CHAPTER 4

The Pursuit of Model Synthesis

4.1 Introduction

Chapter 3 reviewed the range and evolution of techniques which have been applied to capacity planning. Models based on two or more techniques seem to be more capable of capturing the different kinds of complexities and uncertainties than those based on single techniques. This suggests that ***model synthesis*** (using more than one technique) may help to achieve the ideal of comprehensive yet comprehensible models by exploiting synergies across complementary and compatible techniques. Yet the modelling literature has little to offer on strategies and criteria for model synthesis.

This chapter gives an account of the investigations into the ***feasibility*** and ***practicality*** of model synthesis and associated model structures by a conceptualisation of model synthesis (Appendix C), prototyping, and a comparison of model performance (section 4.3). Through a series of modelling experiments (section 4.4), replications of existing approaches (section 4.2) and construction of synthesis prototypes (section 4.5) are assessed according to the dominant criteria of ***comprehensiveness*** (model completeness) and ***comprehensibility*** (transparency and manageability).

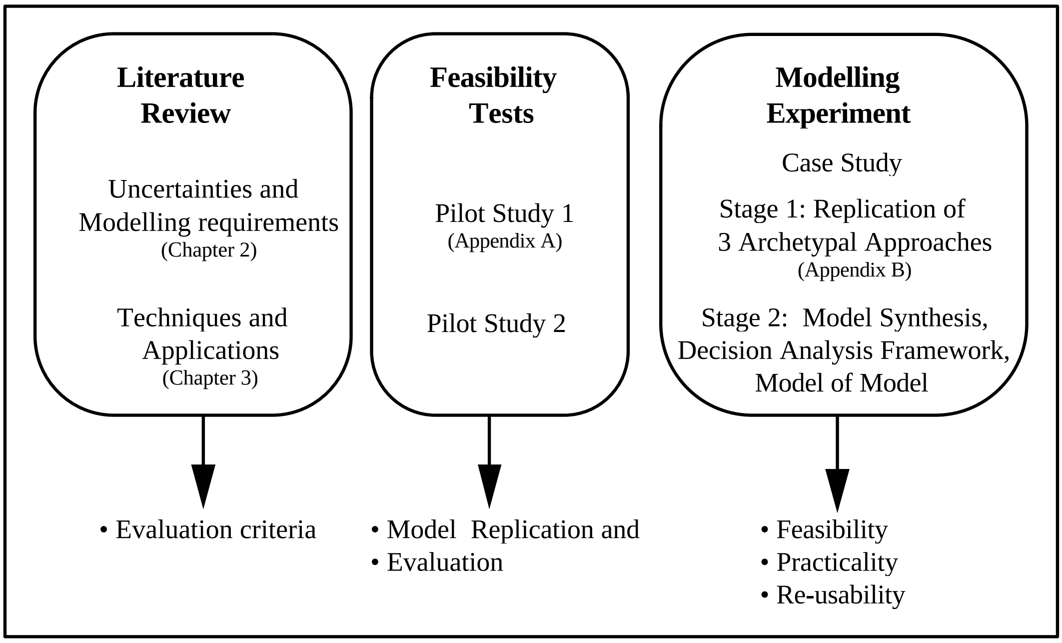
That model synthesis, via the decision analytic framework proposed by this thesis, proved to have major practical limitations raised two important questions. 1) Is model completeness a reasonable goal in the first place? 2) Are there more practical means to compensate for the lack of completeness or deal with the range of uncertainties? Section 4.6 discusses these questions with respect to the concept of flexibility. The last section 4.7 summarises the main findings and proposes an agenda for the rest of the thesis.

4.2 Experimental Protocol

An experimental research protocol, closely resembling a scientific experiment, was adopted to allow an objective and systematic method of inquiry. Figure 4.1 shows the three main components, namely, literature review, feasibility tests, and modelling experiment. Such a case-study based modelling experiment was originally intended to give both methodology and energy policy insight.

First, extensive literature reviews from the previous two chapters identified uncertainties and modelling requirements which formed the basis for a lengthy ***model evaluation criteria*** (section 4.3.4). Second, two pilot studies (section 4.3.2) were conducted to ascertain the *feasibility* of model replication with available modelling software, *applicability* of the evaluation criteria, and *soundness* of the evaluation method (section 4.3.3). Third, a ***case study*** (section 4.4.1) was developed to capture the current concerns in the UK ESI and to inject energy policy insight into the subsequent analysis. Fourth, ***three modelling approaches*** (section 4.4.2) representing those followed in the industry were replicated and evaluated. Fifth, issues of ***model synthesis*** (section 4.5.2) were conceptualised. Several prototypes of model synthesis within a ***decision analysis framework*** (section 4.5.3) were constructed. Similarly a so-called "***model of model***" (section 4.5.4) was tested. Insights from replicating existing approaches were transferred to the second stage of model synthesis, where the construction of ***comprehensive*** yet ***comprehensible*** models via ***complementary*** and ***compatible*** techniques was studied.

Figure 4.1 Experimental Protocol



Apart from minor criticisms[1], the experimental protocol provided a systematic method of model comparison. The next three sections give the rationale, details, and results for each of the main research components.

4.3 Model Replication and Evaluation

4.3.1 Rationale

A mere literature review of applications does not sufficiently expose the full limitation and potential of existing approaches. What is written can be ***biased*** and ***minimal***, supporting the authors' intentions but not illuminating the intricacies of their particular approach. Authors have discretion over what to reveal and

1 Circularity of the modeller as evaluator may cast doubt into the authenticity of the replication and the objectivity of the evaluation. Model replication and synthesis depend greatly on modelling skills and availability of modelling software. Depending on these conditions, different researchers may reach different outcomes.

consequently may hide weaknesses of their approach while presenting them in an undeservingly favourable light. Comparing models described in the literature is further complicated by the implicit standards of ***fairness***, ***objectivity***, and ***thoroughness***.

The applications reviewed in Chapter 3 differ widely in ***content***, ***technique***, and ***detail***. They vary from the evaluation of a particular technology to a range of technologies, from the analysis of demand uncertainty to industry investment behaviour, etc. They also tend to be ***situation-specific***, that is, geared to a particular case study and not always comparable. These fundamental differences complicate the task of model comparison.

We propose a four step method consisting of 1) definition of evaluation criteria from literature review, 2) replication of model using available software, 3) evaluation of model against pre-defined criteria, and 4) comparison of models. Model replication permits a closer examination of uncertainty modelling as well as a more meaningful critique of limitations and potential for synthesis. Application to a single case study anchors the modelled content to enable ease and fairness of comparison. A two staged modelling experiment provides the vehicle for systematic assessment. The first stage replicates and evaluates the three modelling approaches. The second stage combines features of different approaches as well as tests the feasibility of model of model. One of these approaches operationalises the recommendation of the inspector at the Sizewell B public inquiry, that a probabilistic analysis is better than a deterministic one. Another approach transfers the predominantly US-based decision analysis approach to the UK situation.

4.3.2 Method of Replication

Nowadays commercial desktop modelling tools such as spreadsheets, e.g. Excel and Lotus 123, add-ins, e.g. @Risk, and decision software, e.g. DPL, offer the kind of ease-of-use and multi-functionality which facilitate rapid model construction. Most of the models reported in the literature have been painstakingly computer coded from scratch and required major effort in implementation. The new tools allow models to be conceptualised, constructed, and tested much more quickly and effectively. Such tools as these and others can be used to mimic or replicate easily the essential characteristics of capacity planning models reported in the literature.

The feasibility of model replication and evaluation has been established in two unrelated pilot studies. The first study addresses specific issues of the Nuclear Review in the UK. The well-known techniques of sensitivity analysis and risk analysis were applied to a comparison of levelised costs of nuclear, coal, and gas plant based on data taken from various OECD countries. Documented fully in Appendix A, this study exemplifies the level of detail pursued in the modelling experiment. The second study used data from the Hinkley C public inquiry for replicating the deterministic approach, which is later subsumed into the first stage of the experiment in Appendix B. The second proved the feasibility of evaluation as well as replication.

4.3.3 Method of Model Evaluation and Comparison

This case study based modelling experiment contains several standard research components: ***comparative analysis***, ***case study***, and ***experimental design***. Regrettably, few examples in the literature employ such a combination.

Most model comparison studies are not case study based but mere reviews of model specifications. The studies by Dixon (1989) and Davis and West (1987) belong to the category of case study based comparative analysis of models. While Dixon compares existing models to critique and improve upon them, Davis and West compare to show off the model they developed. Dixon comments only on the input and output thus treating the models as black boxes. On the other hand, Davis and West probe into the trade-offs of specific techniques employed in the models. Neither study defines the criteria for comparison beforehand. The basis of comparison is very general and superficial, e.g. *strengths and weaknesses, ease of use*, and *impact of models*.

Not enough has been written about how to evaluate models. Mulvey (1979) develops a workable procedure for comparing competing models for selection purposes, beginning with an evaluation of individual models against a pre-defined criteria. His five dimensions for evaluation consist of *performance*, *realism/complexity*, *information requirements*, *user friendliness*, and *computational costs*. He argues that it is possible to overcome the technique-driven bias provided a methodology exists for evaluating models which are based on different techniques. His models are compared ordinally by preference ranking on each dimension, with the final results compared linearly by dominance. Morris (1967) suggests broad characteristics of models, which are useful but not specific enough for the purposes of assessing large complex models. Beyond roughly describing a model as simple or complex, he proposes other characteristics such as *relatedness, transparency, robustness, fertility,* and *ease of enrichment*.

In contrast to above, our evaluation criteria originates from an extensive literature review, hence more detailed and comprehensive than earlier studies. Instead of ranking all models on one criterion, our evaluation method assesses each model individually against all criteria.

4.3.4 Evaluation Criteria

The detailed enumeration of uncertainties and modelling requirements in chapters 2 and 3 was proved feasible for evaluation purposes in the second pilot study. This original list of requirements, however, was difficult to use for comparison purposes. For example, it was not always possible to compare models with different assumptions and properties. A reduced checklist was more workable but lacked the detail and comprehensiveness for which the evaluation and synthesis were intended. The reduced criteria consist of five major categories for evaluation: 1) level of detail, 2) desirable model characteristics, 3) decision focus, 4) output, and 5) uncertainty representation and analysis. Their sub-criteria are shown in table 4.1 and discussed thereafter.

Table 4.1 Model Evaluation and Comparison Criteria

Main Category	Sub-Criteria (Elements)
Level of detail	• number of variables included • operational detail (technical parameters) • financial detail (costs) • types of plants / technology
Desirable model characteristics	• simplicity (more detail, less simple) • transparency • comprehensiveness (more detail, more comprehensive) • extensibility • complexity • comprehensibility
Decision focus	• types of decisions captured • multiple stages • generation of alternatives
Output	• range of insight • richness of solutions • range and diversity of alternatives • business risk
Uncertainty representation and analysis	• discrete vs continuous • conditional • number of iterations (sampling) • representativeness • dimensionality (or in level of detail) • computational tractability (or in level of detail)

The ***level of detail*** relates to input variable specification which directly contributes to the comprehensiveness of the model. Although the format of input specification was largely ignored in the evaluation, it directly affected the transparency of the model. This category includes questions like how many variables are, can, or must be included; how many types of plants are considered; and the level of operational and financial detail. Operational detail relates to parameters such as load factor, utilisation rate, and thermal efficiency. Financial detail covers costs, e.g. operations and maintenance charges, interest during construction, tax, and discount rates.

Model characteristics can be assessed from the process of replication. A model that is comprehensive in input yet comprehensible in output requires a trade-off of the following desirable features: *simplicity* and *comprehensiveness*, *comprehensibility* (transparency) and *complexity*, and other features like *extensibility* and *reusability*. A simple model structure can hardly capture all details required, i.e. simplicity in structure versus comprehensiveness in specification. The *complexity* of plant economics and *dimensionality* of different kinds of uncertainty call for a *transparent* model for communication purposes. Comprehensibility by the user is important for the understanding of uncertainty.

Decision focus refers to the representation of the decision maker's perspective, such as *risk attitude*, *sequential stages*, and *uncertainty resolution*. Risk attitude can be incorporated in the discount rate, utility functions, and risk tolerance coefficient. Decisions and uncertainties in capacity planning do not occur simultaneously, as modelled in the deterministic and probabilistic approaches.

The ***quality of the output*** is related to the level of detail in inputs. The *range of insight* and *richness of solutions* surface from the range and diversity of alternatives. These and other aspects of the problem, such as *business risk*, reflect the benefit of using a particular approach.

The last category of ***uncertainty representation and analysis*** consists of the following assessments: discrete and continuous probabilities, conditional dependence, number of iterations (data points sampled in the distribution), representativeness, dimensionality, and computational tractability. These pre-defined criteria act as cues for the investigation of the potential, limitation, and effectiveness of each approach in modelling uncertainty.

4.4 Case Study Based Modelling Experiment

4.4.1 Case Study

The case study captures a snapshot of the UK electricity supply industry as at July 1993. It is generic enough to embrace a range of objectives but specific enough (by consolidation of published data) to relate to current industry practice. It reflects the on-going controversies surrounding the major fuels, competition in generation, impact of environmental limits, and other uncertainties.

The utilities involved in power generation in the UK Electricity Supply Industry fall into three categories, broadly labelled as ***unprotected and dominant***, ***protected but competitive***, and ***unprotected but encouraged***. Each of these perspectives are briefly described below, and their plant mix as at July 1993 summarised in associated tables.

The ***unprotected but dominant*** utility describes the two major power generators, National Power and PowerGen. These duopolists are primarily concerned with sustaining marketshare while increasing return to shareholders and therefore strongly motivated by profit. Despite having the financial muscle to invest in different types of plant, these companies face considerable regulatory uncertainty, e.g. threat of MMC[2] referral, caps on electricity prices, the Regulator's scrutiny of anti-monopolistic behaviour, and stringency of environmental allowances. National Power's plant mix as at July 1993 is summarised in table 4.2.

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2 Monopolies Mergers Commission

Table 4.2 Unprotected but Dominant Utility: National Power

Type of Plant	Number	Capacity in MW
Large Coal	7	13,103
Medium Coal	4	3,412
Small Coal	7	1,784
Oil	3	4,484
Open Cycle Gas Turbine (OCGT)	16	1,565
Combined Cycle Gas Turbine (CCGT)	1	620
Hydro	3	40
TOTAL	**41**	**25,008**

The ***protected but competitive*** utility characterises Nuclear Electric, which has not been privatised. Despite heavy subsidy of the nuclear levy and other government protective measures, the nuclear generator has an equally strong profit motive, i.e. to show that it can eventually compete in the private sector when the subsidy expires in 1998. Many of these uncertainties will be resolved with the outcome of the Nuclear Review due in 1995, i.e. privatisation, subsidies, public support, financing of power stations, and the future of nuclear power. Nuclear Electric's plant mix as at July 1993 is summarised in table 4.3.

Table 4.3 Protected but Competitive Utility

Type of Plant	**Number**	**Capacity in MW**
Magnox	7	3,293
AGR	5	6,039
Hydro	1	30
TOTAL*	**13**	**9,362**

*Excludes Sizewell B currently under construction

Finally, the ***unprotected but encouraged*** utility reflects the views and opportunities of independent power generators. Independent power producers are building CCGTs which are tied to back-to-back 15 year fuel contracts as a way for the regional electricity companies to diversify their own distribution and supply business as well as to gain a competitive advantage in this market. Table 4.4 summarises the combined portfolio of all independent power generators by status as at July 1993.

Table 4.4 Unprotected but Encouraged Utility

Status (CCGT, CHP)	Number	Capacity in MW
Transmission Notice and Under Construction[1,2]	9	4,936
Transmission Notice and Section 36 Consent Given	6	4,619 - 5,156
Section 36 Consent Given Only[3]	6	3,124 - 3,354
Transmission Notice Only[4]	10	8,497
Public Inquiry	2	506
Application for Planning Permission	15	5,150 - 5,360
Early Stages (None of Above)	6	1,200 - 1,300
TOTAL[5]	**54**	**28,032 - 29,109**

1 Excludes BNFL's Sellafield CHP 162 MW under construction but not directly connected to system
2 Excludes Sizewell B PWR 1254 MW Under Construction
3 Excludes Hinkley C PWR 1200 MW which is very unlikely to be built
4 Excludes Scottish Interconnectors 750 MW
5 Includes projects in which National Power and PowerGen have stakes

In an increasingly more competitive electricity trading market, with tighter environmental regulation and potential over-capacity, the case study addresses the following question.

> **How should a power generating company in the UK plan for capacity expansion in terms of timing, capacity levels, and plant mix?**

These investment decisions depend on the kinds of technologies available, their economics, and impacts of uncertainty. The cost of a capacity expansion plan is calculated from totalling all investment and operating costs. The relative economics of plant can be determined by its merit order in the entire system.

To answer the capacity planning question, two main types of uncertainties surrounding the decisions to invest new plants and retire old ones are explicitly considered: ***demand*** and ***fuel price***. These uncertainties at the industry level concerns all types of power generators. Therefore differentiation amongst the companies is not required. Uncertainties at the firm level would require differentiation by type of utility; however these firm level uncertainties have not been addressed in this case study.

1) ***Demand uncertainty*** surrounds the seasonal fluctuation of demand as expressed in load duration curves as well as the period growth of demand. The growth and shape of demand depend on factors such as energy efficiency, consumer consciousness, demand side measures, weather, load management, fuel switching, VAT regulations, economic growth, and responsiveness to electricity prices.

2) ***Fuel price uncertainty*** affects the types of fuels used in the technologies. The main factors describing fuel price uncertainty are base price and subsequent escalation rates. Emission regulation, spot prices, and related fuel prices determine the direction and rate of fuel price escalation.

The consolidated industry data used in the replicated models are contained in Appendix B. Briefly, input data specification of plant consisted of 85 existing plant in the system totalling 60 GW of capacity of 10 different technologies (magnox, AGR, large coal, medium coal, small coal, oil, OCGT, CCGT, hydro, and the Scottish and French links). Eight different seasonal load duration curves were specified to correspond to peaks and troughs in demand during the year. Linear trend forecasts were specified for peak demand and each type of fuel for each period in the planning horizon. Capital and operating costs were specified for each of the 85 plants. New alternatives included fossil fuel plant, nuclear, and renewables.

4.4.2 Stage 1: Three Archetypal Modelling Approaches

The first stage of the modelling experiment examines three modelling approaches representative of those followed in the industry. Two extreme approaches characterise capacity planning in the UK electricity supply industry: ***deterministic*** and ***probabilistic***. These have been highlighted in public inquiries into proposals to build new nuclear power plant. The deterministic and probabilistic approaches centre around an optimisation of investment schedules to electricity demand and fuel forecasts. In the US, on the other hand, regulatory hearings have increasingly made use of the ***decision analytic approach*** which combines some features of the deterministic and probabilistic approaches. These three modelling approaches (deterministic, probabilistic, and decision analytic) represent quite distinct norms in the industry and span the range of basic approaches.

1) The deterministic approach is typical of large, public sector, monopolistic power companies, e.g. the former Central Electricity Generating Board (CEGB) in the UK. The CEGB used the techniques of ***scenario analysis***, ***optimisation***, and ***sensitivity analysis***. Their approach is well documented in Greenhalgh (1985), Vlahos and Bunn (1988b), and the Sizewell and Hinkley public inquiries (Layfield, 1987). Five scenarios are postulated from assumptions on world growth and the UK economy. Within each scenario, a linear programming optimisation is performed to produce the best solutions. Uncertainty is investigated afterwards through sensitivity analysis by changing one variable at a time. This deterministic approach considers a few uncertain parameters that are sequentially and independently varied over limited ranges.

2) The probabilistic approach is effectively an ***expanded risk analysis*** demonstrated by Evans (1984) and also discussed in Evans and Hope (1984), Kreczko et al (1987), and Jones (1989). It gives attention to the kind of uncertainty analysis recommended by the inspector Sir Frank Layfield in the conclusions of the Sizewell B public inquiry. However, this recommendation was not followed in the ensuing Hinkley enquiry. This approach is an extension of the first pilot study with the major difference that an optimisation sub-model is run several times using the sample values from the risk analysis-generated probability distributions. By varying more than one variable at the same time, it is possible to get different combinations of input values. In the Sizewell study, fifteen input variables were explicitly included for this uncertainty analysis, with justification for the exclusion of other major variables such as plant lifetime and discount rate.

3) The decision analytic approach is patterned after the North American ***decision analysis*** school, a discipline actively practised by consulting firms such as SDG (Strategic Decisions Group) and ADA (Applied Decision Analysis). We replicate a variant of the Over/Under Model of Cazalet et al (1978). This kind of decision analysis approach is illustrated in Anders (1990) and Peerenboom et al (1989). The approach is heavily decision analysis oriented with emphasis on the technology choice decision. A decision tree is structured to capture the major decisions and uncertainties.

Details of these approaches, their replication, and evaluation are given in Appendix B. Briefly, the deterministic and probabilistic approaches were straightforward replications of the Sizewell B and Hinkley C models but with industry data updated to 1993. The decision analytic approach required more extensive prototyping, i.e. re-structuring of the basic problems in capacity planning.

4.4.3 Comparison of Approaches

The three approaches were replicated and evaluated independently of each other. The plant schedule optimisation central to the deterministic approach provided a link to the probabilistic approach. However, the transition between the probabilistic and decision analytic approaches required a major re-orientation in conceptualisation and construction.

The optimisation programme used in the deterministic and probabilistic approaches captures the operational and financial details missing in the decision analytic approach. Unfortunately, the ***level of detail*** required by the capacity optimisation programme is difficult to attain in the new competitive environment. Commercial confidentiality restricts the publication and availability of detailed plant characteristics and costs. In the absence of actual plant data, estimates may reduce the level of accuracy and detail and adversely affect the reliability of the output. This aspect of modelling, i.e. the inability to model the "full" system given the difficulty of obtaining competitors' data, is even more crucial now.

The level of detail leads to the ***comprehensiveness of specification*** which are met by the first two approaches. Both are developed from a full model specification of the capacity expansion problem. They take a simultaneous approach to decision making, i.e. a single plan is produced rather than the usual multi-staged contingent nature of planning. The decision analytic approach, in contrast, decomposes capacity planning into a sequence of decisions. All three approaches can be extended to include more scenarios, uncertainties, time periods, decisions, alternatives, etc. However, the probabilistic and decision analytic approaches run into dimensionality problems.

The deterministic approach treats ***uncertainty*** in an expanded what-if analysis, whilst saying nothing about the preferences and risk attitudes of the decision maker. Assigning probabilities to scenarios and uncertain parameters enables the consideration of likelihoods. The probabilistic approach merely produces a robust plan, i.e. results that lie within an acceptable range. It gives no indication of the sequence of decisions that should be undertaken. Decision analysis by definition is a decision-focussed technique. It captures the risk attitude and value preferences of the decision maker as well as the multi-stage nature of capacity planning, thereby allowing the explicit consideration of each perspective.

Range and richness of insight in the output depend on the specification of the input. The probabilistic approach allows the expression of all important uncertainties at once and also gives risk profiles of different output parameters at the end of the simulations. The decision analytic approach requires the sequential consideration of inputs and the fulfilment of mutually exclusive and collectively exhaustive conditions. As a result, outputs from decision analysis come from a smaller set of permutations than possible from risk analysis. Risk profiles as constructed from cumulative output distributions can be compared for cost ranges of different alternatives. On the other hand, the decision analytic approach produces discrete pictures of these alternatives, which give much less information. Although the deterministic approach produces outputs that are scenario dependent, it gives different combinations of plant alternatives, which cannot be achieved in decision analysis due to limited input specification.

In theory, ***continuous probability distributions*** can be attached to chance nodes in decision analysis. In practice, finite states and the dimensionality of multiple stages prevent such a formulation. The probabilistic approach, on the other hand, uses efficient sampling methods to propagate continuous distributions to the output. However, these sampling methods assume independent probability distributions. The deterministic approach treats uncertainty in a static and limited fashion. There is no account of asymmetry or likelihood. Table 4.5 summarises the above comparison of modelling approaches by evaluation criteria.

Table 4.5 Comparison With Respect to Evaluation Criteria

Criteria	**Deterministic**	**Probabilistic**	**Decision Analytic**
Level of detail	high	high	low
Model characteristics	comprehensive	comprehensive	comprehensible
Decision focus	optimisation	simulation	decision focussed
Output	scenario-dependent plan	risk profiles	decision sequence paths
Uncertainty	static, discrete by sensitivity	cumulative by sampling	sequential resolution by discrete states

In terms of modelling effort and focus, the deterministic approach is ***input intensive*** as it requires the generation of scenarios and detailed specification of input. The probabilistic approach is ***output intensive*** as evident in the sheer volume of sampling data and simulation results that must be consolidated. In contrast, the decision analytic approach is ***structure intensive***, as it forces the problem to be addressed in terms of controllable and uncontrollable events, i.e. decisions and uncertainties. Table 4.6 summarises the main points in the evaluation of each approach with respect to their contribution to a comprehensive yet comprehensible model.

Table 4.6 Summary of Approaches

Approach	**Positive Features**	**Negative Features**
Deterministic	• credible basis • easy • detailed • captures complexity of merit order	• none of the scenarios may occur • may have sub-optimal plans • tendency towards over-optimism • no account of asymmetries • static view of uncertainty
Probabilistic	• robustness • simultaneous computation of all probabilistic effects	• time consuming iterations • manageability and data control • independence of probabilities
Decision Analytic	• perspectives • multiple stages • risk attitude • flexible construction	• lack of detail • dimensionality problem

As expected, each approach is incomplete insofar as capturing all areas of uncertainties. Deterministic optimisation requires considerable input data. Scenario and sensitivity analyses give limited insight to the kinds of uncertainties that prevail. Risk analysis by means of Monte Carlo simulation of the optimisation model improves the representation and treatment of uncertainty but produces output risk profiles at a high computational cost. Although decision analysis considers decisions and uncertainties explicitly, its structural simplicity cannot incorporate the complicated production costing in electricity generation. These results point to the strengths and weaknesses of each approach and the need to balance the desirable model characteristics.

The deterministic and probabilistic approaches centre around the optimisation algorithm of fitting investment schedules to forecasts of demand, fuel, and other uncertain parameters. Fitting plans to forecasts relies on the accuracy of forecasts. Sophisticated trend-based forecasting methods has performed poorly in the turbulence of the last two decades. Inaccurate forecasts lead to sub-optimal plans. The traditional approach of fitting plans to forecasts of fuel supply and electricity demand is a static answer to a dynamic reality.

Modelling different perspectives in deterministic and probabilistic approaches is difficult, because the optimisation programme optimises the entire system and not with respect to ownership. A decision focus can only be manifested in decision analysis which, on the other hand, is incapable of modelling the intricacies of the power system.

Throughout the experiment, difficulties in meeting the main conflicting criteria of ***comprehensiveness*** (completeness) and ***comprehensibility*** (manageability and transparency) are evident. Each approach is either comprehensive but not comprehensible or vice versa, never both, as summarised below.

1) The deterministic approach is ***incomplete*** and ***inadequate*** in the treatment of uncertainty.

2) The probabilistic approach generates ***too much data*** to be manageable.

3) The decision analytic approach is ***unable to capture the details*** required in power systems planning.

Given the above conclusions, the next stage of the modelling experiment attempts to overcome the deficiencies of individual approaches and resolve the conflicts through synthesis of the essential feature of the first two approaches (optimisation) and an attractive feature of the third approach (decision analysis).

4.5 Model Synthesis

4.5.1 Rationale

Applications based on single techniques lack the breadth to cover the range of strategic issues or the detail to represent aspects of the power system. ***Mathematical restrictions***, ***computational difficulties***, and ***the maintenance of intuitive understanding*** prevent more extensive specifications of the complete problem. The three representative approaches are individually unable to meet the conflicting criteria of comprehensiveness and comprehensibility. These conclusions suggest that a synthesis of techniques, resulting in a larger but more integrated model, should achieve the kind of balance and completeness unattainable by any single technique. Some people, e.g. Linstone (1984) and Brown and Lindley (1986), suggest that it is only by approaching a problem from multiple perspectives that reliable insights can be developed.

Model integration, ***composite models***, ***combining methods***, and ***complementary modelling*** all refer to the term we coined "***model synthesis***". The final synthesized model consists of model components which may be models or techniques. The idea of synthesis is appealing for six reasons.

1) By exploiting synergies between techniques, a synthesis reflects the notion that "the whole is greater than the sum of the parts."

2) A synthesis uses the complementarity of the strengths and weaknesses of components to achieve completeness.

3) Due to the high cost of development (Balci, 1986), it seems easier to use existing readily available models and tools rather than to develop one from scratch.

Synthesis capitalises on familiarity and reusability of existing models. Reisman (1987) urges a synthesis of models rather than the development of more models, as there are too many models already. Synthesis through generalisation and systematisation reduces the jargon and effort required to master new techniques.

4) Instead of new investment (of knowledge, resource, etc), synthesis involves issues of integration and automation.

5) Synthesis makes use of specialisation. Each component in the eventual synthesis addresses what it is good at.

6) The above five reasons are supported by the noticeable modelling trend seen in practice, as explained below.

The energy modelling literature indicates an inevitable trend towards building bigger models through synthesis of existing approaches, e.g. FOSSIL2, MARKAL, NEMS, and WASP in Ruth-Nagel and Stocks (1982), Beaver (1993), and IAEA (1984). While advances in software, hardware, and human capability may help to achieve these modelling goals of completeness, the required amount of effort and resource may well exceed that available to a single utility. This thesis addresses this ***practicality*** issue, i.e. the costs versus the benefits.

The second stage of the experiment determines the feasibility of model synthesis for a typical power company in the UK, given its limited resources. Different prototypes of model synthesis are constructed. Ways to combine other techniques within a decision analysis framework are conceived and tested. Models of models (explained in section 4.5.4) are built to facilitate this synthesis. Beginning with a full conceptualisation of the issues involved in model synthesis in section 4.5.2, the second stage ends with a discussion of the practicalities of synthesis in section 4.5.5.

4.5.2 Conceptualisation of Model Synthesis

Applying more than one technique to achieve synthesis involves the following considerations: familiarity, dimensionality and complexity, system integrity, extensibility and reusability, compatibility, functional and structural synergies. We briefly discuss these concerns and then summarise the conceptualisation of model synthesis found in Appendix C.

Familiarity with these techniques is required beyond a superficial level. The modeller's choice of technique, ability to handle different modelling frameworks and assumptions, and ability to exploit synergies between techniques depend on his familiarity with the model components. This technique-driven bias arises out of the learning curve effect and cognitive limitations.

Dimensionality arises from increases in shared data, interacting variables, and other permutations of uncertainties and errors. These dimensionality issues in turn imply concerns of manageability of data and model, validation, error tracking and diagnosis, conversion and translation of data, and compatibility of model components. Composite models with integrated methodologies contain a higher level of ***complexity,*** including difficult to trace information flow. Higher levels of complexity also arise from dimensionality.

Changes in problem specification and assumptions must be propagated through the model such that resulting changes in the components are consistent and the ***system's integrity*** is preserved. Any extension or changes in problem specifications or using the synthesized model for different purposes will require re-examining all components to preserve system integrity. ***Extensibility*** and ***reusability*** of model components are required to facilitate synthesis.

One of the difficulties of synthesis results from the (lack of) ***compatibility*** of underlying (necessary) assumptions, functionality, and theoretical foundations of model components. If the incompatible or even conflicting fundamental requirements cannot be resolved, the final model may not work. Ironically, the strength and appeal of model synthesis lies in the diversity (and complementarity) of model components!

Synthesis should exploit ***structural*** as well as ***functional synergies*** between techniques. However, methods to facilitate this are not always obvious. Appendix C proposes examining similarities between techniques as a starting point. The above concerns and implications are summarised in table 4.7 below.

Table 4.7 Major Concerns in Model Synthesis

Concern	**Definition and Description**	**Implications**
Familiarity	Modellers' acquaintance and understanding of model components, i.e. techniques and models which are used in the final synthesis.	• tendency to make use of or rely on familiar techniques and under-exploit the less familiar ones • modeller's ability to handle different frameworks and assumptions to achieve a useful synthesis • switching and transitional costs
Dimensionality	Increases in and permutations of inputs, outputs, interactions, and interfacing of data and variables.	• higher level of complexity • data manageability • error tracking and diagnosis • compatibility • conversion and translation • validation
System integrity	The "wholeness" of synthesis.	• consistency throughout • extensibility of components • reusability

Compatibility	Co-existence of model components in a synthesis depends on the underlying assumptions and theoretical foundations.	• feasibility of synthesis • effort required in resolving conflicts of interest
Synergies	Similarity or affinity in functionality and structure of model components.	• added contribution to final synthesis

Model integration is a hot topic in model management. The decision support literature is full of new modelling languages, most notably Geoffrion (1987), but devoid of ways to synthesize existing techniques or models. A conceptualisation of model synthesis in Appendix C attempts to bridge this gap.

Given the availability of so many different types of techniques and models, ***strategies for synthesis*** appear necessary to narrow down the possibilities and avoid the costly method of trial and error. [Appendix C gives three main strategies called ***modular***, ***hierarchica****l*, and ***evolutionary***.]

Beginning with definitions to distinguish between techniques and models, the conceptualisation highlights synergies between techniques in terms of 1) ***structure***, 2) ***functionality***, and 3) the ***complementary contributions*** they add to a synthesis. Structural considerations include the a) ***selection***, b) ***ordering***, and c) ***linkage*** of model components.

Model linkage is complicated by four main factors: dimensionality, communication, interface, and interaction.

1) The required number of interfaces increases with the number of techniques, and this contributes to the ***dimensionality*** problem.

2) Data transfer and sharing complicate the ***communication*** between different models. Output data from a model component is rarely in a form acceptable by another, hence requiring some transformation.

3) Any components requiring direct user input must have appropriate user ***interface***.

4) The frequency and manner of user involvement determine whether a model is ***interactive*** or ***non-interactive***. The former relies on the user or the modeller to guide the process, while the latter only involves the user in the beginning. Linear programming, for example, is traditionally a non-interactive method, as the modeller specifies the inputs in the beginning but does not interfere with the intermediate algorithms.

The above structuring issues are detailed in Appendix C, but summarised in table 4.8 below.

Table 4.8 Structuring Issues

Selection of Components	**Ordering**	**Linkage (supporting argument)**
• structural synergies • functionality • execution costs • input requirements • applicability • software availability • technique familiarity • manageable level of detail • complementarity • compatibility	• increasing complexity • most relevant aspect • most intuitive model to get decision makers involved • peripheral models (scenario analysis)	• sequential (good for error tracking and checking but possible bottlenecks and slow execution) • parallel (faster than sequential linkage but issues of compatibility and interfacing) • feedback or iteration (useful for convergence but may be time-consuming) • embedded or nested (complexity and dimensionality issues) • multi-level, e.g. hierarchical (organisational issues) • integrating module whose sole task is to synthesize and coordinate (extra effort in constructing this)

In addition to the above, a distinction into ***weak*** and ***strong*** forms of synthesis is proposed. This conceptualisation somewhat corresponds to the three levels of synthesis associated with needs of an organisation (Dolk and Kottemann, 1993): ***combination***, ***aggregation***, and ***integration***. At the lowest rung of the organisation ladder, models are generally stand-alone or weakly synthesized, i.e. combined, for operational planning purposes. At the middle level, models are aggregated to pull the information together. At the top level, models are integrated (strongly synthesized) for decision making purposes. In our distinction, the level of synthesis depends on the *degree of dependence* or *communication* between model components. A weak synthesis has less inter-component dependence than a strong synthesis and hence easier to build but possibly more cumbersome to assimilate the results. Here, the model components are not tightly coupled or integrated at all. The deterministic and probabilistic approaches represent weak forms of synthesis, whereas the second stage investigates stronger forms of model synthesis. The strongest level of synthesis is full integration, where each component contributes to each other. In the strong form, individual components are no longer distinct from each other. While the strong form may require more work for the modeller initially, the resulting synthesis provides less work for the user. The modelling work involved in synthesizing is a fixed investment cost, while the additional work involved in using the resulting model is a variable operating cost. Thus model integration provides the rationale for reducing the variable cost (of the user).

After the above conceptualisation, various prototypes are constructed to investigate the practical issues of synthesis. Stage two of this experiment attempts to answer the following questions via the construction of a decision analysis framework explained in section 4.5.3.

1) **How can model synthesis facilitate more extensive uncertainty analysis?**

2) **How can these conceptual methods be practically implemented?**

4.5.3 Decision Analysis Framework

To overcome the conceptual difficulties in synthesis, decision analysis is proposed as a front-end, i.e. a modelling framework to unify and organise the model components. Such a framework brings the complex issues of capacity planning close to the decision maker in a reduced form. The decision tree structure is envisaged as a means of organising other complementary techniques via nodal linkage.

Chapter 3 and Appendix B reveal potentially useful features of decision analysis. The decision tree structure of nodes and branches has synergies with other techniques, as shown in Appendix C. It is simple enough for the representation of decisions and uncertainties and the communication of strategic issues. Until the advent of desk top decision software, decision trees were restricted to structuring simple problems. The tedious task of expected value calculation especially in large multi-state, multi-stage decision trees can now be automated by software such as DPL (ADA, 1992). These developments motivate a re-use of the age-old decision tree for new purposes of synthesis.

Decision trees have rarely been used as a framework for incorporating other techniques or models. This novel approach requires investigation into model interface, i.e. dynamic or static linkages in the decision and chance nodes; a method of capturing single point results of the capacity planning optimisation programme; the propagation of decisions by conditional events as opposed to time intervals; and the construction of a decision tree and its equivalent influence diagram.

As concluded from model replications of the first stage of the experiment, decision trees are too simplistic to incorporate the level of detail required of capacity planning. Even in a decision analysis framework, nodal linkages to separate techniques of optimisation or simulation become overwhelming and troublesome. Using the core optimisation model in its existing data-intensive form within a decision analysis framework poses three operational difficulties.

1) It is very ***time consuming*** to generate several scenarios, each to correspond to a path in the decision tree. The optimisation model based on Benders' (mathematical) decomposition uses iterative convergence to reach the optimum. Each run can take anywhere from a few minutes to well over an hour, depending on the data involved.

2) Each optimisation gives results that require ***considerable reduction and conversion*** for further use in decision nodes.

3) ***Interim processing*** is required to organise the inputs and outputs into an acceptable form.

The above difficulties imply that any further sensitivity analysis or alternative scenario analysis will be time-consuming as well as data intensive.

There are at least three ways to overcome these operational difficulties. 1) One is to build an interface to this optimisation model, i.e. a front-end to act as a filter. 2) Another is to design an interface with other models to generate the necessary data. However, neither solution improves upon the speed and ease of the original optimisation as they are both static links[3]. For these reasons, they have not been further pursued in this thesis. 3) A third proposal is to develop a reduced model of the original large model, which we call a "model of model."

To reduce the complexity of model linkages while still adhering to the completeness of the original optimisation model, we investigate the use of a "model

3 Static ways of referencing a bigger and more complicated model include 1) setting up look-up tables, 2) keeping a database of feasible solutions,3) approximation, 4) using an aggregate function, and 5) sampling and interpolation to extract or read off values from the original model.

of model" to facilitate dynamic linkages. The next section gives a detailed account of this investigation.

4.5.4 Model of Model

4.5.4.1 Introduction

A "model of model" refers to a reduced model which summarises or approximates a larger model. It is a deliberate simplification of the original more complicated model. The reduced model answers the need for less input and output and more speed. It is useful under the following conditions.

1) The original model is too time consuming to execute.

2) Many executions of the original model is required, making it impractical to use.

3) The original model produces too much output, mostly unnecessary for its intended use or requires further manipulation or reduction to be useful.

4) Full accuracy is not necessary.

5) The original model requires too much input data which cannot be obtained easily.

6) The original model is not an end in itself, but a means to an end, therefore approximation is acceptable.

7) The original model cannot be used in model synthesis in its existing form.

In the physical and engineering sciences, ***response surface methodology*** (Box and Draper, 1987) is an established way of building a simpler model from the inputs and outputs of a larger model. It comprises a group of statistical techniques, the most common being the least square method for regression. The reduced regression model can be compared with the full optimisation model for model fit, whereas most regression models are fitted on data which cannot be generated at will.

To operationalise the decision analysis framework, we need to determine the feasibility, practicality, and reusability of a reduced model of the core capacity planning optimisation model. ***Feasibility*** refers to acceptability and reliability. In other words, are the simplifications and approximations acceptable? Is the validation reliable? ***Practicality*** refers to the worthwhile effort in producing and validating a model of model as opposed to constructing a new model. ***Reusability*** is related to the previous two criteria. A reduced model is intended for further use, for example, as input to another model to facilitate further sensitivity or risk analysis. The additional effort required to adapt or transform this model must not be excessive.

4.5.4.2 Methodology

We developed and followed a systematic method of approximating the core optimisation model using multiple regression. Such a systematic method can be repeated for different values of independent variables and different forms of the final reduced model. The next paragraphs explain the seven main steps.

1) Determine k desired outputs (dependent variables Yj, j = 1 to k)

First we determined the payoffs and values needed in the decision analysis framework, as listed in table 4.9 below. These incremental payoffs were intended for attachment to nodes of the decision tree, subject to values of other independent variables or nodes along the path. A regression equation was built for each dependent variable.

Table 4.9 Dependent Variables in the Reduced Model

Dependent Variable	**Original Output File in Optimisation Model (name of file appendix)**
Investment cost	Optimal Expansion Plan (*.OEP)
Operating Cost	
Total cost	
Cumulative new plant installed capacities per plant type for a certain time period (in pre-selected periods)	Production Costing Results (*.PCR)
Marginal Fuel Savings (MFS) of new plants	
Net Capacity Credit at 88% availability (economic attractiveness of newly installed plants)	Net Capacity Credit (*.NCC)

2) Select m associated inputs (independent variables X_i, i = 1 to m)

In the manner of the first pilot study (Appendix A), we used sensitivity analysis to find the main independent variables that determine the previous dependent variables. The reduced form should be much simpler than the full model, hence, which original variables to include is an important decision. Relationships between X_i and Y_j indicate which X's to select. The choice of X's also depend on the choice of which input variables to fix and which to vary in the optimisation model. The most important variables are listed in table 4.10 below.

Table 4.10 Independent Variables in the Reduced Model

Independent Variable in Reduced Model	Original (Input or Output) File in Optimisation Model (name of file appendix)
Reserve margin	Input: Period Demand File (*.PRD)
Diversity in plant mix	Output: Optimal Expansion Plan (*.OEP)
Type of plant available as an alternative in a particular period	Input: New Plant File (*.NEW)
Capacity cost	
Fuel price in base year	
Fuel escalation rate	Input: Escalation File (*.ESC)

3) Determine value ranges for each X_i

Once the dependent and independent variables have been selected, we determined the value ranges for each X_i. We anchored the average value for each X_i, i.e. $E(X_i)$, then fixed a margin above and below it. Thereafter, we adjusted the margins to give a combination of symmetric and skewed ranges.

4) Generate n sets of datapoints for X_i = n*m

There are two main ways to generate data points for independent variables: factorial design or probability distribution.

1) ***Factorial design***, for the generation of combinatorial scenarios and equal-interval permutations, refers to assigning sets of combinations of different values of X's. Bunn and Vlahos (1992) used equal interval permutations to get the data for regressing the model, and then random sampling to get additional data for validation. Full factorial design covers all possible combinations of X values, but this may include meaningless and inadmissible combinations.

2) ***Probability distributions*** reflect how likely and how frequently the input data (values of independent variables) will occur. Hence it is a more realistic (accurate)

reflection of how one would expect to get the data (if available) than the factorial design. The distribution method also allows the use of sampling techniques, such as Monte Carlo and Latin Hypercube Sampling within risk analysis. As a shortcut, we used the sampled data generated from the Probabilistic Approach.

We expect ***n*** (sample size) to increase with ***m*** (number of independent variables. This is supported by Morgan and Henrion (1990), who observed that the complexity of the factorial design increases exponentially while the sampling of probability distributions increases linearly.

5) Automate optimisation runs to get Yj

We modified the spreadsheet macros created during the replication of the Probabilistic Approach to generate new data for regression analysis. We then extracted sets of data for independent variables into text input template files and editted them into an acceptable form for the optimisation programme. Each data set was used for one optimisation execution (run), resulting in one set of output data. The relevant dependent variables were extracted from this output into a spreadsheet. This was repeated for ***n*** sets of data and runs. One hundred to one thousand runs were made for each combination of Y and X's. After all data sets have been processed, we modified the formats to prepare for regression analysis.

6) Regression Analysis

The latest releases in desk-top statistical software offered not only statistical but also visual model fitting facilities. We used the Curve Fit facility in the statistical package SPSS Windows to identify the kind of relationship between a pair of X and Y. We checked various transformations, e.g. linear and non-linear. To build a good regression model, we used facilities such as forced entry (all variables considered at once), forward or backward elimination, and stepwise regression. We checked t statistics to eliminate non-significant estimators and adjusted R square to get the overall fit. We also looked at possible interaction terms, outliers, influential variables, etc.

The R squares were very low, ranging from 0.05% to 32% at best, indicating a poor fit. The variance of R squares was very large. This implied that the form of regression equation or regression as a technique altogether was not satisfactory. The variance of residuals was also large.

7) Validation

We validated the resulting regression equations by generating new data by permutation 1) within the original X ranges, and 2) outside of original X ranges. These two kinds of validation (within and outside range) were aimed to show the acceptability and re-usability of the regression model. A small variance of R squares would indicate consistency and reliability of these models.

The within and out of range validation tests were unsatisfactory as there was no pattern to the outcomes of using new data on reduced models. Along with large residual variance, these results made the reduced models unacceptable and not reusable.

Our negative results seem to contradict that of Bunn and Vlahos (1992) who managed to fit a regression model on a similar optimisation model. Theirs was fitted on a sample size of 1000, i.e. a thousand runs in which 6 independent variables were varied: demand escalation rate, nuclear capacity cost, discount rate, coal price, coal price escalation rate, and the level of Non-Fossil Fuel Obligation (NFFO). The resulting dependent variable is the difference in total cost of the optimal plan *without* the NFFO and *with* the NFFO. The regression model was validated against a further 250 new scenarios. Building such a model was mainly used to demonstrate that such a simplified model could be produced, could be helpful in adversarial debates, and could be useful for subsequent uncertainty analysis. Our choice of independent variables is totally different from theirs as are our dependent variables. The background scenarios (fixed variables not entered into the regression) are also different. In addition to equal permutation (as they have done), we also used probability distributions, which should give a more credible model. These differences question the generalisability of a reduced regression model of the optimisation programme.

4.5.4.3 Conclusions

After substantial modelling effort in which different data sets were produced, we were unable to arrive at a convincing argument for "model of model" using the method of regression analysis for approximating the capacity planning optimisation model. We conclude that "model of model" as a means to capture the production costing detail of the optimisation programme for the decision analysis framework is ***infeasible***, ***impractical***, and ***not re-usable***. These conclusions are supported below.

1) INFEASIBLE

None of the regression models were reliably and consistently representative of the original model. The residuals were large and varied, with no apparent pattern. This made results unpredictable. Poor R square implied that regression may not be a good basis for model building. These results were perhaps due to the parameters chosen.

It was difficult to ensure that the artificial data generated from successive runs of the original model could produce meaningful and admissible combinations for regression analysis.

Both within range and out of range validation of reduced models failed to give convincing results. This not only questions the acceptability of the reduced model but also its propensity for further use.

2) IMPRACTICAL

The effort in producing and validating a regression model was quite large. In fact, it was greater than the sampling and risk simulation work involved in the Probabilistic Approach. This effort should not exceed that of re-using the original model for the same purposes.

3) NOT REUSABLE

The previous two criticisms (infeasible and impractical) foreshadows its reusability. The reduced model, even if well-calibrated to the original, could only be used for the background scenario given, hence of limited use. In other words, each form of the reduced model is confined to the background scenario. This implies that any variation in background scenario requires the construction of a new reduced model. Likewise, changing any parameter that was originally fixed to produce the reduced model does not guarantee valid results as out of range validation showed that the model was limited to the independent variables and ranges specified.

4.5.5 Second Stage Conclusions

Several prototypes within the decision analytic framework were constructed. However, they could not be "operationalised" to the level of detail or functionality required for capacity planning. In its existing form, the core capacity optimisation model was incompatible with decision analysis in data (input and output), structure, and level of detail. The output of optimisation was not meaningful for linking without further reduction. These complexities of data size and form added to the dimensionality problem.

One way to overcome the above problems was by a "model of model." After extensive tests, this approach failed to meet the criteria of feasibility, practicality, and reusability. The difficulties in implementing the conceptualisations of model synthesis are summarised in table 4.11.

Table 4.11 Difficulties of Model Synthesis Implementation

Area of Difficulty	Description
optimisation/decision analysis interface	• incompatible data (size and form) • conflicting technique assumptions
model of model	not feasible, practical, or re-usable
resource limitations: software engineering issues	• available software not capable of dynamic linkage • incompatible interfaces between applications • programming required for data conversion • application handler needed to achieve multi-tasking • no model management system available to overcome above issues

These practical limitations of models synthesis are due to the conceptual difficulties given in Appendix C and the operational difficulties which reveal the importance of compatibility of components at different levels. We raise the following hypotheses for further research, which together with our experimental findings help to explain the impractical pursuit of model synthesis given the limitations of our current state-of-the-art software and the resources and capability of a single utility.

1) Model synthesis requires the resources and capability beyond a single model builder. Utilities in the UK ESI, especially new entrants, have limited resources. Model synthesis may not be a practical solution. Furthermore, a single model builder is biased by the technique familiarity, choosing only to use techniques that

are most familiar and available, thus unable to see the synergies for model synthesis.

2) Even if model synthesis is workable, it is hard to say if the insights from the resulting model are more useful than using different techniques, i.e. without any synthesis. The fixed cost of synthesis may be too great especially if not re-usable.

3) The case study contained too many dimensions to be comprehensibly modelled: perspectives, questions, objectives, and uncertainties. Yet, this case study was already a deliberate simplification of reality. This implies that the actual problem is far more complicated, and may not altogether be sufficiently addressed from a modelling perspective.

Our earlier prescription of “complementary but compatible techniques for comprehensive and comprehensible models” is a difficult goal to achieve by model synthesis. While “complementary” may be a means to “comprehensiveness” or “completeness”, “compatible” is not a means to “comprehensibility” but, rather, “synthesis.” Synthesis implies some form of “co-existence.” As a means to completeness, it requires compatibility of techniques, data, interface, assumptions, and other issues beyond a superficial level.

On the basis of the above conclusions, we turn to other ways of dealing with the range of uncertainties as suggested in the literature. Recent electricity planning literature has called for flexibility in planning and the consideration of flexible technologies. [See Chapter 5 for discussion and references.] Flexibility is frequently mentioned as a response to uncertainty but without guidance to how it can be used within this context. Flexibility as an end in itself radically departs from the previous focus of model synthesis.

4.6 Motivation for Flexibility

4.6.1 Completeness and "Model Unease"

Implicit in the modelling approach is the goal of completeness. ***Model completeness*** refers to the comprehensive coverage of all aspects of the problem, i.e. capturing all uncertainties, as a means to deal with strategic uncertainties. For example, our modelling experiments aimed to achieve completeness by thoroughness of approach, i.e. the consideration of all significant variables for adequate problem representation, close representation of reality (good approximations), and systematic treatment of uncertainty.

Completeness is difficult to achieve since a model, by definition, is a simplification of reality so necessarily incomplete. This begs the question: ***is completeness a reasonable and achievable modelling goal in the first place?*** Aversion to large models in strategic planning has led to simple models, e.g. Ward (1989), for the understanding of uncertainty and related issues.

We argue that completeness is only a means of increasing the level of confidence for the user of the model, i.e. the final decision maker who relies on the model for guidance and defensibility. A high level of confidence ensures that the resulting model will be used and re-used. A low level of confidence suggests that the user experiences "unease" in using the model fully or at all. The real question is: is it possible, and if so, how to remove that "model unease" ?

We illustrate in table 4.12 our interpretation of Mandelbaum and Buzacott's (1990) statement "flexibility compensates for model unease." The left-hand column gives the user's general belief about model completeness, i.e. whether or not models can be complete. The top row gives what the user has been told about the model in question. There is no unease if the user believes that models can be complete, and this particular model is complete. There is model unease whenever the model in question is not complete or if the user does not believe in completeness.

Table 4.12 Completeness and "Unease"

Modeller's Assertion or User's belief about this particular model: User's Belief about all models:	Model is ***complete.***	Model is ***not complete***.
Models can be ***complete***.	No unease.	Intra-model unease. More modelling required.
Models are ***never complete***.	Extra-model unease. Flexibility needed.	Model unease. Flexibility needed.

We distinguish between ***intra*** and ***extra*** model unease. ***Intra-model unease*** refers to the lack of completeness within a model, but may be amended by further modelling such as the use of sensitivity analysis. Model synthesis is an attempt at removing this kind of unease. ***Extra-model unease*** refers to the gap between the user and the model, i.e. the user believes that models can never be complete. Therefore there will always be an unease about what the model gives and what the user desires from the model. This gap between the user and the model characterises the style of decision making in this industry because the decision maker is not the builder of capacity planning models. This gap can be argued as follows.

1) Model and forecast errors always exist. Traditional approaches rely greatly on the accuracy of forecasts. However, forecasts by definition are predictions. Discrepancies (errors) between the actual and the forecast, no matter how small, will always occur. Models are simplifications.

2) The dynamics of model building, decision making, and realisation of plans imply that there is always a gap due to lead time. The nature of the generation business is such that investments have to be made before they are needed, during which time any number of factors may occur and change the expected performance. There are lead times to the construction of a useful model, the effective communication of its results, and understanding and acceptance by the final users.

3) Models do not supply everything the user wants. The user may not understand the model fully, hence unease. The user may want to retain own control, i.e. not rely on the model completely. Other organisational and political reasons may prevent full acceptance of the model.

If we believe that models can never be complete, then there will always be unease. According to Mandelbaum and Buzacott, we should use flexibility to hedge against model unease. This also suggests that the real goal we should be aiming towards, in addressing the problem of uncertainties in electricity planning, is not modelling towards greater completeness, but modelling for (or to produce) practical solutions to cope with uncertainty. Practical means to cope with uncertainty are given in the next sub-section.

4.6.2 "Coping" with Uncertainty

Practical means of coping with uncertainty have been suggested by Hertz and Thomas (1983) and Hirst and Schweitzer (1990). 1) ***Ignoring uncertainty*** allows one to focus on the complexities albeit at a high cost. 2) ***Building more accurate forecasts*** may help to achieve more accurate optimisation, but this does not prevent forecast errors. 3) ***Planning so that future decisions are unnecessary*** is a form of robustness, but this does not eliminate uncertainties. The remaining measures to cope with uncertainty are variations of the flexibility theme.

4) ***Defer decisions*** by waiting until additional information is available or until important uncertainties are resolved. The cost of waiting includes the opportunity cost of expired options.

5) ***Purchase additional information*** to reduce uncertainties. This requires the assessment of *perfect* and *imperfect* information to *eliminate* and *reduce* uncertainties respectively.

6) ***Sell risks*** by conducting auctions for supply and demand resources. Negotiate long term fuel supply and demand contracts.

7) ***Adopt a flexible strategy*** that allows easy and inexpensive changes. One way is to invest in flexible technology, which is characterised by short construction lead time and small modular unit size. Recent electricity planning literature (e.g. CIGRE, 1991 and 1993) has also proposed technical means of achieving flexibility in planning and systems.

4.7 Conclusions

How can we cope with increasing uncertainty and meet the conflicting criteria of comprehensiveness and comprehensibility?

One obvious answer is to build bigger models through ***model synthesis***. Conceptually, model synthesis should be able to overcome deficiencies of individual techniques by exploiting synergies between them. It promises a more comprehensive coverage of areas of uncertainty and a more versatile treatment of different types of uncertainties. Several ways to achieve synthesis have been suggested and two of them pursued in this thesis, namely ***decision analysis*** as an organising framework and a reduced model of the full optimisation model to capture the relevant details, i.e. "***model of model***".

We investigated the feasibility of model synthesis by conducting a two staged modelling experiment which consisted of model replication, evaluation, conceptualisation, and prototyping. The main findings, listed below, cast considerable doubt on further pursuit of "modelling for completeness."

1) The first stage of the modelling experiment showed that ***existing approaches were incapable*** of dealing with the conflicting criteria of comprehensiveness and comprehensibility.

2) The second stage revealed the ***limitations*** of model synthesis as a singular approach to uncertainty modelling.

3) In particular, model synthesis via a decision analytic framework employing model of model for data interface and dynamic linkages was ***infeasible*** and ***impractical***.

4) These results suggest that model synthesis is not a trivial undertaking, and the work involved may well exceed the capacity of a ***single modeller*** and the limited resources of a ***single utility***.

5) Furthermore, synthesis requires ***compatibility*** beyond a superficial level.

We then examined the goal of model completeness and concluded that reducing or removing "model unease" may be a more appropriate goal for dealing with the range of uncertainties in electricity planning.

Flexibility has been suggested as a hedge against model unease and as a practical means to cope with uncertainty. It is an intuitively obvious concept that appeals to the decision maker. That such an ill-defined concept could complement or even substitute the traditional approach of rigorous modelling seems far-fetched. It seems inappropriate to the capital intensive electricity industry, which is characterised by ***irreversibility*** (of capital investments and function-specific infrastructure), ***inflexibility*** (of long lead times and high sunk cost), and ***illiquidity*** (as the sale of uneconomic plant is still a relatively new phenomenon). Assets in the electricity supply industry are not as easily exchangeable or tradeable as those in the financial markets where flexibility is synonymous with liquidity. Electricity trading is not as competitive as the manufacturing and labour markets where flexibility is a much discussed operational objective. The strong engineering culture of the electricity industry requires detailed specification of model requirements and data input; thus the vague concept of flexibility must be precisely defined to be useful to capacity planning.

Although conceptually promising, flexibility requires further research to ascertain its practical usefulness. We need to be able to ***define***, ***measure***, and ***apply*** it to our problem. The second part of the thesis clarifies the concept of flexibility through a broad review of its definitions and applications from various disciplines.