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Distributed Resources: Toward a New Paradigm of the Electricity Business

Capacity Planning Under Uncertainty: Developing Local Area Strategies for Integrating Distributed Resources

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Capacity Planning Under Uncertainty: Developing Local Area Strategies for Integrating Distributed Resources

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This paper presents a methodology that helps DR planners evaluate strategic investment policies under uncertainty. Application of the methodology will not only lower utilities' costs, but also help them prepare for the future with contingency plans and a deeper understanding of the opportunities and risks they face. The formulation responds to the need to evaluate future options as uncertainty unfolds over time. For such problems, the joint consideration of dynamics and uncertainty makes the problem much too large for conventional probabilistic analysis methods and places it beyond the scope of conventional deterministic engineering analyses. The problem is formulated as a dynamic optimization problem under uncertainty. A practical solution technique for solving the problem based on a compact specification of the system state is introduced. An example, taken from actual practice, is presented. The potentially large economic value of DR investments in providing managerial flexibility is quantified. We demonstrate that the optimal level of DR investment found by our approach is superior to the level of DR investment specified by existing methodologies. Although the concepts are presented in the context of electric utility distributed resources planning, they are more widely applicable to other strategic investment problems.

INTRODUCTION

This paper discusses an approach to the problem of Distributed Resources (DR) planning in the electric utility industry. The approach was developed through a set of EPRI-coordinated projects conducted with a group of utility participants (see acknowledgments). The Distributed Resources concept is that generation and storage can be *distributed* throughout the transmission and

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distribution (T&D) system and serve as an alternative to central generation investment and T&D system expansion. The distributed generation may be based on modular and perhaps renewable technologies, modular storage facilities, and specially designed demand-side management programs.

The DR concept responds to changes in the conditions affecting the production, transmission, and distribution of electrical energy. These conditions include increased competition (present and anticipated), broad attention to the environmental consequences of business decisions, changes in capital investment patterns that have resulted in a greater investment in T&D assets than in centrally located production facilities, and development of alternate production technologies. These changing conditions suggest that there are economic benefits to be achieved if modular generation or storage units are placed in the local transmission or distribution system close to selected loads. Further discussion of the DR concept and its emergence as a planning principle may be found in several reports and reviews (Feinstein (1993), Pupp (1993), Feinstein et al. (1997c)).

The transmission and distribution system is designed to meet infrequent but large peak loading. T&D is expensive and the cost is growing; in fact, capital investment in T&D has surpassed investment in generation (Edison (1994), Electrical World (1995)). This suggests that it may be valuable to explore opportunities to shift capital by considering other alternatives. Indeed, recent studies suggest that modular generation or storage units, augmented by specially-designed demand-side management programs, can be used to reduce infrequent load peaks, and do so with less cost than reinforcing or expanding the local T&D system (Zaininger et al. (1990), Orans et al. (1991), Shugar et al. (1991), Chapel (1993), Hoff (1996)). Earlier reports have identified different benefits of siting small-scale dispersed storage and generation assets in a utility's T&D system (Chovaniec et al. (1978), Ma et al. (1979), Lee et al. (1979), Bullard (1980), Davitian (1981), Finger (1981), Koenig (1981), Tabors et al. (1981), Van Horne et al. (1981), Ma et al. (1982), Rigney et al. (1984), Sobieski (1985)). These benefits include reduced capacity requirements of the T&D system, improved reliability, and lowered losses.

BACKGROUND

The focus of this paper is on methodology. It is important to note that there is at present no generally accepted methodology for DR planning. However, with relatively minor variations, four common assumptions characterize the methodologies used to investigate DR planning and measure the value of DR investments:

- Each methodology requires the prior specification of a conventional deterministic expansion plan for the T&D system. Each investment in the expansion plan is assumed to be made at a specific time in the future.

- The future peak load on the system is assumed known with certainty over the entire planning period.

- The capital costs and operating costs associated with future investments are assumed known with certainty over the entire planning period.

- The benefit of investing in distributed resources is assumed to be achieved by deferring the capital investments in the conventional expansion plan.

Practice has revealed that such assumptions are insufficient for DR planning. The shortcomings include the following. First, distribution planners rarely have a prior expansion plan that can be specified for an arbitrarily long period of time (typically 10, 15, or 20 years in the future). Second, the peak load on the system is quite uncertain; it cannot be predicted with certainty even for a short period in the future. We have found utility planners to be uncomfortable with the accuracy of long term deterministic forecasts. Third, the future costs of technology are uncertain. Fourth, contrary to a commonly-held belief, we will demonstrate that deferring a given conventional expansion plan for the longest time possible *does not* yield the least-cost solution to DR planning (see also Feinstein et al. (1997e)).

Planning without explicitly dealing with uncertainty ignores the very real value of management flexibility, that is, the ability to change directions as the future unfolds. We argue below that to ignore management flexibility is to ignore what may be the greatest value provided by DR.

The methodology for DR planning described here is designed to overcome these difficulties. The main elements of the methodology were highlighted, independently, as "necessary elements of a comprehensive analysis" for integrated resource planning with renewable resources, a particularly interesting aspect of DR planning (Logan et al. (1995)). The methodology does not require prior specification of an expansion plan, nor is the objective to maximize the deferral of conventional investments. Rather, the methodology determines an optimal mixture of distributed resources and conventional investments that minimizes the expected net present value of total system costs of serving load. The methodology recognizes that the future is uncertain and allows the user to characterize the important uncertainties that govern the investment problem. Moreover, the methodology explicitly recognizes and attaches an economic value to the management flexibility inherent in DR options. Finally, in recognition of the strategic nature of the problem, the general principle we have followed is to substitute mathematical structure and modeling assumptions for extensive data sets. The methodology has been applied successfully to a set of real utility problems (Lesser (1996), Feinstein (1996), Morris (1996), Chow (1996), Chapel et al. (1996)). Although the methodology is presented in the context of DR strategy, it is more widely applicable to other strategic investment problems.

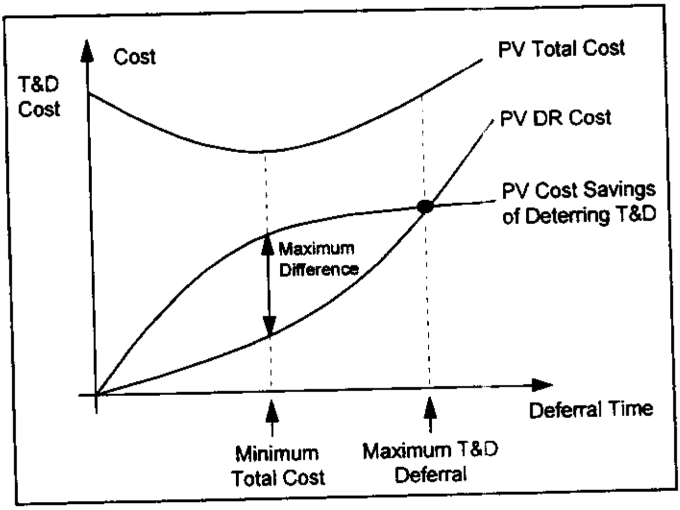
PROBLEM FORMULATION

The objective of the DR planning problem is to meet customers' capacity and energy needs over the indefinite future at the lowest expected present value of all future costs. There are several aspects of this problem statement that require further discussion. It is convenient to develop the ideas in stages. We discuss the problem formulation in some detail in this paper because a fundamental difference between our approach and results and other approaches and results is the formulation itself.

Deterministic DR Problem

We begin with a deterministic formulation assuming continuous time and infinitely divisible assets, and then extend the formulation to consider lumpy investments under uncertainty. The minimum cost objective may seem innocuous, but in fact represents an essential difference between our methodology and other methodologies. Other approaches find a solution that delays the construction of new T&D facilities by investing in DR until the total cost of the DR investments exceeds the total benefit of T&D delay (Orans et al. (1994), Hoff (1996)). This solution is not least cost. The differences in the approaches are shown in Figure 1 (taken from Feinstein et al. (1997e)). The total cost is minimized when the difference between the cost savings due to deferral of T&D and the cost of this deferral, the cost of DR, is maximized. This occurs when the *marginal* cost of deferring equals the *marginal* benefit. Since the maximum T&D deferral time occurs at the point at which the *total* DR cost equals the *total* benefit of deferral, the minimum cost solution is earlier and requires less DR investment. Stated simply, maximal deferral is not the least-cost strategy and, in fact, undervalues the benefits of DR.

Figure 1. Relationship between Least Cost and Maximum Deferral Solutions



The solution to the deterministic DR planning problem is a sequence of capital investments in technology that provides the capacity necessary to meet the area load over time. Let $k(t)$ be a vector whose i^{th} component, $k_i(t)$, is the amount of capacity of type i in the system at time t. The solution to the deterministic DR planning problem is to specify the function $k(t)$ from some initial time t_o to ∞, which represents the indefinite future. Let $L(t)$ represent the aggregate load (i.e., electricity demand) that must be satisfied by the system at time t. Let $C[t, k(t)]$ be the amount of effective capacity provided by vector $k(t)$ of technologies at time t. Then, in order that a solution $k(t)$ be sufficient to satisfy the load, the constraint $C[t, k(t)] \geq L(t)$ must be satisfied. When this constraint is satisfied, no demand is unserved. If we idealize the notion of investment in capacity, we may consider that $k(t)$ is a smooth function and that the derivative $dk(t)/dt = k'(t)$ is well-defined. Let $V[t, L(t), k(t), k'(t)]$ specify the instantaneous cost rate at time t that results from serving the actual load $L(t)$ with capacity $k(t)$ while making investments at the rate $k'(t)$. The objective of the investment policy is to minimize the present value of these costs over the planning period. Let ρ represent the instantaneous interest rate, assumed to be constant, and let the initial conditions on load and system capacity be denoted by L_o and k_o respectively. Then the optimal deterministic DR investment policy will be the vector function $k(t)$ that solves the following problem:

$$\text{Minimize} \int_{t_o}^{\infty} e^{-\rho t} V[t, L(t), k(t), k'(t)] \tag{1a}$$

$$\text{subject to} \quad C[t, k(t)] \geq L(t) \tag{1b}$$

$$L(t_o) = L_o \tag{1c}$$

$$k(t_o) = k_o \tag{1d}$$

This is a problem in the calculus of variations whose solution is a function $k(t)$ that satisfies a set of necessary conditions that includes the Euler-Lagrange differential equation (Bliss (1925)). Finding a solution to that equation can be a formidable challenge, as would be the complete specification of the functions V and C in a form amenable to analysis. More importantly, the investment in capacity assets is not a smooth process. It is more appropriate to consider that the investments in capacity occur at discrete times and in discrete amounts.

We may then reformulate the problem as follows. It is natural to consider that the time interval (t_o, ∞) is composed of periods of possibly variable duration, indexed by the variable t. Let $x(t)$ be the decision vector of additional capacity investments made during period t. This may also include investments that are retired from service during the period, so any component of $x(t)$ could be negative. Let $I[t, x(t)]$ represent the investment cost of acquiring technologies $x(t)$ at the beginning of period t. Let $k(t)$ be the vector of capacity installed in the system prior to period t. Then $k(t+1) = k(t) + x(t)$ is the vector of capacity installed at the beginning of period $t+1$. As before, let $L(t)$ be the load on the system at the beginning of period t. Let $V[t, L(t), k(t), x(t)]$ represent the operating cost of serving the load during period t given that $L(t)$ is the load at the beginning of the period, $k(t)$ is the initial capital stock and new investments $x(t)$ are made during the period. The solution to the discrete deterministic DR planning problem is the investment sequence $\{x(t): t_o \leq t < \infty\}$ that solves

$$Minimize \sum_{t=t_o}^{\infty} e^{-\rho t}[I(t,x(t)) + V(t,L(t),k(t),x(t))] \qquad (2a)$$

$$subject\ to\ \ C[(t,k(t) + x(t)] \geq L(t) \qquad (2b)$$

$$L(t_o) = L_o \qquad (2c)$$

$$k(t_o) = k_o \qquad (2d)$$

The key idea embedded in the above formulation is that time is not indexed by a fixed interval, say year by year, which would define a problem of enormous dimension (e.g., 10 possible technology choices over a 10-year planning period implies 10^{10}, or 10 billion separate strategies that would have to be evaluated). In this formulation, we assume that under current regulatory and economic conditions there will be no cost savings or benefits associated with early installation. Thus, since there is no value to overcapacity, the formulation recognizes that capacity decisions need only be made when capacity is needed (e.g., if the technologies each supplied two years of load growth, there would be only 10^5, or 100,000 separate strategies that would have to be evaluated). The resulting deterministic planning problem is in the form of a discrete optimal control problem, with $x(t)$ as the control variable. The optimal solution to this problem is again a function $x(t)$ that satisfies a set of necessary conditions that are variants of the Euler-Lagrange equations, first developed by Pontryagin and extended to discrete time models (Pontryagin et al. (1962), Kharatishvili (1967)). The discretization of the problem makes it somewhat easier to solve, although the functions V and C still need to be expressed analytically, if one is to make efficient use of the necessary conditions to characterize the solution.

Further, there are two other aspects of the problem that formulation (2) does not address directly: first, the length of each period is unspecified, and second, the behavior of the load during each period and from period to period is unspecified. We address these issues by incorporating a stochastic-process model of load uncertainty into the formulation, and explicitly modeling the ability of the utility to adopt strategies that respond flexibly as the uncertainty resolves over time.

Probabilistic DR Problem: The Value of Management Flexibility

Managerial flexibility in the face of uncertainty about the future is possibly the greatest benefit provided by modular DR technologies to utility planners. Before proceeding, it is useful to consider a simple example. Suppose a planner is faced with a certain load growth of 10 units this year. However, the load next year is uncertain: there is a 60 percent chance of a 90 unit increase due to a potential major industrial electricity user moving into the area, and a 40 percent chance of no increase. In either case, no subsequent load growth is expected. The planner has two alternatives: a large conventional technology with 100 units of capacity at a capital cost of $100M or a DR technology with 10 units of capacity at a capital cost of $20M (twice the large technology's unit cost). Given a discount factor of 0.9 (i.e., $1.00 in a year is valued at $0.90 today), the traditional deterministic approach would assume for the second-year load the most-likely value of 90 units, in which case the least-cost alternative is to install the large technology immediately to cover the two-year load (PV of $100M versus wait-until-year-2 PV of $110M = $20M + 0.9x$100M). Compare this with a "Wait and See" strategy of installing the DR technology, and then installing the large technology only if load grows. The expected present value of the Wait-and-See strategy is easily computed as $74M (= $20M + 0.6 x 0.9 x $100M + 0.4 x $0M). Thus, the DR alternative in conjunction with the flexible Wait-and-See strategy saves the utility planner $26M in expected present value, more than the cost of the DR technology. The value of the DR alternative comes not from its cost characteristics, but from the management flexibility it affords the utility planner. Leaving uncertainty out of a planning analysis systematically undervalues DR alternatives.

We formalize these ideas by postulating that the underlying load dynamics is governed by a stochastic process so that $L(t)$ is a random variable (a specific stochastic process is proposed below). It follows that the cost of meeting the load, the function $V[t, L(t), k(t), x(t)]$, is also a random variable. Therefore, the proper form for the objective (2a) is the expected present value of the cash flow stream. Denoting the expectation operator by E, we formulate the stochastic optimal control problem:

$$\text{Minimize } E\{\sum_{t=t_0}^{\infty} e^{-\rho t}[I(t,x(t)) + V(t,L(t),k(t),x(t))] + e^{-\rho T}V_{\infty}[T,L(T),k(T)]\} \tag{3a}$$

$$\text{subject to } C[t,k(t)+x(t)] \geq L(t) \tag{3b}$$

$$L(t_o) = L_o \tag{3c}$$

$$k(t_o) = k_o \tag{3d}$$

where $V_\infty [T, L(T), k(T)]$ is the expected present value of the cost from time T to infinity, based on estimates of the future capital and operations costs of serving load.

Conceptually, there is a great gulf between problems (2) and (3) not suggested, perhaps, by the apparent similarity in notation. In particular, the following modeling issues must be addressed, which are discussed in the section below:

(a) How can the probabilistic dynamics of load be specified?

(b) How can the probability distribution on time to the next decision be specified?

(c) Is there a practical solution technique for finding the optimal decision strategy and associated costs in real utility DR problems?

(d) Equation (3) contains an implicit assumption that the optimal policy and resulting future costs are functions only of current conditions rather than the entire time history up to time t. How is this assumption justified?

(e) How can we specify a meaningful terminal value model?

MODELING ISSUES

The five modeling issues are interrelated. Due to space limitations, we provide an overview of the key ideas in our approach to each issue. The references cited contain further details.

Modeling Load Dynamics and Uncertainty

Two factors motivated our approach for characterizing load uncertainty. First, for distribution planning, a key issue is at what point in the future will load growth result in new capacity requirements? Thus, a complete description of potential load trajectories over time is required in order to specify the probability distribution on time to the next decision. Second, based on extensive work with utility planners, we found that it is desirable to describe load growth in terms of multiple trends that persist for uncertain durations. For example, area load typically can grow at some steady rate for several years and then transition to a rapid growth spurt for a period of time. This suggests that a good way to model future load conditions is to characterize likelihoods of the possible trends and their durations. A simple yet robust mathematical representation of such a phenomenon that captures the complexity and requires relatively few parameters to be estimated is a Markov chain described by a transition matrix of conditional probabilities. If there are n discrete load growth states, then $n(n-1)$ conditional probabilities must be specified. We have developed a method for estimating these parameters (Feinstein et al. (1997a, b)).

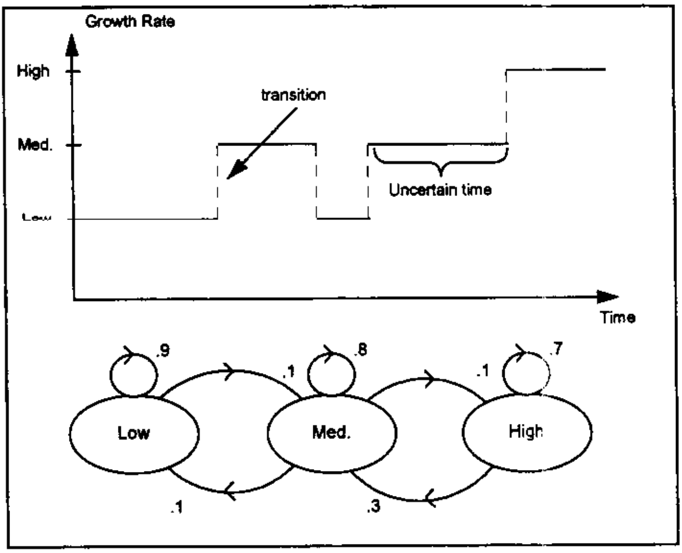
The Markov model is illustrated in Figure 2. The top half of the figure shows that, over time, load may follow a sequence of different growth trends with varying durations. The bottom half of the figure illustrates how transition probabilities can be used to represent the uncertainty in the level of the next trend and the uncertainty in the time to the next trend. In this case, there are three trend states. For example, if load is growing at the medium rate, there is a 0.8 chance that the medium growth trend will persist into the next period, a 0.1 chance of a transition to the low trend and a 0.1 chance of a transition to the high trend. This characterization of load also represents the tendency to stay in a given trend, since the average time in a trend may be expressed as:

$$\text{Average Time In Trend} = 1 \;/\; [\; 1 - p \text{ (staying in same trend)} \;]$$

For example, for the given probabilities, the average time that the load growth will persist in the low state is 10 periods.

It is worth noting how the Markov load model differs from the more traditional approaches. A standard technique is to estimate an average growth rate by fitting a regression line through historical data and to estimate variance using the regression residuals. This ignores trends or correlations in the data and, in so doing, systematically underestimates the future load uncertainty (see Figure 3). Moreover, the regression model presupposes that additional observations provide no information. In the Markov setting, the likelihood of future load behavior depends on the current conditions, so observations modify forecasts.

Figure 2. Probabilistic Dynamics of Load Growth

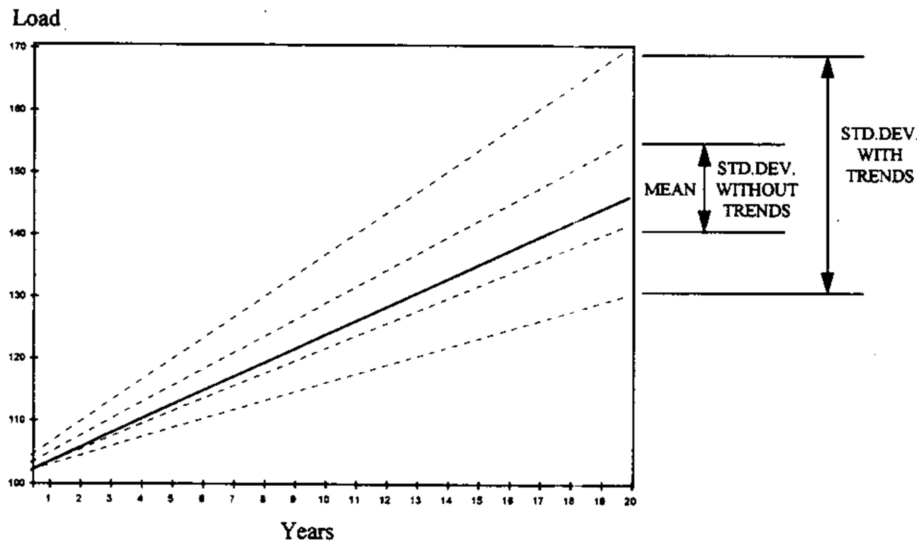


The Markov model also responds to the fact that the distant past is rarely representative of the future, especially for local area planning. Growth trends are driven by real events such as changes in zoning laws and shifts in the local economic conditions. If the future is believed to be different from the past, the model allows the user to specify appropriate parameters that capture those beliefs.

Modeling Uncertainty in Time to the Next Decision

Constraint (3b) implies that no unserved energy is permitted during any period, an assumption required by the utility planners with whom we have worked. This suggests that the time to the next capacity decision depends on the amount of capacity installed and on the load growth.

Figure 3. Comparison of Uncertainty Ranges Between Regression and Markov Models



The Markov load model may be used to determine the dynamic state probabilities that characterize the chance that the cumulative load growth will grow from any level L to any higher level L' over a period of length τ. From these state probabilities, we then determine the first-passage-time probability distribution, which is the probability that starting at level L, cumulative load will reach level L' for the first time in *exactly* τ periods (see Howard (1971)). If we define, for a given capacity installation of size C, $L' = L + C$, the distribution on time to the next decision is identical to the first passage time distribution.

In practice, we employ a discrete three-branch approximation that matches the first five moments of the actual distribution. This approximation is based on Gaussian quadrature (Miller et al. (1983)). For further details on the dynamic probabilistic model of load growth, see Feinstein et al. (1997a, b).

Dynamic Programming Solution Technique

A powerful approach to solving a stochastic control problem is to apply Bellman's principle of optimality (Bellman (1957)). This principle suggests that a complex problem, such as (3), can be viewed as a sequence of simpler problems. The solution procedure that incorporates this principle is known as dynamic programming. The decision variables in the problem are the various investment alternatives. As described above, the timing of the decisions is related to the load uncertainty and the incremental capacity provided by each investment.

We emphasize that dynamic programming is not an algorithm. Rather, successful application of the procedure is based on the art of mathematical modeling rather than on numerical aspects of problem solution. For further discussion, the reader may consult references on dynamic programming (Bellman (1957), Hillier et al. (1986)). We next describe how the modeling ideas presented in this section enable us to create a structure that permits successful application of dynamic programming.

Characterizing the System State

The number of computations required for a solution grows exponentially as the size of the problem increases. There is no general procedure for handling this so-called "curse of dimensionality," but there is a unifying concept, the notion of *state*. We introduce some terminology and then illustrate the idea with an example.

We define a *trajectory* as a sequence of decisions and outcomes. Trajectories can be thought of as paths through a tree representation of a dynamic programming problem. Trajectories can be of any length, depending on the number of stages described by the trajectory. A sample trajectory could be: install two 500 kW engines at time zero; observe that the time to the next decision is 2.4 years; at that time install a 20 MVA substation, which lasts for the next 7.6 years (and beyond), the end of the finite planning period of 10 years.

Let x_k represent the results of all lotteries that occur at stage k in the dynamic program (i.e., the resolution of all load uncertainties), where "stage" refers to the time at which a decision is made. Let a_k represent the action taken at stage k, typically an investment decision. A trajectory of length m, then, is the sequence: $\{a_1, x_1, a_2, x_2, \ldots, a_m, x_m\}$.

Formally, a *state* is a vector that is the result of a mapping ϕ applied to a trajectory. The mapping need not be 1-1, and in general will not be.

We define a three-dimensional state variable $\phi = (\phi_1, \phi_2, \phi_3)$ that defines an *equivalence class* of trajectories. The desirable property of such an equivalence class is such that for all trajectories that have the same state, the future (i.e., the set of all decisions, costs and probabilities) appears identical viewed from any member of the class. Therefore, the future optimal decisions and cost computations need to be specified only once for all the members of the equivalence class. This greatly reduces the number of computations required to solve problem (3).

We define ϕ_1 = permutation ($\{a_1, a_2, \ldots, a_m\}$), which means that the first component of the state is the collection of all investment decisions made through stage m, independent of the order in which they were made. This makes sense as a state descriptor because electric utilities economically dispatch their technologies on hand so as to minimize operating cost, independently of their capital cost or when they were installed.

We define $\phi_2 = \sum_{j=1}^{m} a_j$, if $\sum_{j=1}^{m} a_j = \sum_{j=1}^{m} x_j$, else $\phi_2 = \varnothing$. If ϕ_2 is not empty, then the capacity of the investments made along the trajectory is equal to the load growth along the trajectory. This means that the total load in a state is equal to the total capacity installed, so that we need not define total load as a separate state component. If ϕ_2 is empty, a useful equivalence class cannot be formed.

We define $\phi_3 = x_m$, to be the most recent load growth rate. The Markov load model implies that the current load state is sufficient to describe future load growth behavior.

An example will illustrate the notion of state and how it can dramatically reduce the number of computations in a dynamic programming solution. Consider a problem with 3 stages, such that at each stage one of three decisions $\{d_1, d_2, d_3\}$ may be selected, followed by one of three possible load growth rates $\{l, m, h\}$. For simplicity, in this example, let us assume that the load levels are independent. An example of a complete trajectory is the sequence $\{d_2, h; d_2, l; d_1, m\}$. There are $(3 \times 3)^3 = 729$ unique trajectories for this problem. The total number of computations that would be required to solve the problem, without considering the effect of a state-based equivalence class, is 9 + 81 + 729 = 819 path-cost computations. Now consider what happens when a state variable, the total amount of capacity installed, is introduced. The first stage is as before. Entering the second stage, there are three unique capacity states, so that 3 x 9 = 27 computations are required. Entering the third stage, there are only six unique capacity states, so that 6 x 9 = 54 computations are required. Thus, using the concept of state, the total number of computations has been reduced to 9 + 27 + 54 = 90. For larger problems, the effect is far more striking. In a recent application, the application of the state concept reduced the size of the problem from roughly 100 million path calculations to several thousands.

Terminal Value Model

A final formulation issue concerns the infinite time horizon in the objective function (3a). Although we require a solution over the indefinite future, we are seeking a practical, usable approach to the DR planning problem. We have found that decision makers are able to provide sufficiently accurate data to support detailed decision making until some finite time T. Beyond that time, which varies for each decision maker, there is more ambiguity about future conditions.

It is important to stress that although the future conditions influence the near-term decisions, it becomes less and less appropriate to model the system in detail as we move into the distant future. The essential idea in the formulation of the terminal value model $V_\infty [T, L(T), k(T)]$ is that it ought to represent the best estimate of the "cost-to-go" from any terminal point. By assuming that near-term investments will be operated until their lifetimes expire, and assessing values of capital and operating costs of future assets, the cost-to-go can be relatively simply expressed (Feinstein et al., 1997d). The decision maker can vary the assessments of the future and observe how the optimal policy responds.

OTHER ISSUES

For brevity, we outline three additional issues that can also be addressed in the context of the DR strategy model.

Additional Uncertainties

We have solved examples using problem formulation (3) that included the effects of uncertain weather-related load changes, the consequences of uncertainty about future siting of investments such as substations and transmission lines, and the results of uncertainty in future fuel costs. We illustrate the approach of extending the problem while preserving the formulation with a brief example of weather-related uncertainties.

One consequence of uncertain weather is that the system load may be abruptly increased. Consider the effect of uncertain weather at a remote ski area with its own snow-making equipment, which is used only if there is insufficient natural snow (Lesser (1996)). In each year, the utility faces a lottery on the effect of weather on peak demand. We translated this lottery into a probability distribution on the load level parameters of the Markov model discussed above. We were then able to manipulate the extended model with uncertain parameters into a Markov model of the original form with deterministic but adjusted parameters, thus preserving the structure of problem formulation (3). Also, a decision variable was introduced into formulation (3) that specified how much capacity should be held in reserve to meet weather contingencies. Based on the cost of unserved energy, the optimal value of incremental capacity was determined.

Investment Leadtimes

We define leadtime as the time that must elapse between committing to an investment and actually having the investment available. Leadtime requires decisions to be made at earlier times. If the leadtimes for all investments were identical, the phenomenon would present no modeling difficulty. However, leadtimes generally vary by alternative and there is no obvious way to adjust the time to the next decision without knowing what that next decision will be.

Leadtime has two primary impacts. First, leadtime increases the uncertainty about conditions that will obtain when the investment is available. When leadtime is present, the Markov model of load dynamics finds the probability distribution on the time to the next decision by making one adjustment: the capacity added at the leadtime is the capacity of the alternative under consideration plus the capacity needed to serve the expected load growth during the leadtime. Second, leadtime affects the timing of cash flows. An investment with non-zero leadtime requires cash flows to occur earlier than the time-to-the-next decision logic would suggest if leadtime were zero. Leadtime can be thought of as a requirement for advance payment. The strategy model adjusts for leadtime by shifting all investment costs forward by the leadtime. These adjustments permit the dynamic programming algorithm to solve what appears to be a zero-leadtime problem while in fact evaluating the cash flows and adjusting the uncertainty ranges as if actual leadtimes were included.

Area Load Saturation

We observed that planners generally do not assume that a local area will experience positive growth indefinitely. Based on physical constraints, at some future time the peak load will often stabilize at a relatively fixed level. As an extension to the Markov model of load dynamics, we created a method to capture this phenomenon of load *saturation*. Load saturation can be an important strategic planning phenomenon, since the time over which an investment satisfies demand depends on the dynamics of load growth. Slowly saturating areas permit investments to be delayed. When the saturation level is uncertain, the model permits planners to investigate the increased risk of overcapacity.

The load saturation model allows the planner flexibility in specifying both the load range over which the saturation effect occurs and the rate at which the dynamically varying load approaches saturation. A popular alternative is to permit the load to approach the saturation load asymptotically at some exponentially decaying rate specified by the planner.

USING THE MODELING APPROACH

An Example

The solution determined by the strategy model is the optimal policy for local area expansion. We have defined a policy as a sequence of contingent investment decisions that occur at specific times conditional on the uncertainties that have been resolved.

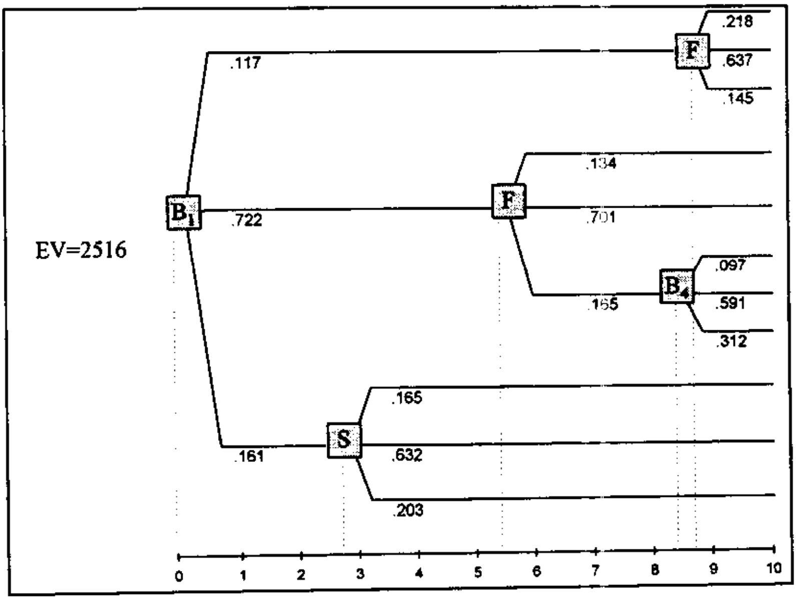
We describe a strategy problem based on an actual case. The problem involved three different kinds of investments. Investment F is a 4.5 MW capacity feeder and investment S is a 20 MVA substation. Distributed resources investments included B1, B2, B3, B4, and B5. Each of these represents a collection of distributed resources such as engines and storage devices. B1, for example, has cumulative capacity 4.5 MW, and is designed to be installed prior to either a feeder or substation. B4 is a similar collection of distributed resources with cumulative capacity 4.9 MW, designed to be installed after a feeder. The cost and probability data were taken from the actual case.

Figure 4 displays the optimal policy as a sequence of contingent decisions. Time is recorded horizontally. The solution to the problem has optimal cost $2,516 (all costs are $000). The first investment decision, install alternative B1, occurs at the beginning of the planning period, at time zero ($t=0.00$). As noted above, load growth uncertainty was translated into a discrete probability distribution on the time required for load growth to exhaust the capacity of the investment, thus determining the time to the next decision. For B1, the discrete probability distribution on time to the next decision is defined by the probabilities {0.117, 0.722, and 0.161} with corresponding durations {8.66, 5.49, and 2.91}.

The next investment decision depends on the resolution of the load growth uncertainty. If the first or second outcomes were to occur, which correspond to relatively low or moderate load growth, respectively, the optimal decision would be to select alternative F at time 8.66 or time 5.49, as denoted by the letter in the box. If the third outcome were to occur, which corresponds to relatively rapid load growth, the optimal decision would be to select alternative S at time 2.91.

After making the second investment decision, the time that load takes to exhaust the additional capacity is observed. The finite time horizon selected for this example is 10 years. Therefore, alternative F has sufficient capacity to meet the load growth under any condition until the end of the planning period, if the prior load growth were low. If the prior load growth were moderate, the capacity provided by alternative F installed at time 5.48 may last until the end of the planning period. This occurs with probability 0.134, for a low load growth outcome, and probability 0.701, for a moderate load growth outcome.

Figure 4. Optimal Policy Integrating Distributed Resources



If the load growth were relatively rapid, which occurs with probability 0.165, alternative F would be exhausted in an additional 2.71 years, so that at time 5.49 + 2.71 = 8.20, additional capacity would be required. At that time, the optimal decision is to install B4, which provides capacity sufficient for incremental load until the end of the planning period. After installing alternative S, which occurred at time 2.91, the capacity provided is sufficiently large so that all additional load within the 10-year planning period can be satisfied.

Value of Modularity

Central to the idea of distributed resources as an approach to infrastructure investment planning is the ability of large-scale, non-modular investments to be deferred, with cost savings, by smaller scale modular investments (Feinstein (1993), Pupp (1993), Feinstein et al. (1997a)). It is important to quantify the value of such modular investments. The problem formulation (3) lends itself to such a quantification by perturbing the solution to discover the value of modularity. A similar approach was taken in Morris et al. (1994).

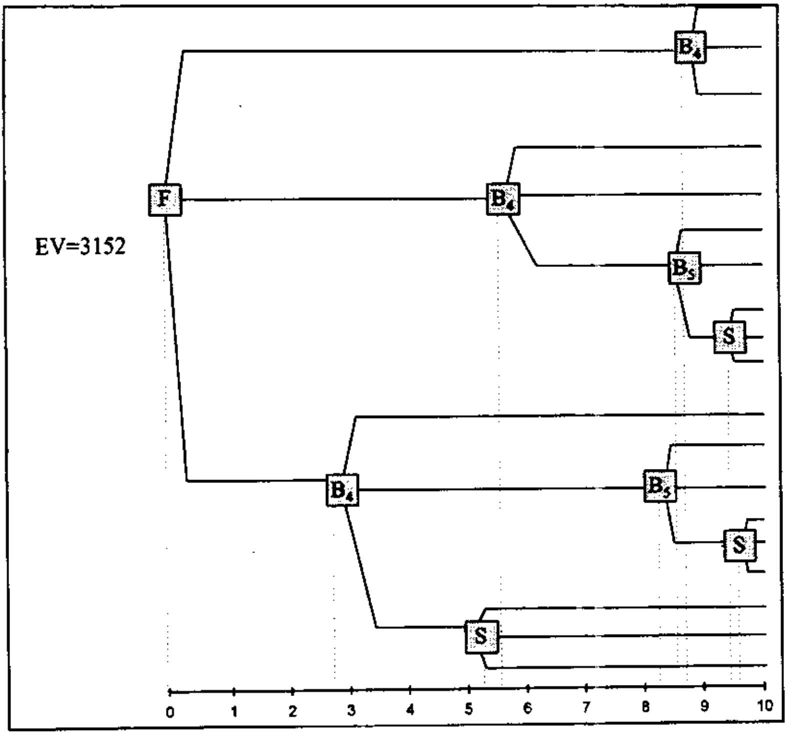
The main question explored in this example is whether the distributed resources can defer the more traditional investments under uncertainty. The optimal solution indicates that such a strategy is appropriate. That is, one way to interpret the optimal strategy is that distributed resources (B1) are installed to defer the substation or the feeder. A second collection of distributed resources, B2, designed to precede the feeder, is not selected in the optimal solution. After installing the feeder, the substation can be deferred even further in the rapid load growth case if distributed resources B4 are selected.

A further question is how valuable are the distributed resources? One way to answer the question is to consider the policies and costs if the distributed resources are unavailable. In this case, the optimal policy is to invest in the substation immediately. The substation lasts until the ten year horizon under all load growth cases. The present value of this policy is $3,253. Recall that the optimal policy with DR has present value $2,516. Thus the modular investments provide a cost savings of somewhat greater than 20 percent. We make no general claim about the value of distributed resources, but it is interesting to note that savings of this order of magnitude have been reported in other analyses as well (Orans et al. (1991), Shugar et al. (1991), Chapel et al. (1993), Chow (1996), Lesser (1996)).

An interesting case is to eliminate B1, so that distributed resources could not be used before a feeder were installed. In this case, the optimal policy cost drops to $3,152 (compared with $3,253 for the substation alone). The optimal policy installs the feeder and uses distributed resources B4 and B5 to defer the substation (Figure 5). Alternatively, eliminating B4 and B5 and restoring B1 yields an integrated policy with expected cost $2,578 (Figure 6). This indicates that the distributed resources are most valuable early in the planning period, when they can be used to defer the substation and the feeder. That is, early application of distributed resources in this particular example yields 20 percent reduction in total costs, while late application of distributed resources yields approximately 3 percent in savings.

Applying the maximal deferral logic (Orans et al. (1994), Hoff (1996)) to this problem yields the policy to defer the substation by installing both B1 and F. At the nominal growth rate of approximately two percent per year, this policy delays the substation approximately nine and one-half years. The model can be used to evaluate this policy under uncertainty by basing the terminal value model on the cost of a substation. Under that assumption, which is implicit in the deferral logic, the expected cost of this policy is $2,272. As we have discussed earlier (see Figure 1), the maximal deferral logic overshoots the optimum. The optimal solution is to install only B1 before the substation, which provides an expected deferral of 5.4 years with expected cost $2,178, approximately 5 percent lower.

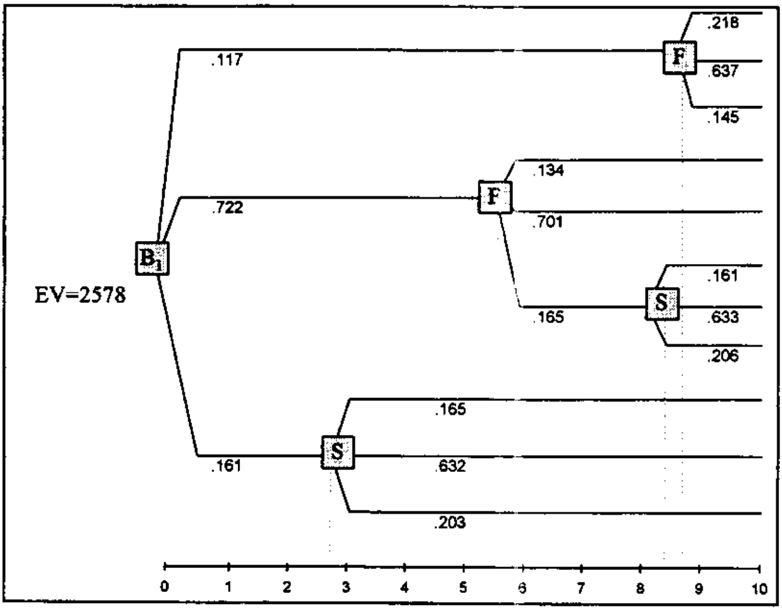
Figure 5. Optimal Policy with No Distributed Resources before Feeder Comparison with Maximal Deferral Solution



Sensitivity Analysis

Sensitivity analysis measures the dependence of the optimal solution on the assumptions made by the planner. The concept of a sensitivity analysis is simple: select an assumption, vary the value that describes the assumption, and observe the change in the solution as a function of the varying value of the assumption. If the solution varies greatly, the sensitivity to the assumption is important and the assumption must be explored further. If the solution does not vary greatly, it is said to be robust and the exact value assumed to hold in the analysis is not very important. We have designed our approach to be simple to use in exploring sensitivities to assumptions.

Figure 6. Optimal Policy with No Distributed Resources after Feeder



A simple sensitivity analysis can be illustrated using the optimal solution presented above. An important variable is the capital cost of distributed resources. In the present solution, the average capital cost of distributed resources is $115/kW. As this value is varied, the optimal solution does not change until the average capital cost becomes approximately $260/kW. At that cost, the optimal investment at the initial time is the substation. The sensitivity analysis has revealed the amount of variation permitted in the capital cost of distributed resources such that the optimal policy remains the same. This establishes the robustness of the solution to this planning assumption.

MODEL IMPLEMENTATION

The model is implemented in C and is easily run from a PC in a Windows 3.1 or Windows 95 environment. The interface to the model is graphical, with simple data formats on various screens. There are several output reports, in addition to the presentation of the optimal policy.

The policy summary (Figure 7) reports the probability that a particular investment is made at any time during the planning period. The policy summary for the example indicates that B1 is always installed sometime during the first year, that S is installed sometime during the third year with probability 0.1602, that the feeder is installed sometime in the fifth year with probability 0.7223 and sometime in the ninth year with probability 0.1175, and that B4 is installed sometime in the ninth year with probability 0.1190. Notice that these probabilities need not sum to one, since the events in question are neither mutually exclusive nor collectively exhaustive.

Figure 7. Policy Summary

	YEARS									
TECHNOLOGY	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	9-10
S			0.1602							
F						0.7223			0.1175	
B1	1.0000									
B2										
B3										
B4									0.1190	
B5										

FREQUENCY OF ACTIONS BY YEAR

The risk profile of the optimal policy cost (Figure 8) is the probability distribution of the cost of the optimal policy. The expected value of the cost is the value of the objective function (3a), in this case $2,516. The values reported in the profile reflect the full range of possible outcomes under the optimal policy.

Figure 8. Risk Profile

Cost Range	Cumulative Probability
1922 to 1999	0.1175
1999 to 2076	0.1175
2076 to 2153	0.1175
2153 to 2230	0.1175
2230 to 2307	0.1175
2307 to 2384	0.7208
2384 to 2461	0.7208
2461 to 2538	0.7208
2538 to 2614	0.7208
2614 to 2691	0.7208
2691 to 2768	0.7208
2768 to 2845	0.8398
2845 to 2922	0.8398
2922 to 2999	0.8398
2999 to 3076	0.8398
3076 to 3153	0.8398
3153 to 3230	0.8398
3230 to 3307	0.8398
3307 to 3384	0.8398
3384 to 3461	1.0000

Mean = 2516.39
Standard Deviation = 462.62
Skewness = 1.10

CONCLUSIONS AND FURTHER WORK

We have described a model and a methodology that help DR planners evaluate strategic policies under uncertainty. Application of the methodology will not only lower utilities' costs, but also help them prepare for the future with contingency plans and a deeper understanding of the opportunities and risks they face. The logic of the process is transparent, and the results easy to communicate and update as new information becomes available.

Our formulation of the DR problem responds to the need to evaluate future options as uncertainty unfolds over time. For such problems, the joint consideration of dynamics and uncertainty tends to make the problem much too large for conventional decision tree-type analysis, even with state-of-the-art software. The presence of uncertainty and the need to evaluate strategic management flexibility also takes the problem out of the scope of conventional detailed deterministic engineering analyses.

Future work can make the methodology even more useful. We are currently incorporating more planning uncertainties into the model. Also, as presently designed, the model relies on exogenous estimates of the effects of capacity decisions on electrical system losses and unserved energy. While this model will never be a substitute for a detailed engineering analysis, it would be useful to have more network effects incorporated into the analysis. This could serve as a high-level approximation of both losses and unserved energy in order to determine sensitivity and whether a more detailed external analysis would affect strategy. It would also be useful to expand the model to deal simultaneously with multiple service areas. Sometimes local areas are interconnected physically; moreover, a major DR initiative impacting a group of planning areas could have interrelated impacts through the overall impact on system costs.

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REFERENCES

Bellman, R. (1957). *Dynamic Programming*. Princeton, NJ: Princeton University Press.

Bliss, G.A. (1925). *The Calculus of Variations*. Mathematical Association of America, LaSalle, Illinois: Open Court Publishing Company.

Bullard, C.W. (1980). "Value of Dispersed Intermittent Electricity Generation." DE81015033. Presented at National Conference on Renewable Energy Technologies, Honolulu.

Chapel, S.W., C.D. Feinstein and R. Orans (1993). "Evaluation of Utility Grid-Connected Battery Plants Using Area- and Time-Specific Marginal Costs." *Fourth International Conference, Batteries for Energy Storage*, Vol. II, 140-71.

Chapel, S.W., and D. Richardson (1996). *New T&D Planning Methodology. EPRI Report IN-105750*, EPRI, Palo Alto, CA.

Chovaniec, C.R., J.L. Maitlen, H.S. Kirshbaum and W. Peduska (1978). "Energy Storage Operation of Combined Photovoltaic/Battery Plants in Utility Networks." Presented at 13th IEEE Photovoltaic Specialists Conference, 1185-89, Washington, DC.

Chow, R. (1996). "Local Integrated Resource Planning: Ontario Hydro TIES Study." Presented at DA/DSM DistribuTECH Conference, Tampa Bay, FL.

Davitian, H. (1981). "Methods for Analyzing the Value and Avoided Costs Associated with Dispersed Technologies." DE82013427. Presented at Utility Planning--Consumer's Side of the Meter Conference, Bloomington, MN.

Edison Electric Institute (1994). *Statistical Yearbook of the Electric Power Industry, 1994.* Washington, DC.

Electrical World. (1995). 1995 Forecast Issue. New York: McGraw-Hill Pub. Co.

Feinstein, C.D. (1993). *An Introduction to the Distributed Utility Valuation Project Monograph. EPRI Report TR-102461, PG&E Report 005-93.13,* EPRI, Palo Alto and PG&E, San Ramon, CA.

Feinstein, C.D. (1996). "New Approaches to Local Area Planning: Methodology." Presented at DA/DSM DistribuTECH Conference, Tampa Bay, FL.

Feinstein, C.D. and P.A. Morris (1997a). *Dynamic Probabilistic Models of Area Load Growth.* EPRI Report (Forthcoming). EPRI, Palo Alto, CA.

Feinstein, C.D., P.A. Morris, S.W. Chapel, M.N. Thapa and S. Wan (1997b). *Load Dynamics: A Model for Developing Probabilistic Forecasts of Load Conditions. User's Guide.* EPRI, Palo Alto, CA.

Feinstein, C.D., R. Orans and S.W. Chapel (1997c). "The Distributed Utility: A New Electric Utility Planning and Pricing Paradigm." *Annual Reviews of Energy and the Environment,* Forthcoming.

Feinstein, C.D. and P.A. Morris (1997d). *An Investment Strategy Model for Local Area Expansion Planning.* EPRI Report, Forthcoming. EPRI, Palo Alto, CA

Feinstein, C.D. and J.A. Lesser (1997e). "Defining Distributed Resource Planning." *The Energy Journal,* (Special Issue) *Distributed Resources: Toward a New Paradigm of the Electricity Business.*

Finger, S. (1981). *Integration of Decentralized Generators with the Electric Power Grid. MIT Energy Lab. MIT-EL-81-011.* M.I.T., Cambridge, MA.

Hillier, F.S. and G.J. Lieberman (1986). "Probabilistic Dynamic Programming." *Introduction to Operations Research,* Oakland, CA: Holden-Day: 354-359.

Hoff, T.E. (1996). "Identifying Distributed Generation and Demand Side Management Investment Opportunities." *The Energy Journal* 17(4): 89-105.

Howard, R.A. (1971). *Dynamic Probabilistic Systems.* New York: John Wiley.

Kharatishvili, G.L. (1967). "A Maximum Principle in Extremal Problems with Delays," in *Mathematical Theory of Control.* Balakrishnan, A.V. and Neustadt L.W., eds. New York: Academic Press: 26-34.

Koenig, E.F. (1981). "Electric Utility Rate Structures and Distributed Thermal Energy Storage: A Cost-Benefit Analysis." *Energy* 6: 457-70.

Lee, S.T., J. Peschon and A. Germond (1979). *Impact on Transmission Requirements of Dispersed Storage and Generation. EPRI Report EM-1192,* EPRI, Palo Alto, CA.

Lee, S.T., and J. Peschon (1979). "Impact of Dispersed Generation on Transmission and Subtransmission Requirements." CONF-791006. Presented at Joint Power Generation Conference, Charlotte, NC.

Lesser, J.A. (1996). "What If It Snows? Weather Uncertainty and DU Planning." Presented at 2nd Annual Distributed Resources Conference, EPRI, Vancouver, BC.

Logan DM, Neil CA, Taylor AS, Lilienthal P. 1995. "Integrated Resource Planning with Renewable Resources." *The Electricity Journal* 8: 26-36.

Ma, F., L. Isaksen and R. Patton (1979). *Impacts of Dispersing Storage and Generation in Electric Distribution Systems. DOE/ET/1212.1,* Systems Control, Inc., Palo Alto, CA.

Ma, F.S. and D.H. Curtice (1982). "Distribution Planning and Operations with Intermittent Power Production." CONF-820134. Presented at IEEE Power Engineering Soc. Winter Meeting, New York.

Manne, A.S. (1961). "Capacity Expansion and Probabilistic Growth." *Econometrica* 29(4) (October): 632-649.

Miller, A. and T. Rice (1983). "Discrete Approximations to Probability Distributions." *Management Science* 29(3): 352-362.

Morris, P.A., K.L. Wong and R.O. Wood (1994). *EPRI Investment Strategies Project, Volume I: Value of Flexibility and Modularity of Distributed Generation. EPRI Report TR-104171,* EPRI, Palo Alto, CA.

Morris, P.A. (1996). "Optimal Strategies for Distribution Investment Planning." Presented at 2nd Annual Distributed Resources Conference, EPRI, Vancouver, BC.

Orans, R., C.K. Woo, J.N. Swisher, W. Wiersma and B. Horii (1991). *Targeting DSM for T&D Benefits: A Case Study of PG&E's Delta District.* EPRI Rep. TR100487, EPRI, Palo Alto, CA.

Orans, R. C.K. Woo and B. Horii (1994). "Case Study: Targeting Demand-side Management for Electricity Transmission and Distribution Benefits." *Managerial and Decision Economics* 15(2): 169-175.

Pontryagin, L.S., V.G. Boltyanskii, R.V. Gamkrelidze and E.F. Mischenko (1962). *The Mathematical Theory of Optimal Processes.* KN Trirogoff, trans. LW Neustadt, ed. Interscience, New York: John Wiley.

Pupp, R. (1993). *Distributed Utility Valuation Project Monograph. EPRI Report TR-102807, PG&E Report 005-93.12,* EPRI, Palo Alto and PG&E, San Ramon, CA.

Rigney, D.M., J. Kekela, S.T. Lee and C.K. Pang (1984). "Expansion Planning with Dispersed Fuel Cell Power Plants on Actual Utility Systems." *IEEE Transactions. Power App. Sys.* PAS-103: 2388-97.

Shugar D, M. El-Gasseir, A. Jones, R. Orans and A. Suchard (1991). *Benefits of Distributed Generation in PG&E's T&D System: A Case Study of Photovoltaics Serving Kerman Substation. PG&E Internal Report,* PG& E, San Ramon, CA.

Sobieski, D.W. and M.P. Bhavaraju (1985). "An Economic Assessment of Battery Storage in Electrical Utility Systems." *IEEE Transactions. Power App. Sys.* PAS-104: 3453-59.

Tabors, R.D. S. Finger and A.J. Cox (1981). "Economic Operation of Distributed Power Systems within an Electric Utility." CONF-810201. Presented at IEEE Power Engineering Society, Atlanta, GA.

Van Horne, P.R., L.L. Garver, A.E. Miscally (1981). "Transmission Plans Impacted by Generation Siting--A New Study Method." *IEEE Transactions. Power App. Sys.* PAS-100: 2563-67.

Zaininger, H.W., H.K. Clark and G.C. Brownell (1990). *Potential Economic Benefits of Battery Storage to Electrical Transmission and Distribution Systems. Final Report EPRI GS-6687, Project 1084-35,* EPRI, Palo Alto, CA.