# Evaluating Risk Management Strategies in Resource Planning

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*Abstract* – This paper discusses the evaluation of risk management strategies as a part of integrated resource planning. Value- and scope-related uncertainties can be addressed during the process of planning, but uncertainties in the operating environment require technical analysis within planning models. Flexibility and robustness are two key classes of strategies for managing the risk posed by these uncertainties. This paper reviews standard capacity expansion planning models and shows that they are poorly equipped to compare risk management strategies. Those that acknowledge uncertainty are better at evaluating robustness than flexibility, which implies a bias against flexible options. Techniques are available to overcome this bias.

*Keywords* – Economics, planning models, integrated resource planning, uncertainty, risk.

## I. INTRODUCTION

Risk management is now an essential part of the planning process in the electric power industry. For the past twenty years, uncertainties in load growth, fuel prices, capital costs, and regulatory standards have challenged industry planners [1]. Competitive forces are adding new risks that make responsible decision-making even more difficult [2]. Planners are shifting from simply optimizing resource investments assuming a certain future to a different mode of planning, assuming uncertainty [3, 4]. Uncertainty imposes risk, and explicit risk management strategies are being developed. This paper discusses how to evaluate such strategies in the Integrated Resource Planning (IRP) context.

Methods for evaluating risk management options should be determined by the characteristics of those options, rather than having the method dictate what gets examined. This paper briefly characterizes uncertainty and reviews the range of risk management alternatives. It then discusses the relative merits of various evaluation techniques, and concludes with comments on the adequacy of modeling frameworks most familiar to utility planners.

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## II. TYPES OF UNCERTAINTY

Many things are uncertain during real decision making processes. These include "locally" unknown items, such as industry best practices, that may be clarified with further research. There are also "unknowable" items, such as future load growth, that may only be estimated. Finally, there are "strategic" items that depend upon decisions made by others.

The degree of uncertainty may vary, ranging from items showing stochastic behavior within a known probability distribution to those exhibiting apparently chaotic behavior. Magnitudes may be known but not frequency or timing. From a system modeling perspective, uncertainty may lie in the value of exogenous inputs and also in the relationships among variables in the system. A representation of uncertainty in a modeling construct may also result from a lack of consensus about assumptions.

Each type of uncertainty has different implications for decision makers and analysts. At the broadest level, three classes of prescriptions exist. For uncertainties in the operating environment of the decision makers (uncontrollable exogenous variables), technical investigation is in order. For uncertainties about the guiding values of the decision makers (weighting factors on the objective function), consultation about policy priorities is needed. Finally, for uncertainties about future decisions on related agendas (variables made exogenous by scoping limitations), coordination among actors is crucial. Hence the familiar call "for 'more investigation,' 'clearer aims,' or 'a broader agenda' as a pre-requisite to more confident decision-making" [5].

The IRP process as a whole must address all three categories -- environmental, value-related, and scope-related uncertainties [6]. This paper, however, focuses on environmental uncertainties that can be managed with the help of technical investigation. Uncertainty provides risks and opportunities, and, as such, is of great interest to investment planners. Investors are typically risk-averse, and thus seek to manage risk. The next section outlines risk management strategies commonly used in the investment planning community that have relevance to utility planners.

## III. STRATEGIES FOR MANAGING RISK

General strategies for dealing with risk include (1) investing for flexibility so that changes can be easily and inexpensively made; (2) investing in projects that are robust, i.e., perform well across a variety of futures; and (3) ignoring risk. Each of these warrants further discussion; see also reference [7].

*Flexibility*

Flexibility allows easy and inexpensive changes to be made if future conditions so dictate. Key features of flexible investments are that they are adaptable, and allow smaller commitments and deferrable decisions.

Smaller Commitments: Flexibility can be achieved by building the system from small, modular components, or by specifying investments with a relatively short lifetime. One might choose to pay a premium for such flexibility. For example, compared to a large nuclear investment, the higher expected life-cycle cost of a gas turbine combined cycle plant might be balanced by lower risk due to a smaller initial capital cost.

Adaptability: The combined-cycle technology might also be preferred because it can easily adapt to changing future circumstances. Its shorter lead time allows planners to better match investments to loads, phase-in opportunities ensure that commitments to peaking capacity can evolve to meet future base load needs, and fuel-switching capability allows operators to respond to shifts in fuel prices.

Deferring Decisions: Additional information typically improves one's decision-making ability. If a great deal of uncertainty surrounds some aspect of a project, waiting, and then possibly purchasing additional information, can improve the quality of the final design. For example, if the attractiveness of a nuclear investment hinges on the passage of legislation limiting $CO_2$ emissions, then waiting for the policy debate to be resolved is worth something. The benefit of a deferred decision and additional information can be quantified.

*Robustness*

Rather than seek flexibility, one could instead select alternatives that perform well across a variety of possible futures. Robust investments may substitute a known initial commitment (with an unknown rate of return) for an uncertain stream of future costs.

Robust Designs: Robust investments may reduce the variance in possible outcomes by reducing the use of an uncertain input. For example, investments in energy efficiency decrease fuel-side risks. Another way to increase robustness is to ensure the availability of the uncertain input. For example, one could lock in long term fuel contracts adequate to meet the lifetime needs of a power plant.

Risk Hedging: Rather than reduce the variance in performance of a single investment by making it robust, one could reduce variance in the performance of the overall portfolio of the firm's investments. Such a hedging strategy would couple investments with complementary vulnerabilities. For example, to hedge against the fuel-side risk of a gas turbine combined cycle plant, one could make a complementary investment in natural gas futures. If gas prices stay low then the plant remains attractive, and if gas prices increase then the futures contract can be sold at a profit, balancing the reduced attractiveness of the plant and ensuring the robustness of the overall portfolio.

Risk Pooling: Enterprises can cooperate to pool risk, taking advantage of diversity in their risk profiles, as well as scale effects that spread the impacts of individual investments over a larger base. For example, utilities in New England jointly own most of that region's nuclear capacity [8]. To exploit complementary risk profiles, a fossil fuel-dominated utility may trade partial ownership of a large fossil plant for a similar share of a nuclear plant owned by a nuclear-heavy utility.

Risk Shifting: An enterprise may also be able to shift risk to other parties. For example, the Price-Anderson Act limits the liability of nuclear utilities for accidents, shifting risk to the large base of U. S. taxpayers who are perceived to be better suited to bear the risk. Similarly, fuel-side risks are passed on to utility customers through an automatic fuel cost adjustment clause, and many IPP contracts allow accelerated recovery of capital costs from utilities (and customers) to reduce investment risk [9].

Note that all flexible strategies are also robust, but that *not* all robust strategies are flexible. Thus flexible strategies are more generally desirable, all else being equal.

*Ignoring Uncertainty*

Sometimes it is rational simply to ignore the effects of uncertainty -- on short-lived projects, small projects, or when one feels confident in predicting the course of future events. For example, long term uncertainty about demand (e.g., will electric vehicles take off?) is irrelevant to short-term power purchase decisions. Likewise, a deterministic life-cycle cost analysis is probably adequate for most residential energy audits; otherwise design costs may exceed net benefits. Confident point estimates are justifiable for some phenomena; for example, the cost and performance of standard generating technologies.

Summarizing, when significant uncertainties exist, they should be acknowledged in the planning process; otherwise the enterprise may specify inflexible, inadequate, inappropriate systems that fail to meet its needs. A different strategy for dealing with uncertainty may be most appropriate for each specific context.

## IV. TRADITIONAL EVALUATION METHODS

The analytical representation of uncertainty has progressed from ignoring it, to perfunctory sensitivity analysis, to sophisticated scenario or Monte Carlo analysis. Practice has lagged significantly behind theory because of implementation complexities. This section discusses the deterministic approach traditionally practiced in engineering investment planning. It represents a baseline, from which the state of the art is progressing towards more complete representations of uncertainty.

Investment planning models for the electric power sector have enjoyed decades of development, and have achieved a significant degree of sophistication. A great deal of work has been done on investment planning models for use under deterministic conditions. The standard approach is to formulate an operating *and* investment cost minimization problem subject to a demand constraint. This applies the normative framework of neoclassical economics and represents the calculation done for each possible level of demand. Techniques that further embrace this economic context by examining the demand curve and maximizing consumer's surplus (rather than minimizing costs) are now entering use [10].

Generalizing reference [11] for any firm with multiple units of productive capacity, the objective is to minimize the life-cycle costs (*LCC*), defined as the sum of capital and operating costs over some future time period *0* to *T*:

Minimize $LCC =$

$$\sum_{v=1}^{T} \sum_{j=1}^{J} C_{jv} \cdot X_{jv} + \int_{t=0}^{T} \sum_{v=-V}^{t} \sum_{j=1}^{J} F_{jv}(t) \cdot U_{jv}(t) \cdot dt \qquad (1)$$

where $X_{jv}$ is the productive capacity of a particular piece of equipment with operational characteristics of type $j$ and vintage (installation year) $v$. The capital cost per unit of productive capacity of machine type $j$ with vintage $v$ is $C_{jv}$. The actual production rate of that piece of equipment at any instant $t$ is $U_{jv}(t)$, where $0 \leq U_{jv}(t) \leq X_{jv}$. The discounted unit production cost for this machine is $F_{jv}(t)$. To obtain the firm's total operating costs during $dt$, we consider both the existing equipment ($v = -V$ to 0) and the new equipment ($v = 0$ to $t$). This minimization problem is subject to the condition that the demand ($Q_t$) at every time $t$ must be satisfied.

$$\sum_{j=1}^{J} \sum_{v=-V}^{t} U_{jv}(t) \geq Q_t \qquad \text{for } t = 1, \ldots, T \qquad (2)$$

This is essentially a search for optimum capacities and optimum operating schedules. It was first solved using linear programming [12], but recent applications have relied on dynamic programming and other approaches [13]. However, all of them are deterministic, that is, they assume perfect foresight.

### *Sensitivity Analysis*

This is not a deterministic world. There is uncertainty regarding the price and availability of inputs, the expected level of demand, and other factors. One can continue using the optimization method of equations (1) and (2) by employing expected values for uncertain variables. The effects of uncertainty regarding key input assumptions then may be tested using sensitivity analysis.

The primary analytical effort is devoted to specifying a detailed, most probable base case. Then *ceteris paribus* changes – one variable at a time relative to the base case – can show the sensitivity of the results to changes in inputs. These changes can be reported on a 'tornado' diagram that shows relative impacts. Sensitivity analysis also tests robustness in a crude way: if a changed input changes the optimal plan, then the plan is not robust.

Existing packaged capacity planning programs can be used to perform sensitivity analysis of key inputs [13]. This helps in understanding the vulnerabilities of a favored plan; however it does not allow easy comparisons across a range of risk management strategies.

## V. PORTFOLIO MANAGEMENT APPROACHES

Many decision makers choose to manage the firm's multiple investments in productive capacity as if they were an investment portfolio. Various technologies have different strengths and weaknesses – some have high capital costs and low operating costs, while others have low capital costs and high operating costs. They may depend on different inputs to produce similar outputs, and thus different pieces of equipment are likely to be susceptible to different risks. In order to account for the effects of uncertainty, the investment planning problem may be re-cast as a portfolio optimization problem.

Formal portfolio analysis requires moving from deterministic cost minimization to the use of a utility function considering more of the decision maker's preferences and attitude towards risk. At its simplest, portfolio analysis applies a mean-variance criterion, in which investors choose among alternative portfolios considering not one, but two attributes – the mean life-cycle cost and its variance given uncertainty [14]. While finance theory usually works with rate of return, an attribute that directly increases utility, the theory also holds for other attributes – such as total resource cost – that decrease utility [15].

The tradeoff between the attributes of (expected) cost and risk obviously depends on the investor's perception of risk. A risk-neutral investor would accept the minimum of the expected value of cost equation (1) as an optimum regardless of its variance under uncertainty, whereas a risk-averse investor would be willing to accept a solution that had a higher expected value but a lower variance in cost.

Decision scientists argue that assessment of a full uni-dimensional utility function is preferable, both in practical and theoretical terms, to the mean-variance method [15]. Equation (3) shows the expected utility of an investment's life-cycle cost $U(LCC_Z)$ across a range of uncertain conditions Z occurring with probability $p_Z$. Utility functions are by nature decision-maker-specific, and must be assessed by querying real people about their preferences for different options under conditions of uncertainty (such as a series of choices between lotteries and their certainty equivalents). Some firms, including utilities, conduct exercises of this sort with their executives in optimizing their investment portfolios [16, 17].

$$E[U] = E[U(LCC)] = \sum_{z=1}^{Z} p_Z \cdot U(LCC_Z) \qquad (3)$$

$$\text{for all } z \text{ where } U\uparrow \text{ as } LCC\downarrow \text{ and } \sum_{z=1}^{Z} p_Z = 1 \qquad (4)$$

The portfolio analysis approach also requires that we know the distribution of possible performance outcomes for the investment portfolio, given the various uncertainties that affect it. Financial applications emphasize the evaluation of financial instruments whose historical performance may be documented [14]. However, for applications targeting physical capital it is more useful to simulate the performance of the various pieces of equipment across a range of operating conditions.

However, not all decision criteria may be reflected in a uni-dimensional utility function, especially in cases where it is not known precisely how exogenous variables affect the cost function [18]. Also, the uni-dimensional approach might collapse several factors together, thereby making it difficult to assess the relative importance of each. Formal utility theory acknowledges the need to translate the effects of all factors into their *util* equivalents. The closest operational approach is to perform the assessment using a multi-attribute utility function. These factors together argue for the development of a multi-attribute simulation capability (see equations 5 and 6 for the case of *n* attributes in addition to *LCC*).

$$U = U(LCC, X_1, X_2, ..., X_n) \qquad (5)$$

for all $z$ where $U\uparrow$ as $LCC\downarrow$ or $X_1, X_2, ..., X_n\downarrow$

$$E[U] = E[U(LCC, X_1, X_2, ..., X_n)] = \sum_{z=1}^{Z} p_Z \cdot U(LCC_Z, X_{1Z}, X_{2Z}, ..., X_{nZ}) \qquad (6)$$

There are various ways to implement this conceptual approach. They are discussed below, in order of increasing difficulty.

*Contingency Analysis*

Instead of specifying a most probable base case, one can devote the primary analytical effort to a "least commitment" case that features low load growth. This represents the minimum likely level of investment to be made. Options for meeting higher possible loads may then be evaluated as contingencies to be covered as they occur [19]. The contingency of most probable load growth needs to be especially closely evaluated.

This approach is executed as a series of scenarios examining different contingencies, e.g., higher load growth in year 1, or year 2, or year 3 of the planning horizon. It relies on the optimization algorithms within the capacity planning package, but restricts the range of options considered within each scenario. This allows analysis of flexibility and deferral of decisions. It draws on the "option value" concept from the theory of contingent claims in finance [20, 21].

*Scenario Analysis with Internal Optimization*

The deterministic optimization algorithms in typical capacity expansion planning packages may be adapted to better acknowledge uncertainty by using scenario analysis. Unlike sensitivity analysis that changes only one variable at a time relative to a base case, scenario analysis constructs several different internally consistent futures and identifies optimal and near-optimal plans for each of them. Such applications model a few distinctive scenarios like "boom," "bust," "high oil prices," and "nuclear moratorium" [22].

Robust elements are those included in most of the optimal plans generated for the range of scenarios. Probabilities may be assigned to the various scenarios to allow expected value comparisons of alternative plans. Standard software is available to facilitate the job of assigning probabilities and identifying robust plans given a large number of scenarios [23, 24]. This type of scenario analysis can be used to assess the risk management strategy of robustness, but it is not well suited for evaluating flexibility.

*Scenario Analysis with External Optimization*

In order to assess flexible options and optimize on multiple criteria, a meta-modeling framework can be built around a modeling "engine" like [13], or a package like that has a built-in scenario organizer can be used [24]. The package is run as a simulator to evaluate plans generated externally. The framework generates many scenarios, the simulator evaluates them, and then either decision analysis or tradeoff analysis techniques identify a preferred plan.

The decision analysis approach assigns probabilities to scenarios and specifies a multi-attribute utility function to guide selection of the optimal plan [15, 24]. The tradeoff analysis approach sorts plans into superior and inferior categories across discrete futures, using increasingly stringent decision rules until a dominant plan emerges [25, 26].

The relative strengths of flexible options, such as power plants with short lead times, can be evaluated with the help of appropriate external capacity planning algorithms. These algorithms generate capacity expansion plans for subsequent simulation. Unlike the perfect foresight required in the linear or dynamic programming techniques, such algorithms operate incrementally and in ignorance of the future. They are simplistic 'imperfect planners' that overshoot and undershoot their target reserve margins, and correct by canceling or delaying units of excess capacity [27].

Technology Mix Specified: One way to design such an algorithm is to first specify a technological strategy, so that the algorithm builds to meet expected load using a specific mix of resource options. It iteratively plans, year by year, performing a forecast, buying options on resources, canceling excess incomplete capacity, and completing units needed in the near future. "Real" load growth and fuel price trajectories are revealed to the algorithm only a year at a time. The algorithm contains a forecasting rule, such as "extrapolate the average of the three most recent years' load growth out twenty years." Each year it then continues construction, cancels, delays, or completes units to meet expected load, based on the latest information available to it. The final capacity expansion plan it produces reflects the value of flexibility in the sense that strategies containing technologies with shorter lead times, etc., would have better adapted to changing conditions than those with longer lead times, etc. A range of uncertainty cases would need to be evaluated, as before, to identify robust but flexible strategies [27].

Decision Rule Specified: An alternative way to adapt an existing optimization package like [13] to evaluate flexible options would be to iteratively run the deterministic optimization model, once for each year of the study period. Outside of the package, the power plant data base would need to be changed to reflect the existing/committed/optional status of power plants based on the previous iteration. Likewise, load and fuel trajectories would need to be updated. This approach has the advantage of using the sophisticated mathematical programming techniques that come with the package for the capacity planning step, thus allowing the program to choose the optimal mix of technologies.

*Stochastic Optimization*

Uncertainty can be brought inside of the optimization process in several ways. Some approaches rely on internal comparisons of scenarios [28, 29, 30] while others perform Monte Carlo simulations [31]. Both approaches handle stochastic variables internally, but must handle chaotically-uncertain variables externally through scenario comparisons.

The joint investment/operation problem of equations (1) and (2) can be decomposed to allow updating of operational outcomes based on expected values derived from simulating multiple uncertainty cases; these updates then influence investment choices [28, 29]. Novel objective functions can be added to this capability to capture mean-variance preferences [30] or minimax regret [29]. Such approaches identify robust options but do not necessarily find flexible options.

Rather than running a range of scenarios representing different discrete load growth cases, one can specify a probability distribution for load growth (and other uncertainties). A capacity expansion planning program can then draw yearly values at random from these distributions. The algorithm performs incremental planning as described above, buying options on new plants, completing new plants, or canceling them. By repeating this analysis a large number of times ($\approx$100), a stable distribution of outcomes emerges. The elements of a superior planning strategy will be those selected most often [31]. This approach captures the benefits of robustness and flexibility.

## V. CONCLUSIONS

There are several types of uncertainties that pose risks for electric power investments. Value- and scope-related uncertainties must be dealt with in the design of the integrated resource planning process. Those related to the operating environment must be addressed in the technical analysis. Flexibility and robustness are two general classes of proactive technical risk management strategies, and each has sub-categories. An ideal evaluation tool will allow comparisons among them and yet remain analytically tractable. Few existing modeling packages can do this, as indicated by the qualitative assessment shown in Table 1.

Table 1:
Capability of Various Modeling Frameworks to Evaluate Risk Management Strategies
(-- = none, x = modest, X = significant)

| Modeling Framework | Flexibility | Robustness |
|---|---|---|
| Deterministic Optimization | -- | -- |
| Sensitivity Analysis | -- | x |
| Contingency Analysis | x | x |
| Scenario Analysis with Internal Optimization | -- | X |
| Scenario Analysis with External Optimization | X | X |
| Stochastic Optimization | X | X |

Among the techniques that incorporate uncertainty, more can evaluate robustness than flexibility. This suggests that current modeling practice may have a bias against flexible options. While techniques are available to counter this bias, they are not yet widely implemented. Modelers have a significant task ahead -- call it an opportunity -- to provide useful analysis of risk management options within the IRP context.

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