

20. Andrew Ford and Jay Geinzer, *The BPA Conservation Policy Analysis Models* (Portland, Oregon: Bonneville Power Administration, Office of Conservation, March 1986).

21. M. Farber, E. Brusger, and M. Gerber, *MIDAS, Multiobjective Integrated Decision Analysis System, Volume 2, Model Documentation* (Palo Alto, California: Electric Power Research Institute, 1988).

22. Illinois Commerce Commission, *Least Cost Energy Planning, Report 86-NOI-2* (Springfield: Illinois Commerce Commission, 1987).

23. Larry E. Ruff, "Least-Cost Planning and Demand-Side Management: Six Common Fallacies and One Simple Truth," *Public Utilities Fortnightly* Volume 121, No. 9, 28 April 1988, pp. 19-26.

24. B. F. Hobbs and S. N. Nelson, "Including Consumer Value in Economic Evaluations of Conservation Programs," *Demand-Side Management: Strategies for the 90s*, by the Electric Power Research Institute (Palo Alto, California: Electric Power Research Institute, in press).

25. National Electricity Reliability Council, *Annual Data Summary: 1987 Electricity Supply and Demand* (New York: National Electricity Reliability Council,1988).

26. E. Berman, M. Cooper, and H. Geller, *Compendium of Utility Sponsored Rebate Programs, Report EPRI EM-5579* (Palo Alto, California: Electric Power Research Institute, December 1987).

27. Thomas W. Keelin and Clark W. Gellings, *Impact of Demand-Side Management on Future Customer Electricity Demand, Report EM-4815-SR* (Palo Alto, California: Electric Power Research Institute, October 1986).

28. Electric Power Research Institute, *Technical Assessment Guide: Volume 1* (Palo Alto, California: Electric Power Research Institute, 1986).

29. H. Averch and L. L. Johnson, "Behavior of the Firm under Regulatory Constraint," *American Economic Review* 52(5) (December 1962): pp. 1053-1069.

30. Electric Power Research Institute, *MIDAS* (Palo Alto, California, 1988).

31. Wood and Wollenberg, *Power Generation, Operation and Control*, pp. 240-254.

32. R. R. Booth, *IEEE Transactions on Power Apparatus and Systems*, Volume PAS-91 January/February 1972, pp. 62-69.

33. Lotus Development Corporation, *Lotus 1-2-3* (Cambridge, Massachusetts, 1986).

34. U.S. Energy Information Administration, *Financial Statistics of Selected Electric Utilities* (Washington: U.S. Department of Energy, 1988).

35. U.S. Energy Information Administration, *Historical Plant Cost and Annual Production Expense for Selected Electric Plants* (Washington: U.S. Department of Energy, 1988).

36. U.S. Energy Information Administration, *Inventory of Power Plants in the United States* (Washington: U.S. Department of Energy, 1988).

37. Electric Power Research Institute, *Technical Assessment Guide (TAG) Volume 1 Electric Supply* (Palo Alto, California: Electric Power Research Institute, December 1986).

38. North American Electric Reliability Council, *1988 Electricity Supply and Demand (for 1988-1997)* (Princeton: North American Electric Reliability Council, 1988).

39. Electric Power Research Institute, *A Compendium of Utility-Sponsored Energy Efficiency Rebate Programs* (Palo Alto, California: Electric Power Research Institute, December, 1987).

40. U.S. Department of Energy, *Annual Summary of Cost and Quality of Electric Utility Fuels*, 1986 (DOE/EIA-0191 (86), Washington, DC, 1987).

41. Vernon L. Smith, "Least-Cost Energy Planning: Past, Present and Future," in *Least-Cost Energy Planning in the Midwest: A symposium*, ed. M. J. Morey (Palo Alto, California: Electric Power Research Institute, 1988), p. 1-1.

42. "Supercomputers for the Utility Future," *EPRI Journal*, October/November 1988, pp. 4-15.

43. The simulation consists of the dispatching of generating units and the calculation of energy produced by each unit. The energy production has to account for the random outages of units. MIDAS allows the use of three alternative methods for treating random outages in simulating

the energy production. The Baleriux-Booth probabilistic simulation has been used for the present study. See R. R. Booth, *IEEE Transactions on Power Apparatus and Systems*.

44. The cost-allocation calculations in MIDAS are bypassed for the following reasons. In MIDAS the user inputs energy, demand, and customer allocation factors. However, these factors can only be estimated after the results of the production costing calculations are available. In MIDAS, the production costing and the cost allocation calculations are carried out sequentially in a single computer run. The two sets of calculations cannot be separated through user intervention. In other words, the user has to run MIDAS to obtain production costs, estimate cost allocation factors off-line, and then rerun MIDAS to find costs of service. It would be more efficient to have a separate cost-allocation routine that can use the production costing results directly from a single run of MIDAS. The cost-allocation procedure reported her is developed for that purpose.

45. The price of $200 per MWh should not be confused with firm purchases. Utility A is modelled to incorporate firm purchases of 400 MW at $45 per MWh. The price of $200 per MWh is used only for emergency purchases. Such purchases are made only at times of system peak when machines are on outage. The production costing simulation gives the expected loss of energy (ELOE) if no purchases were made. The model assumes purchases at $200 per MWh to make the ELOE equal to zero.

46. The concept of levelized rate is based on the following. If P^* is defined as a constant fixed price charged per KWh in every one of the future years under study, the present worth of the revenue stream is given by $\sum_t P^* E_t/(1+i)^t$. The present worth of the annual costs is $\sum_t C_t/(1+i)^t$ where C_t is the cost in year t. Since cost is equal to revenue requirement, the present worth of annual costs is nothing but the numerator of equation (3-1). Equating the present worth of revenue stream to the stream of cost, one obtains the definition of P^* as in equation (3-1).

47. This does not imply that DSM programs are always economic if new plants were to increase electric rates. This is because, under inflation, rate regulation based on the book of value of assets can result in rate increases in the early years of a plant, while causing rates to fall in real terms later. The overall levelized rate can, as a result, either be higher or lower due to the plant addition, depending on several factors.

48. This limiting value for DSM was obtained by running the SMARTS model with increasing values of DSM and by observing if the decision tree analysis would indicate the choice of DSM.

49. Note that this is an assumption in the model. It may be that the utility will seek this additional power from outside parties through competitive bidding. Under those circumstances, the decision tree will have to be restructured to model such an alternative. Then, the results may be different from those indicated here.

50. Absent other factors, e.g., A-J effect (not accounted for here) could counter this result.

51. In figure 6-7, the probability of class 2 RR being at 98.5 percent of its mean is about 0.19 while the corresponding probability for class 2 is about 0.32. At 100.5 percent of mean, for class 1 RR, the probability is about 0.72 while the corresponding probability for class 2 is about 0.79. Similar observations are true for figures 6-8 and 6-9.