CHAPTER 3

Approaches to Capacity Planning

3.1 Introduction

Having identified the scope of uncertainties in the previous chapter, we now consider how to model it. The modelling approach appeals favourably to an engineering-dominated, process-oriented industry. The operational research (OR) techniques that have been used to address the problems in capacity planning are known for their applications to scheduling, resource allocation, routing, queuing, inventory control, and replacement problems commonly found in other capital-intensive, infrastructure-based industries such as telecommunications, military, and transportation. We review these applications according to the ***extent*** to which they capture the areas of uncertainties with respect to ***completeness*** and the ***manner*** in which they treat the types of uncertainties with respect to ***adequacy***.

The next three sections present the most commonly used techniques and their capacity planning applications. These techniques are grouped according to their primary functionality of optimisation, simulation, and decision analysis, delineating the fundamental differences in modelling approaches. ***Optimisation*** in section 3.2 refers to linear programming, decomposition methods, dynamic programming, and stochastic programming. ***Simulation*** in section 3.3 refers to system dynamics, scenario analysis, sensitivity analysis, and probabilistic risk analysis. ***Decision analysis*** in section 3.4 refers to the use of decision trees and other decision-theoretic techniques. In each section, the techniques and respective applications are briefly introduced, with emphasis on their particular treatment of uncertainty. Following individual applications of techniques, we review applications based on two or more techniques, which we call “model synthesis.” Here in section 3.5, the same critique of areas and types of uncertainties is given. Modelling requirements, relating to technique functionality and limitations, are developed in the concluding section (3.6). Several proposals are made on the basis of this review.

3.2 Optimisation

Optimisation refers to the objective of minimising or maximising a function subject to given constraints. "Optimisation" is usually understood in the deterministic sense, whence linear programming, decomposition methods, and dynamic programming readily apply. The next sub-sections present the optimisation techniques in this order, with a final note on stochastic programming, which is a form of non-deterministic optimisation.

As early as the 1950's, capacity planning was perceived as that of meeting least cost objectives within a highly constrained operational environment, and was first modelled with linear programming (Massé and Gibrat, 1957). If the problem becomes too large to handle, decomposition methods (Vlahos, 1990) could be used to breakdown the complexity and to speed up the computation. If viewed as a multi-staged problem in which decisions follow in sequence, dynamic programming (Borison, 1982) can be readily used as an alternative optimisation algorithm. More recently, stochastic programming has been used to model the deterministic and non-deterministic effects.

3.2.1 Linear Programming

Traditionally, capacity expansion has been formulated as a least cost investment problem, utilising the algorithmic strengths of linear programming to minimise total cost subject to fuel availability, demand, capacity, and other constraints.

The objective cost function typically includes capital, fuel, and generation costs, over the entire planning period. The constraints typically include forecast demand, plant availability, and other technical performance parameters. The planning period is usually split into sub-periods for modelling detail variations. The result is an investment schedule of different types of plants with varying sizes to come on stream and retire at different dates.

A demand constraint is usually represented by a linear approximation to the load duration curve (LDC). However, use of the LDC implies that costs and availability of supply depend only upon the magnitude of the load and not on the time at which the load occurs. This assumption is approximate for hydro systems and accurate for thermal systems only if seasonal availabilities are taken into account. Because power demand is highly variable throughout the day and year, the resulting LDC used in the constraint is an average approximation.

In their first trial in 1954, Electricité de France (EdF) developed a schematic linear programming model with only 4 constraints and 5 variables (Levy, 1989). Described in a classic paper by Massé and Gibrat (1957), this is the earliest application of LP to electricity planning. Dantzig (1955) modelled the same problem with 70 constraints and 90 variables.

Some early LP models are discussed and classified in Anderson (1972) into so-called marginal analysis, simulation, and global models. In all cases, cost minimisation is the main objective. The quantities demanded are assumed to be exogenous, and all formulations are deterministic. The results must also satisfy engineering criteria, such as system stability, short-circuit performance, and reliability of supply. Allowances for uncertainty are given in the form of simple spare capacity, which have to be expressed as a mean expected quantity because of the deterministic formulation.

A standard linear programming formulation in McNamara (1976) subjects the objective of minimising the present value of a future stream of operating and investment costs to meeting projected future demand. Projections of future revenues, costs, and capital requirements are made using a corporate financial planning model. The LP model quickly determines the logical implications of known information and the impacts of variations in assumed trends. The results are tested in the sensitivity analysis that typically follows an optimisation run. This post-optimal sensitivity analysis is not a substitute for uncertainty analysis as it does not sufficiently address the uncertainties of the problem.

Greater accuracy and detail, such as to capture the non-linear effects of economies of scale and merit ordering (load duration curves), impede upon the computational speed of linear programming. Nowadays, formulations with tens of thousands of constraints and variables, are common, e.g. Vlahos (1990), but they require other methods of improving the speed. Non-linear programming is one way to overcome this. However, when uncertainty is incorporated in these quadratic functions, the model becomes computationally intractable (Maddala, 1980). The complex, non-separable, but convex objective function of a non-linear programme cannot take advantage of what standard LP computer software can offer, namely, computational speed, standardisation of problem formulation, input and output processors, and integer programming facilities. Furthermore, non-linear programming cannot be readily rewritten to address other issues, in the way that LP can cope with allocation, scheduling, etc. In other words, a non-linear programming formulation is very problem-specific. One way to fit the result to a non-linear framework with uncertain parameters is through sensitivity analysis of the dual and slack variables. But this only gauges the sensitivity of the output result to the input variables. Model validation is not the same as uncertainty analysis.

Schaeffer and Cherene's (1989) mixed-integer linear programme follows the pioneering work of Massé and Gibrat. The first part addresses the short-term dispatching problem, which seeks the optimal utilisation of an existing array of generation plants to meet short-term demand at minimal cost. The second part addresses the long-term objective of optimising the expansion of electricity generation capacity over a planning horizon of several years. As the short run operating cost of the dispatching problem depends on the investment decision of capacity expansion, it is necessary to evaluate both problems. They make use of "cyclical programming" to minimise the cost per cycle over an infinite number of identical cycles of demand constraints, thus allowing the dynamics of demand to be modelled while keeping the number of variables to a minimum. Through this method, uncertainties are incorporated to address the following: level and distribution of future demand, equipment reliability, length of lead times for new equipment, and possible changes in regulation which may affect plant efficiency. To keep the model computationally tractable, reserve margins are used to deal with uncertainty. By using a different technique for short-term details, the model overcomes the need to use a sophisticated probabilistic technique which may increase the complexity of the model.

The advantages for choosing linear programming are nevertheless abundant. Great computational power is built on its mathematical foundations. Fundamental technical and cost relationships can be approximated accurately by linear or piecewise linear functions. Dual variables are useful in post LP analysis though not adequate for the analysis of uncertainty.

As the earliest and most popular of all optimisation techniques, linear programming has been nevertheless superseded by other optimisation methods that overcome some of the following problems when applied to power plant scheduling.

1) Incorporating the probabilistic nature of forced outage into LP is difficult because all dependent variables have to be expressed or approximated by linear functions.

2) The optimal capacity size of a generating unit determined by LP is a continuous function, and therefore must be rounded to the nearest multiple of a candidate unit. This rounding may result in a sub-optimal solution.

3) The discrete nature of generating units can be treated by mixed-integer linear programming, but as the number of integer variable increases, there exists a severe penalty on computational cost. These linear approximations make the outcome less accurate and less optimal.

4) None of the examples above have dealt with objectives other than cost minimisation.

5) Linear programming is incapable of addressing business risk in an acceptable fashion.

6) Neither can it handle the multi-staged nature of capacity planning as there is no resolution of uncertainty.

7) The strict linearity conditions imply that non-linear effects such as economies of scale and reliability cannot be modelled accurately.

8) Linear programming requires considerable computer resources to satisfy the large number of constraints in capacity planning. The complexity and size of formulation quickly reach the limit in efficiency.

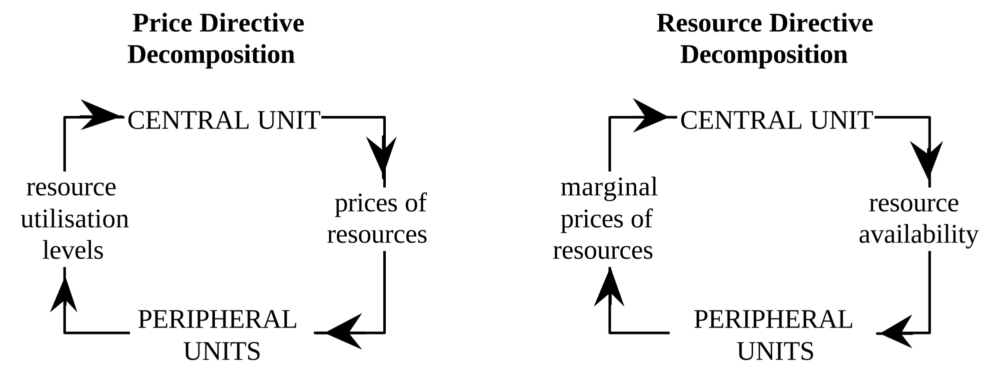
9) It is a technique specific to capacity planning but not uncertainty. It is unable to deal with uncertainty without relying on numerous assumptions, approximations, and post-LP analysis.

3.2.2 Decomposition Methods

Decomposition refers to the breaking down of a large complicated problem into many smaller solvable ones, thereby reducing computer processing time. For example, the linear approximation of the load duration curve can be divided into many periods, each to be solved by bounded variable LP or decomposition methods. The iterative nature of decomposition reaches the optimum by convergence in contrast to the simplex method of mathematical programming.

In the context of linear programming, two types of decomposition are available, namely the ***resource directive*** and the ***price directive***. They differ in the way the information is passed, as depicted in figure 3.1.

Figure 3.1 Decomposition Methods



Source: Vlahos & Bunn (May 1988)

A well known representative of the ***resource directive decomposition*** is Benders' decomposition, which is used to formulate the capacity expansion model in Vlahos (1990) and Vlahos and Bunn (1988a). Different expansion plans are examined iteratively, and the operating cost is calculated with marginal savings from extra capacity. This information is fed back to the master programme at each stage, and a new plan is proposed. Lower and upper bounds to the total cost are set at each iteration, to accelerate convergence.

The state-of-the-world decomposition of Borison et al (1984) uses the price directive decomposition technique, such that "prices" or Lagrange multipliers control the flow of the algorithm. Each state-of-the-world consists of a unique scenario in terms of the information used to characterise the generation technologies but at a fixed point in time with fixed resolution of specified uncertainties. A ***primal dual method*** solves the probabilistic problem using simple static deterministic solution techniques. The main problem is then decomposed into a set of linked static deterministic problems where linkages are enforced through ***Lagrange multipliers***. These problems are solved separately in a primal iteration while the multipliers are updated in a dual iteration.

Decomposition has several advantages over linear programming (Vlahos and Bunn 1988ab, Côté and Laughton 1979), as follows.

1) Non-linearities can be handled in decomposition but not in the LP formulation.

2) Integration of different levels of planning is possible.

3) The advantage of decomposition lies in its efficiency and ability to handle non-linearities.

As a deterministic method, however, it is unable to handle uncertainties adequately.

3.2.3 Dynamic Programming

Anderson (1972) notes that the multi-staged, sequential decision-making nature of capacity planning is analogous to the standard deterministic inventory problem which is often solved by the recursive methods of dynamic programming. Dynamic programming is a computational method which uses a recursive relation to solve the optimisation in stages. A complex problem is decomposed into a sequence of nested sub-problems, and the solution of one sub-problem is derived from the solution of the preceding sub-problem. In this sequentially dependent framework, each stage involves an optimisation over one variable only. Preceding decisions are independent. The problem must be reformulated to uphold Bellman's Principle of Optimality (Bellman, 1957):

> An optimal sequence of decisions has the property that whatever the initial circumstances and whatever the initial decision, the remaining decisions must be optimal with respect to the circumstances that arise as a result of the initial decision.

The least cost investment decision in Boyd and Thompson (1980) uses a conventional ***backward-timing dynamic programming*** algorithm to determine the effect of demand uncertainty on the relative economics of electrical generation technologies with varying lead times. The algorithm evaluates short versus long lead time generation technologies, under different cases. Many assumptions were made in the demand and supply models to reduce the stages, such as the assumption of a linear cost model, e.g. a lumped sum investment due when plant comes on line, rather than the usual progressive payments during the construction period. Several complications were found in practice. The optimal investment plan consists of lists of tables. To get the decision at any stage, one must read off the tables corresponding to the right level of demand that might occur in that period. It is an unrealistic model as tremendous simplifications were necessary to meet the computational requirements.

In a similar manner, Borison's (1982) probabilistic model of the problem focuses on strategic uncertainties of demand, technological, regulatory, and long-term generation expansion dynamics. The four part algorithm consists of a dynamic programming procedure, a primal dual procedure, a recursive technique, and a decomposition technique. While it sounds "comprehensive" on paper, many aspects of the implementation have not been discussed. For example, it is not clear whether this method has been completely computer-coded and tested against other models. Extensions to the model are required to increase the level of detail in financial, operating, and reliability aspects. Flexible decision making in response to the resolution of uncertainty was proposed, but flexibility was not defined or demonstrated.

A theoretical and idealistic approach is described in Richter's (1990) dynamic energy production model. This formulation is two stage with recourse, but contains too many assumptions to be useful for electricity generation. For one thing, the power station must be able to store the energy produced!

The main modules of the commercially available software packages (all documented in IAEA, 1984) EGEAS, WASP, and CERES (Capacity Expansion and Reliability Evaluation System of Ohio State University) are based on dynamic programming. An iterative approach is used to find the unconstrained optimum solution. The number of possible capacity mixes increases rapidly as the planning period is lengthened, implying greater computational requirements. WASP (Wien Automatic System Planning) makes further use of constraints to limit the number of expansion alternatives.

Dynamic programming overcomes many of the restrictions in linear programming, as follows (Borison et al, 1981).

1) The capacity constraints on individual technologies actually make it easier, in contrast to most optimisation procedures where constraints increase computation times.

2) Load duration curves can be of any form, especially without the requirement of linear approximation.

3) There are fewer mathematical restrictions in dynamic programming, unlike the linearity and convexity requirements of linear programming.

4) This approach can also incorporate uncertainties in demand and in fixed and variable costs.

On the negative side, the "curse of dimensionality" predominates.

1) To limit computation time, however, the number of resolved uncertainties must be kept to a minimum. Therefore this technique is not practical for addressing most general closed loop decision making problems, which are to do with decision making as a result of knowing the outcome of uncertain events, i.e. adjustment in response to uncertain events.

2) Furthermore, dynamic programming is unable to treat uncertain capacity constraints, equivalent availability, and capacity factor, as the relationships between installed and operable capacity must be fixed.

3) The sequential manner in which the recursive algorithm searches for the optimum is not conducive to handling decisions in the multi-staged sense, that is, with the stepped resolution of uncertainty.

4) Dynamic programming is not only limited in addressing uncertainties but also burdened by the curse of dimensionality, which is due to the branching and recursion effects.

5) In spite of this "range of solutions", the data is not helpful in assessing the kinds of decisions under different conditions in time.

3.2.4 Stochastic Programming

In a typical optimisation formulation:

Minimise $\mathbf{c'x}$ **subject to** $\mathbf{Ax \geq b}$ **and** $\mathbf{x \geq 0}$,

uncertainty about the demand ***b***, uncertainty about the input prices ***c***, and uncertainty about the technical coefficients matrix ***A*** can be treated in stochastic programming. These three types of uncertainties are related to parameters in linear programming (Maddala, 1980), as follows. An ordinary LP problem becomes stochastic when the set ß = (***A***, ***b***, ***c***) of parameters depends on random states of nature, i.e. ß = ß(s), s ε W, where W is the index set, i.e. the set of all possible states, in the following formulation:

Maximise or minimise $\mathbf{Z = c'x}$,

$$\mathbf{where\ x \in R = \{x \mid Ax \leq b,\ x \geq 0\}}$$

Four different approaches to stochastic programming are considered in Soyster (1980) and Modiano (1987), and the first two described here: two stage programming with recourse, chance constrained programming, stochastic programming via distributional analysis, and expected value / variance criterion in quadratic programming.

Dantzig (1955) was probably the first to demonstrate a way of incorporating uncertainty into linear programming. The two-stage nature of such problems became known as ***stochastic programming with recourse***. In the first stage, a decision vector $\boldsymbol{x}$ is chosen. A random event (or a random vector of events) occurs between the first and second periods. The algorithm solves the decision vector $\boldsymbol{y}$ in the second stage after taking into account the values for $\boldsymbol{x}$ and the random events. The decision vector $\boldsymbol{x}$ represents the investment decision which must be made well before most uncertainties are resolved. Such investment decisions are classified as "***here-and-now***", i.e. taken before uncertainties are resolved. The second decision vector typically describes the operating decisions which are taken after the random events have occurred, hence the "***wait-and-see***" approach.

These two main approaches are also known as the passive and the active (Sengupta, 1991). The ***passive approach*** requires the decision maker to wait for a sufficient number of sample observations, hence, "***wait and see***." The ***active approach*** develops an adaptive control procedure, to follow cautious policy by updating until more information becomes available. Thus it converts the original stochastic problem into a two-stage decision process.

Another variation of linear programming in the class of stochastic programming is ***chance-constrained programming***, which has the same LP objective function but subject to constraints that are satisfied in a probabilistic manner. Instead of satisfying the deterministic constraint

$$\sum_j a_{ij} x_j < b_i \text{ for all } i,$$

the objective function is subject to the following variation:

$$\text{probability} \left(\sum_j a_{ij} x_j < b_i \right) \geq \partial_i \text{ where } 0 \leq \partial_i \leq 1 \text{ for all } i.$$

While a formulation containing random variables (two stage with recourse) can always be solved by replacing the random variables by their expected values, data specification for the chance-constrained model is far more complex as it requires knowledge of joint probability distributions. Consequently very sophisticated constraints can only be obtained at the expense of highly delicate and comprehensive probability distributions of model parameters. These multivariate probability distributions and non-linear feasible regions present difficulties in reaching the optimum.

Capacity expansion can also be treated as a capital cost allocation optimisation under uncertainty. Sherali et al (1984) use a ***two-stage LP with recourse*** in response to a finite, discretely distributed stochastic demand forecast, to determine the marginal cost-pricing strategy for sharing capital costs given an optimal capacity plan. In many ways, the treatment of capacity constraints and demand restrictions is analogous to a transportation problem. This is essentially two stage stochastic programming with recourse under finite discrete probability distributions for the random load event. The main drawback of this technique lies in the large number of constraints required, thus increasing the time to search for the feasibility region.

Maddala (1980) analyses different formulations and solution methods of mathematical programming that take risk into account to see what elements of various methods can be incorporated into programming models of electric supply. His study includes five stochastic programming approaches, as follows:

1) the E-model which minimises expected costs by substituting mean values for random variables;

2) the V-model which minimises the mean-squared error measured from a certain level;

3) the P-model which minimises the probability that costs exceed a certain level;

4) the K-model which finds the minimum level of costs for which there is 100% probability that costs do not exceed this level; and

5) the F-model which minimises expected dis-utility for a given risk aversion coefficient.

Maddala concludes that stochastic programming formulations in the literature are not suitable for incorporating cost uncertainty. The most practical approach is to consider a probabilistic range of alternatives and solve the deterministic cost minimisation for each alternative scenario. The class of two-stage with recourse is well-behaved as it satisfies the requirements of convexity, continuity, and differentiability, but these do not hold for chance-constrained programming.

Stochastic programming cannot go very far in parametretising uncertainty because the overwhelming number of constraints slows down the computation immensely. In other words, dimensionality gets out of control. Non-linear feasible regions and multivariate probability distributions also cause problems in specification.

3.3 Simulation

Optimisation by its goal seeking algorithm is prescriptive in nature. A more descriptive and exploratory approach is achieved by simulation. The tools of simulation are driven by a different set of objectives: not to find the optimal solution but to experiment with different values. To simulate means to mimic. Simulation can be accomplished manually or automated by a computer. Scenario analysis and sensitivity analysis are included here, as the manual counterparts of the computer simulation techniques of system dynamics and risk analysis. Monte Carlo simulation and other sampling techniques also fall into this category.

3.3.1 System Dynamics

System dynamics is a method of analysing problems in which time is an important factor. A key feature is the effect of feedbacks, of which there are two: a re-enforcing loop and a balancing loop. An example of the re-enforcing loop is the spiral of impossibility described in the previous chapter. “Causal loop” or “stock and flow” diagrams can be used to structure the problem. Many off-the-shelf software, such as DYNAMO (Richardson and Pugh, 1981) and ITHINK (High Performance Systems, 1990), are available to translate these diagrams into complicated differential equations, which describe the dynamic interactions. Such user-friendly software allow quick “what-if” analyses of future scenarios. Powerful graphic capabilities portray the complex interactions during the simulation runs and provide statistical results afterwards.

The system dynamics model of Ford and Bull (1989) represents eight categories of investment by continuous approximations to the discrete number of generating units in the system. A spreadsheet pre-processor translates costs and savings into cost efficiency curves which are then used to generate electric loads. The more common iterative approach used by utilities links a series of departmental models together but is time-consuming in the preparation and completion of a set of internally consistent projections. In comparison, a system dynamics model offers greater flexibility in modelling policy options as it allows the consideration of many alternatives and “what if” scenarios.

Two strategies for capacity planning are tested in Ford and Yabroff (1980) by simulating different types of investments with respect to price, consumer reaction, recession, demand, capacity, and other parameters. Trade-offs between short lead time and long lead time technologies are also examined in the system dynamic models of Boyd and Thompson (1980).

The industry simulation model of investment behaviour of Bunn and Larsen (1992) considers the interplay of demand, investment, and capacity and their effects on the determinants of price, i.e. LOLP and VOLL (explained earlier in Chapter 2). This model has also been used to determine the optimal capacity level of each of the players given the interactions of market forces as well as to hypothesize the effects of changing different variables under different scenarios, effectively a sensitivity analysis within a scenario analysis. This type of causal modelling is suitable for the analysis of market uncertainties.

The system dynamics approach has been greeted with mixed feelings by the electricity supply industry. Because traditional models have been data-intensive and very detailed, planners are suspicious of models which do not require that level of detail in the input specifications. Yet at the same time, system dynamic models usually produce voluminous output which requires careful validation.

3.3.2 Scenario Analysis

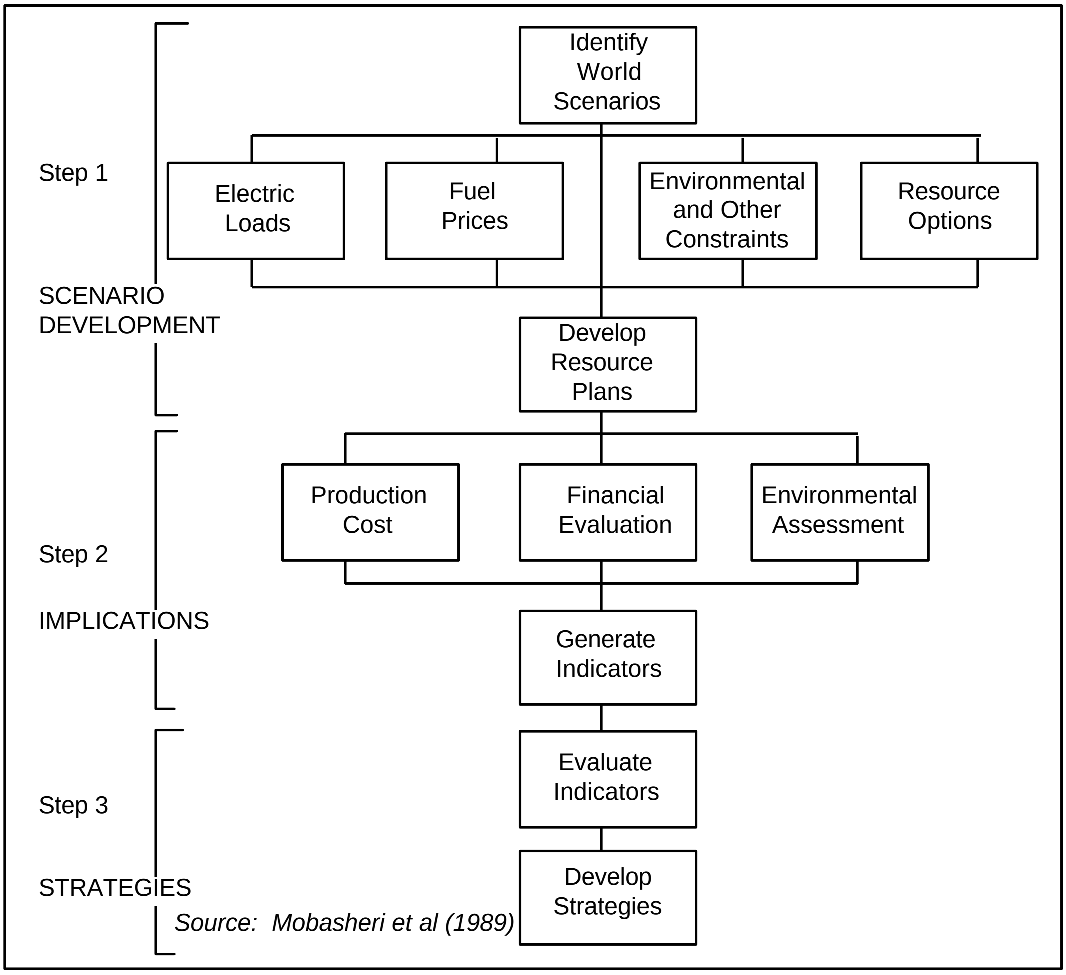
System dynamics is often used as a sophisticated but time-consuming means of generating scenarios of the future. A less formal and less structured method of scenario generation and analysis, called simply ***scenario analysis***, makes use of judgement and discussion. Kahn and Weiner (1967), where scenario analysis probably first originated, defines a ***scenario*** as a hypothetical sequence of events constructed to focus on causal processes and decision points.

Scenarios can be of several types, the most common being “favourability to sponsor,” e.g. optimistic or pessimistic. “Probability of occurrence,” e.g. most likely or least likely, is also very popular although very subjective. Others include “single, dominant issue,” e.g. the economy, status quo or business as usual, and “theme-driven,” e.g. economic expansion, environmental concern, or technological domination.

Five scenarios of the future were constructed in CEGB's assessment of Sizewell B (Greenhalgh 1985, Hankinson 1986.) Firstly, the consumer sector was divided into three main categories: domestic, industrial, and commercial. Within each category, causal links were developed for a highly disaggregated matrix framework which allowed for changes in activity level and energy efficiency. Against assumptions of world economy, world energy prices, and the UK economy, a forecast of future energy requirements was converted into each scenario and translated into future electricity demand. The five scenarios were credible pictures of the future: 1) a high growth and high services scenario, 2) high growth and high industrial production, 3) a middle of the road, 4) stable but low growth, and 5) unstable low growth scenario. CEGB's scenarios were based on forecasts unlike Shell's approach (Beck, 1982) of self-consistent scenarios for contingency planning.

Following Shell's approach but in a more structured manner, Southern California Edison (SCE) found that scenario development by a multi-disciplinary team was more suitable than traditional forecasting methods for planning purposes. Documented in SCE (1992) and Mobasheri et al (1989), their scenario planning process (in figure 3.2) is technique for analysing alternative futures and developing business strategies. It does not produce better forecasts, only a better understanding of the forces that can change the future.

Figure 3.2 Scenario Planning Process



Other ways to conduct scenario analysis are discussed in Huss and Honton (1987), O'Brien et al (1992), and Bunn and Salo (1993). They make use of intuitive logics, trend-impact analysis, and cross-impact analysis. The last approach is accomplished through surveys, interviews, Delphi techniques, and morphological analysis.

In a survey of American utilities, Hirst and Schweitzer (1990) found ***scenario analysis*** to be one of the four most popular methods to assess uncertainty, the others being ***sensitivity analysis***, ***portfolio analysis***, and ***probabilistic analysis***. It is popular for the following reasons.

1) Scenario analysis prepares the firm to rapidly adjust to changing conditions.

2) It relies less on computing power and more on brainstorming and discussions than other types of analysis. Scenario analysis encourages people to think more creatively and broadly about the future, unlike traditional extrapolation techniques.

3) The use of scenarios is particularly helpful in the projection of long range, complex and highly uncertain business environments.

4) Scenario analysis encourages the examination of underlying assumptions by focusing on consequences of events.

5) It is most suitable for situations where few crucial factors can be identified but not easily predicted, where uncertainty is high, where historical relationship is shaky, and where the future is likely to be affected by events with no historical precedence.

6) It is based on the underlying assumption that if we are prepared to cope with a small number of scenarios by testing plans against scenarios then we are prepared for almost any outcome.

Although scenario analysis has become more popular as a corporate planning tool, it is not free from criticism.

1) Unless the chance of occurrence of each scenario is explicitly analysed and specified, planning to different scenarios could be quite costly.

2) These scenarios may never occur, so we may be preparing needlessly. Instead, a combination or some in between scenario may surface and possibly at different points in time.

3) It is hard to predict the interacting events in the future. Furthermore, human judgement is prone to biases.

4) Care must be taken that there are not too many factors involved, else it would be mere speculation. There is a trade-off between the feasibility of considering a large number of factors and the validity of considering a few.

3.3.3 Sensitivity Analysis

Whereas scenario analysis is achieved by hypothesizing discrete, countable futures each with a different set of assumptions, sensitivity analysis is concerned with identifying and screening the most important variables. Hirst and Schweitzer (1990) describe this as a way to see which factors trigger the largest changes in performance and which options are most sensitive to the change. If a change in an estimate has very little effect on the output, then the result is not likely to depend to any great extent on the accuracy of that input variable.

Defining sensitivity analysis as ***the examination of impacts of reasonable changes in base case assumptions***, Eschenbach (1992) advocates the consideration of reasonable limits of change for each independent variable, the unit impact of these changes on the present worth or other measure of quality, the maximum impact of each independent variable on the outcome, and the amount of change required for each independent variable whose curve crosses over a break-even line.

Sensitivity analysis is very rarely used as a stand-alone technique. Its main purpose is to challenge the "uncertainty-free" view of the world. It is often conducted at the end of a rigorous optimisation study or scenario analysis to validate the results, e.g. in the manner of OECD/NEA (1989) and UNIPEDE (1988).

Sensitivity analysis involves looking at major assumptions and exercising one's judgement. However, it is incomplete as only a small number of outcomes is considered and also one at a time. Other criticisms of sensitivity analysis follow.

1) Brealey and Meyers (1988) criticise the use of optimistic and pessimistic estimates because their subjective nature gives ambiguous results.

2) As the underlying variables are likely to be inter-related, looking at variables in isolation under-estimates the interaction effects.

3) A sensitivity analysis does not involve probabilities and therefore does not indicate how likely a parameter will take on a value.

4) A percentage change in one variable may not be as likely or comparable with the same percentage change in another variable.

5) Changing more than one variable at a time may not be feasible due to possible dependence between variables.

6) It does not attempt to analyse risk in any formal way, leading some authors, such as Hull (1980), to propose a follow-up with risk analysis.

3.3.4 Probabilistic and Risk Analysis

The injection of random elements such as probability distributions into scenario and sensitivity analysis departs from the deterministic view of the world. Any technique that assigns probabilities to critical inputs and calculates the likelihood of resulting outcomes is considered a ***probabilistic analysis***, according to Hirst and Schweitzer (1990). These probabilities are subjective, i.e. based on the judgement of planners or experts. Correlations among uncertainties are specifically considered. Probabilistic methods help gauge the combined effects of multiple uncertainties in cost and performance.

Compared to deterministic or fixed point approaches, probabilistic approaches give the additional information of likelihoods and sensitivities of ranges. These two dimensions of ***range*** and ***probability*** translate into a greater permutation of factors, i.e. ***fractional designs***. Dependence of factors calls for the assessment of conditional probabilities, entailing additional analysis. Skewness and asymmetry of probability distributions mean that more iterations are necessary for completeness. The selection of an appropriate distribution requires judgement.

Most standard post-optimal sensitivity analyses do not treat uncertainty in any probabilistic manner. Dowlatabadi and Toman (1990) introduce an entirely different way of incorporating stochastic sensitivity into their cost-minimisation LP model. Instead of using point estimates for values of input parameters, they use subjective probability distributions to reflect judgements about the nature of uncertainty surrounding central parameter values. Their model maps these input distributions to outputs and employs statistical analysis to find the inputs which have the greatest impacts on outputs. This "***stochastic sensitivity analysis***" is similar to the method of risk analysis, which is explained next.

While there may be many ways to analyse uncertainty, the term "***risk analysis***" refers to a specific kind of analysis, first described in the classic paper by Hertz (1964). Risk analysis denotes methods aimed at developing a comprehensive understanding and awareness of risk associated with a variable. Hertz and Thomas (1984) introduce two kinds of approaches: ***analytical*** and ***simulation***. In the analytical approach, input probability distributions are combined using statistical distribution theory to calculate the mean, variance, skewness, and other parameters of the output distribution. In the Monte Carlo simulation approach, sets of equations are specified, and the input probability distributions are sampled and put through the equations to give output distributions. The analytical approach is difficult and impossible to solve for a multi-staged problem containing dependent non-linear variables. It is also time-consuming and not applicable if the distributions are not standard. Simulation is practical for non-normal distributions, especially when exact probabilities are not known. In this sense, it is distribution-free. Risk analysis by Monte Carlo simulation or other sampling methods is called ***risk simulation***, which can be automated in spreadsheet add-in software such as @RISK (Palisade Corporation, 1992). The main arguments for and against using risk analysis are given in Hertz and Thomas (1984) in table 3.1.

Table 3.1 Arguments For and Against Risk Analysis

FOR	AGAINST
• Provides a systematic and logical approach to decision-making	• Sometimes provides few guidelines to aid problem formulation
• Permits a thorough analysis of alternative options particularly in complex decision problems	• Sometimes time-consuming. More useful for complex decision problems.
• Enables the decision-maker to confront risk and uncertainty in a realistic manner	• Lack of acceptance by some organisations
• Helps communication within the organisation as experts in other areas are consulted in decision-making	• Difficulties sometimes exist in obtaining probability assessments
• Allows decision-makers to judge how much information to gather in a decision problem	• Managers sometimes find difficulty in interpreting the output of the risk analysis process
• Allows judgement and intuition in decision-making to be presented in a meaningful way	• Not prescriptive, helps decision maker in assessing range of values but does not articulate the decision maker's preferences, i.e. decision-neutral.

Source: Hertz and Thomas (1984)

3.4 Decision Analysis

Between the extremes of hard and soft techniques lies decision analysis, a term coined from the marriage of decision theory and system analysis. The explicit representation of the decision maker's risk attitude and preferences distinguishes decision analysis from optimisation and simulation. [See Raiffa 1968, Keeney 1982, Bunn 1984, Watson and Buede 1987, and Covello 1987 for descriptions.]

Thomas and Samson (1986) generalise the usual steps in decision analysis in table 3.2 below.

Table 3.2 Steps in Decision Analysis

1	**Structuring the problem**	definition of the set of alternatives strategies, the key uncertainties, the time horizon and the attributes or dimensions by which alternatives should be judged
2	**Assessing consequences**	specification of impact or consequence measures for the decision alternatives
3	**Assessing probabilities and preferences**	assessment (or definition) of probability measures for key uncertainties and utility measures to reflect preference for outcomes
4	**Evaluating alternatives**	evaluation of alternatives in terms of a criterion of choice, such as the maximisation of expected utility
5	**Sensitivity analysis**	in relation to the optimal strategy, which may lead to further information gathering
6	**Choice**	of the most appropriate strategy in the light of the analysis and managerial judgement leading to implementation of the preferred strategy

Source: Thomas and Samson (1986)

Decision analysis encompasses a range of decision theoretic techniques, including decision trees, influence diagrams, and multi-attribute utility analysis. Decision trees and influence diagrams are complementary structuring tools for decision analysis. Decision trees capture the chronological sequence of decision and chance events, while influence diagrams capture conditionality and dependence of events. Besides being more compact than decision trees, influence diagrams reveal probabilistic dependence and information flow.

Several difficulties with a decision analysis formulation should be noted here.

1) ***Decision analysis imposes an analytical pattern of thinking***, i.e. step by step, which may restrict other possible ways of approaching the problem, e.g. creatively or holistically.

2) Capacity planning has traditionally been treated in the optimisation sense and computationally data intensive, with little part for the decision maker because of heavy data demands. Decision analysis essentially restructures the problem into strict component parts of a decision: options, chance/uncertain events, outcome,

preferences etc. There is a concern that ***decision trees may over simplify the problem and exclude some of the essential details***.

3) Decision analysis ***assumes that the model is being developed in direct consultation with the decision makers***. This is often not the case with capacity planning models where "analysts" build the models and present the results to the executive level. This assumption ignores the possible gap between the analyst (modeller) and the decision maker (user), e.g. whether the analyst is really modelling what the decision maker wants and whether the decision maker really understands or uses the results of the model. This aspect of decision making and modelling is discussed in Chapter 4 and again in Chapter 6.

4) Reduction methods are needed to screen out dominated options as the ***decision tree can get messy or bushy very quickly***. As mentioned before, the dimensionality problem occurs when the permutation of the number of stages and branches becomes too large to handle. In a decision tree, there is also the question of how to propagate the stages, whether by time or by event.

5) Other drawbacks of decision tree analysis given Thomas (1972) and others include the ***need to specify discount rates beforehand***, problems with ***probability elicitation and assignment***, and ***pre-specification of mutually exclusive scenarios***.

Moore and Thomas (1973) also question the usefulness of decision analysis techniques in practice and present the pros and cons in table 3.3 below.

Table 3.3 Pros and Cons of Decision Analysis

Pro	Con
1) Systematic and logical approach to decision making.	1) Time consuming.
2) Permits a thorough analysis of alternative options.	2) Lack of acceptance that all relevant information can be encapsulated in the analysis.
3) Separation of utility assessment (preference assessment for outcomes) from probability assessments for uncertain quantities.	3) Assessments of probabilities and utilities are difficult to obtain.
4) Allows decision-maker to judge how much information is worth gathering in a given decision problem.	4) Evaluates the decision in "soft" number terms because input data at present are often "soft" in the sense that only crude measurement is possible.
5) Helps communication within the firm and enables experts in other areas to be fruitfully consulted.	

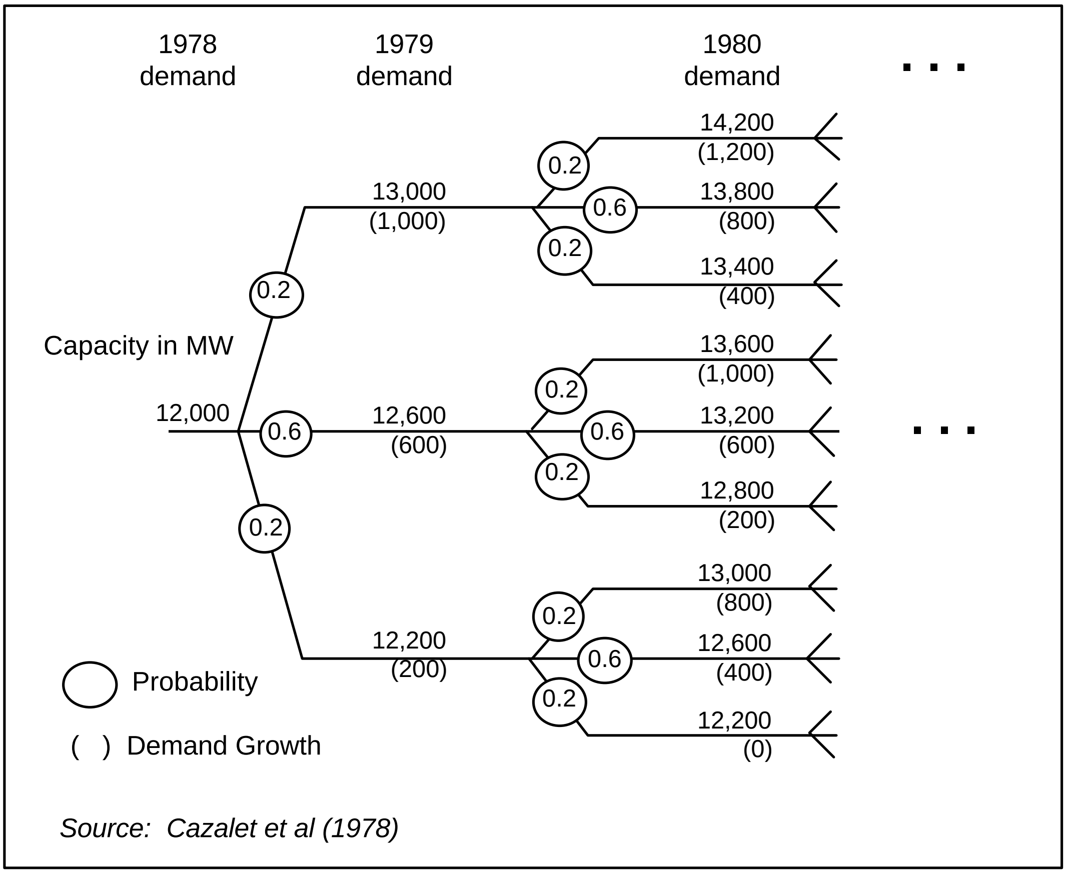
In spite of the above criticisms, the use of decision analysis in capacity planning has been well documented in several US studies as shown in the following sub-sections. This suggests that it may become better received in the UK now that the industry has been considerably restructured, with greater emphasis on individual decisions, uncertainties, and strategic rather than operational issues. For these reasons, we reserve the following sub-sections to illustrate and describe four examples of decision analytic applications. These illustrations show the versatility of decision tree as a structuring tool.

3.4.1 A Classic Application - the Over and Under Model

The first major study to harness decision analysis in the power planning context was the so-called Over/Under Model (Cazalet et al, 1978). It centres around the adjustment of planned capacity in three project stages according to the level of demand. If installed capacity plus work-in-progress is short of the actual demand, additional capacity is planned. If capacity is greater than the actual demand plus a margin, then the project is delayed. The main objective is reliability, i.e. to ensure no short-fall of capacity. Its simplicity and generic representation of capacity planning introduced decision analysis to the modelling of such problems.

Depicted in figure 3.3, this model tracks the way the uncertainty of demand growth is resolved over time, the role of uncertainty in load forecasts, and the effect of plant lead times on capacity planning. Its primary objective is to estimate the levelised consumer cost with respect to the reserve margin requirement. Uncertainty of load demand is expressed in the form of probability functions. It uses conditional expected demand in unfolding the actual demand in a sequential manner. Capacity expansion is reduced or accelerated according to how well current capacity matches the current demand.

Figure 3.3 **The Over and Under Model**



Demand is the only uncertainty that drives the Over/Under Model from period to period. It relies solely on adjusting the reserve margin in response to demand uncertainty, but this assumes that the adjustment is costless. Furthermore, it does not account for adjustments in the technological mix. Although grossly over-simplified, the Over/Under Model can be extended to multiple periods, representing a new period with each stage of the tree. The time horizon is relatively short (less than 20 years) compared to other models. It is nevertheless a breakthrough in new methodological development and, as a result, often cited in subsequent capacity planning applications.

3.4.2 An Extension of the Baughman-Joskow Model

Many of the earlier models addressed only one of the following three aspects of capacity planning: supply, demand, or regulatory processes. Baughman and Joskow (1976) were the first to simultaneously address all three aspects by basing the planning and investment decisions on expectations rather than as inputs of actual realisations of parameters. These aspects are represented in three sub-models which are integrated together by a transfer of information through the use of a rolling horizon.

A similar approach to assess the effect of uncertainty is found in a more aggregate and regional model in Baughman and Kamat (1980) which looks at the rate of change of demand rather than absolute demand levels. This study shows how easily the single utility case can be extended to cover a broader geographic scope and compares relative costs and benefits of over- and under-capacity. The tree representation together with the payoff matrix of figure 3.4 and graphical results permit a good discussion of impacts of over- and under-capacity. Only demand uncertainty is considered although extensions are possible.

Figure 3.4 Matrix Model of Decisions and Outcomes

Capacity Expansion Decision	Demand Growth Outcome: SLOW	MODERATE	RAPID
SLOW	No shortage Adequate capacity	Shortage Under-capacity	Severe shortage Under-capacity
MODERATE	No shortage Over-capacity	No shortage Adequate capacity	Shortage Under-capacity
RAPID	No shortage Over-capacity	No shortage Over-capacity	No shortage Adequate capacity

Matrix Model of Decisions and Outcomes

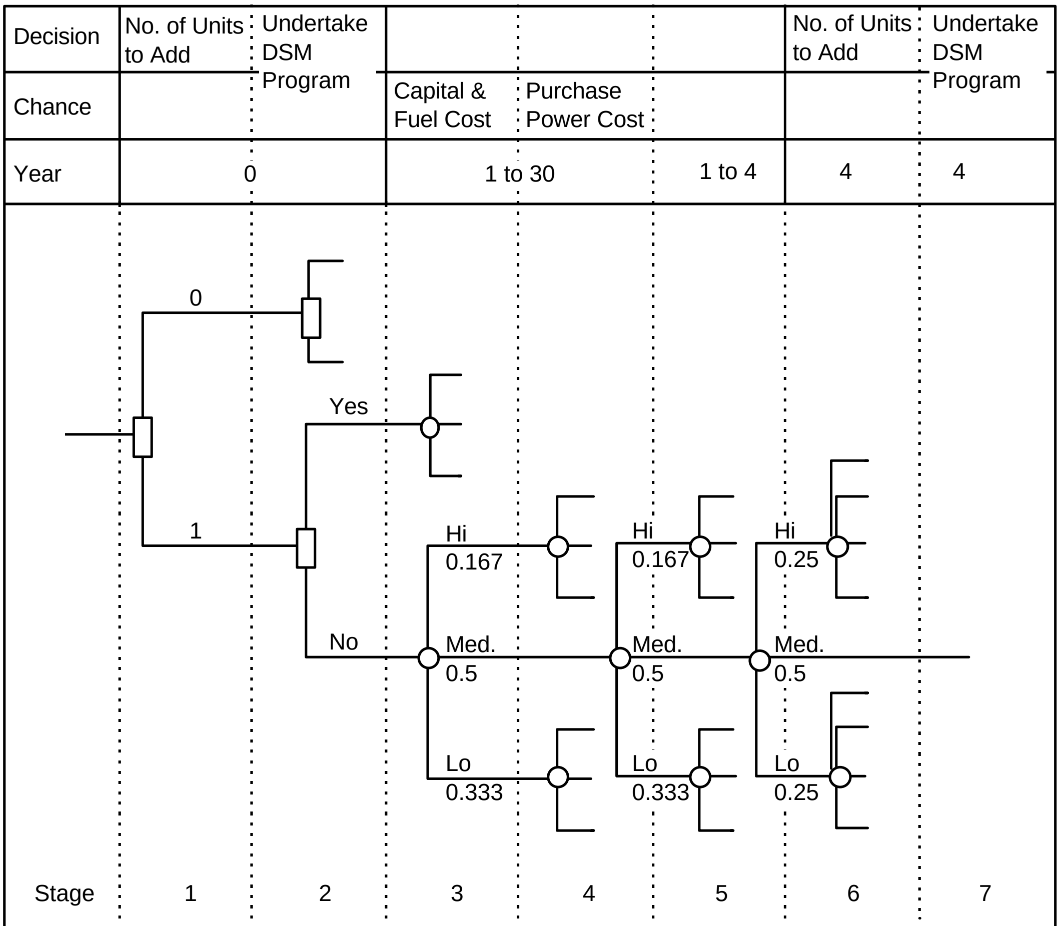
Source: Baughman and Kamat (1980)

3.4.3 Multiple Objectives Under Uncertainty

Decision analysis can also be used to examine the effect of pursuing different objectives under uncertainty. An example of this is the SMART/MIDAS application of Hobbs and Maheshwari (1990). They address the effects of using different planning objectives under uncertainty and the impact upon costs and electricity prices of risk averse decision making. The four conflicting objectives in the assessment of the benefits of small power plants and conservation when load growth is uncertain are 1) minimising levelised retail electricity prices, 2) minimising expected total costs, 3) minimising excess capacity, and 4) maximising consumer surplus. They also examine the effects of different degrees of uncertainty in demand growth, fuel prices, capital costs, and imported power upon optimal utility plans, the value of information, and the variance of electricity prices and total electricity production costs.

This example suggests the attractiveness of applying a simple model (figure 3.5), such as decision analysis in the Simple Multi-Attribute Risk Trade-off System (SMARTS), to explore a wide range of uncertainties and options, and then a detailed model to focus on the critical ones. Once the range of uncertainties and options is reduced, the problem can be addressed by the data intensiveness of the detailed model, called the Multi-Objective Integrated Decision Analysis System (MIDAS). In a later extension of this model, Hobbs and Maheshwari included additional uncertainties such as fuel price, capital cost, and imported power.

Figure 3.5 Decision Tree in SMARTS



Schematic of the decision tree used in the SMARTS analysis

Source: Hobbs and Maheshwari (1990)

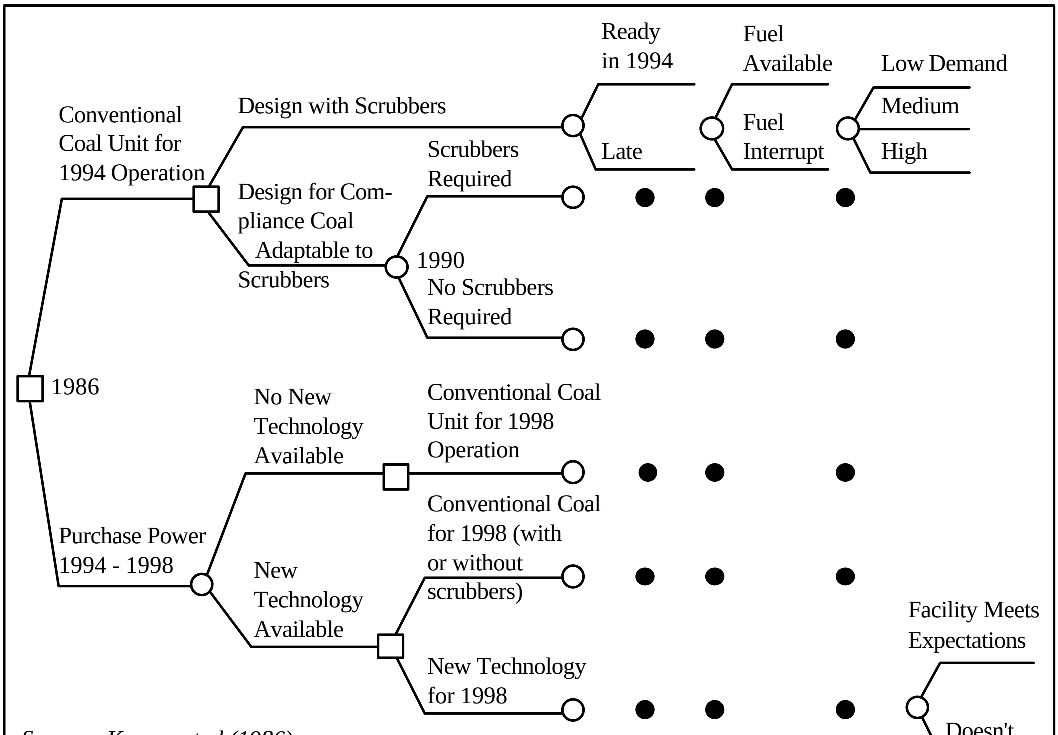
Several criticisms are noted. 1) Only two time periods are used. 2) The probability of growth rates for the two time periods are independent, clearly not the case in reality. 3) Perfect correlation was boldly assumed between fuel and capital costs. 4) Three point probability distributions were used rather than more specific continuous distributions. 5) The ratio of peaking to baseload unit is fixed. 6) The study inherently assumes that delays can be made if necessary.

3.4.4 Multi-Attribute, Objectives Hierarchy

Values and preferences of different decision makers and stakeholders translate into more than one and possibly conflicting objectives. Keeney and Sicherman's (1983) model of Utah Power and Light's planning process emphasizes the aspect of building a ***multi-attribute objective hierarchy*** to clarify preferences. Subsequently, but still based on the original technology choice decision, the Baltimore Gas Study (Keeney et al, 1986) extends the objective hierarchy and adds new uncertainties to the analysis.

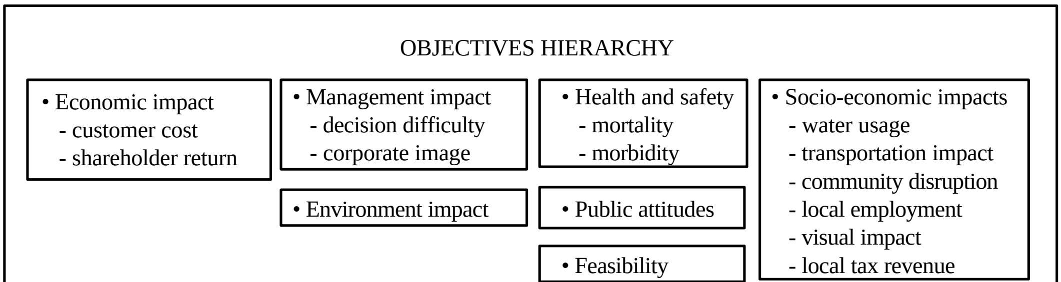
The Baltimore Gas Study uses the decision tree in figure 3.6 to capture the choices available to a utility and the uncertainties that result through time. This analysis addresses both the dynamic and multiple objective aspects of the problem. The corresponding objectives hierarchy in figure 3.7 enables the systematic consideration of economic, management, and other impacts. Sensitivity and break-even analyses are performed afterwards to confirm the best strategies chosen. Decision analysis provides a common framework for communication and documents the process step by step.

Figure 3.6 Technology Choice Decision Tree



Source: *Keeney et al (1986)*

Figure 3.7 Technology Choice Objectives Hierarchy



Source: Keeney et al (1986)

3.5 "Model Synthesis"

The previous three sections reviewed applications of primarily single techniques to focus on their specific modelling strengths and weaknesses. Most applications, particularly at the national or regional system level, involve more than one technique, which we call "model synthesis". ***Model synthesis*** refers to any formal attempt to use two or more of the above-mentioned techniques to achieve the same objectives as that of a single technique. We present examples of model synthesis in practice to illustrate 1) the kinds of techniques that are suitable for synthesis, 2) how well they address the areas and types of uncertainties, and 3) the manner of synthesis.

3.5.1 Commercially Available Software

Most commercially available software packages reviewed in IAEA (1984) make use of different techniques to address different aspects of standard capacity planning problems. Not all packages are integrated as some would require the user to import data from different modules and perform separate analyses. Generation planning is divided into different functions, such as sectoral demand analysis, production costing, and plant scheduling.

Electric Generation Expansion Analysis System (EGEAS), developed by the US-based Electric Power Research Institute (EPRI), contains an ***LP option***, a ***generalised Benders' decomposition*** option for non-linear optimisation, a ***dynamic programming*** option, ***scenario generation*** following ***sensitivity analysis***, and data collapsing for ***trade-off and uncertainty analysis***. These options are selected by the user. For uncertainty analysis, the user specifies uncertain input parameters, assumptions, range of values, and jointly varying subsets of uncertain input parameters. The model then generates scenarios for each possible combination of uncertain parameter values.

These commercial packages are composed of modules which share the same data base and have a common interface. Packages such as EGEAS, WASP, and WIGPLAN have voluminous data requirements. Designed to run on mainframe computers, they are not flexible for modification or customisation. These packages are not transparent to the user and therefore not customisable or extensible. They are not tailored to unique situations or unknown technologies.

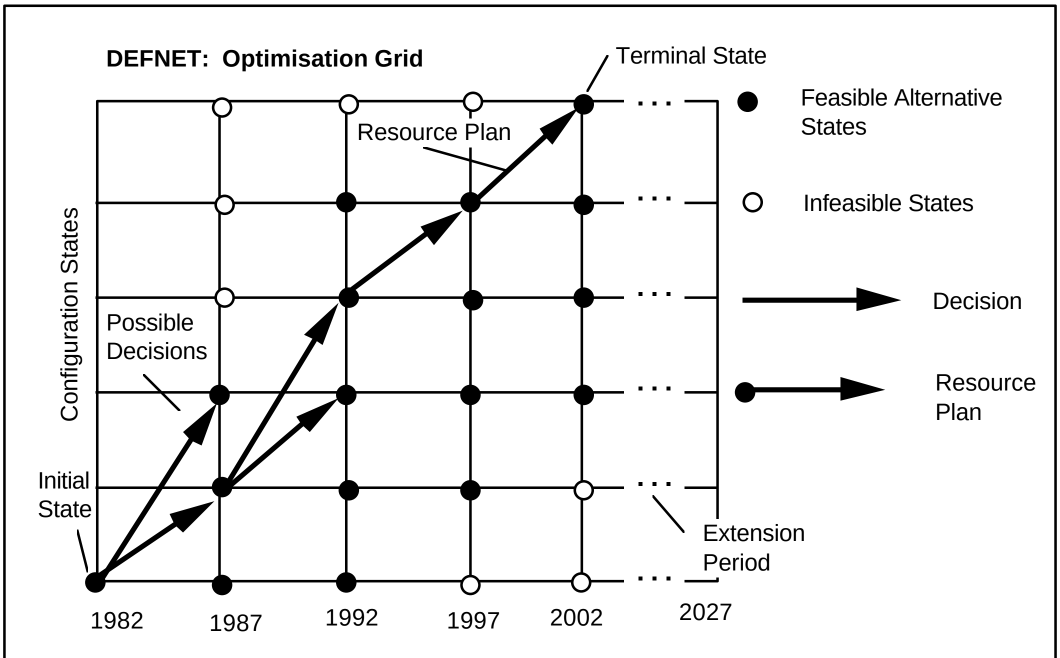
3.5.2 Decision Analysis with Optimisation

We describe three examples of synthesis of decision analysis and optimisation techniques.

DECISION ANALYSIS AND DYNAMIC PROGRAMMING

Lo et al (1987) combine decision analysis and forward dynamic programming to produce a Decision Framework for New Technologies (DEFNET). It is a strategic planning tool that can be used to model uncertainties in load growth, fuel and capital costs, and performance of new generation technologies. The power system planners' risk attitudes and value judgements are captured in the multi-attribute utility functions, with the decision criterion to find the least expected cost or the maximum expected utility. DEFNET can also incorporate attributes other than cost, such as environmental impact, licensing and operating delays due to regulations, system reliability, corporate image, etc. The optimisation grid of figure 3.8 depicts possible decision paths which branch out from an initial state. More information available in the near term translates to finer details as opposed to the coarser or wider range of possibilities in the future. This is analogous to the increasing variance of probability distributions in the longer time horizon. The model can be run deterministically or stochastically in optimisation or simulation mode.

Figure 3.8 Optimisation Grid



Source: Lo, Campo, and Ma (1987)

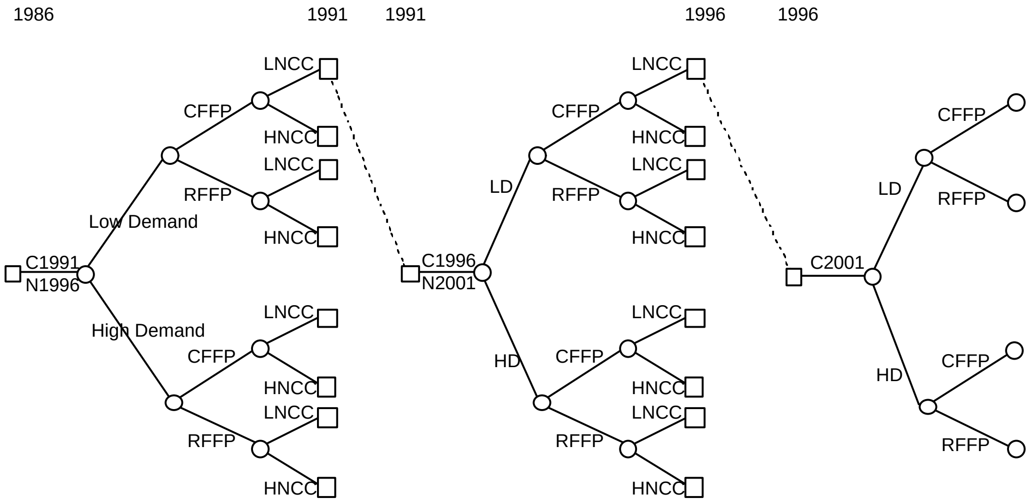
DECISION ANALYSIS, DECOMPOSITION, AND STOCHASTIC FRAMEWORK

Capacity expansion planning can be viewed as investment decisions made for the long term, adjusted by operating decisions made in response to the changing environment in the short term. Gorenstin et al (1991) represent the investment sub-problem as a multi-stage, mixed-integer programme which is solved by a branch and bound algorithm. The operation sub-problem is a multi-stage, multi-reservoir hydro-thermal scheduling problem with the objective to minimise operation cost. Benders' decomposition technique integrates the two sub-problems by feeding back the decision consequences at each iteration. The operation sub-problem is solved for different demand scenarios simultaneously, to give expected operation costs. Within this decomposition and stochastic optimisation framework, a minimax decision rule is used to select the optimal cost. Sixteen scenarios are generated from the combinations of uncertainties in a binary decision tree. The optimal expansion strategy minimises the maximum regret obtained from evaluating the binary tree of different growth rates and decisions. This elaborate methodology has nevertheless been only applied to the Brazilian system which consists of mostly hydro-plants, hence parameters specific to one type of technology.

DECISION ANALYSIS AND DECOMPOSITION

A decision tree structures the capacity planning problem in Mankki (1986). The problem is then formulated as a linear programme and solved by a decomposition method. The decision tree shown in figure 3.9 captures the uncertainties of demand, fossil fuel prices, and nuclear capital costs. The method of probability elicitation or assignment was not discussed.

Figure 3.9 Decision Tree with Optimisation Algorithm



C1991 = coal power plant (production start 1991); CFFP = constant fossil fuel prices; RFFP = rising fossil fuel prices; LNCC = low nuclear capital costs; HNCC = high nuclear capital costs

Source: Mankki (1987)

3.5.3 Scenario Generation

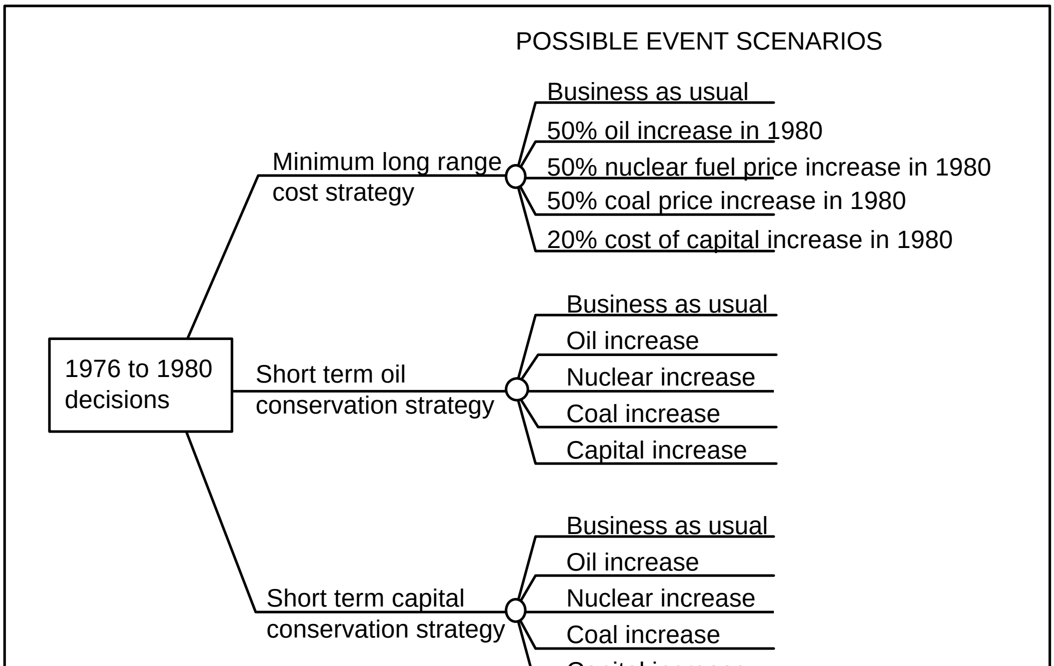
EXTENSION OF THE OVER/UNDER MODEL

Clark (1985) extends the Over/Under Model described earlier to generate scenarios for the analysis of demand uncertainty. This integrated demand forecasting model consists of a production simulation model, financial model, rate model, and an econometric model. The probability of each scenario is determined by the probabilities of cost, commercial operation date, equivalent availability, and demand growth components. A sensitivity analysis produces a ranking of trade-offs. The model is also used to examine excess capacity rules in the adjustments of reserve margins.

DECISION ANALYSIS FOR SCENARIOS

Garver et al (1976) use a decision tree (figure 3.10) to generate three strategies and five event scenarios for a five year period. The decision alternatives and possible event scenarios are propagated yearly. Two criteria are used to evaluate strategies: 1) expected value is computed from likelihood weighting of present worth costs, and 2) the cost of uncertainty represents the opportunity loss. Although the time horizon is relatively short and the scenarios few, this example illustrates the potential for structuring extensive scenario analysis in a decision tree framework.

Figure 3.10 Scenario / Decision Analysis



Source: Garver et al (1976)

MULTI-OBJECTIVE LP, SENSITIVITY ANALYSIS

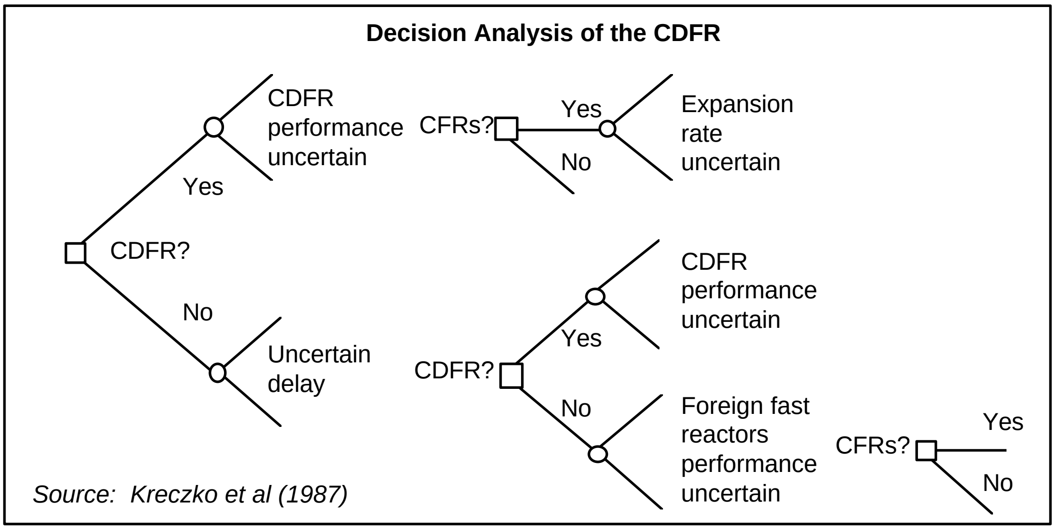
The multi-criteria formulation of Amagai and Leung (1989) combines multi-objective linear programming with sensitivity analysis. For this study, country risk was assessed by a scoring system based on the weighted sum of a subset list of factors that affect legislation and regulation related to the shipping of fuel. The simply formulated LP is driven by four scenarios, which are determined by the demand for electricity, fuel costs, controllability (how closely a power plant can follow the load duration curve), utilisation rate for each type of plant, and daily load curve. However, the dimensionality of extensive scenario analysis due to the number of stages, decision alternatives, and range of uncertainties hinders efficient analysis.

3.5.4 Decision Analysis as a Framework

DECISION ANALYSIS AND LINEAR PROGRAMMING

The "soft" or "descriptive" side of decision analysis is helpful in structuring a multi-stage problem with interactions of uncertainty. Kreczko et al (1987) track the decisions regarding whether or not to build a new type of technology and then use a linear programme to calculate its effect on costs and installed capacity. A utility function called the net decision benefit is used to propagate the decision tree in figure 3.11. Lack of experience with the operation of this new type of technology implies uncertainties in future costs. Capital costs are derived from a multiple of related technological cost estimates. Other costs are elicited from different estimates found in the literature and justified by rational assumptions made on the basis of industry understanding. This application shows the importance of addressing uncertainties, especially the subjective and judgemental nature of estimates required in place of unavailable data.

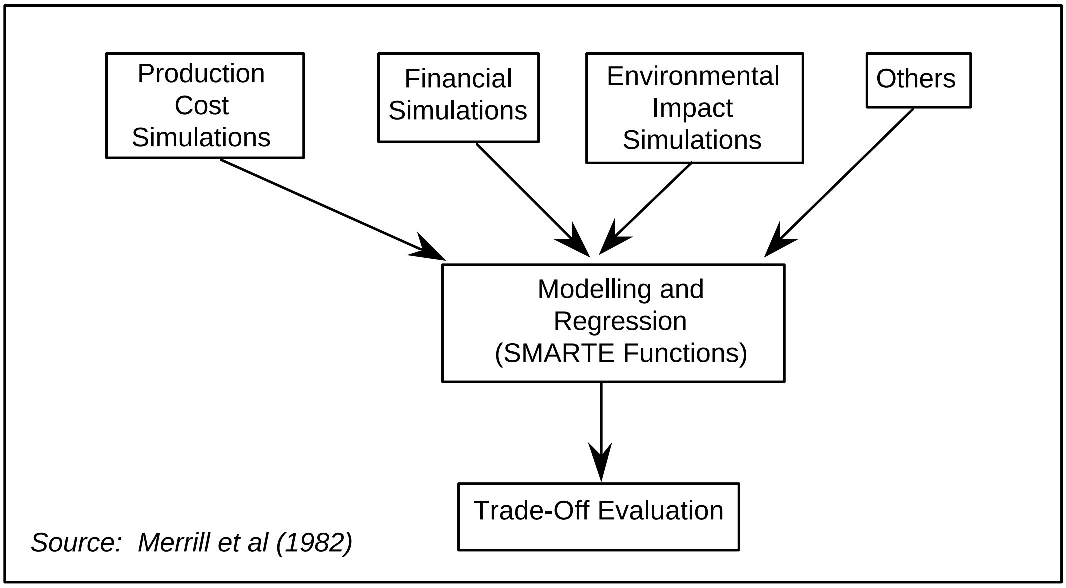
Figure 3.11 **Decision Tree of New Technology Evaluation**



SIMULATION AND OPTIMISATION

Results from different types of simulation in Merrill and Schweppe (1984) are synthesized to incorporate the multiple and often conflicting objectives and uncertainties found in strategic planning. Their Simulation Modelling and Regression Trade-off Evaluation (SMARTE) makes use of user-postulated "SMARTE" functions to answer specific questions related to strategic planning. SMARTE, depicted in figure 3.12, is not a computer programme but a set of techniques for extracting maximum information from available simulation tools, whether manual or computer based. The resulting functions are validated using t statistics, coefficients of correlation, sums of squares of mismatches and goodness of fit to the data base. User's insights are introduced into the model, hence the large subjective element. SMARTE applications are found in Merrill (1983) and Merrill et al (1982) which feature the combined use of simulation and optimisation. Some statistical manipulation, such as bootstrapping an optimisation, may be required to facilitate a simulation.

Figure 3.12 SMARTE Methodology



Source: Merrill et al (1982)

3.6 Conclusions

This extensive review of techniques and applications to electricity capacity planning reveals the limitation of existing approaches and the potential for greater model completeness through synthesis. The main conclusions are presented and supported below.

1) **All kinds of OR techniques have been applied to the problem of capacity planning, albeit the areas and types of uncertainties are modelled with different degrees of completeness and adequacy.**

   These techniques pictured in figure 3.13 span the range of optimisation, simulation, and decision analysis. Table 3.4 summarises the critique of techniques with respect to uncertainties.

2) **Models (or applications) based on single techniques are able to capture some aspects very well and others not at all. Adding greater detail does not compensate for what the technique is designed to do.**

   Models based on single techniques are not functionally versatile or comprehensive enough to address all the issues. For example, models without a decision analytic focus have difficulty capturing the multi-staged nature of decisions and the associated risks. One cannot use optimisation techniques for decision analysis purposes as the assumptions are not compatible. Likewise, one cannot use scenario analysis to achieve optimality.

In many applications, the treatment of uncertainty is inadequate. Deterministic treatment of parameters is followed, at best, with sensitivity analysis, which gives no indication of the likelihood of the uncertain values. The approach of following a rigorous optimisation with sensitivity analysis is regarded mainly to validate a deterministic analysis, e.g. McNamara (1976). The validation process bears no relation to the actual resolution of uncertainty in time. Uncertainty is also treated in the same sense as variability. Rather than building something intrinsic to deal with uncertainty, many consider sensitivity analysis to be sufficient in assessing uncertainty albeit the attention to uncertainty is considered almost as an after-thought. The primarily deterministic techniques are simply unable to address uncertainties. Others give limited but inadequate attention to this issue. The attitude that “a recognition of uncertainty and some attention to it is better than none at all” is reflected in the ad hoc manner in which uncertainty is handled. Increasing uncertainties have often called for softer approaches such as scenario analysis which is only able to address partial aspects of the problem.

3) **The critique of techniques with respect to areas and types of uncertainties reveal the the lack of completeness of coverage, inadequacy of treatment, and further difficulties of manageability, computational tractability, and other problems.**

The modelling critique supports the above conclusions. Table 3.4 presents the assessment of each technique against the uncertainties of Chapter 2 with additional difficulties noted alongside.

Table 3.4 Critique of Techniques

Technique	Areas and Types of Uncertainties (Chapter 2)	Difficulties
linear programming	• difficulty incorporating operational/technical characteristics • cannot incorporate risk attitude • unable to handle conflicting objectives • unable to handle multi-staged decisions • unable to handle uncertainties directly • confusion of validation with uncertainty analysis • confusion of variability with uncertainty analysis	• many technical and operational characteristics are non-linear • manageable level of model size and accuracy • computational tractability • strict mathematical requirements of technique
stochastic programming	• limited multi-stage via SP with recourse • can handle uncertainties but not comprehensively	• able to handle non-linearity • probabilities introduce dimensionality problem • software inflexibility and difficulties
decomposition	• can integrate different levels of detail • can integrate different types of decisions • no evidence of multi-criteria • no evidence of uncertainties	• computational efficiency • feasibility of handling uncertainties questionable
dynamic programming	• not able to cope with closed loop decision making, i.e. resolution of uncertainty, recourse • voluminous output	• dimensionality problem • mathematical restrictions
system dynamics	• not optimal • systemic but not from a decision maker's perspective • difficult to validate • hard to calibrate	• time requirements • computing requirements • validation difficulties
scenario analysis	• not multi-staged • not optimal	• subjective • conceptual and not prescriptive
sensitivity analysis	• not multi-staged • few number of factors considered • rarely used alone • not optimal	• not prescriptive • problems with dependence • factors considered one at a time • no account of likelihoods • no interaction effects considered
risk analysis	• use of probabilities • parametric uncertainty, but not due to model structure • lack of decision focus	• dependence/independence issue • selecting appropriate probability distribution • skewness and asymmetry • interpretation of results • multi-variate probability distributions • adequate number of factors to simulate

decision analysis	• considers multi-staged resolution of uncertainty • decision criteria and multi-attribute utility functions • role of decision maker • not detailed enough • not optimal	• how many stages to consider • subjective probabilities or historic evidence for uncertain events • which decisions to consider • how to propagate decisions, by individual factors or scenarios

4) The additional modelling difficulties translate into new modelling requirements, which reflect the conflicting criteria of comprehensiveness and comprehensibility and practicality.

The above modelling difficulties can be condensed into five main areas: 1) mathematical restrictions, 2) functionality, 3) computational tractability, 4) data specification, and 5) uncertainty representation. These are briefly explained below.

1) ***Mathematical restrictions*** lay the rules and foundation for any technique and sets the boundaries and conditions for its functionality. Linearity and convexity requirements of linear programming prevent its applicability to non-linear and non-convex relationships.

2) These structural conditions for ***functionality*** determine the way in which the problem can be formulated. For example, multi-stage resolution of uncertainty cannot be achieved within a linear programming framework while optimisation with respect to given constraints cannot be accomplished by decision analysis or system dynamics.

3) There is a trade-off in ***computational tractability*** of meeting the dimensionality of variables, interaction effects, algorithm efficiency, and software performance. Although some aspects of the problem formulation may be approximated at the expense of efficiency and realistic representation, models usually become too large to be computationally tractable. Borison et al (1984) note that uncertainty greatly increases the number of conditions under which each technology choice decision must be evaluated.

4) Many of the problems of dimensionality and algorithm efficiency are related to ***data specification***, that is, the level of complexity and realism that can be modelled without sacrificing tractability. Assumptions, approximations and reduction of information which are undertaken to simplify the problem to a manageable level must be assessed against the need for completeness. These considerations imply

judgement, trade-off evaluation, and decision making at the model construction stage.

5) The final difficulty concerns ***uncertainty representation***. Chapter 2 has listed various types of uncertainties, from values and parametric relationships to the unforeseeable surprise events in the future. The applications reviewed in this chapter dealt with uncertainties by:

- representation by probabilities
- accurate depiction of interactions
- consideration of all types of scenarios and uncertainties imaginable.

However, not all techniques are capable of representing and adequately treating uncertainties.

5) A balance of hard and soft techniques is needed to address the different aspects of capacity planning.

We distinguish between "hard" and "soft" techniques for the purposes of this discussion. ***Hard techniques*** are data intensive, mathematically rigorous and computational in nature. They are suitable for well-structured problems and are aimed at solving bigger problems more quickly and efficiently. Towards the other end of the spectrum lie ***softer methods*** that are less formal but more qualitative in scope, suitable for uncertainty and strategic analysis. They are more descriptive than prescriptive as the purpose is often to understand rather than to solve.

Capacity planning traditionally has been approached in the domain of hard disciplines because of its data requirements, technical and physical constraints. Capacity planning encompasses short-term production costing or merit ordering and long-term investment and retirement decisions, which entail many parameters specific to plant and system.

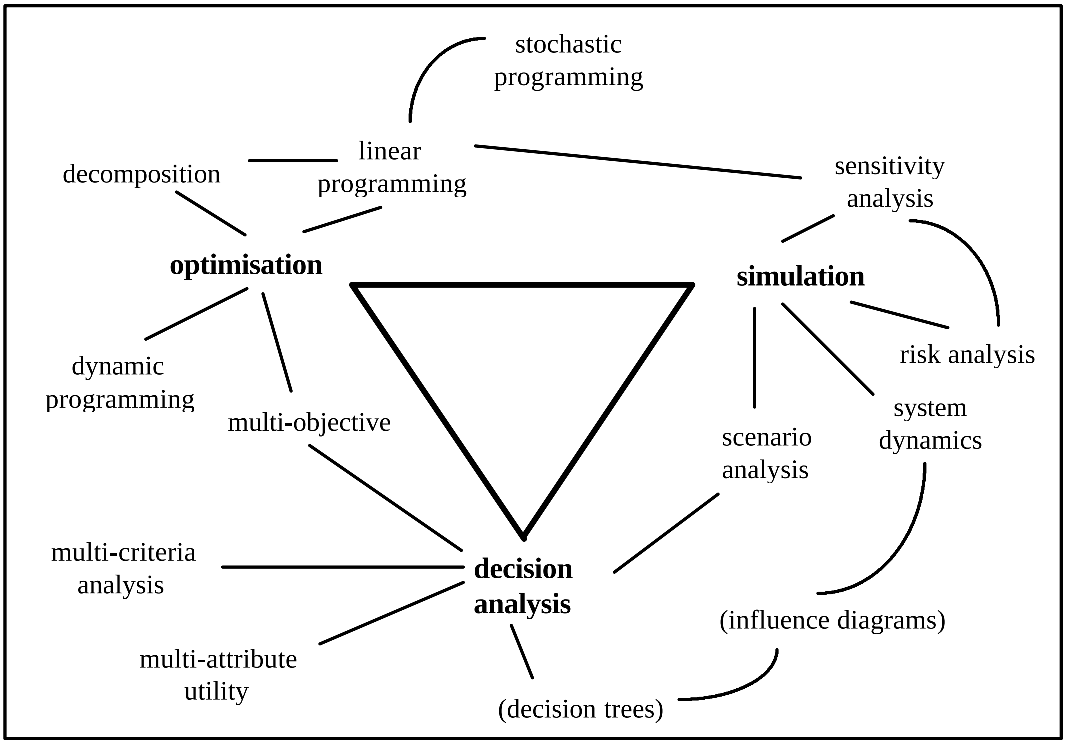
The privatised electricity supply industry in the UK is characterised by new kinds of uncertainties, conflicting objectives, rapid changes, high costs and risks. These aspects are not well addressed by hard prescriptive techniques. Ill-representation or total exclusion of such uncertainties and characteristics of capacity planning has been preferred to make the problem tractable. The well-specified problems that constitute capacity planning have evolved into an environment that is ill-specified, requiring a balance of hard and soft approaches. Strategic decisions have high cost implications, and the uncertainties that affect such decisions require "soft" techniques which can handle the subjective, non-quantifiable parameters. To model uncertainty in capacity planning, both types of techniques are needed, i.e. those hard techniques that capture the intricacies of electricity generation scheduling and the softer methods of uncertainty analysis. Hard and soft techniques are "complementary" to each other in addressing the range of issues.

6) Similarities and synergies in techniques suggest possibilities for synthesis.

In the past, the focus was towards efficiency of algorithms via the continued improvement and specialisation of stand-alone techniques. As a result of this technique-driven mentality, synergies across different approaches were not identified or exploited.

Some techniques that have been used in electricity planning share similar characteristics and functionality. Others have synergies in structure. On this basis, these techniques are arranged and linked in figure 3.13.

Figure 3.13 OR Techniques



Complementary modelling, as prescribed in Bunn et al (1993), shows how different techniques or approaches can balance the objectives and assist towards a more complete model. For example, system dynamics and optimisation allow a more comprehensive analysis of different impacts of uncertainty and different effects of privatisation than each technique alone.

7) **Model synthesis has the potential to overcome the deficiencies of single technique based models by exploiting synergies between techniques and achieving a balance of techniques.**

Intuitively, synthesis communicates “the best of both worlds.” Hence, model synthesis should be capable of supporting the balance of hard and soft techniques which complement each other in functionality towards completeness. Our review of applications based on two or more techniques support this view.

8) **Decision analysis emerges as a versatile technique with proven potential for synthesis with other techniques.**

This review has deliberately steered towards decision analysis, which has not received much attention in the UK (as compared to the US). Recent desk-top decision software, such as DPL (ADA, 1992), has automated the previously tedious process of decision tree structuring and expected value calculation. Influence diagrams complement decision trees, further supporting the versatility in its use.

9) **A fair method of model comparison beyond the literature review is needed to evaluate model characteristics and performance to a greater level of detail and depth.**

This review has attempted to assess the capacity planning models reported in the literature as fairly and insightfully as possible. However, it is restricted to what has been reported in the literature. To determine the applicability of these techniques to capacity planning in the privatised UK ESI and methods of overcoming the difficulties found in this review, it is necessary to look into the model, e.g. via a replication of existing models.

QUESTIONS FOR MODEL SYNTHESIS

The strong engineering culture of electricity capacity planning has evolved from modelling operational uncertainties to more competitive uncertainties, ultimately resulting in models with more detail. In light of this, the following emerge.

1) **How can a single utility, given its limited resources, expand existing techniques to cope with all these uncertainties (in Chapter 2) given the modelling difficulties listed above?**

2) **Can model synthesis *feasibly* and *practically* overcome these difficulties?**

3) **How can we compare models in more *fairly* and in greater *depth*, to get beneath what is written and reported?**