A COMPREHENSIVE APPROACH TO ELECTRICITY INVESTMENT PLANNING FOR MULTIPLE OBJECTIVES AND UNCERTAINTY

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DECLARATION

I hereby declare that all the work presented in this thesis is my own unaided work, except where otherwise stated.

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Abstract

Appropriate Energy-Environment-Economic (E3) modelling provides key information for policy makers in the Electricity Supply Industry (ESI) faced with navigating a sustainable development path. Key challenges include engaging with stakeholder values and preferences, and exploring trade-offs between competing objectives in the face of underlying uncertainty. As such, a comprehensive framework is needed that integrates multiple objectives and uncertainty into a transparent methodology that policy makers and planners can use to analyse and plan for investment in the ESI, in a way which shapes decision outcomes, and enables confident choices to be made. This thesis is aimed at developing such a framework.

As a case study the South African ESI was represented using a partial equilibrium (Energy-Economic-Environment) E3 modelling approach. This approach was extended to include multiple objectives under selected future uncertainties. This extension was achieved by assigning cost penalties (PGPs – Pareto Generation Parameters) to non-cost attributes to force the model's least-cost objective function to better satisfy non-cost criteria. It was shown that using PGPs is an efficient method for extending the analysis to multiple objectives as the solutions generated are non-dominated and are generated from ranges of performances in the various criteria rather than from arbitrarily forcing the selection of particular technologies. Extensive sections of the non-dominated solution space can be generated and later screened to allow further, more detailed exploration of areas of the solution space.

Aspects of flexibility to demand growth uncertainty were incorporated into each future expansion alternative (FEA) by introducing stochastic programming with recourse into the model. Technology lead times were taken into account by the inclusion of a decision node along the time horizon where aspects of real options theory were considered within the planning process by splitting power station investments into their Owner's Development Cost (ODC) and Equipment and Procurement Cost (EPC) components.

Hedging in the recourse programming was automatically translated from being purely financial, to include the other attributes that the cost penalties represented. The hedged solutions improved on the naïve solutions under the multiple criteria considered as well as better satisfying the non-cost objectives relative to the base case (least cost solution). From a retrospective analysis of the cost penalties, the correct market signals could be derived to meet policy goal, with due regard to demand uncertainty.

Next a methodology for the ranking and selection of FEAs given multiple objectives and uncertainty was developed and demonstrated using the South African ESI. This methodology used a value function Multiple Criteria Decision Analysis (MCDA) approach that was augmented to compare the relative performance and credibility of FEAs across discrete futures. A portfolio of preferred alternatives was then identified based on performance and confidence criteria. This approach was also used to elicit the regret associated with each alternative by evaluating the spread of each alternative across the rank order. Finally a more detailed analysis of the reduced solution set examined short-term technology investment details alongside attribute performance information, so as to gain insight into the decision problem and relate it back to real life actions.

This work demonstrated that focusing only on alternatives that achieve the preferred rank may exclude important alternatives from the portfolio set and therefore from detailed analysis and final selection. Using a portfolio approach and focussing on a greater range in rank than just the preferred alternative increases the robustness of the selection process by reducing the effect of valuation and empirical uncertainties, allowing for a less intensive uncertainty analysis to be done prior to the detailed analysis of preferred alternatives. More specifically, the case study in chapter 5 highlighted that decisions relating to technology investment may need to be made even within a preferred set of alternatives with similar overall value scores and similar rank and credibility information. In a case such as this, the stakeholders would have to re-evaluate their preferences in relation to the specific trade-offs at hand such that a preferred alternate can be identified. Conversely, this case study also demonstrated that it is possible for the *initial short term investments for different alternatives in a portfolio of preferred alternatives to be so similar as to not require any major decision in differentiating the alternatives for implementation. The dominant effect that decision maker (DM) preference information has on the alternatives that enter the portfolio set was also demonstrated in the case study.*

It was then evaluated whether or not there would significant differences in the absolute performance of alternatives in terms of their attributes when dealing with technical empirical uncertainties in the generation phase as opposed to the selection phase. The relative performance of alternatives was then examined by comparing the rank order and frequency information obtained from dealing with technical empirical uncertainties in the generation phase with the rank and frequency information obtained from dealing with technical empirical uncertainties in the selection phase. Finally these differences were analysed in relation to other uncertainties in the system (such as valuation uncertainty around decision maker preferences) to determine whether they are in fact significant or if they are "drowned out" by valuation uncertainties.

It was found that integrating technical empirical uncertainty into the generation phase as opposed to the selection phase resulted in minor differences in the overall performance results. After examining the portfolios of preferred alternatives using different preference situations, it was determined that the additional effort and complexity of doing a robustness analysis on technical empirical uncertainty in the generation phase as opposed to the selection phase may not be justified given that similar alternatives make up the portfolios of preferred alternatives using both methods and differences would mainly seen in the unstable sections of the weighting sensitivity diagram where valuation uncertainties would have the greatest effect on results.

In the process of doing this comparison the normalisation process whereby attribute performance values are converted to value function scores was examined with a specific focus on weighting bias. It was found that using pseudo-minima and maxima to normalise attribute performance scores with a modified indifference weighting approach *to articulate DM preferences reduces effective weighting biases by reducing the artificial inflation or deflation of value function scores based on improbable values. Differences were seen in the lower rank order of alternatives when comparing this method with the standard method of normalisation.*

Finally a methodology for integrating forced outage uncertainty into the comprehensive multi-objective framework was developed and demonstrated. This was achieved by separating the model into a master (investment) and slave (operational) problem and using the amount of unserved energy in each year of the slave problem as a feedback mechanism for inflating demand in the master problem to account for forced outage.

Using unserved energy as a convergence criterion between the master and slave problems for each year in the time horizon was shown to be an effective method for exploring the solution space and identifying the levels of inflated demand required to account for forced outage. This method also highlighted the trade-off between unserved energy and total discounted system cost, allowing the decision maker to make an informed choice around this trade-off.

It was demonstrated that the optimal inflated demand level varies little with DM preferences as unserved energy is minimised due to the high cost of unserved energy and the fact that the existing system is the same for all the alternatives generated. Therefore the master-slave used routine to determine the optimal level of inflated demand needed for each year in the time horizon can be carried out on the base case, and then used to generate further alternatives satisfying a range of DM preferences using the methodology presented in chapter 4. In this way forced outage uncertainty can be integrated into the multi-objective framework presented in this thesis without having to do large numbers of model runs for each alternative. If however the distribution of unserved energy for the preferred alternative was found to be unacceptable by the DM, the level of investment for that alternative could be increased using the methodology presented in chapter 7.

The benefits of comprehensively integrating multiple objectives and uncertainty into the planning process are significant. For example; correctly planning for forced outage uncertainty can significantly reduce the probability of blackouts. Poor environmental performance can be reduced by using a transparent methodology where decision makers are accountable for their choices and stakeholders outside of the decision making process can engage with those choices. The benefits of presenting decision makers with relevant information in a framework that they can engage with and understand would influence the decisions being made dramatically. The closer the gap between energy model and policy maker, the greater the chances of a sound plan being implemented. The more transparent the decision making methodology, the closer the gap between the policy maker and society.

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CHAPTER 1 INTRODUCTION

In both centrally planned national utilities and fully deregulated markets, strategic investment planning for the electricity supply industry (ESI) is a complex task. It is the job of policy makers and planners to ensure that demand will be met in an economically efficient, environmentally sound and socially responsible manner.

Investment decisions in the electricity supply industry typically involve multiple objectives that are often conflicting and incommensurate. Examples of such objectives include: minimizing cost, minimizing environmental damage, maximizing job potential and minimizing resource utilization. Policy makers and planners have to reach acceptable trade-offs between these objectives before recommendations can be made about future investments. Each potential new power station can be evaluated in terms of a set of criteria relating to these objectives. However it is rarely the case where the choice of technology is obvious given the multiple conflicting objectives of the stakeholders and the typically opposing performance attributes of power stations (i.e. stations that perform well in terms of cost usually perform badly in terms of environmental criteria and vice versa).

Uncertainty exists in each part of the investment modelling process. These uncertainties include technical empirical uncertainties relating to model data such as investment costs and emission coefficients[1], technical model parameter uncertainties such as reserve margin, discount rate and time horizon and valuation model parameter uncertainties such as inter- and intra- criterion preference information as well as uncertainty relating to the choice of model used (i.e. model form uncertainty).

[1] Emission coefficients are the values relating the quantity of pollutants emitted from a power station per unit of electrical output (e.g. ton CO_2/MWh).

At this point it may be useful to note the significance of the role of the decision maker (DM[2]) and the objective of this thesis. At one extreme, the DM may be a policy maker who explicitly determines all aspects of new investments (as is done in centrally planned national utilities like South Africa), on the other, the DM may have to use incentives, anti-monopoly rules, emissions caps, a myriad of Renewable Energy promotion policies and other instruments to shape future capacity investments. Preceding the set-up of these rules, it is vital that the DM understand what the most appropriate FEA may be in terms of their preferences. A method for evaluating FEAs from a global, or in this case, national perspective is presented in this thesis. This information can then be used by the policy maker to guide the rules that govern the market. This thesis does not focus on how to develop the market rules, nor is its focus the reaction of investors to those rules. It focuses on evaluating, to the best of our current knowledge of the uncertainties involved, which FEA may be most appropriate given a set of preferences, from the perspective of a policy maker. Although power market restructuring has resulted in investment decisions in much of North America, Europe and East Asia being made from the perspective of individual firms (based on their own profitability criteria), the methodology developed in this thesis is still applicable in those markets from the perspective of a regulator or policy maker.

This thesis aims to develop a comprehensive framework that integrates multiple objectives and uncertainty into a transparent methodology that policy makers and planners can use to analyse and plan for investment in the ESI.

This chapter will begin by defining some of the key terms used in ESI modelling and will then go on to briefly outline each chapter of thesis.

[2] A decision maker can be a single person or, when a group of people are involved, it could be a consensual position defined by a set of commonly held objectives.

1.1. KEY DEFINITIONS

The following definitions relate to technical terms used in this document and their specific meaning within analysis and modelling of the ESI:

OPTIONS AND TECHNOLOGIES

Options for capacity expansion planning or integrated resource planning may include supply-side capacity additions or *technologies*, demand-side load shifting and energy efficiency programs or any other measure for meeting or reducing electricity demand. Each option has a set of specifications that govern its behaviour in an investment planning model (e.g. availability factors[3], efficiencies, costs, emission coefficients, capacity constraints, ect.)

FUTURE EXPANSION ALTERNATIVES (FEA)

A *future expansion alternative* is an investment strategy comprising of a range of different technologies, built over a medium to long term time horizon (typically 10-50 years), that satisfies the demand for electricity over this time period. The model time horizon is often extended beyond the study period to allow for investment in the final years of the model to account for future demand beyond the study period. The choice of which *options* to build, when to build them and how much capacity of each *option* to build is included in this *plan* or *alternative*. This investment strategy can then be optimised for stakeholder defined objectives such as cost, as well as environmental and social objectives. The *plans* typically optimise for both the investment and operational parameters (load factors) of the power stations.

[3] The availability factor is the maximum percentage of the year that a power station is available to produce electricity, given its' planned and forced outage.

UNCERTAINTIES AND FUTURES

Uncertainty can be broken down into uncertainties relating to technical model parameters (e.g. discount rates, reserve margins and model time horizon) which are decided by the DM, technical empirical uncertainties relating to data (e.g. costs, emission coefficients, efficiencies and other technical parameters) which may be outside the control of the DM and valuation model parameter uncertainties (e.g. choice of criteria, choice of multi-criteria method to be used and inter- and intra-criterion preference articulation) which are highly dependant on the preferences of the DM. A future is an outlook based on a single set of values for all uncertain parameters in the model.

OBJECTIVES, CRITERIA AND ATTRIBUTES

The objectives of the optimisation are defined so as to represent the preferences of the DM. Criteria are then chosen to represent those objectives in the model. Attributes are the outcomes by which the relative performance of a particular alternative is measured. These may include financial or economic indicators, technical performance attributes, environmental attributes, as well as social attributes. These attributes are the performance indicators for the various criteria deemed important by the DM. Attribute performance is a function of the options and uncertainties and are determined through model runs. If minimising global warming was defined as an objective, global warming potential would be the criterion under which the performance of an alternative would be evaluated in terms of the attribute of CO_{2EQ} emissions.

1.2. CHAPTER OUTLINE

REVIEW OF THE LITERATURE

Chapter 2 discusses some of the relevant methods used for modelling investment in the ESI based on the international literature. Each phase of the modelling process is addressed, and discussed in terms of the relevant literature.

UNCERTAIN PARAMETERS IN ESI INVESTMENT MODELLING

Chapter 3 outlines the problem of modelling investment in the ESI in more detail based on the literature review in chapter 2. This chapter discusses some of the key uncertain parameters and how they have typically been addressed in ESI modelling. It then defines the research hypotheses and key questions of this thesis.

GENERATION FOR MULTIPLE OBJECTIVES UNDER UNCERTAINTY

Chapter 4 then goes develop an approach for generating FEAs for multiple objectives under demand growth uncertainty. It outlines a methodology for doing this and demonstrates this methodology using the South African ESI. It focuses specifically on finding the most appropriate method for generating FEAs for multiple objectives within the overall framework presented in this thesis. It also focuses on building flexibility towards demand growth uncertainty into the generation of FEAs.

RANKING AND SELECTION OF POWER EXPANSION ALTERNATIVES FOR MULTIPLE OBJECTIVES UNDER UNCERTAINTY

Chapter 5 is focussed on the ranking and selection of FEAs given multiple objectives and uncertainty. It specifically addresses technical empirical parameter uncertainty such as technology costs and emission factors and valuation model parameter uncertainty such as DM preference information. A methodology is developed for evaluating the performance and robustness of alternatives given these uncertainties and for isolating a portfolio of preferred alternatives for detailed analysis. A detailed analysis of the short term investment strategies of these preferred alternatives is then done and the insights are related back to real life actions (i.e. what choices mean in terms of actual technology investment decisions).

THE EFFECTS OF INTEGRATING TECHNICAL EMPIRICAL UNCERTAINTY INTO THE GENERATION PHASE

Chapter 6 compares the results of integrating technical empirical uncertainty into the generation phase with integrating it into the selection phase. It begins by examining the weighting bias effect that normalising attribute scores on a conventional 0-1 range can have and then outlines a method for overcoming this; both in the normalisation procedure and when articulating preference information from the stakeholders. It then goes on to evaluate whether or not there are in fact significant differences in the results obtained from dealing with technical empirical uncertainties in the generation phase as opposed to the selection phase and also whether other uncertainties in the system (such as uncertainty around DM preferences) would be more significant. It also evaluates whether the additional computational time and data management burden of this approach is justified given the results.

INTEGRATING PLANT AVAILABILITY UNCERTAINTY AND RESERVE MARGIN INTO THE MULTI-OBJECTIVE FRAMEWORK

Chapter 7 is aimed at integrating plant availability uncertainty into the multi-objective framework developed thus far. A methodology for modelling plant availability in terms of planned and forced outage is developed and integrated into a framework that can model demand both chronologically and in high resolution such that both the frequency and duration of outage can be adequately represented, all within a multi-objective framework with a comprehensive analysis of system wide uncertainty.

OUTLINE OF OVERALL METHODOLOGY AND CONCLUSIONS

Chapter 8 outlines the overall methodology for comprehensively integrating multiple objectives and uncertainty into ESI investment modelling developed in this thesis. The hypotheses presented in chapter 1 are then reiterated and the conclusions drawn from each chapter are related back to these hypotheses.

CHAPTER 2 REVIEW OF THE LITERATURE

This chapter will discuss some of the relevant methods used for modelling investment in the ESI in light of research hypotheses and key questions presented in chapter 1.

2.1. BACKGROUND

The field of electrical supply industry modelling is diverse and may include the expansion of generating capacity, transmission and distribution systems and plant scheduling. The following section will focus mainly on the approaches used to deal with investment analysis and planning for the electrical supply industry as well as the decision making techniques used to identify preferred expansion alternatives.

Capacity expansion planning is well known to inherently involve multiple objectives that are often conflicting and incommensurate (Hobbs, 1995; Georgopoulou et al., 1997; Antunes et al., 2004). The planning process has been reformed to include environmental and social objectives as it is no longer sufficient or acceptable to plan on cost arguments alone (Georgopoulou et al., 1997; Linares and Romero, 2000; Antunes et al., 2004).

Typical ESI modelling methodology can be split into two phases: A primary step is the generation phase, where solutions are generated in an energy systems modelling framework. A subsequent selection phase identifies preferred alternatives from within the set generated, based on policy maker and stakeholder preferences and value judgements. Both of these phases can be explored against a set of policy making objectives, and both contain inherent uncertainties which relate to empirical and model parameter uncertainty as well as uncertainty relating to valuation arguments. The following section will discuss the generation phase while the selection phase will be discussed in section 2.2.2.

2.1.1. BACKGROUND (GENERATION)

The purpose of the generation phase is to develop detailed strategies to meet future electricity demand. Which technologies (type of power stations) to build, when to build them and how much capacity of each technology to build is decided in this phase. Power expansion alternatives/plans generated in this phase would then be investment strategies comprising of a range of different technologies, built over a medium to long term time horizon (typically 10-50 years), that satisfy the demand for electricity over this time period (taking into account the demand level beyond the study period). These investment strategies are usually optimised for stakeholder defined objectives, the most common being cost but also environmental objectives such as the minimisation of pollutant emissions (SO_2, CO_2, NO_x), radioactive wastes, resource consumption, as well as social objectives such as job creation and quality of service (Mavrotas and Diakoulaki, 1999; Soloveitchick et al., 2002; Lahdelma et al., 2003; Antunes et al., 2004; Martins et al., 2004).

Capacity expansion models typically have constraints relating to issues such as demand satisfaction, investment/capacity limitations, resource limitations, technical or political technology restrictions, energy security, availability of technologies and the annual build rate for new technologies. In some cases, constraints are used for pollutant emissions rather than treating them as separate objective functions (discussed in more detail in section 2.2.1).

Some models have extended the analysis from only supply side options to include demand-side management (DSM) options within the framework of integrated resource planning (IRP) (Hobbs and Horn, 1997; Martins et al., 2004; Heinrich et al., 2007). DSM is typically modelled as an equivalent generating group with constraints on operation.

Different modelling approaches have been used to answer different types of policy and planning questions. Broadly they can be split into optimisation and simulation models although there are many sub-categories of each.

Simulation models are completely defined by the modeller (in terms of the investment and operational parameters of the power stations) and are used to explore the effects of different policy decisions or to examine different future scenarios. They are used to answer “What will the effects be if we do this?” type of questions.

Optimisation models are used to inform the modeller on the best course of action to take given a set of technologies (with cost and performance data), a set of objectives and a demand to be met. The objective function is either minimized or maximized within the context of the specifications and constraints of the model. The results then inform the user on how to best achieve their objectives rather than informing the user how a given course of action will result, as in simulation models. This thesis will focus on optimisation models rather than simulation models as the aim is to develop a framework for the generation and selection of future expansion alternatives (FEAs) for multiple objectives under uncertainty rather than answering “What if…?” type of questions.

Optimisation methods can be divided into linear, non-linear, mixed integer and mixed integer non-linear methods. Large linear programming (LP) optimisation models have been used extensively over several decades in ESI modelling (Hobbs, 1995; Cormio et al., 2003). This is the most commonly used formulation for energy system models since it guarantees that a global optimum can be found, provided that the solution space is a closed convex set. The most common algorithms used to solve linear programming problems are based on either the simplex algorithm (see (Dantzig, 1963)) or an interior point method (see (Karmarkar, 1984)).

Non-linear programming (NLP) is similar to LP but consists of non-linear equations (includes terms such as x^y or log x), which usually increases the complexity of the solution process. In NLP, the obtained optimum represents only a local optimum as opposed to the global optimum in LP and a global optimum cannot be guaranteed. It is often possible to approximate the non-linear equation into a linear form by introducing integer variables. Model formulations that use both integer programming and continuous variables are called mixed integer programming (MIP).

In reality technology units are sold in specific sizes (e.g. 720MW turbines) and therefore the output of a LP model may require post-processing for the discretisation of continuous solutions accounting for the actual modular capacities of available technology units. This problem has been addressed through mixed integer linear programming (MILP) models for both single and multi-objective cases (e.g. Mavrotas and Diakoulaki, 1999; Antunes et al., 2004).

Dynamic programming (DP) has been proved to be especially useful for capacity expansion planning by converting a multistage optimisation[1] problem into a series of simple problems. DP problems can be solved easily because of the recursive application of the principle of optimality on the objective. The DP modelling approach has been used in conjunction with many commercially available expansion planning tools such as EGEAS[2] and WASP[3]. A major drawback of DP models is the issue of dimensionality due to the fact that all possible solutions are searched for in order to find the optimal sequence of decisions that lead to the optimal state. This may involve excessive requirements in terms of computing time and data storage space. It is however possible for the modeler to reduce the decision space considerably by applying realistic constraints such as reserve margins as well as capacity and resource availability constraints. Further enhancement may be achieved by introducing multiple objectives and random parameters into the DP models, resulting in multi-objective dynamic programming and/or stochastic dynamic programming models (Dapkus and Bowe, 1984; Mo et al., 1991; Tanabe et al., 1993; Kanudia and Shukla, 1998; Loulou and Kanudia, 1998; Heinrich et al., 2007) (discussed in more detail in section 2.4.1).

Modelling with single objective functions has been a powerful tool in optimizing power station expansion under specific environmental constraints, as well as for examining the economic feasibility of new options in the energy market. This type of analysis, done in partial equilibrium[4] frameworks, has provided policy makers with the "perfect market"[5] response to future scenarios that are valid for both regulated, centrally planned power markets, as well as for efficient fully deregulated markets (from the perspective of a regulator). Although this type of modelling has enjoyed

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[1] A multistage problem is a problem with multiple time periods which must be solved to obtain an overall solution.

[2] EGEAS (Electric Generation Expansion Analysis System) developed by the Electric Power Research Institute (EPRI), http://www.epri.com.

[3] WASP (Wien Automatic System Planning Package) developed for the International Atomic Energy Agency (IAEA), www.iaea.org/.

[4] Partial equilibrium frameworks represent part of the overall economy (i.e. the energy sector) and have the properties that the prices and quantities of fuels and other commodities will be such that supply will meet demand exactly, in each time period, and further that total economic surplus will be maximized over the time horizon.

[5] Note however, that for modelling the response of an individual utility to investment planning decisions within a multi player market, other approaches may be more appropriate (e.g. systems dynamics, agent based modelling or game theory).

some success for integrated resource planning in the past, resource planning today has become a far more complex task (Hobbs, 1995). What such an approach fails to deliver is explicit consideration of trade-offs between different objectives and the need to address uncertainty comprehensively in the modelling process.

2.2. CONSIDERING MULTIPLE OBJECTIVES

According to (Brundtland, 1987) the foundation of a sustainable world is one which conducts itself appropriately today so that future generations will be able to enjoy the same resources and opportunities available to the current generation. Sustainability is often interpreted as: "able to be maintained at a fixed level without exhausting natural resources or damaging the environment". In a more topical context this has been extended from purely environmental to include social and economic criteria, although environmental sustainability is still the primary concern (see for example Haimes, 1992; Azapagic, 2004; Clift, 2006). If sustainability considerations are to be integrated comprehensively into any ESI modelling approach, they need to be considered from the problem definition stage to the final sensitivity analysis and selection phase. Sustainability objectives need to form an integral part of the generation phase so as to ensure that solutions are generated that attempt to satisfy all the objectives considered, at least to some degree. Not all of the DM preference criteria can or need to be explicitly defined as optimisation criteria; however there need to be non-cost objectives that represent sustainability arguments present in the generation phase to force the model to balance the cost and non-cost criteria. Non-optimisation criteria (e.g. qualitative criteria) as well as the optimisation criteria can be used after the generation phase for screening alternatives and for evaluating alternatives based on DM preferences.

The choice of method for integrating multiple objectives into the problem framework needs to consider both the generation and selection phase of the problem. It needs to be decided whether stakeholder interaction would be best integrated into the generation phase, effectively combining generation and selection, or whether it would be preferred to generate a range of solutions in the generation phase from which a preferred alternative or set of alternatives could be isolated in a separate, more detailed selection phase. At issue here is the concept of transparency with regard to the planning methodology and the ease with which the consequences of choices can be seen. These issues are discussed in more detail with reference to some of the approaches to solving multi-objectives problems in section 2.2.1 below.

Multi-criteria decision making (MCDM) methods may be broadly classified into two categories: the multi-objective decision making (MODM) type of approach and the multi-attribute decision making (MADM) type of approach. Both types of approaches are used for problems with often conflicting criteria, incommensurate units, and may deal with qualitative and quantitative attributes. The main difference between these two types of approaches is the decision space being considered (Huang et al., 1995). In the MODM type of approach, the decision space is continuous and the alternatives are generated from the objectives within the constraints of the problem (generation phase). In the MADM approach type of approach, the decision space is discrete and each alternative has a set of attribute performance values associated with it. These attribute scores can then be used to compare the alternative for given preference defined by the DM (selection phase). Each of these types of approaches is discussed in turn in sections 2.2.1 and 2.2.2 respectively.

2.2.1. Multi-objective decision making (MODM)

In order to develop FEAs to meet future demand for electricity the DM needs to decide on which technologies to include for consideration in the optimisation model, the optimisation objectives need to be defined and the demand projections need to be decided upon. Once this has been done all the relevant information for each of the technologies (e.g. costs, efficiencies, availabilities) as well as the demand information (profile and growth projections) and any constraints can be inputted into the model. Given specific objectives, then model can then choose which technologies to build, when to build them and how much capacity of each technology to build. Some of the different approaches for locating efficient or non-dominated[6] solutions to multiple objective linear programming (MOLP) models (see Cohon, 1978; Steuer, 1986; Diwekar, 2003) are discussed below:

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[6] An efficient, non-dominated or Pareto optimal solution can be defined as a solution where a single attribute cannot be improved upon without sacrifice in another of its attributes.

One approach is to analyse the trade-offs through a common objective, usually being cost, by assigning cost benefits or penalties to each of the major non-cost criteria. A sensitivity analysis performed on these parameters helps establish their individual effects on the overall cost. This method has been used in particular energy market analyses by permuting arbitrary "emission taxes" to generate efficient solutions for MOLP models with the aim of providing decision makers with a trade-off situation between cost and CO_2 emissions (e.g. Hobbs and Meier, 1994; Koroneos et al., 2004). Although much work has been done to quantify the damage to both human health and the environment (e.g. Ottinger et al., 1991; Friedrich and Bickel, 2001), when used in this form, the "emission taxes" do not imply to represent the actual cost to society resulting from the generation of electricity, but are merely used as parameters to force a model to generate solutions in relation to multiple objectives. This said, "taxes" used to generate preferred solutions may find value in providing policy makers with appropriate market signals to influence market behaviour. This method can easily be applied to many existing electricity expansion tools (e.g. EGEAS, WASP and TIMES[7]) and therefore is readily accessible to a wide range of planners. A disadvantage of this approach is that it is manually intensive as it does not guarantee a well-spread representation of the non-dominated solution set. The burden of adequate representation of the solution set lies with the modeller, although new solutions can quickly be generated based on a cursory examination of the solution set. This is discussed further in chapter 4.

Another approach is to re-cast all but one of the objective functions as a set of constraints operating on the remaining objective function. Examples of this are common in the process engineering literature – see, e.g. the *e*-constraint method, described, amongst others, by (Diwekar, 2003). The range of constraints is explored systematically to generate a representation of the non-dominated solution space. In energy modelling, environmental objectives are typically recast as a set of emission, pollution or temperature (for climate change models) constraints, informed often by regulatory regimes (e.g. Manne and Richels, 1997; van der Zwaan et al., 2002; Cormio et al., 2003). This method is also easily applied to electricity planning tools

[7] TIMES (The Integrated MARKAL-EFOM System) developed by ETSAP.

that allow for "emission caps" or upper bounds to be placed on emissions (e.g. WASP, TIMES, MESSAGE[8]). While this the solution space can be systematically explored using this approach, it does not readily yield the market signals necessary to influence the market towards a preferred state (i.e. taxes) and it does not allow for flexibility towards multiple objectives to be explicitly integrated into the model (discussed further in chapter 4).

A third approach is to evaluate the objective functions separately and to explore the solution space using weighted sums of the individual objective functions or by measuring the composite distance from an "ideal" or reference point. This involves interactive participation with stakeholders in the definition of the weights or goals until a satisfactory solution has been reached for the case of a single solution or a permutation of weights or goals to generate a representation of the non-dominated solution space. In the latter case, the weights or goals would effectively be used as generating parameters rather than being "true" weights representing preferences. Examples of interactive procedures include reference point methods such as goal programming (Charnes and Cooper, 1961) and achievement functions (see Wierzbicki, 1982; Wierzbicki, 1986), the STEM method (Benayoun et al., 1971) and the interactive weighted Tchebycheff approach (Steuer and Choo, 1983; Sun et al., 2000). Applications of interactive methods in energy planning can be found in the literature, see (Linares and Romero, 2000) for an example of a reference point method, (Antunes et al., 2004) for an example of combining a reference point method with the STEM method and (Linares and Romero, 2002) for an example of a goal programming approach. While this approach offers a comprehensive manner in which the generation and selection of preferred alternatives can be integrated, it requires significant stakeholder participation in the modelling process. This method also has the disadvantage of being unable to reveal Pareto points on the concave sections of non-inferior sets resulting from using integer variables (e.g. for lumpy investments). As discussed in the following paragraphs, this is not appropriate for all stakeholder situations. Another limitation of this approach is that a weighted aggregation function approach cannot be readily used within existing single objective energy planning approaches without significant reformulation of the tools.

[8] MESSAGE (**M**odel for **E**nergy **S**upply **S**trategy **A**lternatives and their **G**eneral **E**nvironmental Impact) developed by the International Institute for Applied Systems Analysis (IIASA).

Where explicit consideration has been given to multiple objectives in power expansion planning, the techniques for solving deterministic optimisation problems can be broken into three general classes requiring prior, progressive or posterior articulation of preferences by the DM (Ringuest and Graves, 2000). The choice of where in the modelling process to include DM preferences comes down to practicality relating to the problem being addressed in terms of the greater problem definitions and problem solving framework, transparency in terms of the choices being made and the consequences of those choices and the possible value of the outcomes resulting from the methodology chosen. Each of the general classes of preference articulation will be briefly described below, and discussed in terms of their implications:

With prior articulation methods, the stakeholders make trade-offs among the objectives before optimisation. Often stakeholder meetings are held prior to the modelling phase in the planning project and the relative importance of criteria are decided upon (typically represented by weights). While this approach works well in theory, most stakeholders are not fully aware of the trade-offs that occur between FEAs as a consequence of their initial preferences until after the modelling is done. As a result, there are few applications of this approach being used in practice (Ringuest and Graves, 2000).

Progressive articulation methods or interactive methods (see Zionts and Wallenius, 1976) require the interaction of the stakeholders to provide trade-off information during the course of the progressive modelling procedure. These techniques shift importance away from predefined weights as the stakeholders interact with the trade-off decisions continuously in the modelling process. These methods are however, time consuming and can be computationally intensive as the size and complexity of the problem increases. This may cause the stakeholders to lose interest in the process and may not be suitable for processes where multiple stakeholders exist. This method also results in a situation where the trade-offs between objectives are not obvious to outsiders or stakeholders that were not involved in the modelling process and therefore are better suited to situations with small numbers of decision makers and stakeholders (Novac and Ragsdale, 2003).

Posterior articulation methods (or generating methods) first generate a representative set of efficient or non-dominated solutions and then allow the stakeholders to identify the preferred solution. This approach has the benefit of allowing the stakeholders to make a choice knowing the consequences of their decision relative to the other alternatives with regard to the predefined objectives. This method is also more transparent and easily understandable to stakeholders outside of the decision process and therefore creates a situation where the DM is more accountable for his or her choices. This method can however overwhelm the stakeholders with too much information unless a suitable framework to guide them through the selection process is in place.

It is also possible to integrate methods of articulation by for instance using a generating method to give the stakeholders an initial sense of the possible range of attributes for the problem and then to use an interactive method to refine and generate a set of appropriate solutions for the problem, from which a preferred solution can ultimately be selected.

2.2.2. Multi-attribute decision analysis (MADA) methods in energy planning

MADA provides a structured framework to support decision making in the presence of multiple objectives which are often non-commensurate and conflicting (Keeney and Raifa, 1976; Von Winterfeldt and Edwards, 1986). The problem structuring phase is the starting point of any MADA application (Diakoulaki et al., 2005). In this phase stakeholders are identified and agreement is reached on the options to be included for consideration as well as the criteria that will be used to judge the performance of the alternatives. The criteria can be both quantitative and qualitative. The next stage is the problem analysis phase where the alternatives are evaluated based on the criteria selected by the DM for given preferences. This is typically followed by the selection of a preferred alternative or set of alternatives and an uncertainty/risk analysis to ensure the robustness of the solution/s.

The purpose of using a MADA method in the context of this work would be to select a preferred FEA or set of FEAs based on the multiple objectives chosen by the stakeholders, whilst considering the uncertainties involved. The usually conflicting nature of the cost vs. environmental/social criteria as well as the often opposing stakeholder preferences relating to these criteria would pose challenges for the ranking and selection of preferred alternatives. The inherent uncertainty in attribute data would further compound the complexity of the decision problem.

There are a number of different MADA methods that have been used in ESI modelling. The following sections provide a background on the following list of methods, which were seen to be the most applicable within the context of this work:

- Multi attribute utility theory (MAUT)
- Multi attribute value theory (MAVT)
- Analytical hierarchy process (AHP)
- Outranking methods (including ELECTRE (The Elimination and Choice Translating Reality) family of methods and the PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) method

While all the methods listed above will be discussed, the focus will be on one of the major schools of thought that have been used in this field and will discuss two of the methodologies within this school of thought; namely Multi attribute utility theory (MAUT) and Multi attribute value theory (MAVT). These methods are discussed below, as is the distinction between them:

2.2.2.1 MULTI ATTRIBUTE UTILITY AND MULTI ATTRIBUTE VALUE THEORY IN ENERGY PLANNING

MAUT and MAVT are well suited for energy planning and policy analysis where problems have large numbers of variables, multiple criteria and uncertainty (Huang et al., 1995). According to (Diakoulaki et al., 2005) MAUT and MAVT have been the preferred methods for selection of competing energy projects and action plans as well as for selecting a subset of preferred energy projects.

MAUT and MAVT methods are often mentioned together in the MCDA literature. Both methods use aggregated functions to represent the performance of alternatives based on DM preference information. The difference between them is that MAVT is formulated such as to assume that the performance of each alternative is known with certainty whereas MAUT is formulated to explicitly consider the uncertainty in performance (or the outcome) of each alternative. Where MAVT uses a value function (described below) to represent the performance of deterministic alternatives, MAUT uses a utility function (which is based on the expected utility of each alternative). MAUT requires the DM to answer complex questions (called lotteries) relating to their preferences between probability distributions and the expected utilities of the uncertain performance of the alternatives being considered. These questions are used to determine the risk attitude of the DM. MAVT only requires the DM to answer questions relating to their preferences (discussed in more detail below) in terms of deterministic alternatives. Both value function and utility theory are discussed in detail by several authors (see for example (Keeney and Raifa, 1976; Beinat, 1997; Belton and Stewart, 2002) for value function theory as well as (Keeney and Raifa, 1976), (Von Winterfeldt and Edwards, 1986) and (Wenzel et al., 1997) for utility theory).

In a MAUT approach, stakeholders are involved twice in the decision process; firstly to articulate their preferences so that the utility functions can be developed for each attribute and then later to assign probabilities to the outcomes of each alternative (De Montis et al., 2000). The utility function for each attribute would then represent the expected utility of each alternative for the given attribute and would therefore be useful in choosing between alternatives with uncertain outcomes based on their expected utility (and the DM's risk attitude). Only uncertainties that can be represented in probabilistic terms can be considered using MAUT (Morgan and Henrion, 1990), and other uncertainties (such as uncertainty in DM preferences which are explored in detail in chapters 5 and 6) are often more important in environmental decision making (Meier, 1997).

The work presented in this thesis has a focus on the uncertainty associated with the technical empirical parameters that are used to generate the alternatives and in turn, the effects that these uncertainties have on the performance of alternatives, as well as the valuation parameters relating to DM preferences which affect the selection of a preferred alternative. Although MAVT does not explicitly model uncertainty in outcomes, it allows for the propagation of uncertainty in attribute values through the value function using sampling techniques (e.g. Monte Carlo and Latin Hypercube).

This would yield a performance value for each attribute, in each alternative for each uncertain sample and could therefore be readily used for a robustness analysis on technical empirical parameter uncertainty (demonstrated in chapter 5). This would allow for the likely range in performance of each alternative to be evaluated as well as for alternatives to be compared across each discrete sample of uncertain parameters (discussed in more detail and demonstrated in chapter 5). The same type of analysis could be done using a MAUT approach except it would not add value due to the absence of risk attitudes towards each of the outcomes considered. Using a MAVT approach in this way would not require the stakeholders to assign probabilities to each outcome as the uncertainties in outcomes are propagated from the uncertainties in attribute values. MAVT is also less demanding on the stakeholders as complicated questions around the risk of outcomes can be avoided. The assessment of the appropriate utility function is also a complex process which leads to difficult questions around the properties of the DM's preferences (see Vincke, 1992) which can be avoided by using MAVT. Finally it is argued that in most cases MAVT coupled with a sensitivity analysis can provide essentially the same results as MAUT (Beinat, 1997; Belton and Stewart, 2002).

In light of the points made above, using MAUT would be unnecessary (given the added complexity and increased difficulty of assessment compared to MAVT) and inappropriate for this problem (given the focus around uncertainty in DM preferences) and therefore the following section will focus on the value function approach and how it can be augmented to model uncertainty in the ESI.

Using the additive aggregation model the value function $V(x_{ij})$ is constructed:

$$V(x_{ij}) = \sum_{j=1}^{n} w_i v_i (x_{ij}) \tag{2-1}$$

Where w_i is the weight of criterion i,

and $v_i(x_{ij})$ is the partial value function defined over the set of criteria i for alternative j.

In practice, partial value functions $v_i(x_{ij})$ are defined for each of the attributes before an overall value function can be constructed. The partial value functions are constructed by defining a value scale for the performance of alternatives (based on their attribute scores) in specific criteria (intra-criterion preferences). The partial value functions typically map the attribute scores of the alternatives onto a commensurate 0-1 scale. These partial value functions can be defined in a local sense (from the performance ranges of the alternatives in a specific criterion) or globally (from the conceivable ranges in performance given the decision context).

Using water consumption as an example, if the partial value function were to be defined globally, the range of possible water consumption levels for other power systems internationally could be used to scale the water consumption attribute for each alternative. Alternatively, if the partial value function were to be defined locally, the performance of alternatives with regard to water consumption would be scaled based on the range of attribute scores for the alternatives considered. It is argued that local scales enable a more sensitive and rapid assessment of the alternatives while global scales contextualise the alternatives more broadly.

These value scores can be elicited directly from the stakeholders by asking them to assign value scores to each alternative in each attribute (direct rating) or mathematical functions can be generated to represent the mapping. The shape of these functions (e.g. linear, sigmoidal, concave, and convex) is a modelling choice for the DM which reflects strength of preference informed by the performance scores within a single criterion. The concave function in Figure 2-1 illustrates how preference can be modelled using a mathematical function. Using this function, the value score quickly improves as the performance increases from x_{ij*} to x_{ij} but improves more slowly from x_{ij} to x_{ij}^*. This would represent a situation when the DM strongly dislikes poor performance in a particular attribute and therefore rewards movement away from x_{ij*}, but only weakly prefers high performance and therefore only marginally rewards movement from x_{ij} to x_{ij}^*. This sort of preference situation could occur when emission limits are in place with penalties for emitting over a particular level.

Therefore emission values below this level would be strongly preferred but preference there would be no incentive to reduce emission levels further.

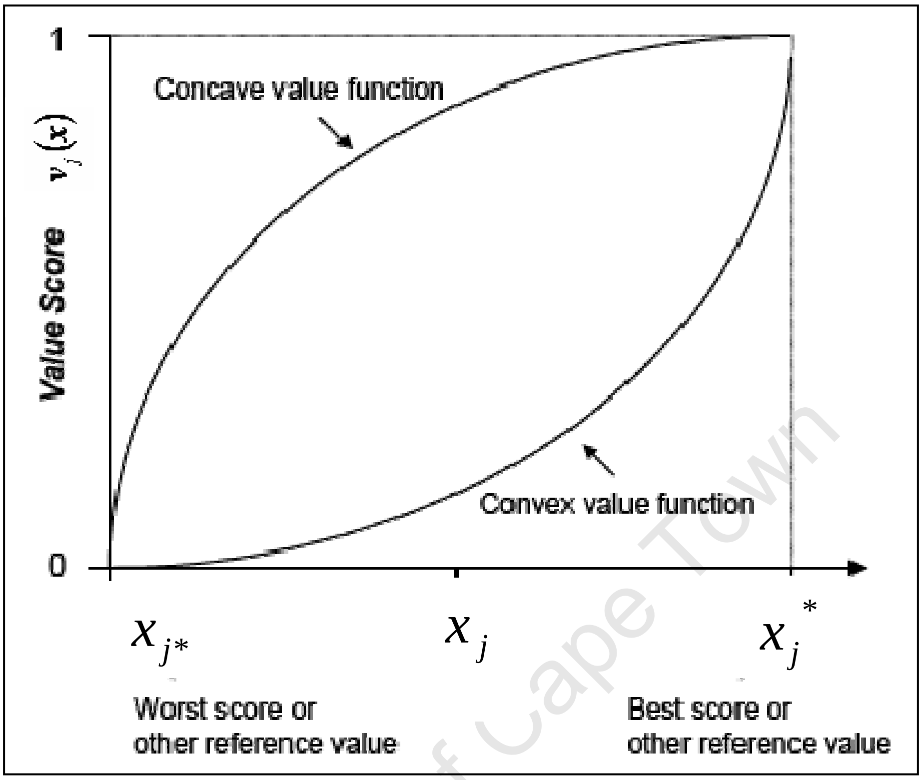

Figure 2-1 Example of value functions (Basson, 2004)

MAVT methods require explicit statements from the stakeholders regarding acceptable trade-offs between the attribute performance scores of alternatives in the different criteria. The overall value function then aggregates this performance information into a single index for each alternative which represents the degree to which each alternative meets the overall decision objective. Combining each of the partial value functions into a single global value function can be done additively or multiplicatively depending on the DM preferences, although additive aggregation is prevalent due to its intuitive appeal that makes it accessible to those involved in the decision making process (Beinat, 1997; Belton and Stewart, 2002). Additive aggregation models are the most commonly used (Keeney and Raifa, 1976; Belton and Stewart, 2002; Basson, 2004) and are likely to be more than adequate in the vast majority of settings (Stewart, 2005). Using the simpler additive aggregation model (as opposed to, for instance, a multiplicative or multi linear model) can result in biases if DM preferences follow more complicated models, but it requires less demanding inputs (in terms of preference statements) from the DM, and is inherently more stable (the results are less sensitive to minor changes in preference) (Stewart, 2005). It was also found that the errors introduced by using the additive aggregation model instead of more complicated models were in fact significantly smaller than the errors introduced by the incorrect modelling of the partial value functions (e.g. using a linear model when preferences follow a concave function) (Stewart, 2005).

Additive aggregation has three fundamental requirements which need to be satisfied in order to justify its form for the global value function $V(x_{ij})$. The first requirement relates to the manner in which the criteria are defined while the other two relate to the interpretation of the partial value functions and weights respectively. These requirements are discussed below based on the text in (Belton and Stewart, 2002).

- Criteria must be defined such that mutual preferential independence holds.
    - This implies that preferences in the performance of a criterion must be independent of performance in the other criteria, and vice versa.
- The interval scale property for partial value functions must hold.
    - This implies that strength of preference needs to be modelled as well as preference order such that the relative magnitudes of the differences between values of $v_i(x_{ij})$ have meaning, due to the fact that a natural zero point rarely exists and therefore some minimum value of performance is assumed to be the zero reference point. This implies that an increase of performance from an attribute value of 4 to one of 5 must result in an increase of 25 % in value function score.
- The trade-off property for weights must be satisfied.
    - The weights should reflect the trade-offs that the DM finds acceptable with reference to the attribute ranges over which the value functions have been defined.

A criticism of MAVT approaches has been that compensation can occur between criteria due to the fact that the partial value functions are combined into a global value score. This can occur if, for instance, good performance in an economic criterion counterbalances poor performance in an environmental criterion. This problem can be overcome in many cases by defining minimum levels of performance for the alternatives in each criterion through stakeholder interaction and discarding alternatives that fail to meet these minimum performance criteria. A thorough sensitivity analysis of the results can also be done to explore the extent to which compensation occurs.

Inter-criterion preference information or weighting

When defining the weighting parameter w_i in equation 2.1, it has been shown that no single weighting method is preferred by all stakeholder groups (Hobbs and Horn, 1997) but the most commonly used techniques for weight elicitation are the methods based on cross attribute indifference judgements and the swing weighting method (Von Winterfeldt and Edwards, 1986; Beinat, 1997; Belton and Stewart, 2002). This said, in the field of energy planning and policy analysis, AHP (discussed in section 2.2.2.2 below) was found to be the most commonly used (Huang et al., 1995).

Indifference weighting techniques are based on the concept of equivalent or indifferent situations. The decision maker is presented with a situation and asked to find an equivalent situation by trading off performance in one criterion for the improvement of performance in another. Examples of different weighting techniques based on indifference can be found in texts such as (Keeney and Raifa, 1976; Belton and Stewart, 2002). An indifference technique is mathematically described below where the trade-off between reference criterion i and criterion j for alternatives X and Y is represented by equation 2-2:

$$w_i.v_i\left(x_{iX}{}^*\right)+w_j.v_j\left(x_{jY*}\right)=w_i.v_i\left(x_{iX}{}'\right)+w_j.v_j\left(x_{jY}{}^*\right) \qquad (2\text{-}2)$$

This equation represents the situation where on the LHS criterion i is at its best and criterion j is at its worst. The RHS of the equation then represents the situation where criterion i is at an acceptable level if criterion j were at its best. This equation can be seen to represent the indifference or trade-off question: "What sacrifice in terms of the best performance in criterion i would you be willing to make, to achieve an improvement from worst to best performance in criterion j?" The typical situation where the value score range between 0 and 1 is illustrated in Figure 2-2 where the attribute performances in criteria i and j are represented by x_i and

x_j respectively.

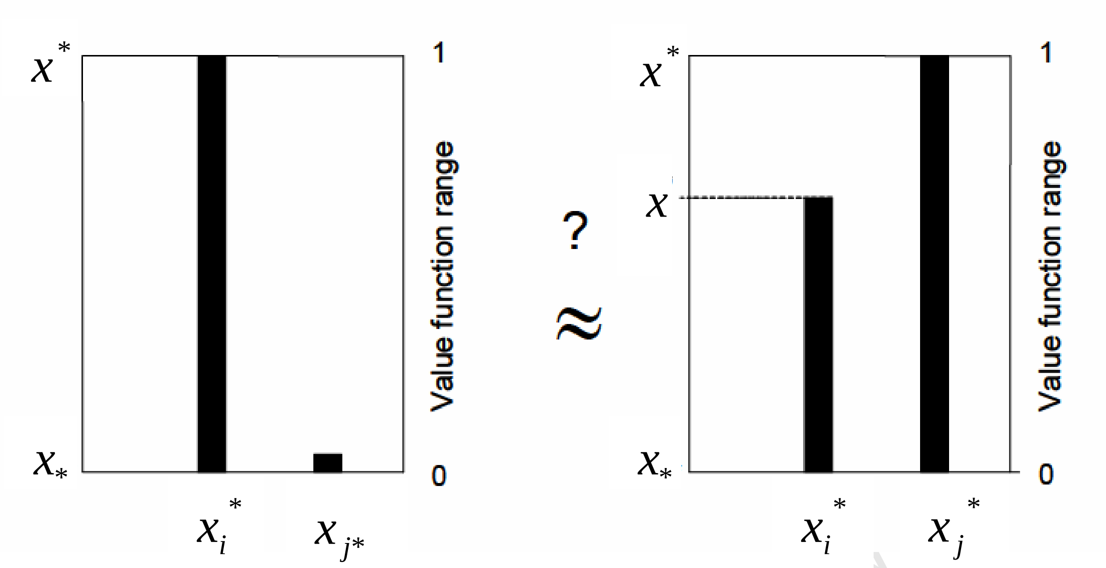

Figure 2-2 Indifference situation for typical 0-1 value function range (Basson, 2004)

In order to determine the weight of each criterion, a reference criterion (α) is chosen. The criterion that the decision maker regards as "most important" is typically chosen to be the reference criterion. The ranges in performance of all other criteria are then considered in a pairwise manner relative to the range in performance of the reference criterion α. In the first pairwise comparison, the reference criterion α and the next criterion β are used to define an indifference equation to obtain the ratio of the weight of criterion β and criterion α, which is termed *b*:

$$w_\alpha.v_\alpha\left(x_{\alpha X}^{\ *}\right)+w_\beta.v_\beta\left(x_{\beta Y*}\right)=w_\alpha.v_\alpha\left(x_{\alpha X}{'}\right)+w_\beta.v_\beta\left(x_{\beta Y}^{\ *}\right), \qquad (2\text{-}3)$$

in the case where the value function range is 0-1, this simplifies to:

$$w_\alpha.1+0=w_\alpha.v_\alpha\left(x_{\alpha X}{'}\right)+w_\beta.1$$

$$\frac{w_\beta}{w_\alpha}=1-v_\alpha\left(x_{\alpha X}{'}\right)=b$$

The trade-off questions would be asked for all other criteria in relation to a sacrifice in the reference criterion. The resulting weights could then be calculated from the ratios of the trade-offs, and normalised:

$$\frac{w_\chi}{w_\alpha} = c \qquad \frac{w_\delta}{w_\alpha} = d \tag{2-4, 2-5}$$

With weights normalised to sum to 1:

$$w_\alpha + w_\beta + w_\chi + w_\delta = 1 \tag{2-6}$$

Therefore:

$$w_\alpha + bw_\beta + cw_\chi + dw_\delta = 1$$

And

$$w_\alpha = \frac{1}{(1+b+c+d)}$$

In this way the individual weights can be calculated from the ratios of the weights (b, c, and d).

The swing weighting technique (Beinat, 1997; Belton and Stewart, 2002) on the other hand articulates the trade-offs the DM is willing to make between criteria by quantifying the value improvement associated with a swing from the worst to best performance within the defined attribute range.

This method is illustrated using an example from (Beinat, 1997) in Figure 2-3, for a soil remediation study. The process begins from a worst case profile where all performance scores are at their lowest level. The DM then selects the criteria for which a swing from worst to best performance within the specified attribute ranges results in the greatest value improvement. This criterion has the highest weight. This process continues until all the criteria are ranked in order of importance.

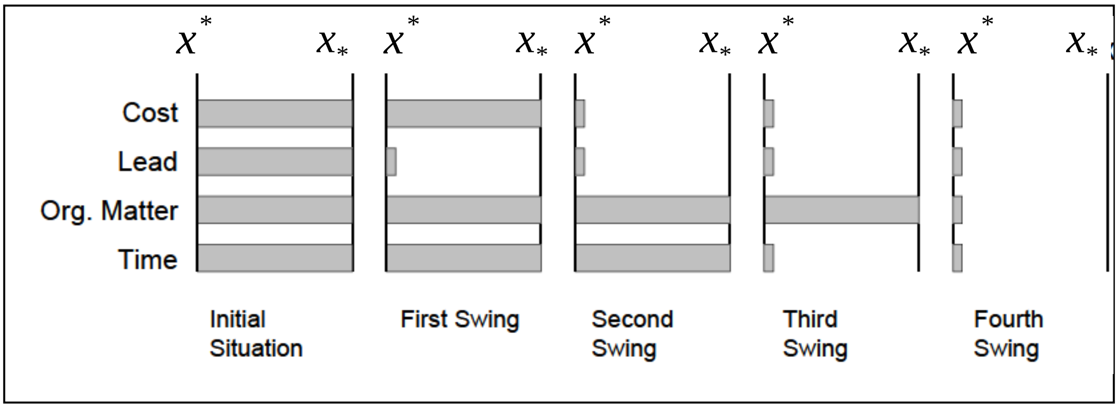

Figure 2-3 Example of swing weighting technique (Beinat, 1997)

Based on Figure 2-3 above, with x^* being the best performance score and x_* being the worst, it can be stated that: $w_{lead} \rangle w_{\cos t} \rangle w_{time} \rangle w_{Org.Matter}$.

Once the importance order of the weights has been determined, the next step of the swing weighting technique quantifies the relative weights of the criteria by assigning a score of 100 to the hypothetical best profile (i.e. where all scores are at their best level) and a score of 0 to the hypothetical worst profile (i.e. where all scores are at their worst level). In this way each consecutive swing can be scored in relation to the best and worst profiles. Therefore a score of 25 means that the value of improvement resulting from moving a performance score from its worst to its best level is a quarter as great as that obtained from moving the performance score in the criterion chosen first. The weights of the criteria are highly dependant on both level of preference between criteria and the attribute ranges for the criteria.

Indifference weighting techniques may appear more complex than the swing weighting method and can be result in confusion with stakeholders however it has been demonstrated that indifference weighting methods led to more plausible preference modelling, when dealing with particular corporate decision situations involving the South African electricity utility, Eskom (Basson, 2004). This was found to be particularly true when the reference criterion was expressed in terms of cost or profit sacrificed for an increase in performance of another non-cost criterion. This being said, ideally the weighting exercise should be repeated using a different criterion as the reference criterion to ensure that the weights obtained are not influenced by the choice of reference criterion. This can however be impractical in a real decision making environment due to time constraints.

Simpler weighting techniques such as direct weighting, ratio estimation and ranking of criteria are less demanding in terms of preference statements from the stakeholders because they do not require attribute ranges to be explicitly considered. However, it is questionable whether these techniques can be regarded as valid methods for weight elicitation for additive aggregation functions given the specific meaning of weights in the additive aggregation value function (Basson, 2004).

Using different weighting methods can yield different results with the same group of stakeholders and therefore it is advisable to use multiple methods to build confidence into the planning exercise (Hobbs and Horn, 1997). However, this can become impractical in corporate decision environments due to time limitations in which case a parametric sensitivity analysis could be done to investigate the full effect that weighting has on the overall results and the insights related to the stakeholders (Basson, 2004; Petrie et al., 2004). More recently other approaches using Bayesian methods have also been used to statistically correct known biases (see for example Anderson and Hobbs, 2002). A detailed sensitivity analysis on weighting is demonstrated in chapter 5.

2.2.2.2. Analytical hierarchy process (AHP)

Analytical hierarchy process (AHP) (Saaty, 1977), which is structurally similar to MAVT but with difference preference measurement assumptions, has been used widely in the energy planning field to elicit partial utility functions and weights possibly due to its ability to convert complex problems into simple hierarchies and the availability of computer aids to do this (Pohekar and Ramachandran, 2004). The AHP method breaks down a complex problem into a hierarchy with the goal objective at the top, criteria and sub-criteria at levels and sub-levels of the hierarchy and decision alternatives at the bottom. See Figure 2-4 below:

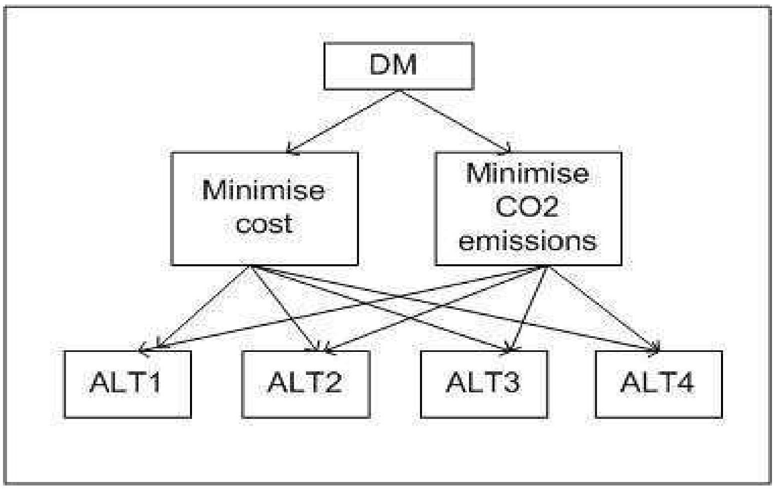

Figure 2-4 – Representation of hierarchy for AHP

The elements at each level are compared in a pairwise manner to asses their preference in terms of each of the elements at the next highest level of the hierarchy. The strength of preference between alternatives for each element is articulated using Saaty's fundamental scale of 1-9, with 1 being equal importance and 9 being extremely more important.

A matrix A is created to elicit pair wise comparisons between alternatives at a given level. This is done by putting the result of pair wise comparison of element i with element j into the position a_{ij} as shown in equation 2-7 below:

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{1n} \\ a_{21} & a_{21} & a_{2n} \\ a_{n1} & a_{n2} & a_{nn} \end{bmatrix} \qquad (2\text{-}7)$$

Once this matrix has been obtained, it is multiplied by the weight coefficient[9] of the element at the next highest level that was used as a criterion for the pair wise comparison. This procedure is repeated upward for each level until the goal objective at the top of the hierarchy is reached. The final weight coefficient with respect to the goal objective for each alternative is then obtained. The alternative with the highest weight coefficient is then the most preferred alternative for the given preferences.

[9] The weight coefficient is obtained through stakeholder rating of the relative importance of the criteria at that level of the hierarchy.

AHP has advantages such as inconsistency checks with respect to decision maker preferences at different levels of the hierarchy however it does however have some documented shortcomings (Millet and Saaty, 2000; Ramanathan, 2001) with the most controversial being the issue of rank reversal when new alternatives are introduced. Millet and Saaty have addressed some of these shortcomings by introducing a mode of calculation for AHP software that preserves rank (Millet and Saaty, 2000). Although AHP provided DMs with simple method for eliciting weights for decision problems with complex hierarchies of objectives, this work is focused on evaluating the trade-offs between multiple objectives under uncertainty in terms of both the DM preferences and the technical empirical and model parameters used to generate the alternatives. As AHP does not explicitly engage with the trade-offs between the objectives in the preference elicitation process and the uncertainties involved, it was decided that AHP would be inappropriate for this problem.

2.2.2.3. Outranking methods

The outranking methods perform pair-wise comparisons across the attributes of alternative plans under evaluation. Alternatives are classed as strongly preferred, weakly preferred or indifferent through the use of indifference thresholds. There are different methods within the outranking methodology with the two most prominent being the ELECTRE (The Elimination and Choice Translating Reality) family of methods and the PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) method.

Outranking methods have been extensively used in the energy field (Pohekar and Ramachandran, 2004). Methods such as the ELECTRE family and PROMETHEE provide a scientific basis for choosing between alternatives under multiple criteria by making pair wise comparisons between alternatives for each criteria. Outranking methods are aimed at avoiding what are perceived to be overly restrictive assumptions of the utility based methods. They address concepts of real decision making such as preference strength and the incomparability of alternatives and can therefore give considerable insight into the degree to which one alternative is preferred to another.

The ELECTRE III, IV and TRI procedures model partial preferences in a sophisticated manner through the use of threshold values. Weights do not represent scaling factors as with the utility based methods but rather some notion of global importance or the "voting power" of a criterion. The aggregation procedures are however complex and therefore can be inaccessible to most stakeholders. It has been noted that by adding or removing an alternative, the existing preferences of the remaining alternatives may change due to the dependency of the distillation procedure (final ordering of alternatives) on the entire set of alternatives (Belton and Stewart, 2002). These discrepancies often make this method inappropriate for direct interaction with stakeholders unless detailed analysis could be done on the results with support staff, in which case much could be learnt about the alternatives and the decision process. The somewhat arbitrary way in which thresholds are defined is also a controversial aspect of the outranking approaches. Although a thorough sensitivity analysis is recommended when using these methods (Belton and Stewart, 2002), the task of doing a comprehensive analysis of the threshold values and weights has been illustrated to be potentially unmanageable (Roy and Bouyssou, 1986). Therefore a sensitivity analysis would generally be done in an ad hoc manner as suggested by (Belton and Stewart, 2002).

The PROMETHEE method combines some of the simplicity and transparency of the early ELECTRE methods with the sophistication of the preference modelling of ELECTRE III. This is done by specifying the intensity of preferences for pair wise alternatives for each criterion using functions based on the performance levels of each alternative rather than by specifying indifference or preference thresholds as with the ELECTRE III method. The distillation process can however yield counter-intuitive results as with the ELECTRE III method (Belton and Stewart, 2002).

Outranking methods have established a place in the energy and environmental planning fields, mainly due to the imprecision associated with measurement and evaluation of parameters which in turn require the DM to express their reservations in the modelling process (Diakoulaki et al., 2005). The use of outranking approaches has been considered an integral part of the decision making process in situations where stakeholder involvement has been considered a priority (Georgopoulou et al., 1997; Georgopoulou et al., 1998). However, it is precisely the arbitrary way in which the thresholds are defined that cause doubt about these methods (Diakoulaki et al., 2005). Outranking methods may therefore be more appropriate for "backroom" analysts than for direct involvement with stakeholders due to the possibility of counter-intuitive results and complexities in the modelling process (Belton and Stewart, 2002).

One of the primary goals of this thesis is to develop a transparent methodology for evaluating the effects that uncertainties in DM preferences and technical empirical and model parameters have on the ranking and selection of preferred alternatives. As a thorough sensitivity analysis on threshold values may not practically be possible for large ESI problems as well as the issues around stakeholder interaction mentioned above, it was decided that a value function approach would be more appropriate for this problem.

2.2.2.4. INTEGRATED METHODS

The use of integrated methods for decision making using multiple techniques has been suggested for a more comprehensive approach to the problem (Huang et al., 1995; Hobbs and Horn, 1997; Belton and Stewart, 2002; Basson, 2004) combining detailed optimisation type methods, used in the creation of decision alternatives, with structured decision making methods, used for choosing between discrete alternatives given multiple objectives and uncertainty. The use of integrated methods is demonstrated later in this thesis whereby MODM is used in chapter 4 in the generation phase to generate solutions that satisfied multiple objectives to varying degrees and an MADM method is used in chapter 5 for the ranking and selection of preferred alternatives given multiple objectives and uncertainty.

2.3. DEALING WITH UNCERTAINTY IN ESI MODELLING

Various types of uncertainty exist within ESI modelling. Some of these uncertainties are specific to the ESI such as those relating to technical model parameters (e.g. discount rates and model time horizon) which are decided by the DM and technical empirical uncertainties relating to data (e.g. costs, emission coefficients[10], efficiencies and other technical parameters) which may be outside the control of the DM. Other types of uncertainty such as valuation uncertainties (e.g. choice of criteria, MCDA method and inter and intra-criterion preference articulation) which are highly dependant on the preferences of the DM are common to all MCDA problems.

Uncertainty in ESI modelling exists at each stage of the process; from generation to the selection of a preferred alternative. Different methods have been used to deal with different types of uncertainty, in different phases of the process. At issue when considering uncertainty are the concepts of "robustness" and "flexibility" of the solutions generated (Ku, 1995; Loulou and Kanudia, 1998; Fankhauser et al., 1999; Galeotti et al., 2006). In the context of ESI modelling, robustness can be defined as the degree to which a solution is affected (in terms of cost or any other attribute) by unknown future parameters or changing assumptions (Hobbs et al., 1994; Ku, 1995). Flexibility can then be defined as the degree to which a solution can be adapted at a future point in time (without substantial loss/change of performance in relation to the objectives), and in light of the resolution of, or changing opinions about, unknown future parameters (Gorenstin et al., 1993; Hobbs et al., 1994; Ku, 1995). It can then be said that a robust solution will perform well under a range of unknown futures, while a flexible solution could easily be adapted to changing future conditions at minimal loss of performance in relation to the objectives. Flexibility must be integrated into the generation phase so as to build this characteristic into the generation of alternatives. These alternatives must then be assessed against a range of possible future conditions to determine the robustness of each alternative's performance across multiple attributes in light of uncertainty.

Some of the common methods used for evaluating the influence of uncertainties include scenario analysis, sensitivity analysis and probabilistic analysis. While these methods can be applied to a range of fields and problems, they are discussed here mainly within the context of ESI modelling.

[10] Emission coefficients are the values relating the quantity of pollutants emitted from a power station per unit of electrical output (e.g. ton CO_2/MWh).

In ESI modelling, scenario analysis is typically carried out in the generation phase. Different representations of the future are constructed (called scenarios), each containing the same core data but with different views as to how the future may unfold. Expansion alternatives or plans are then generated for the planning horizon with respect to each individual scenario. This method is best suited for answering "What if…?" questions, rather than as a comprehensive analysis of uncertainty in the system as this would require a probability weighting for each scenario as well as that scenarios are mutually exclusive and exhaustive (Kann and Weyant, 2000).

The purpose of a parametric sensitivity analysis is to assess the impact of data perturbations on the model's outputs. In sensitivity analyses, several optimised plans are developed according to a set of base assumptions. The performance of each of these plans is then examined in light of the uncertain parameters. This type of analysis typically focuses on uncertainty in technical empirical parameters. Parameters of interest are typically varied using their extreme points (5^{th} and 95^{th} percentile values) while all other parameters are set at mean values (Kann and Weyant, 2000). This method is useful in identifying sensitive parameters by analysing the effects that varying inputs have on the model output. It does not determine the robustness of alternatives to uncertain parameters (as new alternatives are generated for each set of uncertain parameters) nor does it build flexibility towards uncertainty into any alternative.

A probabilistic analysis of technical uncertainties within ESI modelling may be more valuable than scenario analysis and sensitivity analysis (Pan, 1999). A key limitation of both scenario analysis and sensitivity analysis is that flexibility and robustness towards uncertainty are not specifically integrated into the solutions explored. Probabilistic analysis includes a variety of approaches such as Monte Carlo simulation and stochastic programming. Such an analysis may involve the propagation of either discrete or continuous probability distributions of the uncertain parameters. Given probabilistic values for uncertain input parameters, the expected values for model output responses can be calculated. Therefore each point on the output distribution represents the outcome of the optimisation of a sample of the uncertain input variables. This is not an accurate representation of reality as it implies that decisions are made with uncertainty resolved, whereas in reality policy makers need to make decisions before uncertainty is resolved (Kann and Weyant, 2000).

This leads on to more sophisticated approaches involving attaching probabilistic weights to different scenarios and performing stochastic programming to determine the optimal expansion plan including flexibility towards uncertainty. While this approach is theoretically the most comprehensive way of integrating and analysing uncertainty, it may not be practical for representing all types of uncertainty in large, continuous optimisation models (Kann and Weyant, 2000). This is because the complexity of the problem (and the computation time) increases exponentially with each uncertain state of the world, for each uncertain parameter and each period of the model in the time horizon that has to be optimised. This said, this methodology has been demonstrated for uncertainty in technology costs by introducing a penalty term (based on the difference between the cost of each solution and its variance) in the least-cost objective function of the MESSAGE III model (Messner et al., 1996). This methodology is however very computationally expensive and may only be practical for single objective optimisation, taking only limited uncertain parameters. Adding uncertainty to non-cost parameters and obtaining multiple solutions representing a range of policy maker preferences would increase the complexity of the problem to an impractical size using this methodology.

Decision tree or influence diagram models have also be used in probabilistic analysis to graphically represent complex multistage decision problems in the energy planning field (Huang et al., 1995).

2.4. CONSIDERING UNCERTAINTY AND MULTIPLE OBJECTIVES

2.4.1. GENERATION

Relatively few studies have undertaken the challenge of solving power expansion optimisation problems for a market faced with uncertainty, when there is an explicit desire to accommodate multiple objectives within the decision framework. Studies into this area generally propose methodology tailored to specific (and limited) applications (Kunsch and Teghem, 1987; Cheng et al., 2003). It is challenging to extend such approaches to much larger, dynamic long-term analyses because of the exponential increase in complexity that arises with larger models and the computational burden related to this Another issue arising from including multiple objectives into the problem coupled with uncertainty is the overwhelming amount of information generated. Interpretation of this information could present a substantial challenge for decision makers.

The concepts of flexibility and robustness are key to the methodology developed in this thesis, and will be explored in chapter 4 and chapter 5. Before doing so, however, there is merit in describing two of the most relevant methods used to account for uncertainty and multiple objectives in the generation phase: the "trade-off/risk approach"; and stochastic programming. These are discussed in turn below.

The trade-off/risk approach (developed by Merrill and Schweppe, 1984) emphasises the trade-offs between objectives and the identification of robust solutions rather than finding a single optimal solution for a given system. Principles of this method were used in an electricity sector trade-off analysis whereby multiple objectives were addressed under conditions of demand and fuel price uncertainty through the generation of future scenarios (Connors et al., 2003). Through the process of stakeholder interaction, a range of possible future technology configurations was generated. Overlaying the range of modelling uncertainties onto this set of options allows a large number of permutations to be simulated. EGEAS[11], a single objective, linear programming tool (with probabilistic production costing), was used for this purpose. This vast solution set was then reduced by screening out consistently inferior solutions based on predefined objectives. The reduced solution set was evaluated against all proposed futures to determine the performance of each solution for the given objectives under uncertainty. In this way solutions that were both robust to the uncertainties involved and that performed well under all of the objectives were isolated.

While this analysis is valuable and can provide policy makers with insight into the problem and the trade-offs involved, it has the disadvantage of generating a set of both dominated and non-dominated solutions from which non-dominated solutions need to be chosen, as well as the disadvantage that individual solutions do not have inherent flexibility in the face of uncertainty. When using this method, optimality can

[11] EGEAS (Electric Generation Expansion Analysis System) developed by the Electric Power Research Institute (EPRI), http://www.epri.com.

be traded-off against robustness due to the fact that many efficient solutions may not form part of the feasible region. This is because the solution space is generated by predefined scenarios based on technology configurations rather than from the objectives themselves. While it is agreed that solutions that are robust to uncertainty are often preferable to decision makers than solutions that are efficient and not robust (Linares, 2002), it is argued that solutions that are both efficient and robust (especially if there are numerous objectives) may be missed by generating the solution space based on predefined scenarios with regard to technology configurations rather than from the objectives themselves. It is however acknowledged that a robustness analysis is essential to energy modelling and should be integrated into any comprehensive ESI modelling methodology (discussed in chapter 5).

Stochastic programming techniques have been used to model uncertainty in the ESI since the 1980s (Dapkus and Bowe, 1984; Mo et al., 1991; Gorenstin et al., 1993; Tanabe et al., 1993). This was typically done through use of multiple cost-based objective functions (each representing a different future state of the world[12]) which were weighted according to the probabilities of each state of the world. Minimising the overall objective function then resulted in minimising the total expected system cost for all futures and building flexibility towards cost into the power station mix in light of the uncertainties considered. Previous work did not focus on building flexibility towards non-cost objectives into the solutions.

Stochastic programming models with recourse (Dantzig, 1963) are used for near term modelling in light of long term uncertainties through the development of short term strategies with inherent flexibility towards long-term uncertainties, as well as long term contingency plans once more information becomes available about the uncertain parameters. The recourse problem is formulated with different future states of the world coming into being after designated points in the time horizon (see Figure 2-5 for an example of the two-stage problem). This is different to stochastic programming without recourse, which outputs a single strategy for the entire time horizon which is optimal, on average, for all scenarios. The recourse solution is then optimised such that each stage of the model is best positioned to meet the multiple

[12] A state of the world is a representation of the future, whereby uncertain parameters are given specific values, making up a coherent view of the future, typically with an associated probability of occurrence.

future conditions, thus including an aspect of flexibility in the solution. Two-stage stochastic programming is best suited for modelling future uncertainties that have a definite date of resolution (such as legislation associated with emission limits) but it can also be used to model demand growth and fuel price uncertainties (e.g. Dapkus and Bowe, 1984; Kanudia and Shukla, 1998). Stochastic modelling with recourse has also been used to generate flexible least cost solution strategies for global climate change (Loulou and Kanudia, 1998).

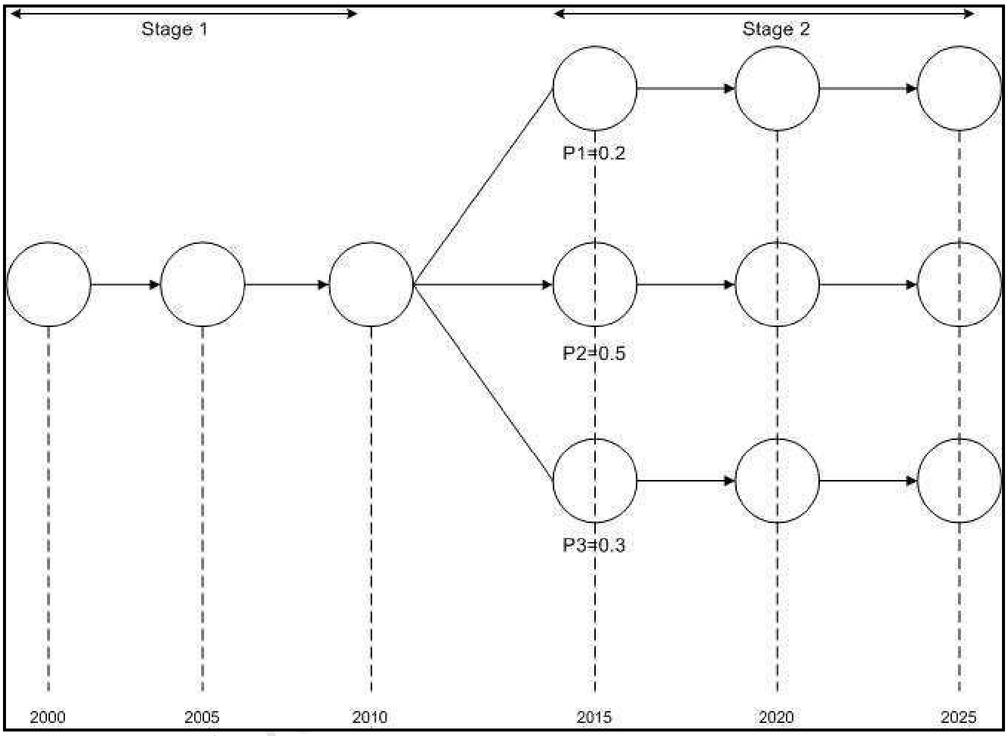

Figure 2-5 Example of an event tree with three states of the world and resolution time at 2015

Note that, with regard to the simultaneous consideration of multiple objectives, all three classes of methods for locating efficient solutions to MOLP models described in section 2.2.1 are applicable to stochastic models (Heyman and Sobel, 1984).

2.4.2. Selection

MADA methods specifically deal with making decisions in the presence of multiple objectives. MADA methods can be augmented to deal with valuation model parameter uncertainties (e.g. sensitivity analyses on weighting and preference thresholds values between alternatives) as well as with technical empirical parameter uncertainties (as discussed in section 2.2.2.1). MAUT specifically deals with uncertainties in outcomes that can be represented by probability distribution but as mentioned in section 2.3.2, other uncertainties are often more important in energy /environment modelling.

The benefits of combining MADA and scenario analysis were discussed in (Stewart, 2005) and it was suggested that MADA could enrich the evaluation process in scenario planning, while the scenario planning approach could contribute to deeper understanding of the effects of uncertainties outside of the control of the DM in MADA.

Preliminary suggestions for the integration of scenario analysis and MADA were made in (Belton and Stewart, 2002) and were later extended to suggest two different modelling approaches for combining scenario analysis with MADA in (Stewart, 2005). The first modelling approach is formulated by constructing a preference model across all possible outcomes (combinations of alternatives and scenarios). Aggregation is then done across the original criteria and a table can be constructed, giving the aggregate performance of each alternative for each scenario. A further evaluation is then required to select the most robust alternative (the alternative which performs "best" across all scenarios). The second model treats each of the criterion-scenario combinations as metacriteria (similarly to the STRANGE method (Teghem et al., 1986)). An appropriate MADA method is then applied to the problem of comparing the alternatives in terms of the metacriteria.

Stochastic multi-criteria acceptability analysis (SMAA) (Lahdelma et al., 1998) has also been used to explore the effects of uncertainty in multi-criteria decision making. These methods are based on exploring the decision space (in terms of preferences represented by weights) in order to articulate the preferences that make each alternative the most preferred one. This method was developed specifically for problems where neither the criteria measurements nor the weights are precisely known (as with the ESI modelling problem). The problem is represented by a value function where uncertain criteria data is represented by stochastic variables and the DM unknown or partially known preferences are represented by a weight distribution within the feasible weight space (described in detail in (Lahdelma et al., 1998)).

The primary outputs of SMAA are:

- *Rank acceptability indices* relating to the variety of preferences resulting in a certain rank for an alternative (which are calculated from the share of all feasible weights that make the alternative acceptable for a particular rank).
- *Central weight vectors* representing the typical preferences favouring each alternative.
- *Confidence factors* which is the probability for an alternative to obtain the first rank when the central weight vector is chosen.

The SMAA methods do not guarantee a recommendation in situations where criteria and weight information are highly uncertain or where alternatives are very similar in terms of the selected criteria. The SMAA methodology was therefore extended to include *cross confidence factors* (Lahdelma and Salminen, 2006) which assist in classifying alternatives into preferred or competing sets of preferred alternatives. The cross confidence factor can be interpreted as the probability that an alternative will be preferred, for a given set of preference weightings (usually defined by the central weighting vectors of the other competing alternatives). Reference sets can then be created by specifying confidence thresholds for the cross confidence factors such that only alternatives that have a minimum level of probability for obtaining the first rank for a range of weighting vectors (defined by the other competing alternatives) become part of the reference set.

A potential disadvantage of the SMAA methodology is that the confidence factors are based on the probability of an alternatives achieving first rank, for the central weighting vector. It may be more valuable to get a broader perspective of the effect of DM preferences by doing a sensitivity analysis on the entire range of preferences rather than focusing on the central weighting vector for the preferred alternatives alone. It may also be beneficial to report the probabilities or confidence factors of alternatives across the full rank order rather than basing confidence factors on Rank 1 only.

The cross confidence approach (Lahdelma and Salminen, 2006) improves on basing confidence factors on central weighting vectors alone, however only alternatives that achieve a rank of 1 (for the given range of weighting vectors) can become part of the reference set. This may exclude alternatives that perform consistently well, yet not best for the range of futures considered. This is discussed further in section 6.3.4 of chapter 6.

A methodology that examines the full rank order of alternatives is presented in chapter 5. This methodology has parallels with the reference set and cross confidence intervals used in the SMAA methodology except that this methodology is based on the credibility levels of all alternatives for a given set of DM preferences rather than on the central weighting vectors of alternatives that achieve a rank of 1. This method goes on to isolate a preferred set of alternatives set based on minimum performance levels (e.g. rank) and credibility whereas SMAA develops reference sets based on the confidence of alternatives being preferred (i.e. rank best) only. Using both rank and credibility to isolate alternatives allows new alternatives to enter the preferred set of solutions by relaxing performance levels and credibility levels individually. This freedom gives the DM the opportunity to differentiate between performance and credibility and to explore the effect that each have on the solution set. This is demonstrated in more detail in chapters 5 and 6.

The following chapter will outline the ESI investment problem and will discuss some of the key uncertain parameters in both the generation and selection phase.

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CHAPTER 3 OUTLINE OF PROBLEM, HYPOTHESES AND KEY QUESTIONS

This work is focussed on providing and demonstrating a comprehensive approach to the planning and analysis of investment in the ESI. In summary of the previous chapter, there are different methods for handling different types of uncertainty and multiple objectives in each phase of the ESI modelling process. The problem at hand is combining these methods into a comprehensive framework, integrating the analysis of uncertainty and multiple objectives into a methodology that can inform the stakeholders and policy makers as to the alternatives available and the trade-offs between them and finally providing a framework for the selection of a preferred alternative or set of alternatives given the multiple objectives and uncertainties involved.

A general outline of the problem will be presented and some of the key uncertain parameters will be discussed. The hypotheses and key research questions of this thesis will then be presented.

3.1. OUTLINE OF THE PROBLEM

The ESI problem can be broken down into two main phases, each with various inputs and outputs. The generation phase is where optimal solutions are generated in energy modelling frameworks to meet a projected electricity demand within a set of technical and practical constraints. A subsequent “alternative or plan selection” phase identifies preferred alternatives from within the set generated, based on DM preference information. Both of these phases can be explored against a set of policy making objectives, and both contain inherent uncertainties which relate to aspects of model definition, empirical quantities as well as valuation arguments. Figure 3-1 below outlines a representation of the ESI modelling problem.

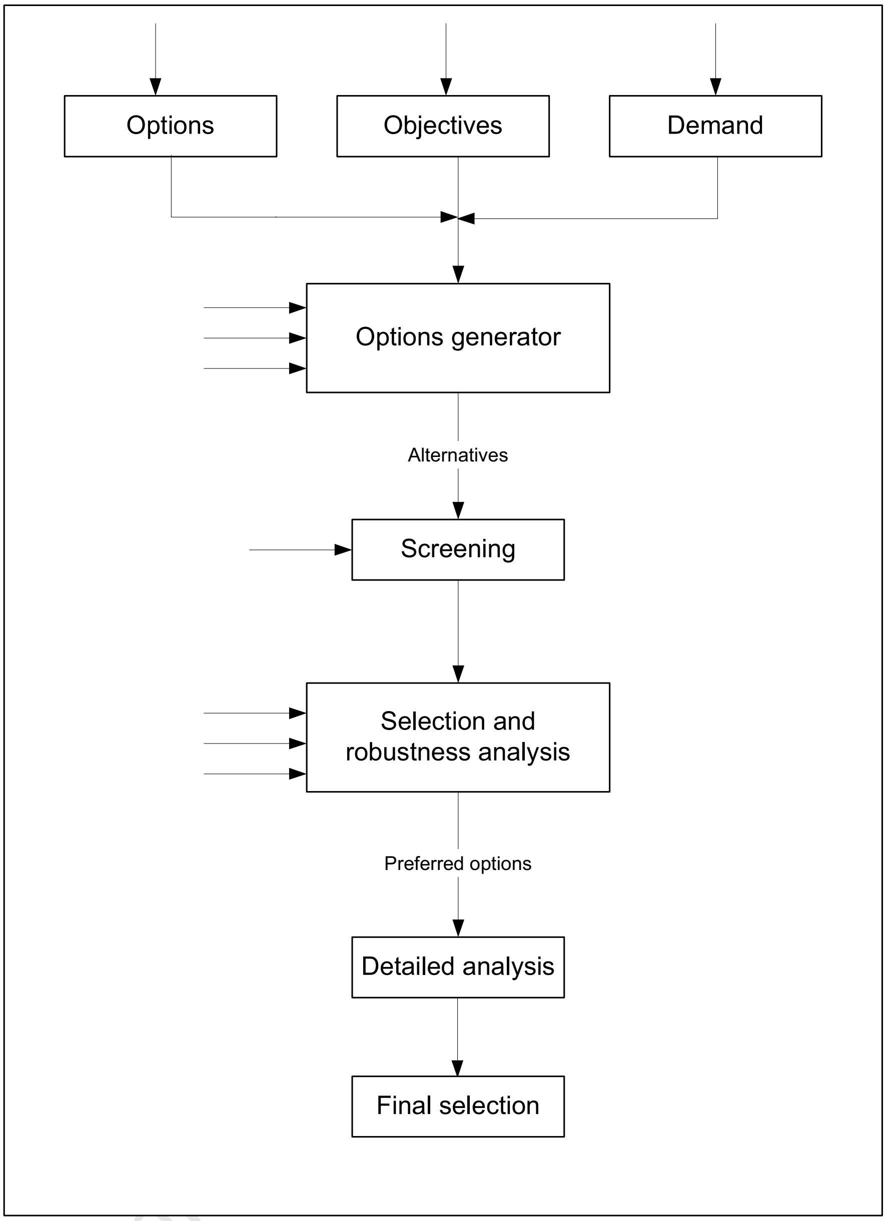

Figure 3-1 Flowchart representation of the ESI modelling problem

3.2. UNCERTAINTY IN THE GENERATION PHASE

Uncertainty exists in most of the parameters relating to the generation phase. There are technical parameters relating to the model such as discount rates, reserve margin and model constraints as well as technical empirical parameters such as costs, emission factors and demand forecasts. Each of these parameters has a degree of uncertainty related to it and they are typically dealt with in different ways depending on the nature of the parameter and of the uncertainty related to it. Figure 3-2 below illustrates a representation of the generation phase and the parameters relating to it.

Table 3-1 contains the information relating the uncertain parameters in Figure 3-2. The typical methods for dealing with each type of uncertain parameter are listed in Table 3-1 and then discussed further below:

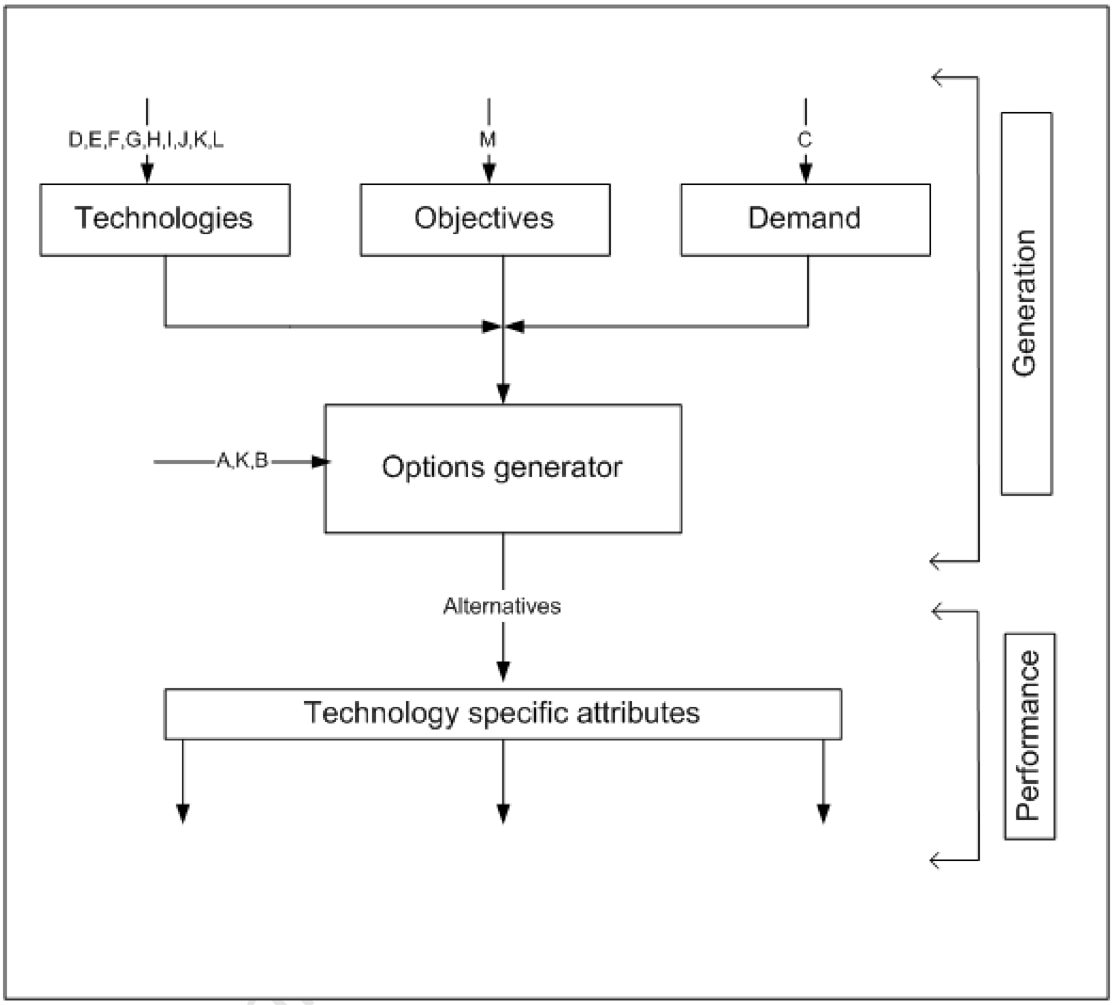

Figure 3-2 Flow diagram for generation phase

Table 3-1 Parameter uncertainty information for generation phase

	Parameter	Type of uncertainty	Generic approach to uncertainty
	Non technology specific parameters		
A	Reserve margin	Technical model parameter	Scenario analysis (within generation phase), or an output of the modelling process
	Discount rate	Technical model parameter	Settled by expert agreement although could be explored using scenario analysis
	Time horizon	Technical model parameter	Settled by expert agreement
B	Emission equivalent conversion factors	Technical empirical parameter	Different methods would yield moderately different results for the effects depending on the modelling assumptions used for each method. A parametric analysis could be done using different methods to determine their effect.
C	Demand profile (shape)	Technical empirical parameter	Scenario analysis could be used to explore the effect of different demand shapes if this was of interest and relevance to the particular case study
	Demand forecast	Technical empirical parameter	Stochastic programming could be used to hedge for demand growth uncertainty. Alternatively scenario analysis could be used to evaluate different demand scenarios. Uncertainty in demand growth could also be dealt with using the reserve margin.
	Demand probabilities	Technical empirical parameter	Scenario analysis (within generation phase)
	Demand uncertainty resolution date	Technical empirical parameter	Scenario analysis (within generation phase)

	Standard technology parameters that go into plan generator	Type of uncertainty	Generic approach to uncertainty
D	Investment cost	Technical empirical parameter	Parametric sensitivity analysis within generation phase or error propagation/robustness analysis outside of generation phase. Alternatively stochastic programming could be used to hedge for uncertainty if it was found that it was significant for this parameter
	Generation costs (O&M)	Technical empirical parameter	Parametric sensitivity analysis within generation phase or error propagation/robustness analysis outside of generation phase. Alternatively stochastic programming could be used to hedge for uncertainty if it was found that it was significant for this parameter
E	Emission coefficients	Technical empirical parameter	Parametric sensitivity analysis within generation phase or error propagation/robustness analysis outside of generation phase. Alternatively stochastic programming could be used to hedge for uncertainty if it was found that it was significant for this parameter
F	Availability Factor	Technical empirical parameter	Settled by expert agreement
G	Thermal efficiency	Technical empirical parameter	Settled through expert opinion/literature survey. Parametric sensitivity analysis can be done in the generation phase to explore the effect of uncertainty in this parameter
H	Fuel cost	Technical empirical parameter	Parametric sensitivity analysis within generation phase or error propagation/robustness analysis outside of generation phase. Alternatively stochastic programming could be used to hedge for uncertainty if it was found that it was significant for this parameter
I	Plant lead times	Technical empirical parameter	Expert agreement or scenario analysis in the generation phase
J	Plant lifetime	Technical empirical parameter	Settled by expert agreement
K	Pareto generation parameters	Technical model parameter	Extensive range of values used to generate a representation of the Pareto surface
	Station type (peaking, mid-merit, base load)	Technical model parameter	Settled by expert agreement
	Annual investment limit	Technical model parameter	Settled by expert agreement
	Total investment limit	Technical model parameter	Settled by expert agreement

3.2.1. Technical model parameter uncertainty

Model parameter uncertainties are typically explored if expert agreement cannot be reached on the values or if there is consensus that there would be merit in analysing the effect of different model parameter values. This can be done using scenario analysis where identical scenarios are created in the options generator using all the same "base" data and varying the values of the parameters of interest.

A particularly interesting model parameter is the reserve margin. In many modelling frameworks (e.g. MARKAL[1], TIMES[2], MESSAGE[3]) and methodologies the reserve margin is specified by the modeller as an input or constraint on the model. The reserve margin is used to ensure sufficient generating capacity will be in place to account for forced or unplanned plant outage, as well as for unforeseen demand growth. While this methodology may be adequate for situations when stakeholders or planners have an in depth understanding of the relationship between the required reserve margin and unplanned plant outage, this is not usually the case. This relationship is highly dependant on the number of plants in the system and the modular size of the units due to the fact the units are usually forced out independently. This implies that a lower reserve margin would be required for a 10 GW system with smaller modular units than for a 10 GW system with larger modular units. The trade-off between this phenomenon and economies of scale would have to be made in the planning process. When plant outages are modelled probabilistically instead of using fixed availability factors, the reserve margin can be an output of the modelling process (e.g. using EGEAS). The probabilistic modelling of outage is discussed in more detail in chapter 7.

[1] MARKAL (MARKet AnaLysis) developed by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency, http://www.etsap.org.
[2] TIMES (The Integrated MARKAL-EFOM System) developed by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency, http://www.etsap.org.
[3] MESSAGE (Model for Energy Supply Systems Analysis and their General Environmental impact) developed by the International Institute for Applied Systems Analysis (IIASA), http://www.iiasa.ac.at/Research/ECS/docs/models.html#MESSAGE.

3.2.2. TECHNICAL EMPIRICAL PARAMETER UNCERTAINTY

Technical empirical uncertainties can be explored using numerous methodologies. Within these empirical parameters there are distinctly different types of parameters which may need to be treated in different ways. There are data parameters relating to the costs of energy generating technologies, emission coefficients and future uncertainties relating to fuel prices and demand growth.

Demand growth uncertainty (like plant availability uncertainty) is different to other technical empirical parameters in expansion planning in that the penalty that would be paid for not meeting demand requirements would be system failure, rather than poor performance in an objective. It is therefore believed that this uncertainty parameter should be handled differently to the other technical empirical parameters. This is discussed further in chapter 4.

The uncertainties in data parameters have been modelled in various ways including scenario analysis (e.g. Meristö, 1989; Connors et al., 2003; Stewart, 2005), parametric sensitivity analysis and probabilistic methods (e.g. Messner et al., 1996; Seebregts et al., 2001) (discussed in detail previously in section 2.3). Methods for dealing with technical empirical and model parameter uncertainty and discussed further in chapters 4, 5, 6 and 7.

3.3. UNCERTAINTY IN THE SELECTION PHASE

The variables that influence this phase are mainly valuation model parameters relating to model form. These include the choice of criteria, the structure of the value tree and the choice of attributes although these parameters have been addressed to some degree in the generation phase to generate solutions that satisfy multiple objectives to varying degrees. Figure 3-3 below illustrates a representation of the selection phase. Table 3-2 contains information relating to the uncertain parameters in Figure 3-3. The typical methods for dealing with each type of uncertain parameter are listed in Table 3-2 and then discussed further below:

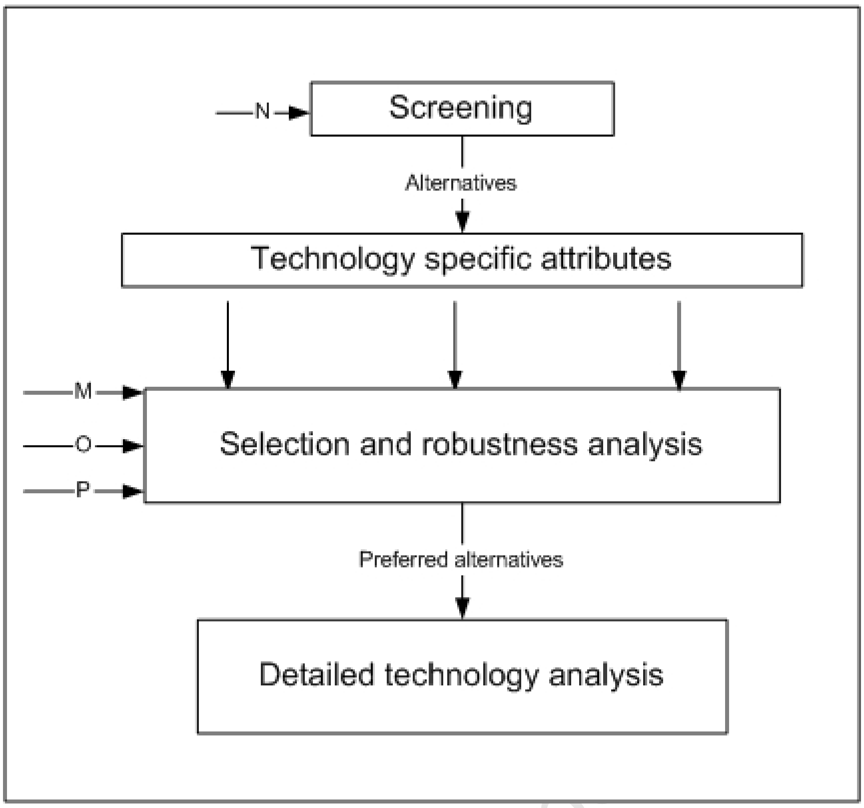

Figure 3-3 Flow diagram for selection phase

Table 3-2 Parameter uncertainty information for plan selection phase

	MADA related parameters	Type of uncertainty	Generic approach to uncertainty
M	Choice of criteria	Valuation model form	Choices settled through expert (or stakeholder) agreement unless specific reason for scenario analysis
	Structure of value tree	Valuation model form	Effect considered as part of the weight elicitation phase. Scenario analysis can be done if there is specific interest in effects of the tree structure
	Choice of attributes	Valuation model form	Choices settled through expert (or stakeholder) agreement unless specific reason for scenario analysis
	Choice of MADA method	Valuation model form	Choice typically settled through expert (or stakeholder) agreement based on case study. Scenario analysis can be done where insight is required into the effect of method, particularly with regard to compensation arguments.
N	Thresholds for preliminary screening	Valuation model form for selection of screening criteria and technical empirical parameter for values	Choices settled through expert agreement unless specific reason for scenario analysis. Parametric sensitivity analysis is typically done on values.
O	Inter-criterion articulation of preferences	Valuation model parameter for scaling values. Valuation model form for weighting method	Parametric sensitivity analysis on values: Weighting diagram can provide very useful information as to the effect that DM weighting could have on the overall results. Can also be used to back calculate the trade-offs that would be made in order for rank orders to change. Weighting method resolved by expert agreement or scenario analysis if no resolution possible
P	Intra-criterion articulation of preferences	Valuation model form for choice of shape. Valuation model parameter for numerical values	Scenario analysis for different shapes and parametric sensitivity analysis on numerical values

The choice of MADA method is typically settled through expert (or stakeholder) agreement based on case study at hand, but scenario analysis can be done where insight is required into the effect of method, particularly with regard to compensation arguments (e.g. outranking vs. value function methods) (Basson, 2004).

Inter-criterion preference choices have valuation parameters relating to model form that are typically settled by expert agreement (Belton and Stewart, 2002). These include the structure of the value tree, the method of aggregation and the weighting technique. A scenario analysis can be done on different weighting methods if expert agreement cannot be reached (Basson, 2004). A parametric sensitivity analysis or interval programming approach can then be used on the actual weighting values to determine their effect on the overall preference results (demonstrated in chapter 5).

Intra-criterion preference choices also have valuation parameters relating to model form that are typically settled by expert agreement (Basson, 2004). These include method of normalisation (discussed in detail in chapter 6) and value function shape. A scenario analysis can be done on using different value function shapes followed by a parametric sensitivity analysis on the numerical values (Basson, 2004).

3.4. Key areas of focus for this work

This work is focused on developing a methodology for the analysis and planning of investments in the ESI that is comprehensive with respect to multiple objectives, and comprehensive with respect to the uncertainties inherent to this problem. In this light the following hypotheses were drawn, and some key questions were defined:

3.4.1. Generation for multiple objectives under uncertainty

Hypothesis 1: Multiple objectives representing policy maker preferences can be integrated into existing single objective energy modelling frameworks.

Key questions relating to this hypothesis:

- What is the most appropriate method for extending single objective energy modelling to multiple objectives?
- Can this be done within existing energy modelling frameworks?
- What valuable new information can be yielded from this type of analysis (e.g. relationships between DM preferences and technology choice, emission tax values necessary to induce a change in technology choice)?

Hypothesis 2: Flexibility towards future uncertainties can be built into each optimal solution for multiple objectives.

Key questions relating to this hypothesis:

- What is the most appropriate method for accounting for future uncertainties within the generation phase to build flexibility into the solution set?
- How can this method be extended to build in flexibility towards uncertainty for multiple objectives?

- How should technology lead times be accounted for within this approach so that investments do not occur before they are in allowed to in light of the additional decision nodes when using a multi-stage, non-deterministic model?

3.4.2. Selection for multiple objectives under uncertainty

Hypothesis 3: A comprehensive analysis of uncertainty can be integrated into the selection phase to find robust solutions that best satisfy the multiple objectives chosen.

Key questions relating to this hypothesis:

- Which multi-attribute decision analysis (MADA) method would be most appropriate for the ranking and selection of a preferred alternative given multiple objectives and uncertainty?

- How would the MADA methodology be extended to compare the performance of alternatives for their multiple attributes over a range of discrete futures?

- What would the most appropriate method for a multi-objective robustness analysis be for this problem and how can this be integrated into the problem structure?

- How can a portfolio of preferred alternatives be identified for detailed analysis based on both performance and credibility?

3.4.3. Normalising attribute scores

Hypothesis 4: Normalising attribute scores using a non-standard value range can reduce the effective weighting bias due to inflated minima or maxima.

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Key questions relating to this hypothesis:

- What method for data normalisation across the problem attributes would be most appropriate for this problem, especially when comparing different output data sets?

- How can the weighting procedure for articulating stakeholder preferences be modified to account for the normalisation methodology?

3.4.4. The relative effect of specific uncertainties on the ranking and performance of expansion alternatives

Hypothesis 5: An analysis of the effects of using different approaches to dealing with technical empirical uncertainty can give insight into the relative importance of different uncertain parameters and the relative value of the approaches in light of the importance of the parameters and the time and effort taken for each approach.

Key questions relating to this hypothesis:

- What uncertainties dominate the ESI modelling problem and what implication does this have on where should the focus of the analysis should be?

- More specifically, would reoptimising the operational parameters for each discrete future add significant value to the methodology?

3.4.5. Integrating plant availability uncertainty and reserve margin into the multi-objective framework

Hypothesis 6: Plant availability uncertainty can be integrated into the multi-objective framework by finding the minimum required reserve margin for the system.

Key questions relating to this hypothesis:

- Can demand be modelled both chronologically and in high resolution such that both the frequency and duration of outage could be adequately represented?
- What type of analysis of the ESI investment problem can be practically used to represent plant availability uncertainty?
- How can this methodology be integrated into a multi-objective framework with a comprehensive analysis of system wide uncertainty?

3.5. REFERENCES

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CHAPTER 4 GENERATION FOR MULTIPLE OBJECTIVES UNDER UNCERTAINTY

4.1 INTRODUCTION

Electricity supply industry (ESI) modelling is a challenging task due to diversity of the supply-side technology options available (influencing model size and complexity), the temporal evolution of parameters over medium to long term time horizons, the non-linear nature of the systems under consideration, environmental and social arguments, as well as aspects of uncertainty in all realms of the modelling process. More recently, increasing deregulation of power markets has added to the uncertainty and has necessitated new methodologies and models to better understand the systems at hand (e.g. Botterud, 2003; Murto, 2003; Madlener et al., 2005).

ESI modelling methodology can be split into two phases: A primary step is the generation phase, where solutions or Future Expansion Alternatives (FEAs) are generated in an energy systems modelling framework. A subsequent selection phase identifies preferred FEAs from within the set generated, based on policy maker and stakeholder preferences and value judgements. Both of these phases can be explored against a set of policy making objectives, and both contain inherent uncertainties which relate to empirical and model uncertainties, as well as valuation arguments.

The aim of this chapter is to outline a methodology for the generation of solutions within an ESI modelling framework that considers multiple objectives, and includes aspects of flexibility to demand growth uncertainty into each solution. As such, the scope of this chapter is limited to the generation of ESI scenarios only, and illustrates this approach for the South African ESI. Alternative selection and robustness analysis are not addressed in any detail in this chapter as chapter 5 is dedicated specifically to these issues.

4.2. BACKGROUND

As mentioned in chapter 2; large linear programming models have been used extensively over several decades to address ESI modelling (Hobbs, 1995; Hobbs and Meier, 2000; Cormio et al., 2003). Modelling with single objective functions has been a powerful tool in optimizing power station expansion under specific environmental constraints, as well as for examining the economic feasibility of new options in the energy market. This type of analysis, done in partial equilibrium frameworks, has provided policy makers with the "perfect market" response to future scenarios that are valid for both regulated, centrally planned power markets, as well as for efficient fully deregulated markets. Although this type of modelling has enjoyed some success for integrated resource planning in the past, resource planning today has become a far more complex task (Hobbs, 1995). What such an approach fails to deliver is explicit consideration of trade-offs between different objectives and the need to address uncertainty in the modelling process.

That said, this type of analysis and approach are familiar to many energy market analysts, and continues to form the basis of ESI planning in many instances. It is therefore argued that there is merit in exploring to what extent the "single objective least-cost" approach in partial equilibrium frameworks can be augmented to include other objectives and specific forms of uncertainty analysis to deliver more valuable outcomes from an energy modelling exercise.

4.2.1. RATIONALE FOR METHODOLOGY

As discussed in section 2.2.1, an interactive approach to articulating stakeholder preferences requires significant stakeholder participation in the modelling process and therefore may not be appropriate for processes where multiple stakeholders exist. This work is focussed on developing a transparent methodology for considering multiple objectives and uncertainty in the ESI and therefore articulates preferences prior to the generation phase such that the trade-offs between objectives are obvious to outsiders or stakeholders that were not involved in the modelling process.

Of the methods for considering multiple objectives described in section 2.2.1, a weighted aggregation function approach cannot be readily used within existing single objective energy planning approaches without significant reformulation of the tools. However, both a constraint-based method and a cost penalty based method could easily be applied within these frameworks to explore multiple objectives.

As discussed in section 2.4.1, stochastic programming with recourse is a powerful technique for addressing future uncertainties (such as demand growth) due to the incorporation of flexibility within a dynamic optimisation framework. It has the advantage of generating only non-dominated solutions as the solution space is generated from the objectives themselves rather than from predefined technology mixes. While stochastic programming methods have included multiple objective functions to represent different future states of the world (e.g. Dapkus and Bowe, 1984; Mo et al., 1991; Gorenstin et al., 1993; Tanabe et al., 1993), they have not been extended to include multiple (environmental or social) objectives into the power expansion problem formulation.

When considering both multiple objectives and uncertainty within a stochastic programming with recourse formulation, using a cost penalty based method as opposed to a constraint based method (see chapter 2 section 2.2.1 for discussion on approaches for locating efficient solutions to multiple objective linear programming (MOLP) models) would have the advantage of extending the recourse modelling to include flexibility to uncertainty for all objectives, whereas a constraint based method would only include flexibility to cost. This is due to the inclusion of the cost penalties into the model's objective function (discussed in detail in section 4.4.3) and therefore into the hedging action taken by the recourse approach. It also has the advantage of providing policy makers with an indication of the market signals necessary to influence the market towards a preferred state in the form of emission taxes.

This method can however be manually intensive as it does not guarantee a well-spread representation of the non-dominated solution set. The burden of ensuring such a representation now lies with the modeller. Unlike with constraint-based methods, the performance value of each attribute for each solution is obtained as an output of the model rather than specified as an input (with cost penalties being the changing input parameter causing the objective function to find new solutions). However, this being said, new solutions "to fill the gaps" can quickly be generated based on a cursory examination of the attributes scores of the solution set and the taxes used to generate the existing solutions. The additional effort required by the modeller to ensure a well spread representation of the non-dominated solution space is considered a necessary trade-off for the benefits of using the cost penalty-based approach stated above.

With this in mind, the proposed approach to generation in ESI modelling adopted here relies on an extension of the two-stage recourse problem for multiple objectives using a cost penalty based method. The full methodology is described below.

4.3. METHODOLOGY

4.3.1. GENERATING A BASE CASE SCENARIO

The first step in the proposed modelling process is to develop a base case or "business as usual" scenario. This can be done using energy planning models such as MARKAL, EGEAS, MESSAGE which typically include a complete supply-side representation (including all costs and emissions coefficients) of all existing power stations in the system, as well as a range of technology options for future stations. The models operate within a series of constraints that must be satisfied in order for a solution to be considered feasible. Such constraints typically include mass and energy balances, meeting demand projections, satisfying peak and base-load requirements within a given reserve margin, obeying emission constraints as well as any technology specific constraints. The base case scenario is then simply a least cost optimised FEA for the represented power system.

MARKAL was chosen as the framework to demonstrate this methodology, due to its wide usability, its capacity to include taxes on emissions as well as the two-stage stochastic recourse programming module available for this software.

4.3.2. EXTENSION OF SOLUTION SET TO INCLUDE MULTIPLE OBJECTIVES

The next step in the proposed methodology is to expand the solution set from the base case scenario by the inclusion of other objectives, which will likely result in technology options not present in the base case scenario.

The approach taken here is to expand the solution set to satisfy multiple objectives using a dynamic partial equilibrium[1] optimisation framework. Here, cost penalties are introduced in the model to capture the performance of technology options in those attributes which relate to the “non-cost” objectives. The least-cost objective function is retained in the optimisation, but due to the cost penalties, the solution space is now searched for non-dominated solutions that force the model to better satisfy the non-cost objectives (consistent with the first approach discussed in section 2.2.1). This is explained in more detail below:

The MARKAL model objective function, described in (Loulou et al., 2004), can be summarized mathematically as follows:

$$NPV = \sum_{t=1}^{t=NPER} (1+d)^{NYRS*(1-t)} \bullet ANNCOST(r,t) \bullet \left(1+(1+d)^{-1}+(1+d)^{-2}+....+(1+d)^{1-NYRS}\right) \quad (4.1)$$

Where:

NPV is the net present value of the total cost to be minimized (the objective function)

ANNCOST(r,t) is the annual cost for period *t*,in region *r*

d is the general discount rate

NPER is the number of periods in the planning horizon

NYRS is the number of years in each period *t*

Various decision variables, which represent the choices made by the model to minimize total cost, are considered within this MARKAL model, as described in (Loulou et al., 2004). Some of these are elaborated on here:

INV(r,t,k)*:** new capacity addition for technology ***k, in period ***t***, in region ***r***.

CAP(r,t,k): installed capacity of technology ***k***, in period ***t***, in region ***r.***

ACT(r,t,k,s): activity level of technology ***k***, in period ***t***, in region ***r***, during time-slice ***s.***

[1] Demand was assumed to be inelastic.

ENV(r,t,p): Emission of pollutant ***p*** in period ***t*** in region ***r.***

The total annual cost ***ANNCOST(r,t)*** is the sum over all technologies ***k,*** and all input fuels ***f,*** of the various costs incurred, namely: annualized investments, annual operating costs (including fixed and variable technology costs, fuel delivery costs, costs of extracting and importing energy carriers), minus revenue from exported energy carriers and taxes on emissions. Mathematically, ***ANNCOST(r,t)*** is expressed as follows:

$$
\begin{aligned}
\boldsymbol{ANNCOST(r,t)} \quad = \; & \Sigma_{k} \{Annualized\_Invcost(r,t,k) * INV(r,t,k) \\
& + Fixom(r,t,k) * CAP(r,t,k) \\
& + Varom(r,t,k) * \Sigma_{s,s} ACT(r,t,k,s) \\
& + \Sigma_{c} (Delivcost(r,t,k,c) * Input(r,t,k,c) * \Sigma_{s} ACT(r,t,k,s)) \} \\
& + \Sigma_{c,s} \{ Miningcost(r,t,c,l) * Mining(r,t,c,t) \\
& + Importprice(r,t,c,l) * Import(r,t,c,l) \\
& - Exportprice(r,t,c,l) * Export(r,t,c,l) \} \\
& + \Sigma_{c} \text{(Madlener et al., 2005)} \qquad (4.2)
\end{aligned}
$$

Where:

Annualized_Invcost(r,t,k) is the annual equivalent of the lump sum unit investment cost, obtained by replacing this lump sum by a set of equal annual payments over the life of the equipment, in such a way that the present value of the stream is exactly equal to the lump sum unit investment cost, for technology *k*, in region r and period t;

Fixom(r,k,t), Varom(r,t,k), are unit costs of fixed and operational maintenance of technology k, in region r and period t;

Delivcost(r,t,k,c) is the delivery cost per unit of commodity c to technology k in region r and period t;

Input(r,t,k,c) is the amount of commodity c required to operate one unit of technology k, in region r and period t;

Miningcost(r,t,c,l) is the cost of mining commodity c at price level l in region r and period t;

Importprice(r,t,c,l) is the import price of commodity c in region r and period t;

Exportprice(r,t,c,l) is the export price of commodity c in region r and period t;

Tax(r,t,p) is the tax on emission p in region r and period t;

The objective function is then minimised subject to the following constraints:

Satisfaction of demands

For each time period *t*, region *r*, demand *d*, the total activity of end-use technologies servicing that demand must be at least equal to the specified demand. Hence:

$$\sum\nolimits_{Over\ \ all\ \ k} CAP(r,t,k) \geq D(r,t,d) \tag{4.3}$$

Capacity transfer

For each technology *k*, region *r*, period *t*, the available capacity in period *t* is equal to the sum of investments made by the model at past and current periods, and whose physical life has not ended yet, plus capacity in place prior to the modelling horizon and still in place.

$$\boldsymbol{CAP(r,t,k)} = \sum_{t'}^{t} INV(r,t',k) + RESID(r,t,k) \tag{4.4}$$

Where *RESID(r,t,k)* is the capacity of technology *k* due to investments that were made prior to the initial model period and still exist in region *r* at time *t*.

Use of capacity

For each technology *k*, period *t*, region *r*, and time-slice *s*, the activity of the technology may not exceed its available capacity, as specified by a user defined availability factor

$$\boldsymbol{ACT\ (r,t,k,s)} \leq AF(r,t,k,s)*\ CAPUNIT\boldsymbol{*\ CAP(r,t,k)} \tag{4.5}$$

Where *CAPUNIT* is the unit of acitivy /unit of capacity (e.g. PJ/MW)

Energy Balance

For each commodity ***c,*** time period ***t***, region ***r***, (and time-slice ***s*** in the case of electricity, this constraint requires that the disposition of each commodity may not exceed its supply. The disposition includes consumption in the region plus exports; the supply includes production in the region plus imports.

$$\sum_{Over\ all\ k} Output(r,t,k,c) \bullet ACT(r,t,k,s) + \sum_{Over\ all\ l} Mining(r,t,c,l) + \sum_{Over\ all\ l} FR(s) \bullet IMP(r,t,c,l)$$
$$\geq \sum_{Over\ all\ l} Fr(s) \bullet EXP(r,t,c,l) + \sum_{Over\ all\ k} Input(r,t,k,c) \bullet ACT(r,t,k,c,s) \tag{4.6}$$

Where:

Input(r,t,k,c) is the amount of commodity ***c*** required to operate one unit of technology ***k***, in region ***r*** and period ***t;***

Output(r,t,k,c) is the amount of commodity ***c*** produced per unit of technology ***k***, and

FR(s) is the fraction of the year covered by time-slice ***s*** (equal to 1 for non-seasonal commodities).

Electricity and heat Peak Reserve Constraint

For each time period ***t*** and for region ***r***, there must be enough installed capacity to exceed the required capacity in the season with largest electricity (heat) commodity ***c*** demanded by a safety factor *E* called the *peak reserve factor*.

$$\sum_{Over\ all\ k} \mathrm{CAPUNIT} \bullet \mathrm{Peak}(\mathrm{r,t,k,c}) \bullet \mathrm{FR(s)} \bullet \mathrm{CAP(r,t,k)} + \mathrm{FR(s)} \bullet \mathrm{IMPORT(r,t,c)}$$
$$\geq [1 + ERESERVE(r,t,c)] \bullet \sum_{Over\ all\ k} Input(r,t,k,c) \bullet FR(s) \bullet ACT(r,t,k,s) + FR(s) \bullet EXPORT(r,t,c) \tag{4.7}$$

Where:

ERESERVE(r,t,c) is the region-specific reserve coefficient, which allows for unexpected down time of equipment, for demand at peak, and for uncertain hydroelectric, solar, or wind availability.

Peak(r,t,k,c) (never larger than 1) specifies the fraction of technology *k*'s capacity in a region *r* for a period *t* and commodity *c* (electricity or heat only) that is allowed to contribute to the peak load.

As mentioned above, additional objectives are considered through the use of cost penalties, hereafter called Pareto Generation Parameters (PGPs), which operate on the cost minimisation objective function. These are incorporated in the model as emission taxes and act directly on the investment **(*INV(r,t,k)*)** and activity **(*ACT(r,t,k,s))*** decision variables through the pollutant emission parameter, **(*ENV(r,t,p))*.** Individual emission tax parameters are defined using the **Tax(t,p)** parameters in the model (described below).

As total system cost is minimised through the objective function, the model attempts to minimise emissions because of the cost penalty associated with each emission defined using the **Tax(t,p)** parameters. The degree to which the model will improve the attribute performance of each of the non-cost objectives depends on the magnitudes of the PGPs, as the costs associated with the emissions (through the **Tax(t,p)** parameter) are traded off against the other system costs in the optimisation. Therefore by varying the emission tax values for each PGP, the model will provide a range of solutions that satisfies each of the non-cost objectives to varying degrees. The challenge is to ensure that a representative range of emission taxes is considered for each additional objective, so that the expanded solution set includes adequate diversity in technology options within each scenario to address stakeholder interests. This approach is outlined below, and demonstrated in the case study of section 4.4.2.

These PGPs resemble externality costs[2] in that monetary values are assigned to by-products of the electric supply process (in the form of emission taxes). The difficulty in calculating externality costs is widely acknowledged, with different methods yielding different values for the same problem (see for example (Schleisner, 2000; Sundqvist, 2004)). The value of using externality costs for guidance in policy decisions despite the uncertainties involved is discussed in (Krewitt, 2002). However, in this method the PGPs are merely used as parameters to generate a representation of the multi-objective solution space. No claim is made that the PGPs represent the

[2] Externality costs can be defined as the "damages" or "unpaid value" of environmental damage caused by, in this case, electric power services (Ottinger et al., 1991) but paid for by society as a whole.

actual monetary cost for any damages suffered by humanity or the environment[3] due to the electricity generation process. These values are determined iteratively based on the performance ranges of the non-cost attributes that stakeholders wish to investigate (discussed below).

An algorithm for the procedure to generate a representation of the non-dominated solution space is outlined below:

- Decide on a set of non-cost criteria to include into the optimisation. There is a real need to consider the environmental and social aspects of sustainability in ESI modelling. Taking this as the starting premise, consideration is limited in this current work to selected environmental issues by way of demonstration, and here focus is placed on a range of impacts which span global, regional and local spatial and temporal scales, and which are believed to be of genuine concern to stakeholders. The non-cost criteria chosen to illustrate the methodology in this chapter are: climate change potential, acidification potential, and water consumption.

- Identify attributes within the model that relate to each of these criteria - e.g. all contributions to potential climate change are measured in equivalent units of CO_2 emissions; acidification potential is defined in terms of SO_2 equivalents; and specific water consumption is the total water volume consumed. These are consistent with attributes used in environmental impact assessment approaches such as Life Cycle Assessment (see ISO 14040 series of standards (ISO, 1997)). However, in this model, the holistic footprint of these attributes is not considered on a full life-cycle basis, but limited to a consistent process boundary (being the power generation process) for all technologies which make up a given expansion alternative.

- The range of values for each PGP is defined, such that the solution corresponding to the highest PGP value achieves the necessary performance levels defined by DM in the corresponding non-cost attribute. In this way, the

[3] However, it is possible to make inferences from the PGP values that produce the set of power station investments that are ultimately selected based on policy maker preferences.

effect that each PGP individually has on the final solution (in terms of attribute scores and the build plan) is demonstrated unambiguously. The combined effect of using different PGPs simultaneously may generate solutions whose performance exceeds the required performance level for each individual attribute. Should this be so, it would be necessary to screen solutions (see section 4.3.3), both to reduce the number of solutions, and to focus on a section of the solution space of interest to the DM (which is identified by stakeholder engagement). The specific PGP values which give rise to the extremities of the performance ranges of each attribute can be identified straightforwardly, and serve as a check on stakeholder acceptability. These extremes may be modified progressively as stakeholder understanding of the problem develops.

- Once a satisfactory range has been determined for each PGP individually (based on the stakeholder defined ranges in attributes), each range must then be sampled so that the solution space can be explored. Enough values should be chosen so as to allow for individual attribute performance as well as interactions to be seen, bearing in mind that the number of model runs will increase exponentially with the number of samples from each PGP range. This choice is therefore case study dependant and fully up to the discretion of the modeller.

- The model is then rerun for all permutations of the samples of the PGPs determined above. This maps out a space of non-dominated solutions spanning ranges in performance for each of the attributes represented by the PGPs. In this way, the model can be seen to accommodate multiple objectives.

By using a posterior articulation method (where DM preferences are articulated after a range of solutions have been generated so that preferred alternatives can be selected) for integrating DM preferences into the approach developed here, a range of solutions satisfying multiple objectives to varying degrees can be generated. This approach has the benefit of allowing the stakeholders to make a choice knowing the consequences of their decision relative to the other alternatives with regard to the predefined objectives. This method is also more transparent and easily understandable to stakeholders outside of the decision process and therefore creates a situation where the DM is more accountable for his choices.

4.3.3. Screening of alternatives for further analysis

At this stage, the solution space contains only non-dominated solutions. However, the number of solutions in this set could be unmanageable due to the exponential effect of the number of objectives and the number of PGPs values chosen to explore those objectives. Screening for financial viability and other stakeholder defined constraints such as technology diversity, technical risk, reserve margin or minimum performance parameters in any of the attributes can be done at this stage to reduce the solution set before further analysis is conducted. The intention here is merely to reduce the solution set to a manageable number of alternatives for subsequent detailed analysis of uncertainty. The degree to which alternatives are screened is a trade-off between representing a large enough portion of the decision space to explore stakeholder interests and reducing the number of alternatives and therefore computing time and data.

4.3.4. Modelling for future uncertainties

Up to this stage of the analysis, the effects of uncertainties have not been considered explicitly. However, even after screening, the number of solutions that remain would still be far in excess of what could realistically be considered in detail; hence conducting the preceding analysis steps without explicit consideration of uncertainty is not considered to be of adverse consequence. This assumes that the screening process takes into account the fact that due to uncertainty the average performance of alternatives may change slightly and therefore the screening range should be wider than the area of interest. . However, the effect of uncertainty needs to be taken into account for the remaining (i.e. screened) sub-set of options. For example, the solutions need to be robust to different future states of the world (such as different fuel prices) and need to have built-in flexibility to meet unknown futures (such as differences in demand growth). This can be addressed using hedging, or “least regret” strategies.

The following sections will discuss the method used for implementing stochastic programming with recourse into the model and will highlight some of the valuable analysis that can be done when using this method of dealing with uncertainty. It will also mention the uncertainties not dealt with at this stage of the analysis.

4.3.4.1. Stochastic programming with recourse

It is proposed that future uncertainties such as demand growth can be integrated into the current model using stochastic programming with recourse (described in section 2.4.1), as has been used previously to increase the flexibility of power expansion plans (Dapkus and Bowe, 1984; Loulou and Kanudia, 1998).

Demand growth was chosen as the future uncertainty parameter to demonstrate this methodology. It is different to most other technical empirical parameters in expansion planning in that the penalty that would be paid for not meeting demand requirements would be system failure, rather than merely poor performance in an objective. This is part of the reason why reserve margins are included into the planning process (The other main reason is to account for plant outage uncertainty – discussed in more detail in chapter 7). However in some cases these may not provide sufficient protection against demand growth uncertainty. It was therefore decided to integrate demand growth uncertainty into the generation phase using stochastic programming with recourse to ensure flexibility towards this uncertainty. Although using stochastic programming (with recourse) would be seen as the most comprehensive way of integrating uncertainties such as technology costs and emission coefficients into the model, it may not be practical for large, continuous optimisation models (Kann and Weyant, 2000), especially where the focus is on developing a transparent decision methodology for multiple objectives, as in the case presented in this thesis. As discussed in section 2.3, using stochastic programming with recourse is very computationally expensive and may only be practical for single objective optimisation, taking only limited uncertain parameters. Adding uncertainty to non-cost parameters and obtaining multiple solutions representing a range of policy maker preferences would increase the complexity of the problem to an impractical size using this methodology.

4.3.4.2. Accounting for technology lead times

Central to this recourse problem is the concept of technology lead times (especially when addressing demand growth uncertainty). Because power stations have long lead times, decisions to build or get a station to the "ready to build" stage need to be made well in advance. In deterministic models, planners incorporate lead times by setting constraints on the investment parameters of technologies, until their lead times have passed. In stochastic programming with recourse the concept of a lead time for each new technology has to be accounted for at the beginning of the time horizon and then again at the decision node, if hedging for the uncertain future is intended. It would be inconsistent for the model to build a technology immediately after the decision node in one future and not another as this would violate the concept of technology lead times. In the work presented here, this problem has been addressed by splitting power station investments for each major new technology into two irreversible phases, namely the owners' development cost (ODC), encompassing the conceptual and feasibility phases of the project, and the cost of the equipment procurement and construction (EPC), encompassing the equipment procurement and construction phase of the project, each with their corresponding lead times[4].

Splitting investments into phases introduces aspects of real options theory (Dixit and Pindyck, 1994), in which there is a value assigned to delaying an investment. Initial investments (ODC investments) into a technology may be made to "buy" time; to "wait and see" what happens with future uncertainties, and whether, under such conditions, the technology may be an economically viable option. This initial investment can then either be taken further to the full development and execution of the technology (EPC phase) when uncertainty unfolds, or the initial investment can be written off as a loss if the uncertainty unfolds in a way which would make it uneconomical to build this technology.

In this way, the model is allowed to build capacity in the second phase of a technology (EPC phase) only when that generating capacity has previously been

[4] The ODC component typically constitutes a minor component of the total investment cost for a power station when compared to the EPC cost (NER et al., 2004).

brought to the "investment ready" stage in the first (ODC) phase. The implication of this is that ODC investment is limited to before the decision node for the stochastic model. This forces decisions (and primary investments) to be made before the resolution of uncertainty, hence hedging for future uncertainty. This methodology can create discrepancies in lead times for technologies built towards the end of the time horizon, as it forces all initial decisions (and investments) to be made before the decision node, when in reality some of these decisions could be made at a later stage, if the time horizon is long enough or the lead times short enough. This could be remedied by allowing technologies at the end of the time horizon to be built as a single entity (instead of splitting them up) as long as their lead time requirements are not violated.

4.3.4.3. Expected Cost of Ignoring Uncertainty (ECIU)

In order to evaluate the benefit of using stochastic programming with recourse (as opposed to a deterministic approach) a quantity called the Expected Cost of Ignoring Uncertainty (ECIU) (see Morgan and Henrion, 1990) can be constructed. This is achieved by creating an equivalent stochastic scenario for each set of PGPs (called the naïve solution), where the probability of the median future occurring is almost 100 % (e.g. 99.8 % for the median future and the remainder of 100 % being made up from each of non-median futures). This forces the model to ignore the fact that multiple futures can occur when hedging for the second stage of the solution (unlike in hedged solutions where the probabilities of the non median futures have significant values), and creates a new solution that contains multiple futures after the resolution date but where no hedging has been done for those futures. The hedged solution can then be compared to the naïve solution to determine the value of explicitly considering uncertainty using stochastic programming. In a single objective optimisation exercise, the total discounted system cost of the naïve solution could be compared to that of the hedged solution. In this case, due to the inclusion of PGPs into the model runs as a means of extending the analysis to multiple objectives, the performance in both cost and the other predefined non-cost attributes can be compared. This is a powerful extension of the approach to date.

A major difference between the stochastic modelling done in previous work (Dapkus and Bowe, 1984; Mo et al., 1991; Gorenstin et al., 1993; Tanabe et al., 1993; Loulou and Kanudia, 1998) and the work presented here is that the previous work generally focussed on using several probability weighted cost-based objective functions to model different states of the world, while this work extends that formulation to include multiple environmental objectives as well.

The stochastic variant of MARKAL (see appendix A for equations) redefines the objective function shown previously (equations 4.1 and 4.2) so that the overall objective function becomes the weighted sum of the expected costs for each state of the world, weighted by their probability of occurrence. The hedging that is done in the recourse programming is then automatically translated from purely financial to include whatever attributes the PGPs represent due to the cost penalties that the PGPs impose on the objective functions for each state of the world. This implies that the model will attempt to minimise both cost and non-cost objectives in light of the uncertain futures involved. However, due to the cost penalties that the PGPs impose, the model may find it optimal to reduce non-cost attributes over cost, for a particular set of PGPs. This could result in some hedged solutions being more expensive than naïve solutions for the same scenario (which cannot happen in a scenario without PGPs). However, the hedged solution would then have better performance in other attributes than the naïve solution.

This type of analysis enhances the multi-objective nature of the proposed methodology by including multiple objectives into the hedging process for future uncertainty. Aspects of uncertainty can be addressed in terms of multiple objectives rather than a single objective and therefore the entire generation process can be explored in a more holistic manner in relation to multiple objectives.

4.3.4.4. Expected value of perfect information

Another useful quantity to define is the expected value of perfect information (EVPI). This is useful for determining the worth of investing more time and money into reducing uncertainty. EVPI can be calculated by assuming that each of the possible futures under consideration occurs with certainty. Optimal solutions are then generated for each of the futures and the total costs (for the case of a single objective) are then weighted according to the probability of occurrence of each of the futures.

This value is then compared to the hedged solution and the difference is the EVPI. The relationship between the EVPI and the ECIU, and between the naïve, hedged and perfect information decisions are summarised in Table 4-1 below:

Table 4-1 Summary of relationships between ECIU, present information and EVPI

Information available when making stage 1 decision	**Naively assuming uncertainty**	**Present information**	**Perfect information**
Information on uncertainties	Ignored	Considered	Considered
Knowledge about which future will occur	No	No	Yes
Expected value of considering uncertainties or new information	← ECIU	●	EVPI →

Adapted from (Kim et al., 2003)

4.3.4.5. Uncertainties not directly addressed

Although fuel price and other data uncertainty (capital costs, O&M costs, emission coefficients, ect.) have not been directly addressed within this chapter they are addressed in chapter 5, which is dedicated specifically to the ranking and selection of preferred alternatives under data, fuel price and decision maker preference uncertainties.

Table 4-10 in Appendix A outlines some of the key parameters in the generation phase of this problem, where the data came from and how uncertainty in each of the parameters is typically handled.

The model could be adjusted to deal with uncertainty relating to technology change through endogenous technology learning (ETL), already a feature of some existing energy models (see for example MESSAGE (Messner, 1997), MARKAL (Seebregts et al., 2000), POLES (Kouvaritakis et al., 2000a; Kouvaritakis et al., 2000b), and ERIS (Barreto and Kypreos, 2004)).

While market liberalisation has not been directly addressed in this work, partial equilibrium frameworks provide results that are valid for both regulated, centrally planned power markets, as well as for efficient fully deregulated markets. The short term effects of market liberalisation may be better modelled using system dynamics, agent based modelling or game theory, where the interaction between firms in specific market environments are accounted for (see for example (Dyner and Larsen, 2001; Botterud, 2003). However, the current methodology and results would still be valid for centralized planning of a competitive market (e.g. from the perspective of a regulator).

Plant availability was modelled by derating each power station so as to limit the availability in all time periods to the availability factor (which is defined as (1-forced outage)*(1-planned outage)). The reserve margin is then used to ensure that sufficient capacity exists to meet demand in times of coinciding outages of different plants. The value of this parameter is typically settled exogenously by expert opinion based on the existing system and the modular sizes of the plants. While this is a common approach in practice, it is not ideal. More complex approaches such as the probabilistic forecasting of outages may yield a more accurate representation of the problem. Another approach based on probabilistic methods is presented in chapter 7.

4.4. Case study: The South African power sector

The case study used to illustrate the proposed methodology is the South African Electricity Supply Industry (ESI). South Africa currently has a state owned, regulated and centralized, mainly coal based generation portfolio (93 % of the 39716 MW_e installed capacity in 2002 (NER et al., 2004)) due to the abundance of "cheap" coal available. The transmission and distribution system is also run by the state utility Eskom. The country also has small amounts of nuclear (5 %) and pumped storage/hydro power (2 %). South Africa's base load coal power stations burn pulverized coal. Electrostatic precipitators are used for particulate removal, although bag filters are installed on a few stations. To date, there is no desulphurization technology installed on any plant (although, in some cases, some removal of pyritic sulphur occurs during coal beneficiation). Emission of nitrogen oxides is limited only through use of low-NOx burners. Due to the local water shortage problem in many of the areas where the power plants are located, advanced water saving technologies, which include dry cooling and dry ash disposal, have been developed which result in South Africa's newer coal stations being amongst the most water efficient in the world (Dutkiewicz and Gore, 1998). South Africa is now at a critical stage in its development, where it is necessary to decide on which power stations to build in the future to meet increasing demand. The problem is compounded by the age of many existing coal-fired stations as well as significant challenges relating to water availability and regional air quality.

4.4.1. The base case

The "base case" (hereafter called BASE) was set up to represent the South African ESI including the existing generating system and a range of viable future technologies to meet the growing demand. The starting point for the power station and the "moderate" demand data used in this chapter was the South African National Integrated Resource Plan (NIRP) of the National Electricity Regulator (NER et al., 2004). The NIRP data was used as a basis for this study, from which the methodology presented in section 4.3 could be demonstrated. It should be noted however that in future studies the baseline data could well be expanded. For example, though nuclear power station costs include estimates for decommissioning, a full life cycle representation of the nuclear cycle would be useful (together with an analysis and formal treatment of the uncertainties therein).

Electricity demand was assumed to be inelastic. In the case of South Africa, due in part to the low price of electricity (currently lowest in the world), price elasticities are very low (Pouris A. and Dutkiewicz, 1987) and (Dutkiewicz, 1994). The price of electricity in South Africa has historically been so low as to attract energy intensive industrial operations such as aluminium smelters. Evidence to support the low price elasticity of demand for electricity in the residential sector for developing countries was also found in India (Yoo et al., 2007) and the World Energy Outlook 2006 report (IEA, 2006). This said, this analysis could be extended to include detailed demand response if the electricity price were to increase significantly.

The base case also includes investments that are already committed to, such as the recommisioning of out-of-service coal stations and a pumped storage scheme, as well as demand side management (DSM) projects. Detailed technology and economic data as well as the assumptions[5] used for the case study were based on the NIRP. All data, assumptions as well as the full report can be downloaded from http://www.ner.org.za.

A basic description of each new technology considered in the NIRP is given below (more detailed descriptions for each technology can be found in NIRP appendix 3 (NER et al., 2004). A summary of the costs and performance data for these technologies is then listed in Table 4-2.

A Conventional pulverized fuel (PF) coal fired (CF) station

Taking the low cost of coal into account, producing electricity from a new coal fired power stations is relatively inexpensive compared to other technologies. This technology also has the advantage that fuel is mined locally and therefore security of supply is not considered a problem. The major disadvantages of coal fired stations are that they release high levels of CO_2 related emissions contributing to global warming, high levels of local pollutants such as SO_2 and NO_x, which have environmental and health impacts as well as significant amounts of solid waste. PF coal stations also have long lead times (8-12 years (NER et al., 2004)).

Nuclear stations

Advanced light water reactors (ALWRs) and the new pebble bed modular reactor (PBMR) were new nuclear options considered for South Africa in the NIRP. Nuclear power stations are currently slightly more expensive than coal stations. Nuclear technologies are global warming and local air pollution friendly due to the fact that they have zero emissions. Nuclear fuel is inexpensive to transport (due to the high energy density of the fuel) which allows for flexibility in site selection. This flexibility allows for the possibility of the sea water cooling and minimization of transmission losses. The PBMR sites can be upgraded as more capacity is needed. The key disadvantage of nuclear technologies is the issue of nuclear waste. As there are no authorized sites for the disposal of nuclear waste, all waste needs to be kept on site. Lead times are expected to be around 10 years.

[5] A conversion rate of R9/US$ was used as per the NIRP.

Gas turbines

Gas turbines can be separated into two types: Open cycle gas turbines (OCGTs) and combined cycle gas turbines (CCGTs). OCGTs can run on various fuels including paraffin, diesel and natural gas. These plants have relatively short lead times (4-6 years), low capital costs and high fuels costs and are therefore usually run as peaking plants. CCGTs are have longer lead times (6-8 years), higher capital cost than OCGTs but also have higher efficiencies and can therefore be run as baseload plants with the capability to follow load if necessary. Turbines running on natural gas have lower CO_2 and SO_2 related emissions than coal plants and therefore perform better in terms of global warming and local air pollution criteria. They are however more expensive than coal plants, and their fuel price is more volatile (based on international gas market trends) without definite local gas reserves. In South Africa the gas would either come from fields in Mozambique (Pande gas field – unproven capacity) or from imported liquefied natural gas (LNG).

Pumped storage (PS)

Pumped storage stations pump work as load shifting technologies by pumping water from a lower dam to a higher dam in times of excess electricity production and generate electricity during periods of peak demand by allowing water to flow from the higher dam back down to the lower one. Two new pumped storage schemes were considered in the NIRP, one that has already been commissioned and was therefore forced in the plan and another potential option. The lead times are expected to be around 9 years for a new pumped storage station (NER et al., 2004).

Fluidised bed combustion (FBC)

FBC boilers are capable of burning South Africa's low quality/low cost discard coal. As yet there are no FBC plants in South Africa. Although FBC may compete closely with CF stations in terms of cost, depending on the location of the plant, transport costs may dictate the economic viability of building an FBC station. The lead time for FBC is expected to be 8 years (NER et al., 2004).

Wind turbines

Wind turbines have the obvious advantage that they run on a renewable resource and fuel is free. The capital cost for wind turbines are still high (making them far more expensive than coal or nuclear) although it is believed that costs will continue to drop making them competitive in the future. Other disadvantages of wind technology include unpredictable generation due to natural wind variation (cannot be depended upon to meet peak demand) and small unit size (insufficient potential to meet large electricity demands). There are also environmental concerns with the construction of wind farms in pristine areas.

Solar thermal

The solar thermal plant considered in the NIRP was a solar parabolic trough (to be potentially built in Upington), which concentrated solar heat onto pipes containing a molten salt heat transfer fluid (HTF). Solar thermal, like wind power has the advantage of free fuel, but also has high investment costs. The station would also have zero gaseous pollutant emissions but due to the fact that the station would be built in a hot desert region, its water requirement for cooling would be relatively high.

Imported hydro

A new option to import hydro power from Mozambique was identified and included as a supply side option in the NIRP.

Demand side management (DSM)

Large potential still exists for reducing electricity demand through DSM. DSM measures include projects like solar water heating in the residential and commercial sector, load shifting, increased efficiency in industry and compact florescent lighting initiatives. These programs often have low or negligible costs when compared to building new generation capacity, as well as the obvious environmental benefits of reducing the need to produce electricity.

Other technologies

Other technologies identified by the Department of Minerals and Energy (2004) such as small, medium and large landfill gas technologies, as well as a range of hydro refurbishments and modifications were included in addition to the NIRP technologies.

Costs (investment and O&M) (see Table 4-2 below) as well as emission coefficients and specific water consumption coefficients were included for all technologies considered. Using the Inter-Governmental Panel on Climate Change (IPCC) characterization factors (IPCC, 2001) for direct global warming potential and the (Danish) Environmental Design of Industrial Products (EDIP) effect factors (Wenzel et al., 1997) for acidification potential , the emission coefficients were converted to CO_2 and SO_2 equivalents to represent the criteria of global climate change and regional acidification potential. The issue of water consumption was also chosen as a criterion due to its local relevance in South Africa. Note that costs and emissions were not accounted for on a life cycle basis (i.e. taking costs and emissions into account from "cradle to grave" or in this case from extraction of fuel (e.g. mining) to final disposal of spent fuel, including the entire production process and transport of fuel). Given that the goal of this chapter is to present a new methodology, this is not considered to be a limitation. However, where the goal would be to develop defensible plans for the South African ESI, the consideration of costs and emissions on a full life cycle basis is considered essential.

Table 4-2 Summary of cost and performance data for new supply side options (NIRP (NER, 2004))

	Type of Station	No of Units	Station size	unit size	Lifetime	Overnight Capital		PV Capital (10 %)	EPC Lead	Fixed O&M	Variable O&M	Fuel price	Efficiency (HHV)
			MWSO[6]	MWSO	Years	Rm	R/kW	R/kW	Years	R/kW/a	R/MWh		%
New Coal-Fired Plants												R/ton	
CF Dry + FGD	Non-peaking	6	3850	642	30	37723	9799	12324	4	125.28	7.51	60	34.59%
Pumped Storage													
Pumped Storage (Braamhoek public data)	Peaking	4	1330	333	40	4200	3158	5179	7	90.00	9.00		76.00%
Pumped Storage (generic)	Peaking	3	998	333	40	7182	7200	8857	7	90.00	9.00		76.00%
Gas Turbines												R/GJ	
CCGT (Without Trans benefits) pipe	Non-peaking	5	1935	387	25	9797	5063	5659	3.0	175.26	10.58	20	47.04%
CCGT (With Trans benefits) pipe	Non-peaking	5	1935	387	25		4405	4925	3.0	156.48	9.45	20	47.04%
CCGT (Without Trans benefits) LNG	Non-peaking	5	1935	387	25	9797	5063	5659	3.0	175.26	10.58	32	47.04%
CCGT (With Trans benefits) LNG	Non-peaking	5	1935	387	25		4405	4925	3.0	156.48	9.45	32	47.04%
GT-Open Cycle (kerosene)	Peaking	2	240	120	25	920	3833	3949	2.0	79.80	65.88	72	32.26%
GT-Open Cycle (LNG)	Peaking	2	240	120	25	920	3833	3949	2.0	79.80	65.88	32	32.26%
GT-Open Cycle (Local syngas)	Peaking	2	240	120	25	920	3833	3949	2.0	79.80	65.88	28	32.26%
GT-Open Cycle (LPG)	Peaking	2	240	120	25	920	3833	3949	2.0	79.80	65.88	56	32.26%
New FBC												R/ton	
Greenfield FBC	Non-peaking	2	466	233	30	4508	9669	11511	4.0	204.61	19.54	10	36.65%
Imports													
Imported hydro	Non-peaking	4	1200	300	30	17044	14203	19948	6.5	204.88	0.00	n/a	n/a
Renewables													
Solar Thermal	Peaking	3	300	100	30	10043	33477	34589	3.0	147.29	0.13	0	n/a
Wind	Peaking	20	20.00	1	20	154	7714	7768	2.0	167.02	0.00	0	n/a
Nuclear												R/MWh	
PBMR (1st MM incl. trans benefits)	Non-peaking	8	1320	165	40		16533	17340	4	157.65	6.75	45	40.54%
PBMR (1st MM excl. trans benefits)	Non-peaking	8	1320	165	40	24693	18707	19651	4	157.65	6.75	45	40.54%
PBMR (Series MM excl. trans benefits)	Non-peaking	8	1364	171	40	14678	10761	10853	4	161.20	6.75	45	44.50%
PWR (incl. trans benefits)	Non-peaking	2	1747	874	40	27944	15995	15139	4	507.22	0.00	45	31.48%
PWR (excl. trans benefits)	Non-peaking	2	1747	874	40	25389	14532	15290	4	507.22	0.00	45	31.48%

[6] MWSO – sent out capacity (after own use has been taken into account).

1 US$ = ± 7 ZAR at time of publication.

The base case was explored as a least cost optimisation exercise in MARKAL, over a time horizon of 20 years (matching the NIRP), and starting in 2002 (so as to include some historical data into the model). This timeline closely resembles that of the NIRP except it started a year earlier. An overall discount rate of 8 % (based on the NIRP) was used to discount future cash flow in the case study. This value was chosen in the NIRP to represent a private investor market in South Africa. However, in the light of sustainable development (i.e. not deferring our expenses to future generations); a lower discount rate could be used (see (Fisher and Krutilla, 1975; Markandya and Pearce, 1991) for discussions on the use of social discount rates for sustainable development), thereby favouring technologies with relatively higher capital cost to operating and maintenance cost components.

It must be noted that currently (in 2007); the NIRP assumptions are no longer valid due to updated demand projections, delayed investment decision changing circumstances. This being said, the data used in this thesis was deemed satisfactory for demonstrating the methodology developed here.

Figure 4-1 illustrates an investment summary for the base case scenario[7] over the time horizon:

[7] This solution set was generated using linear programming assuming all variables to be continuous rather than using mixed integer linear programming (MILP). The work done in chapter 7 extends this analysis such that investment would occur in technologically consistent blocks rather than continuously. This was not done at the time due to the inability to use stochastic programming and MILP simultaneously in MARKAL. This was NOT seen as a shortcoming in demonstrating the methodology presented here.

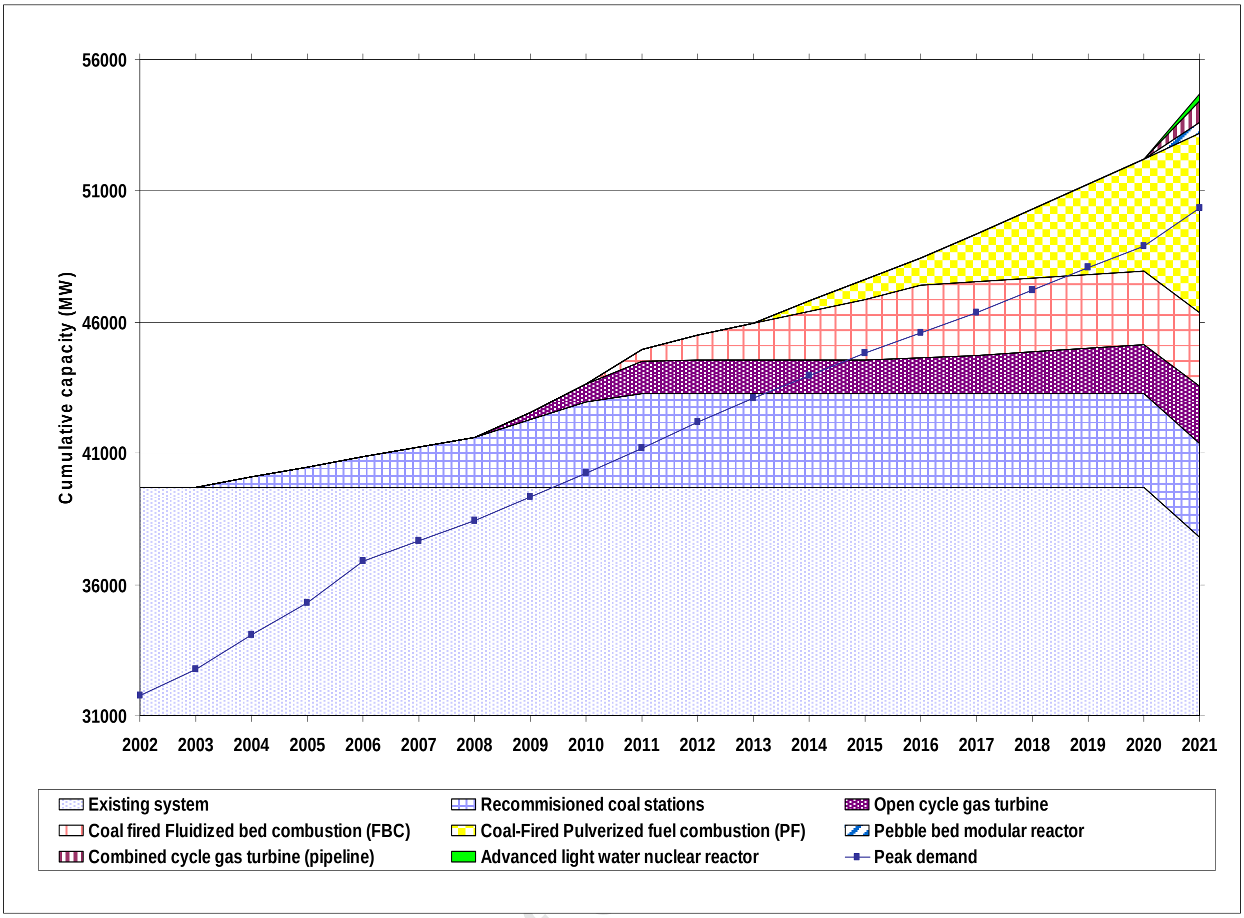

Figure 4-1 Technology capacity summary for BASE

It can be seen from Figure 4-1 above that most of the investment in new capacity in the base case scenario is in coal fired power stations (PF and FBC). There is also significant investment in open cycle gas turbines (as peak load stations) and a small investment into nuclear technologies and combined cycle gas turbines right at the end of the time horizon to replace the existing capacity that is assumed to be decommissioned in 2021. See NIRP appendix 3 (NER et al., 2004) for a description of each technology option.

4.4.2. EXTENDING THE SOLUTION SET TO CONSIDER MULTIPLE OBJECTIVES

Following the methodology outlined in Section 4.3, explicit consideration was given to global impacts such as climate change and regional impacts such as local air quality (due to this being a key focus in South Africa's high coal power station density region-Mpumalanga) and water consumption (due to national water shortages). This was done by introducing cost penalties on CO_2-eq emissions, SO_2-eq emissions and water consumption into the least cost model.

A range of five levels for each PGP was chosen to demonstrate a representation of the non-dominated solution space. Choosing five levels for each PGP would yield five solutions for each PGP, demonstrating the effect that each PGP individually has on the final solution (in terms of its attribute scores and build plans). The extreme value for each PGP was chosen such that a reduction of above 10 % from BASE was achieved in each of the corresponding attributes when the other PGP values were set to zero. When combining the permutations of the five levels for each PGP, 109 different solutions (including the BASE case) were generated. These solutions had a diverse range of technology configurations which resulted in reductions of up to 30 % in CO_2 equivalent emissions, up to 33 % in SO_2 equivalent emissions, and up to 48 % in water consumption. These increased reductions were due to the combined effect of using different PGPs simultaneously. These solutions spanned a cost range up to an increase of almost 100 % over the base case. Given this last figure, the range of alternatives generated by this method was deemed to be sufficient for subsequent analysis and demonstration of the methodology but would require screening to reduce the number of alternatives based on DM defined viability.

Table 4-3 PGPs used to generate unscreened solution set

	CO_2 equivalent emission coefficient (ZAR/ton)	SO_2 equivalent emissions coefficient (ZAR/ton)	Water consumption coefficient (ZAR/ton)
Initial value	137	23544	83
Level 1	0	0	0
Level 2	39	6661	16
Level 3	193	24424	47
Level 4	219	36636	73
Level 5	258	44407	83

To demonstrate how the non-cost attributes are considered in the model, the performance of one particular alternative (Alternative 11), which is considered in some detail in section 4.4.3 below, is examined here. Table 4-4 shows the performance of Alternative 11 against the “base case”.

Table 4-4 PGP values and attribute performance results the base case and ALT 11

PGPs values	**Base case**	**Alternative 11**	**Base case with tax**
CO_{2EQ} emissions (kZAR/kt)	0	0.00	0.00
SO_{2EQ} emissions (kZAR/kt)	0	24424	24424
Water consumption (kZAR/kt)	0	16	16
Performance			
Cost (kZAR)	2.621E+08	2.732E+08	2.621E+08
CO_{2EQ} emissions (kton)	2.658E+06	2.513E+06	2.658E+06
SO_{2EQ} emissions (kton)	1.564E+04	1.478E+04	1.564E+04
Water consumption (kton)	4.309E+06	4.073E+06	4.309E+06
Total cost including tax (ZAR)	2.621E+08	6.978E+08	7.114E+08

Alternative 11 was generated when a specific value of emission tax was introduced for SO_{2EQ} emissions and water consumption. Here, a tax of ZAR 24423.75/ton was defined using the **Tax(t,p)** parameter, to introduce a cost penalty on all SO_{2EQ} and a tax of ZAR 15.62/ton was defined using the **Tax(t,p)** parameter, to introduce a cost penalty on all water consumption in the model. If the investment and operational decision variables (***INV(r,t,k)***) and ***ACT(r,t,k,s)*** respectively*)* were to remain unchanged from their values in the base case, the overall system cost including tax would have become 7.114E+08 kZAR. However, as the objective function attempted to minimise overall system cost (including the cost penalties to capture environmental performance), investment into, and the operation of high SO_{2EQ} emission producing and water consuming technologies was reduced. This resulted in investment Alternative 11 (described in more detail in section 4.4.3), having a higher total discounted system cost (excluding taxes), but lower CO_{2EQ} and SO_{2EQ} emissions and water consumption values than those of the base case. This reduction in emissions resulted in Alternative 11 having a lower total system cost including taxes (6.978E+08) than the base case scenario with taxes included. This demonstrates how using PGPs forces the model's least-cost objective function to minimise emissions and therefore better satisfy non-cost objectives.

4.4.3. Screening of options for further analysis

The 105 solutions generated in this manner were then screened on financial performance assuming a hypothetical threshold of 20 % above base case total discounted system cost[8], which amounted to an increase in cost of over 50 billion ZAR (in 2004 terms) over the base case. The hypothetical threshold was chosen to demonstrate the proposed methodology for a reduced solution set containing a diverse range of attribute performances. The solutions could also have been screened at this stage on other user defined constraints or attribute performances.

The screening on total discounted system cost resulted in retention of the following set of alternatives, where their attribute performance values are shown relative to the base case (where minus signs denote a decrease from the base case). A summary of the short terms investment strategies for each of these alternatives can be found in Appendix A as well as detailed investment strategies in Appendix E (on CD).

[8] Note: Total discounted system cost is the true cost and does not include the attribute cost penalties.

Table 4-5 Attribute performance ranges for screened solution set

Alternative	Cost	CO_2-eq	SO_2-eq	Water Consumption
BASE	0.00%	0.00%	0.00%	0.00%
ALT 1	0.19%	0.72%	0.61%	-9.13%
ALT 2	0.35%	-0.25%	0.10%	-8.71%
ALT 3	0.35%	-3.73%	-1.96%	9.75%
ALT 4	0.36%	0.76%	-0.14%	-9.18%
ALT 5	1.05%	0.40%	1.13%	-10.71%
ALT 6	1.07%	0.27%	-0.29%	-10.24%
ALT 7	1.41%	-0.17%	0.80%	-10.99%
ALT 8	1.52%	-4.21%	-2.80%	-4.60%
ALT 9	2.29%	-1.49%	-1.80%	-10.49%
ALT 10	2.99%	-6.39%	-3.98%	9.62%
ALT 11	4.21%	-5.47%	-5.52%	-5.48%
ALT 12	5.37%	0.04%	1.22%	-14.82%
ALT 13	5.83%	-1.41%	0.33%	-14.83%
ALT 14	6.17%	-7.38%	-3.93%	-6.66%
ALT 15	6.43%	-7.01%	-6.76%	-5.88%
ALT 16	6.98%	-8.27%	-5.74%	8.83%
ALT 17	7.60%	0.26%	-0.61%	-16.32%
ALT 18	8.87%	0.04%	0.48%	-17.54%
ALT 19	13.03%	-9.65%	-9.56%	-9.62%
ALT 20	13.77%	-10.29%	-9.11%	-10.10%
ALT 21	14.84%	-10.66%	-9.48%	-10.66%
ALT 22	15.07%	-10.45%	-10.32%	-10.72%
ALT 23	15.63%	-10.61%	-10.60%	-10.16%
ALT 24	17.00%	-11.49%	-8.58%	-12.46%

The new solution set shown above in Table 4-5 contains the base case and the remaining non-dominated alternatives after screening. It can be seen from Table 4-5 above that as the cost of each alternative increases, performance in the non-cost attributes generally improve. It must be noted however that not all of the non-cost attribute performance values correlate directly with increasing cost. Due to a degree of compensation between performances in the various non-cost criteria, it is not necessary that improvements in all the non-cost attributes occur simultaneously with increasing cost. Reductions in emissions and water consumption are mainly due to increased investment in “cleaner” technologies such as nuclear and gas, as illustrated for Alternative 11 in Figure 4-2, whereas the base case mainly invested in coal based generation (see Figure 4-1).

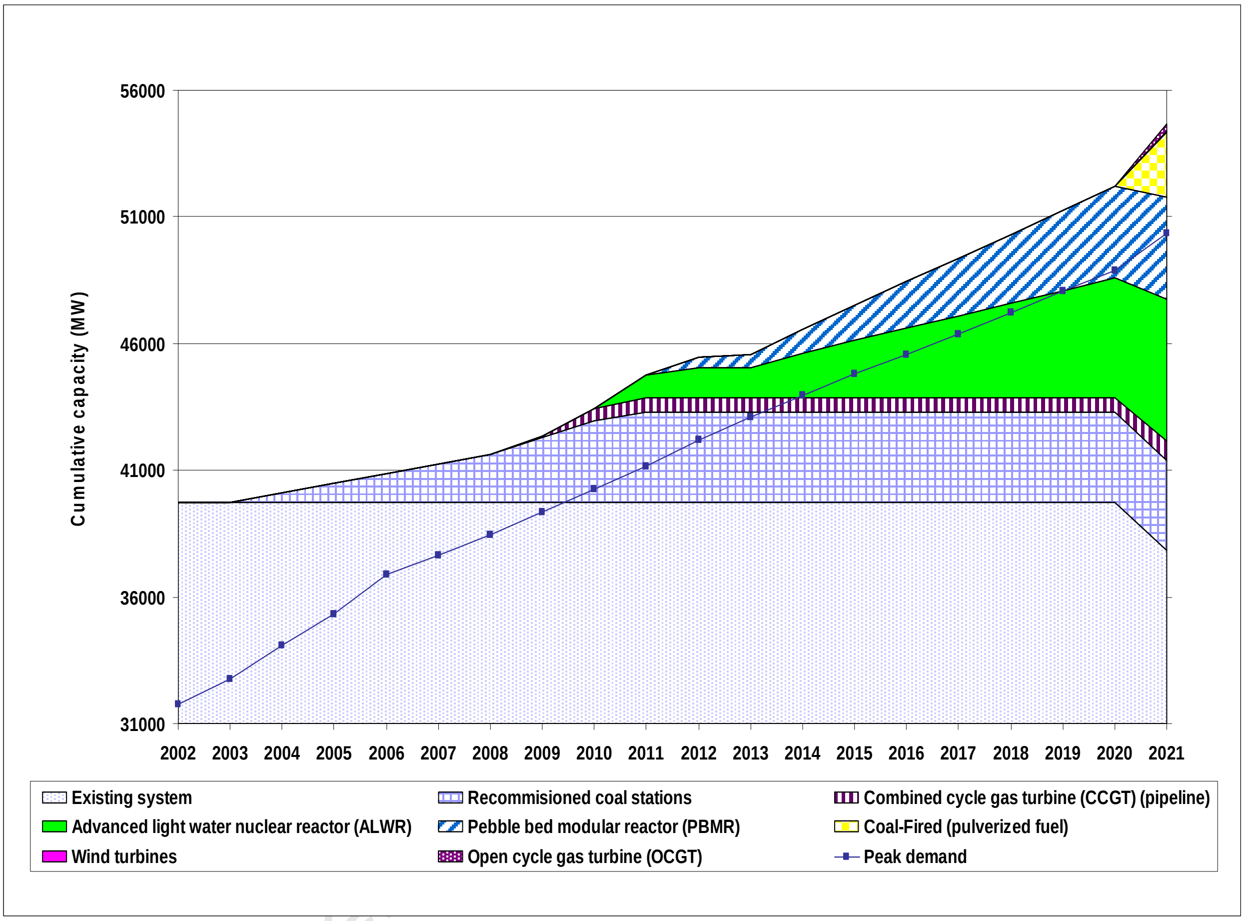

Figure 4-2 Technology capacity summary for Alternative 11

As can be seen from Figure 4-2, Alternative 11 invests in significant amounts of nuclear power[9]. There are also small investments in open cycle gas turbines and wind power at the end of the time horizon. This results in the decrease of over 5 % in CO_2-eq and SO_2-eq emissions as well as a decrease in water consumption of over 5 %. These environmental improvements compared to the base case can be gained at an increase in cost of less than 4.5 %.

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[9] The cost of decommissioning nuclear power stations was included into the investment cost of the power stations although the environmental effects of spent nuclear fuel were not quantified, nor were they listed as specific decision criteria. Where the intent is to generate defensible plans for the South African ESI, the consideration of a more comprehensive set of impacts, including those associated with waste management for the different kinds of technologies, is considered essential.

The solution set thus contains alternatives with varying technology mixes which result in a diverse range of attribute performance values. Each solution represents a different trade-off between the various objectives that would have to be evaluated by the policy makers. The selection of a preferred solution will not be elaborated upon in this chapter, but forms the second phase of the proposed methodology which is described in detail in chapter 5.

4.4.4. Modelling for future uncertainty in demand growth

Now that a methodology to better satisfy multiple environmental objectives has been demonstrated in section 4.4.2 and 4.4.3, the issue of uncertainty needs to be addressed within a multi-objective framework. This will be done using stochastic programming with recourse (as described in section 4.3.4) to include flexibility to uncertainty in demand growth. Other uncertain parameters such as technology costs, fuel prices and emission coefficients are dealt with using other methodologies (see chapter 5 and 6), due to the increased model complexity and computational burden of dealing with these parameters using stochastic programming with recourse (refer back to section 2.3 for discussion).

The deterministic model was adjusted to a two-stage stochastic model by allowing different demand futures to unfold. The futures were split after the decision node to represent the low, medium and high demand forecasts published in the NIRP (NER et al., 2004). The growth rates for these forecasts are presented in Table 4-6.

Table 4-6 Demand scenarios for various futures from NIRP (NER et al., 2004)

Demand Scenario	% growth per annum		
	L	M	H
2002-2008	1.6%	3.2%	4.3%
2008-2013	1.0%	2.3%	3.1%
2013-2021	0.9%	1.8%	2.6%

As a demonstration of the methodology, the decision node was positioned early in the time horizon (2009) to address the possibility of demand growth uncertainty as soon as possible, but to also allow time for the model to hedge for demand growth risk given the technology lead times involved. Investments for major new technologies were split into their Owners' Development Cost (ODC) and Equipment and Procurement Cost (EPC) components to account for technology lead times, and to include an element of real options theory into the analysis. The timing of the decision node is itself a variable, whose influence could be explored via a parametric sensitivity study. This is not undertaken here.

Two versions of the stochastic model were run: one to yield the "naïve" solution and the other to yield the "hedged" solution. In the "naïve" model, the medium demand scenario was given a 99.8 % probability of occurrence so that no hedging would be done for the alternate demand futures (see section 4.4.3). In the hedged model, each demand profile was given an equal probability of occurrence [10] to explore the possible hedging that could be done for demand growth uncertainty. The reduced set of scenarios used previously to generate the deterministic solutions (which included PGPs to better satisfy multiple objectives) were then rerun in a stochastic version of the model to generate the naïve and hedged stochastic solutions. The alternatives' numbers used for the stochastic model runs correspond to the sets of PGPs used previously in the deterministic model runs.

The hedged solution was then compared to the naïve solution for each alternative to calculate the Expected Cost of Ignoring Uncertainty (ECIU) under all attributes. The results are shown in Table 4-7 which indicates the difference between the naïve and

[10] Sensitivity analyses can be done on the probabilities assigned to each state of the world, in order to determine the effect that the probabilities have on the solutions. This is not illustrated here, but would be important to do to generate defensible plans.

hedged solutions. Positive values indicate that the hedged solution had lower values (i.e. costs, CO_2-eq emissions, SO_2-eq emissions or water consumption) than the naïve solution hence indicating a positive penalty for ignoring uncertainty.

Table 4-7 Expected cost of ignoring uncertainty for each attribute

Alternative	**Cost Difference**	**CO_2-eq Difference**	**SO_2-eq Difference**	**Water Consumption Difference**
	Million ZAR	Million ton	Thousand ton	Million ton
BASE	1400	-4	-15	10
ALT 1	1400	-4	-15	11
ALT 2	1400	-4	-4	13
ALT 3	-900	3	34	37
ALT 4	-400	2	24	24
ALT 5	600	1	10	15
ALT 6	700	0	-16	9
ALT 7	1800	-3	-16	8
ALT 8	1500	-5	-21	10
ALT 9	-100	8	-20	38
ALT 10	800	3	-104	35
ALT 11	-200	-6	-3	32
ALT 12	1400	-4	-41	16
ALT 13	1900	-5	-14	6
ALT 14	1500	-5	-15	14
ALT 15	2600	-9	-30	16
ALT 16	-900	3	34	28
ALT 17	2000	-6	-28	7
ALT 18	-1600	14	23	24
ALT 19	-500	4	34	31
ALT 20	2300	-14	19	3
ALT 21	1900	1	-6	19
ALT 22	2600	-17	-12	13
ALT 23	-200	8	-80	46
ALT 24	-2400	17	-125	89

It can be seen in Table 4-7 above that the ECIU can be either positive or negative for any of the attributes individually; however no naïve solution ever outperforms the hedged solution in all attributes simultaneously. This occurs because the model is attempting to hedge for multiple objectives and there is compensation occurring in the hedging process between the performances in the different criteria. This compensation is directly affected by the values of the PGPs as they inform the extent to which each attribute is contributing to the overall value of the objective function (i.e. overall discounted system cost). Therefore, for a given set of PGPs, the model may find it optimal to reduce one attribute at the expense of another as long as the overall objective function is minimized in the process. It can therefore be said that the hedging process is consistent with the overall multi-objective framework as it too is informed by the value of the PGPs to the extent to which the non-cost objectives should be considered in the optimisation.

To illustrate what hedging for demand growth uncertainty may imply for technology selection, the investments in Pebble bed modular reactor (PBMR) and Combined cycle gas turbine (CCGT) technologies for Alternative 11 for the hedged and naïve stochastic demand scenarios are compared in Table 4-8 and Table 4-9.

Table 4-8 Excerpt from investment summary for hedged stochastic solution for Alternative 11

	Hedged solution (MW)						
	Pebble bed modular reactor			**Combined cycle gas turbine (LNG)**			
Demand scenario	Low	Medium	High	Low	Medium	High	
2002	-	-	-	-	-	-	
2003	-	-	-	-	-	-	
2004	-	-	-	-	-	-	
2005	-	-	-	-	-	-	Phase 1 ODC
2006	-	-	-	-	-	-	
2007	-	-	-	-	-	-	
2008	3080	3080	3080	9500	9500	9500	
2009	0	0	0	0	0	767	
2010	0	0	0	0	0	0	
2011	0	0	0	0	0	427	
2012	0	440	440	0	0	0	
2013	0	440	440	0	0	0	
2014	0	440	440	0	0	0	
2015	0	440	440	0	0	835	Phase 2 EPC
2016	0	440	440	0	0	778	
2017	0	440	440	0	0	796	
2018	0	440	440	0	0	827	
2019	0	0	0	0	705	1515	
2020	0	0	0	0	1325	1626	
2021	440	0	0	0	1935	1935	
Total	**440**	**3080**	**3080**	**0**	**3960**	**9500**	

Table 4-9 Excerpt from investment summary for naive stochastic solution for Alternative 11

	Naive solution (MW)						
	Pebble bed modular reactor			Combined cycle gas turbine (LNG)			
Demand scenario	Low	Medium	High	Low	Medium	High	
2002	-	-	-	-	-	-	Phase 1 ODC
2003	-	-	-	-	-	-	
2004	-	-	-	-	-	-	
2005	-	-	-	-	-	-	
2006	-	-	-	-	-	-	
2007	-	-	-	-	-	-	
2008	3960	3960	3960	4175	4175	4175	
2009	0	0	0	0	0	738	Phase 2 EPC
2010	0	0	0	0	0	261	
2011	0	0	0	0	0	427	
2012	0	440	440	0	0	203	
2013	0	440	440	0	0	220	
2014	0	440	440	0	0	803	
2015	0	440	440	0	0	745	
2016	0	440	440	0	0	752	
2017	0	440	440	0	0	26	
2018	0	440	440	0	0	0	
2019	0	440	440	0	305	0	
2020	0	0	440	0	1935	0	
2021	440	440	0	0	1935	0	
Total	**440**	**3960**	**3960**	**0**	**4175**	**4175**	

It can be seen that the hedged solution invests in more CCGT and less PBMR before the decision node in 2009 than the naïve solution. This is due to the fact that, when ignoring uncertainty, and therefore assuming that all ODC investments will lead to EPC investments, it is cheaper to invest in PBMR than in CCGT, within the limits of information currently available on PBMR. However, when demand uncertainty is taken into account, and it is no longer assumed that all ODC investments will be followed by EPC investments, it becomes cheaper to invest in more CCGT initially (getting it "investment ready") to hedge against uncertain demand profiles because of the far lower ODC component of the CCGT investment compared to PBMR. This initially increased investment allows for investment in larger amounts of CCGT after the decision node in the hedged solution, whereas the naïve solution is limited to building less CCGT. This contributes to the hedged solution being cheaper than the naïve solution as well as having lower water consumption levels as can be seen in Table 4-7 above. It does however also contribute to the hedged solution having higher CO_2-eq and SO_2-eq emissions due to the increase use of gas instead of nuclear power. It must be noted however that the hedged solution for Alternative 11 still resulted in an increase in total discounted system cost of 4.21 % relative to the **base case**[11], and a decrease in CO_2-eq emissions of 5.47 %, a decrease in SO_2-eq emissions of 5.52 % and a decrease in water consumption of 5.48 % all relative to the **base case**.

As an example, retrospective analysis of Alternative 11 yields PGP values of 0 ZAR/ton CO_2-eq, 24423.75 ZAR/ton SO_2-eq and 15.62 ZAR/ton H_2O. The PGP values could simply be translated into equivalent (and appropriate) taxes. For example, a water tax in this case would be 15.62 ZAR/ton water consumed. Equally this could be expressed in terms of a tax per unit of electricity generated by station type (e.g. 0.28 c/kWh for a new coal fired station for this system). With these taxes in place, the preferred solution for the market represented by this model would be Alternative 11. Conversely, if Alternative 11 was the preferred solution, then these would be the taxes necessary to achieve this solution in an efficient market.

Including PGPs into a stochastic programming model with recourse and splitting investments into their ODC and EPC components thus yields solutions that improve on the corresponding **naïve solutions** on the basis of multiple objectives defined by the PGPs while still better satisfying the non-cost objectives relative to the **base case** scenario.

4.5. Conclusions

This chapter has demonstrated that a partial equilibrium[12] optimisation framework can be extended to include multiple environmental objectives through the addition of

[11] The base case referred to in this section is the least cost solution (no PGPs) using the hedging model.
[12] Demand was assumed to be inelastic in the case study.

Pareto Generation Parameters (PGPs) introduced into the optimisation in the form of cost penalties. This forces the optimisation routine to find solutions that attempt to satisfy multiple objectives. It is an efficient method for extending the analysis to multiple objectives as the solutions generated are non-dominated and are generated from ranges of performances in the various criteria rather than from arbitrarily forcing the selection of particular technologies. Extensive sections of the non-dominated solution space can be generated and later screened to allow further, more detailed exploration of areas of the solution space.

This chapter has also demonstrated that this analysis can be extended to include uncertainty in demand growth through stochastic programming with recourse. By splitting new power station investments into owner's development costs and equipment procurement and construction phases, the concept of technology lead times can be accounted for in light of a decision node in the time horizon and an element of real options theory can be included into the model. The model can now invest into the ODC component of a technology (if it is optimal) and then "wait and see" how uncertainty unfolds before deciding whether to invest into the EPC component of that technology. This allows the model more freedom to hedge for demand growth uncertainty. The hedging that is done in the recourse programming is automatically translated from purely financial to include whatever attributes the PGPs represent, due to the cost penalties that the PGPs impose on the solutions. The hedged solutions improve on the naïve solutions under the multiple objectives considered as well as better satisfy the non-cost objectives relative to the base case.

The methodology provides a framework for modellers to generate a solution set for the power expansion problem that represents a range of solutions that each satisfies multiple objectives to a varying extent. The solutions also have built-in flexibility to demand growth uncertainty. The set of solutions generated in this manner can be used as part of a transparent decision making process in which policy maker preferences can ultimately inform the selection of a preferred solution. This approach has the benefit of allowing the policy makers to make a choice knowing the consequences of their decision relative to the other alternatives with regard to the predefined objectives. This method is also more transparent than other preference articulation methods and easily understandable to stakeholders outside of the decision process and therefore creates a situation where the DM is more accountable for his choices. They also give policy makers an indication of the appropriate market signals necessary to influence the market towards a preferred state. This would be done retrospectively from the preferred solutions, through an analysis of the PGP values used to generate those solutions.

4.5. APPENDIX A

Table 4-10 Parameter Uncertainty information relating to options generation

Parameter	Data representation
Non technology specific parameters	
Reserve margin	Decided by NIRP advisory review committee
Discount rate	Decided by NIRP advisory review committee
Time horizon	Decided by NIRP advisory review committee
Emission equivalent conversion factors	Inter-Governmental Panel on Climate Change (IPCC) characterization factors (IPCC, 2001) for the direct global warming potential and the (Danish) Environmental Design of Industrial Products (EDIP) effect factors (Wenzel et al., 1997) for acidification potential
Demand shape	Based on NIRP data
Demand forecast	Taken from NIRP data for low, median and high demand values
Demand probabilities	Modeller defined values
Demand uncertainty resolution date	Modeller defined
Standard technology parameters that go into options generator	
Investment cost	Adjusted mean value taken from NIRP literature survey on international values. Values were adjusted to represent South African conditions in NIRP
Generation costs (O&M)	Adjusted mean value taken from NIRP literature survey on international values. Values were adjusted to represent South African conditions in NIRP
Emission coefficients	Adjusted mean value taken from NIRP literature survey on international values. Values were adjusted to represent South African conditions in NIRP
Availability Factor	Decided by NIRP advisory review committee (based on World Energy Council best quartile results 2003)
Thermal efficiency	Adjusted mean value taken from NIRP literature survey on international values
Fuel cost	Values taken from NIRP
Plant lead times	Values taken from NIRP
Plant lifetime	Values taken from NIRP
Pareto generation parameters	Case study relevant and stakeholder/modeller defined range chosen
Station type (peaking, mid-merit, base load)	Taken from NIRP
Annual investment limit	Values taken from NIRP
Total investment limit	Values taken from NIRP

MARKAL stochastic programming with recourse formulation:

Minimize $$Z = \sum_{w \in W(t)} \sum_{t \in T} C_{t,w} \bullet X_{t,w} \bullet p_{t,w} \qquad (3)$$

subject to: $$A_{t,w} \bullet X_{t,w} \geq b_{t,w}, \ \forall t \in T, \forall w \in W(t)$$

where: t = time period

T = set of time periods

t^* = resolution time

w = outcome index (state of the world)

$W(t)$ = set of outcome indices for time period t. For all t prior to resolution time t^*, $W(t)$ has a single element (stage one). For $t \geq t^*$, $W(t)$ has multiple elements (stage two);

$X_{t,w}$ = the column vector of decision variables in period t, under scenario w

$C_{t,w}$ = the cost row vector in time t under scenario w;

$p_{t,w}$ = probability of scenario w in period t; $p_{t,w}$ is equal to 1 for all t prior to t^*, and $\sum_{w \in W(t)} p_{t,w} = 1$ for all t.

$A_{t,w}$ = the coefficient matrix (single period constraints) in time period t, under scenario w

$b_{t,w}$ = the right-hand-side column vector in time period t, under scenario w

Table 4-11 New short term capacity investment (in MW) in selected technologies for all alternatives[13]

	Coal (pf)	Nuclear (ALWR)	Nuclear (PBMR)	OCGT	Pumped storage	FBC	CCGT (pipe)	CCGT (LNG)	Wind1	Wind2	Wind3	Small landfill gas	Medium landfill gas	Large landfill gas	Hydro modifications and refurbishments
BASE	5740	0	440	1728	272	2796	774	5946	450	100	50	18	21	4	1555
ALT1	5756	0	440	1820	143	2796	774	5909	450	100	50	18	21	4	1513
ALT2	5532	0	440	1719	0	2796	774	6287	538	100	50	18	21	4	1498
ALT3	4728	113	440	1561	256	2796	774	6807	596	100	50	18	21	4	1685
ALT4	4732	108	440	1561	0	2796	774	6945	714	100	50	18	21	4	1603
ALT5	4967	0	440	1562	107	2796	774	7267	706	100	50	18	21	4	1218
ALT6	5936	0	440	1721	4	2796	774	6294	572	100	50	18	21	4	1206
ALT7	4157	20	1190	1576	0	2796	774	7388	612	100	50	18	21	4	1285
ALT8	2472	171	2640	1471	0	2796	774	7128	619	100	50	18	21	4	1610
ALT9	2117	664	2640	992	363	2796	774	7690	1150	100	50	18	21	4	1182
ALT10	0	1398	3520	807	224	2796	774	7340	1235	100	50	18	21	4	1729
ALT11	1441	1555	3080	1273	0	0	774	9500	565	100	50	18	21	4	1611
ALT12	7566	0	440	1576	507	2796	774	5591	700	100	50	18	21	4	724
ALT13	4208	20	2200	665	955	2796	774	7632	700	100	50	18	21	4	739
ALT14	0	2064	3520	665	583	2796	774	7108	1233	100	50	18	21	4	1442
ALT15	0	2493	3520	884	0	0	774	9654	987	100	50	18	21	4	1551
ALT16	0	2086	3520	665	562	2796	774	6593	1446	100	50	18	21	4	1645
ALT17	7457	0	440	665	998	2796	774	6012	809	100	50	18	21	4	720
ALT18	7704	0	440	1114	938	2796	774	5535	651	100	50	18	21	4	720
ALT19	0	3496	3520	0	998	0	774	9932	1140	100	50	18	21	4	938
ALT20	0	5244	3520	0	483	1359	774	6038	1500	100	50	18	21	4	1180
ALT21	0	6118	3520	0	998	1359	774	5919	1156	100	50	18	21	4	894
ALT22	0	5244	3520	0	998	0	774	8365	1050	100	50	18	21	4	845
ALT23	0	5456	3520	0	998	0	774	8503	700	100	50	18	21	4	782
ALT24	0	6992	3960	0	998	1825	774	4352	1050	100	50	18	21	4	710

[13] This solution set was generated using linear programming assuming all variables to be continuous rather than using mixed integer linear programming. Chapter 7 extends this analysis such that investment would occur in technologically consistent blocks rather than continuously.

4.6. References

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CHAPTER 5 RANKING AND SELECTION OF POWER EXPANSION ALTERNATIVES FOR MULTIPLE OBJECTIVES UNDER UNCERTAINTY

5.1. INTRODUCTION

Investment decisions in the electricity supply industry (ESI) are influenced by a number of factors including cost, environmental performance and social acceptability. Global environmental issues such as climate change as well as local issues like acidification and water shortages have forced planners and policy makers to revaluate the role of conventional coal fired power stations, and to examine the possibilities of transition fuels such as natural gas as well as nuclear and renewable options. With cost no longer being the only criterion for evaluating the performance of Future Expansion Alternatives (FEAs), the modelling of ESI alternatives has become increasingly complex and the selection of FEAs has become more challenging in light of multiple decision criteria and uncertainty in both valuation arguments and empirical data.

Once a set of FEAs have been generated that satisfy multiple objectives to varying degrees and have built in flexibility towards demand growth uncertainty (as described in chapter 4), the next phase in the process is the selection phase where one or more FEAs are isolated from the solution set created in the generation phase based on DM preferences. This process needs to account for the multiple objectives of the DM as well as the robustness of the alternatives selected to the uncertainties involved. A structured framework needs to be developed to integrate the multi-attribute information from the generation phase for each of the alternatives, such that a set of preferred alternatives can be isolated based on DM preferences. These alternatives can then go to a final detailed analysis so that a single preferred solution can be identified. See Figure 5-1 below for a graphical representation of this approach.

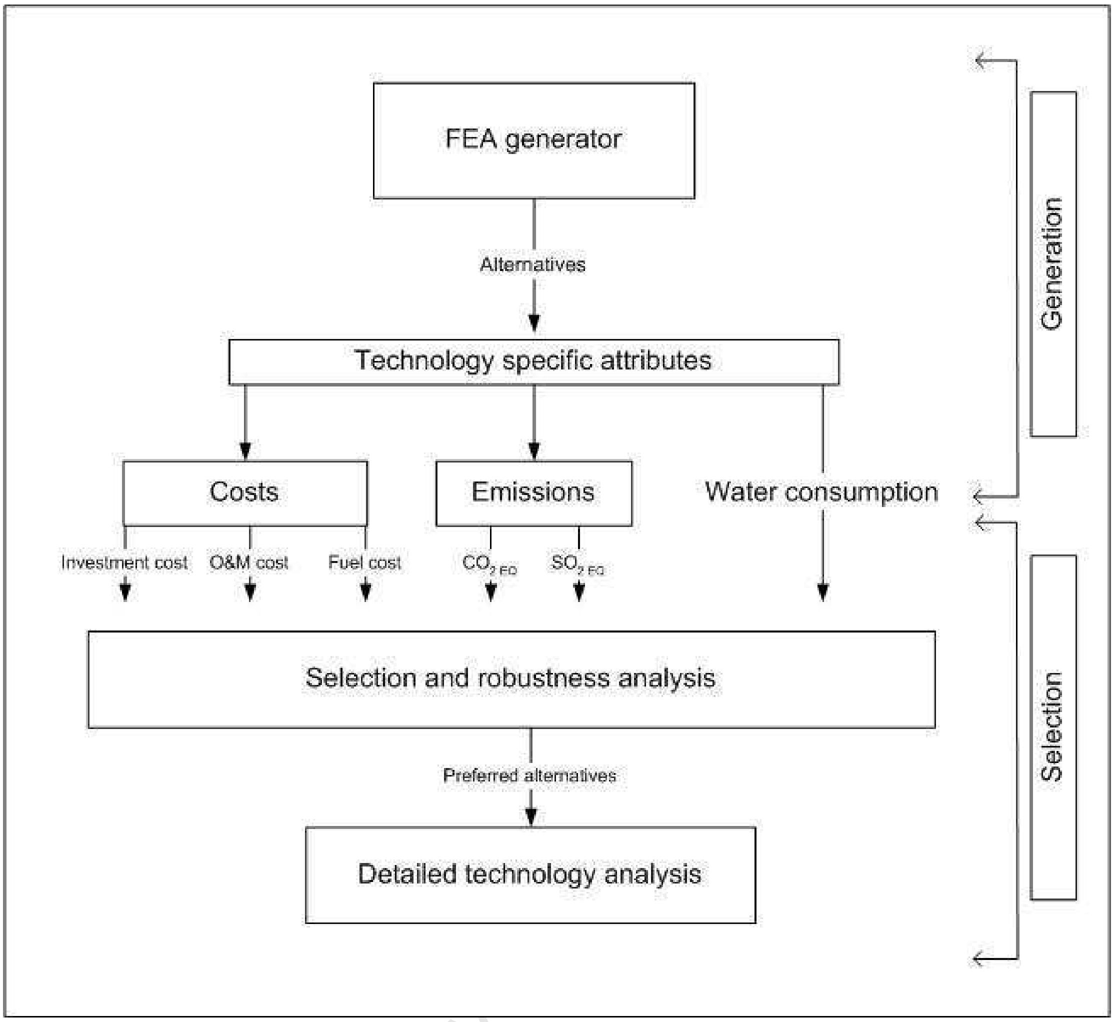

Figure 5-1 Flow diagram for generation and selection of FEAs

The objective of this chapter is to outline and demonstrate a methodology, using the South African ESI, for ranking FEAs based on multiple objectives representing stakeholder or policy maker preferences as well as to address aspects of uncertainty in data, fuel price and preference arguments. It then goes on to isolate a portfolio of preferred alternatives based on performance and confidence criteria. The scope of this chapter is limited to the selection process, although it will build on the work which considered the generation phase under demand uncertainty in chapter 4.

5.2. BACKGROUND

5.2.1. ESI MODELLING FOR MULTIPLE OBJECTIVES UNDER UNCERTAINTY

Few methodologies have been developed for the generation of power expansion alternatives that consider multiple objectives and uncertainty simultaneously. There has however been work done on extending the generation of power expansion alternatives to include multiple objectives through methods such as compromise programming (e.g. Linares and Romero, 2000; Antunes et al., 2004; Martins et al., 2004), scenario analysis (Connors et al., 2003), constraint methods in the form of emission caps (Manne and Richels, 1997; van der Zwaan et al., 2002; Cormio et al., 2003) and cost penalty based approaches (Hobbs et al., 1994; Koroneos et al., 2004; Heinrich et al., 2007).

Chapter 4 described a methodology for generating a representation of the Pareto optimal surface for energy planning problems, using energy modelling software such as MARKAL[1], EGEAS[2] and MESSAGE[3]. Demand growth uncertainty was integrated into the generation of alternative expansion alternatives through the use of two-stage stochastic programming with recourse (Dantzig, 1963). This resulted in a solution set representing alternatives that were flexible to demand growth uncertainty and better satisfied multiple objectives representing stakeholder or policy maker preferences compared to the optimal least cost solution. The logical extension of this work was to develop a methodology for identifying an alternative from the non-dominated solution set and to demonstrate an approach for dealing with some of the key uncertainties inherent in this process.

The set of alternatives generated in chapter 4 ranged from the least cost solution (the "BASE" case) to solutions that performed significantly better (generally greater than 10 % improvement over the BASE case) in selected non-cost criteria (being CO_{2EQ} emissions, SO_{2EQ} emissions and water consumption). These criteria were chosen in chapter 4 to give explicit consideration to global impacts such as climate change and regional impacts such as local air quality (due to South Africa's high coal plant density region (Mpumalanga)) and water consumption (due to national water shortages). See Table 4-11 in chapter 4 appendix A and Table 5-8 in the appendix B

[1] MARKAL (MARKet AnaLysis) developed by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency, http://www.etsap.org.
[2] EGEAS (Electric Generation Expansion Analysis System) developed by the Electric Power Research Institute (EPRI), http://www.epri.com.
[3] MESSAGE (Model for Energy Supply Systems Analysis and their General Environmental impact) developed by the International Institute for Applied Systems Analysis (IIASA), http://www.iiasa.ac.at/Research/ECS/docs/models.html#MESSAGE.

for detailed short term investment strategies and mean partial value score [4] results respectively.

5.3. APPROACH AND DEMONSTRATION

The approach taken here couples a sensitivity/robustness analysis to assess the effects of technical and model parameter uncertainties on the performance of FEAs, with an MCDA approach to rank the alternatives and select preferred alternatives from the ESI option set, given multiple objectives and uncertainty in valuation model parameters (such as inter-criterion preferences).

The existing South African electricity supply system was modelled taking into account the actual technologies currently being used and their technical constraints (availabilities, resource limitations etc.). The new technologies considered (including renewable resources and intermediate technologies such as gas turbines) were based on the NIRP (NER et al., 2004) (see Table 4-2 in chapter 4). The methodology used to generate the FEAs as well as the South African ESI was discussed in more detail in chapter 4.

The starting point for this chapter is the consideration of some of the key technical empirical uncertainties which impact on the attribute performance scores of the technology investment alternatives from the generation phase in chapter 4. These investment alternatives differed in the technologies used (see Table 4-11 in chapter 4 appendix A for the short term investment strategies for each alternative). Non-cost objectives were satisfied to varying degrees in the solution set, which gave technology mixes ranging from the least-cost solution which invested mainly in coal based technologies to the alternatives which invested in mainly nuclear and gas options. Empirical uncertainties are propagated through the ESI model by sampling their representative probability distributions. The input parameters that were sampled were investment costs, operating and maintenance (O&M) costs, fuel costs and emission values for each technology which contributes to a given investment alternative. At this point it is possible to build model "scenarios" for each alternative from the sampled sets of uncertain parameters. In effect, this generates a range of performances for each

[4] Partial value scores are attribute performance scores that have been normalised onto a commensurate scale (typically 0-1) – refer back to section 2.2.2.1for discussion on partial value scores.

of the non-dominated alternatives in the original list. Using an appropriate MADA technique, it is then possible to construct a preference model across all possible outcomes (generated from the sampled distributions of input parameters) and thus compare the performance of each alternative in whatever number of decision objectives were identified during the problem structuring phase of the decision analysis.

This methodology differs from scenario planning in that a comprehensive range of values is explored for each of the uncertain parameters (similar to a classic sensitivity analysis) whereas in scenario planning a limited number (usually less than four (Stewart, 2005)) scenarios are constructed to analyse likely or relevant projections of the future. This method also differs from a standard sensitivity analysis in that the build plans of the alternatives are fixed in the options generator so as to effectively test the robustness of each alternative rather than allowing the model to generate new alternatives for the changing conditions. This methodology is therefore focused on assessing the robustness of each alternative rather than identifying the sensitivity of outputs to input variable uncertainty (as discussed in section 2.5). It must be noted though that this methodology does not build in flexibility towards these uncertainties into each FEA (as using a method such as stochastic programming would). The focus of this methodology is to provide policy makers with a set of FEAs that span a range of performances in the multiple objectives they are interested in and then to guide them through the selection process, given their uncertain preferences and the technical empirical parameter uncertainties inherent in the process. Therefore, although using stochastic programming to build flexibility towards uncertainty would be the most comprehensive approach available, it is not practical for the current situation where the focus is on developing a transparent decision methodology for multiple objectives given uncertainty in all of the technical empirical uncertainties considered here.

Were this approach to use fixed build plans but still allow the model to reoptimise each alternative in terms of operational parameters (power station load factors), a large number of model runs would be required to cover the full data space of uncertain parameters. Each sampled set of the uncertain parameters would need to be run in the options generator for the fixed build plans representing each of the alternatives. Large amounts of data would be generated which would pose additional challenges to data management in further analysis. It is proposed that instead, technical empirical uncertainties can be propagated through a static model, yielding the likely attribute performance ranges for each of the previously optimised FEAs.

Caveats

One of the potential limitations of this approach is that the operational characteristics of the system are not reoptimised for each discrete future scenario (defined by a sample of the uncertainties involved) as would be the case in an actual ESI situation. If the operational characteristics of the system were optimised for each discrete future scenario, the load factors for individual power stations would be reoptimised (within technical and contractual constraints) so as to best meet the overall system objectives given each discrete future scenario even though the investment strategy would be fixed. However, as the power expansion alternatives were originally generated within a least-cost optimisation framework, this caveat would only result in a slightly pessimistic view of the future. In other words, the higher end of the uncertainty range for each attribute in each alternative could be slightly higher than in reality (i.e. performance would be worse), as each alternative system would have been reoptimised (in terms of the load factors of individual power stations) to meet the realised future, even though investment plans were fixed. Of course some alternatives would be better positioned to adjust to those uncertainties and therefore it would be possible that changes would occur in the rank order and only an indication of that would be captured in this analysis. This issue is addressed in more detail in Chapter 6.

5.3.1. CHOOSING A ROBUST SOLUTION FROM THE NON-DOMINATED SET WITH TECHNICAL EMPIRICAL AND DM PREFERENCE UNCERTANTIES

A value function MCDA approach was chosen for the problem of isolating preferred solutions defined by multiple stakeholder objectives under uncertainty. This approach was then modified to associate a confidence measure with the ranking of alternatives (see section 5.3.2.3). The effects of valuation model parameter uncertainty in preference information on the rank order of alternatives was also explored within this approach and demonstrated in section 5.3.3.2.

The proposed methodology is outlined in Figure 5-2 and discussed below.

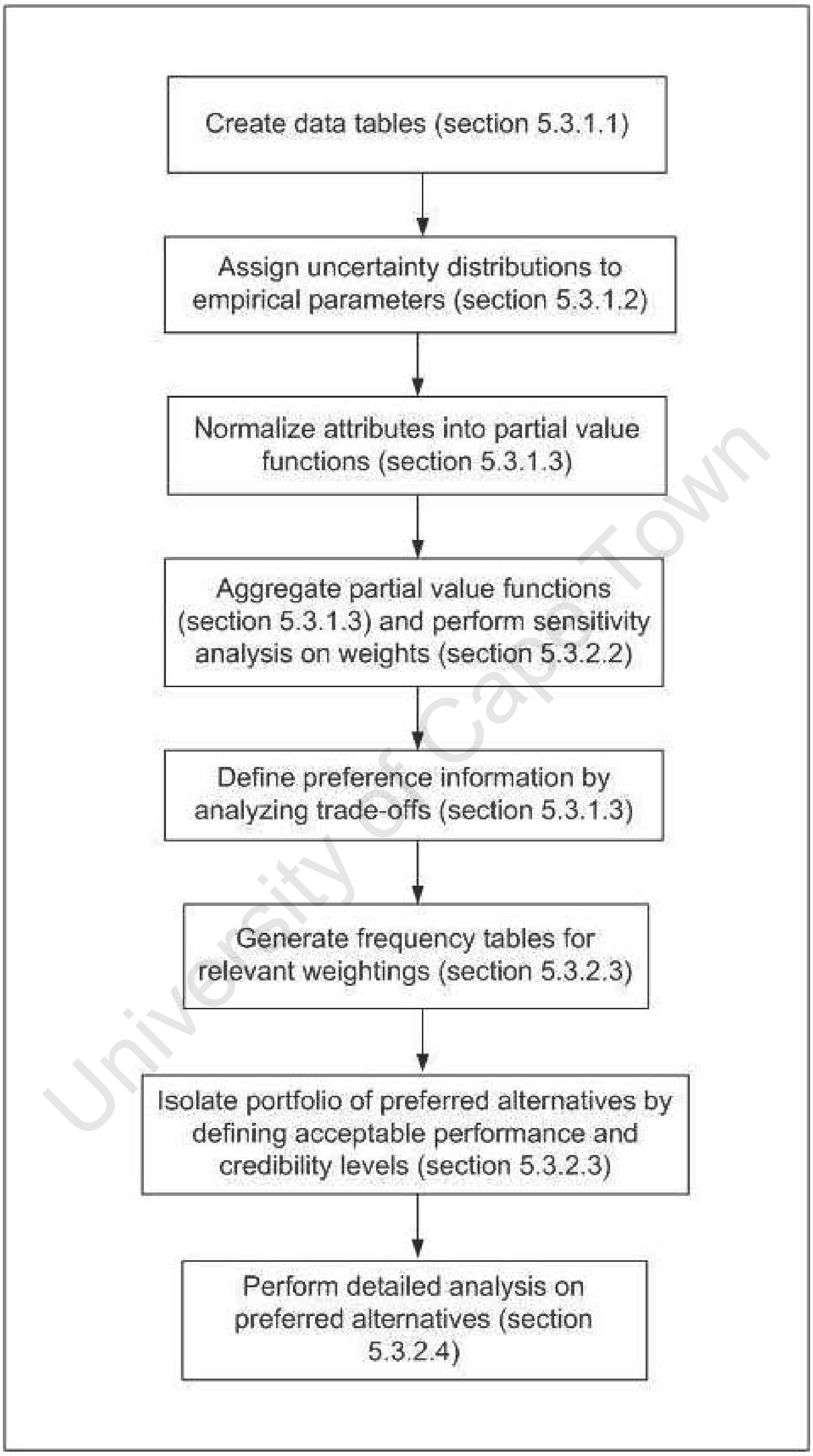

Figure 5-2 Flowchart of proposed methodology

5.3.1.1. Data representation

Data tables were formed to capture the performance of all FEAs in the measured attributes, such that the values were specified by technology for each expansion alternative (Table 5-1). This allowed uncertainty associated with each technology (which is part of any particular alternative), to be identified firstly, and then propagated through the model.

Table 5-1. Example of a data table for a single attribute (e.g. investment cost)

	Tech $_1$	Tech $_2$	Tech $_n$
Alternative $_1$	-	-	-
Alternative $_2$	-	-	-
Alternative $_n$	-	-	-

The data tables were populated from the detailed results obtained in the generation phase of the problem. As total system cost was made up of investment cost, O&M cost and fuel cost, separate tables were defined for each of these performance attributes. Tables were also defined for each of the other non-cost attributes in a similar manner. These tables can be found in appendix B. The next step in this analysis was to include uncertainty into the model.

5.3.1.2. Representation of uncertainty

Uncertainty in technology cost data (investment, O&M) was incorporated into the model using data from the NIRP (NER et al., 2004), which formed the core data set for the work done in chapter 4. Estimated values based on available data for fuel price and emission factor uncertainty for each technology were included in order to demonstrate the capability of the model ((Notten, 2001) and (Eskom, 2001)).

An uncertainty distribution was defined for each technology, for each of the uncertainty parameters (investment cost, O&M cost, fuel cost and emission factors). Triangular distributions are best used when only the bounds and the mode are known, therefore they were used to represent uncertainty in parameters where data was available but limited (e.g. cost data from (NER et al., 2004)). Uniform distributions are best used when only the bounds are known and were therefore used where only a minimum and maximum for a range was available (e.g. CO_2 emission factor ranges for pulverised coal fired stations from (Notten, 2001) and (Eskom, 2001)). Tables containing the probability distribution data for each of the parameters can be found in appendix B. The uncertainty in each of these parameters was then propagated through each of the individual data tables defined by technology type, for each attribute, using a median Latin hypercube sampling technique. In this way, it becomes possible to determine the effect that technology specific uncertainty has on the performance of each alternative.

5.3.1.3. Value function model

Using an additive aggregation model (see section 2.2.2.1 for rational for choosing additive aggregation), the value function $V(a_i)$ is constructed:

$$V(a_i) = \sum_{j=1}^{n} w_j v_j(a_i) \tag{5.1}$$

Where w_j is the weight of criterion j,

and $v_j(a_i)$ is the partial value function defined over the set of criteria j for alternative i.

Intra-criterion preference information

The partial value functions $v_j(a_i)$ were defined for each of the criteria chosen in chapter 4 (total discounted system cost, total CO_{2EQ} emissions (representing global climate change), total SO_{2EQ} emissions (representing acidification potential) and total water consumption) to evaluate the expansion alternatives. Total cost was broken down further into investment cost, operating and maintenance (O&M) cost and fuel cost.

Linear value functions based on locally defined attribute ranges were used to represent intra-criterion preference relationships. Other value function shapes such as the concave function discussed in section 2.2.2.1 could have been used to represent more complex situations such as that when emission limits legislation is in place.

Locally defined partial value functions enable a more sensitive and rapid assessment of the alternatives, as well as being considered more appropriate than global scales for this problem due to the ranges in attributes being defined by the unique ESI system being considered. This approach was taken to represent intra-criterion preferences instead of direct rating techniques, in order to avoid preconceived notions and prejudices (e.g. around technology choice), as well as being a simple and intuitively understandable mathematical representation for the problem (Basson, 2004). Depending on the degree of acceptance amongst stakeholders of value function shapes and local/global scales, there may be merit in undertaking a thorough sensitivity analysis of intra-criterion preference information to further explore and articulate stakeholder preferences. This was not pursued in this thesis.

The values for each attribute were normalised such that the "worst" and "best" outcomes in each criterion are assigned values of 0 and 1 respectively. As the attribute ranges now included uncertainty, the range bounded by highest of the high attribute values and lowest of the low were used to normalize each set of attributes.

Inter-criterion preference information

In order to determine the preferences of the DM, questions regarding the acceptable trade-offs between criteria need to be asked. It has been shown that no single weighting method is preferred by all stakeholder groups (Hobbs and Horn, 1997) but the most commonly used techniques for weight elicitation are the swing weighting method and methods based on cross attribute indifference judgements (Belton and Stewart, 2002). Indifference weighting techniques may appear more complex than the swing weighting method. However, previous work has shown that indifference weighting methods were found to be more readily understandable to stakeholders and led to more plausible preference modelling, when dealing with particular corporate decision situations involving the South Africa utility, ESKOM (Basson, 2004). This was found to be particularly true when the reference criterion was expressed in terms of cost or profit sacrificed for an increase in performance of another non-cost criterion. This being said, ideally the weighting exercise should be repeated using a different criterion as the reference criterion to ensure that the weights obtained are not influenced by the choice of reference criterion. This can however be impractical in a real decision making environment due to time constraints. Given the role of ESKOM in the case studies of both chapter 4 and this chapter, the indifference weighting approach was adopted here.

The indifference trade-off questions are asked in the form of: “What sacrifice in terms of the best performance in reference criterion i would you be willing to make, to achieve a gain from worst to best performance in criterion j?” The trade-off questions are asked for all other criteria in relation to a sacrifice in the reference criterion. The resulting weights are then calculated from the ratios of the trade-offs, and normalised (see section 2.2.2.1 for equations).

Once these weights were established, additive aggregation was used to combine the partial value functions into a single, overall or global value score representing the preferences of the DM (see equation 5.1 above). This value function included uncertainty in attribute values and therefore the results in section 5.3.2 appear as probability distributions rather than discrete values.

A sensitivity analysis was done on the weights to provide stakeholders with a visual representation of the effect that their preferences have on the rank order across the full range of preferences (see section 5.3.2.2 for results and more detailed discussion). This was done by stepping through the weighting values in the reference criterion, while keeping the ratios of the other weights equal to each other[5]. This was repeated using each of the criteria in turn as the reference criterion, in order to evaluate the sensitivity of the results to the weighting of each of the individual criteria.

The choice of criteria and attributes were decided upon in chapter 4 using a flat hierarchy of preferences, therefore no value tree structure was defined. Had there been a hierarchy of preferences, uncertainty in these choices would typically be resolved through expert agreement unless a sensitivity analysis was specifically required.

[5] In practice it may be more appropriate to define the ratios between the weights in a stakeholder exercise before doing a sensitivity analysis; however it was assumed that keeping the ratios of the non-reference criteria equal would demonstrate the methodology sufficiently.

5.3.2. Model outputs

5.3.2.1. Attribute performance results

Overall value function results may be viewed either as cumulative probability distributions or probability density functions. In this way the response of each expansion alternative to the uncertainties specified previously could be viewed relative to the other alternatives. This approach is equivalent to a robustness analysis, illustrating how each alternative performs under a range of possible futures (defined by the technical empirical uncertainties in this case study). This is illustrated below for a subset of alternatives generated in the generation phase in chapter 4.

The performance of each alternative in each attribute can now be examined so as to investigate the effect that uncertainty has on the attribute values for each alternative. This is illustrated for investment cost using cumulative probability functions:

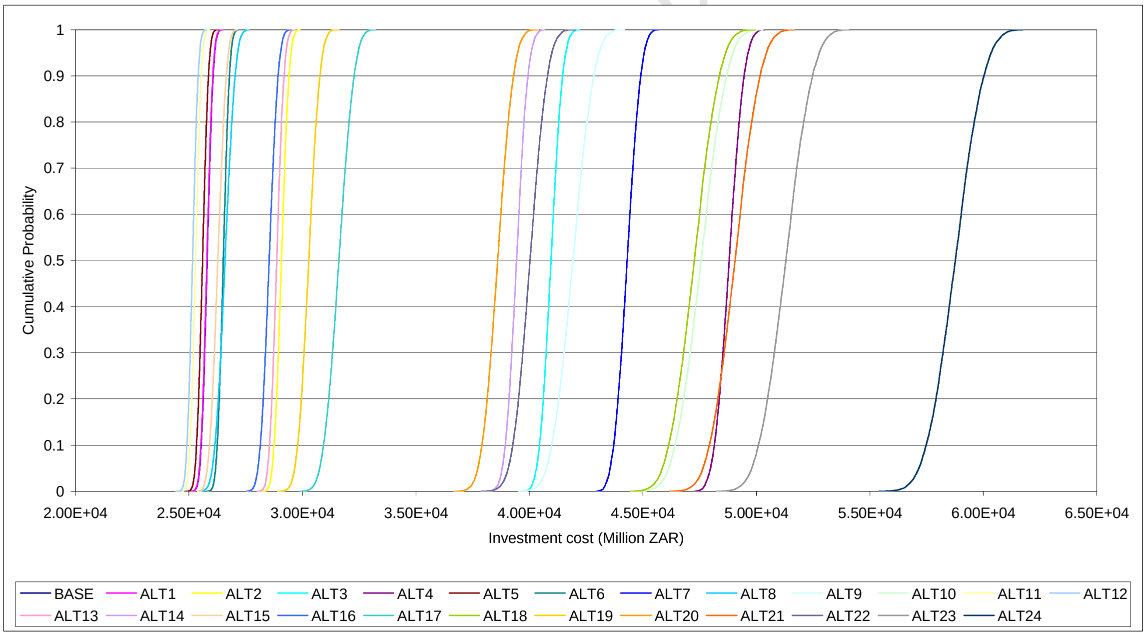

Figure 5-3 Performance results for investment cost

Figure 5-3 illustrates the possible ranges for investment cost in each alternative power expansion plan given the uncertainty distributions for each technology (see Table 4-11 in chapter 4 appendix A for the short term investment summary of each alternative). It can be observed that some alternatives have more uncertainty in their investment cost than others (illustrated by a wider spread in the cumulative distribution function). This information is available for all attributes defined in the model before they become aggregated into an overall value function representing the DM preferences. In this way the likely ranges of all attributes in each FEA can be examined, individually or in an aggregated form, in terms of robustness to the uncertainties involved. Comparing the performance ranges of alternatives to one another is equivalent to a continuous evaluation of uncertainty (where performance ranges are compared rather than discrete points). This type of analysis is useful when evaluating the robustness of alternatives as the sensitivity of each alternative to uncertainty can be seen. This may be particularly useful for illustrating the effects that particular uncertainties of interest may have on the performance of preferred alternatives (see section (5.3.2.2 and 5.3.2.3).

The partial value functions were then combined into an overall value score as described in section 5.3.1.3. The overall value score could also be viewed in the same way as Figure 5-3. This is demonstrated in Figure 5-4 below.

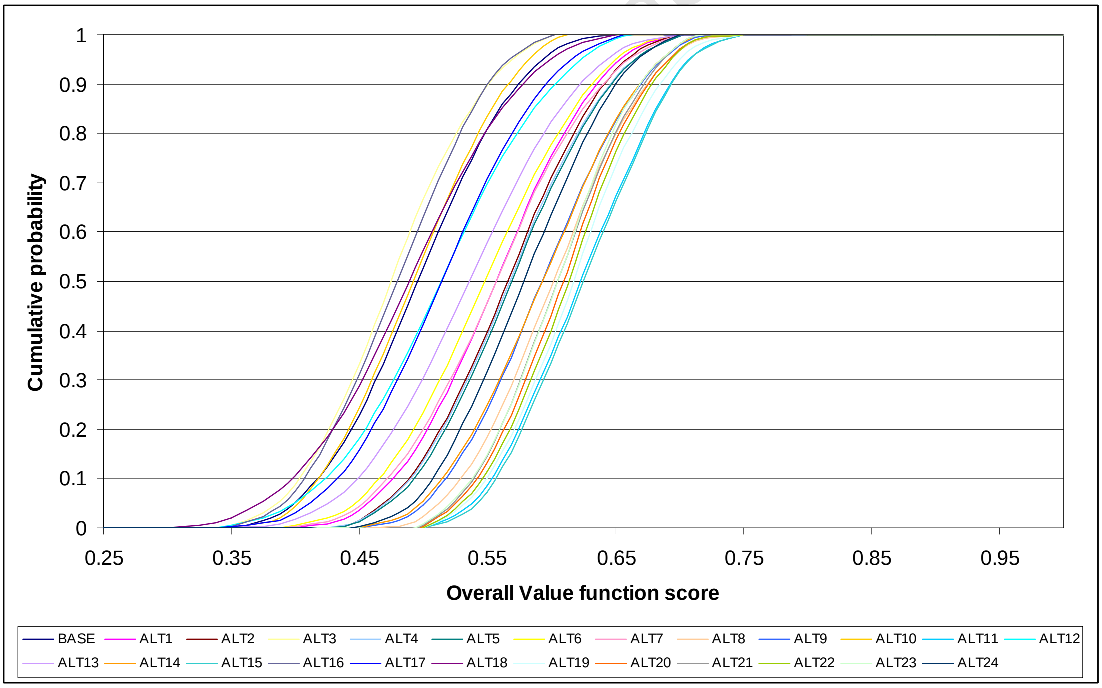

Figure 5-4 Overall value function results at a relative cost weighting of 0.28

Stochastic dominance (Hadar and Russell, 1969; Whitmore, 1970) is a tool that is used to evaluate the dominance of one alternative over another over a range of samples. First order stochastic dominance occurs when one alternative outperforms another alternative at every level of probability (in terms of Figure 5-4 above, ALT 15 outperforms BASE at every level of probability, i.e. the lines do not cross). In graphical terms second order stochastic dominance occurs when one alternative outperforms another alternative over a specific range of probability values but the graphs intersect and then performance in reversed. The degree of dominance is then determined by the ratio of the areas under each graph. This would be the more common case of stochastic dominance for closely competing alternatives as their graphs would overlap. For a more detailed explanation of first and second order stochastic dominance see Hadar and Russell, 1969 as well as Whitmore, 1970 for an explanation on third order stochastic dominance. While Figure 5-4 and the concept of stochastic dominance may be useful to determine to what extent alternatives overlap and therefore obtain an indication of their distinguishability, it would be more appropriate to examine each future discretely as opposed to viewing the overall results in a continuous manner (see section 5.3.2.3 below for full explanation).

It is interesting at this point to illustrate the significant effect that the inter-criteria preference information (weighting) has on the overall value score.

5.3.2.2. Inter-criterion preference results

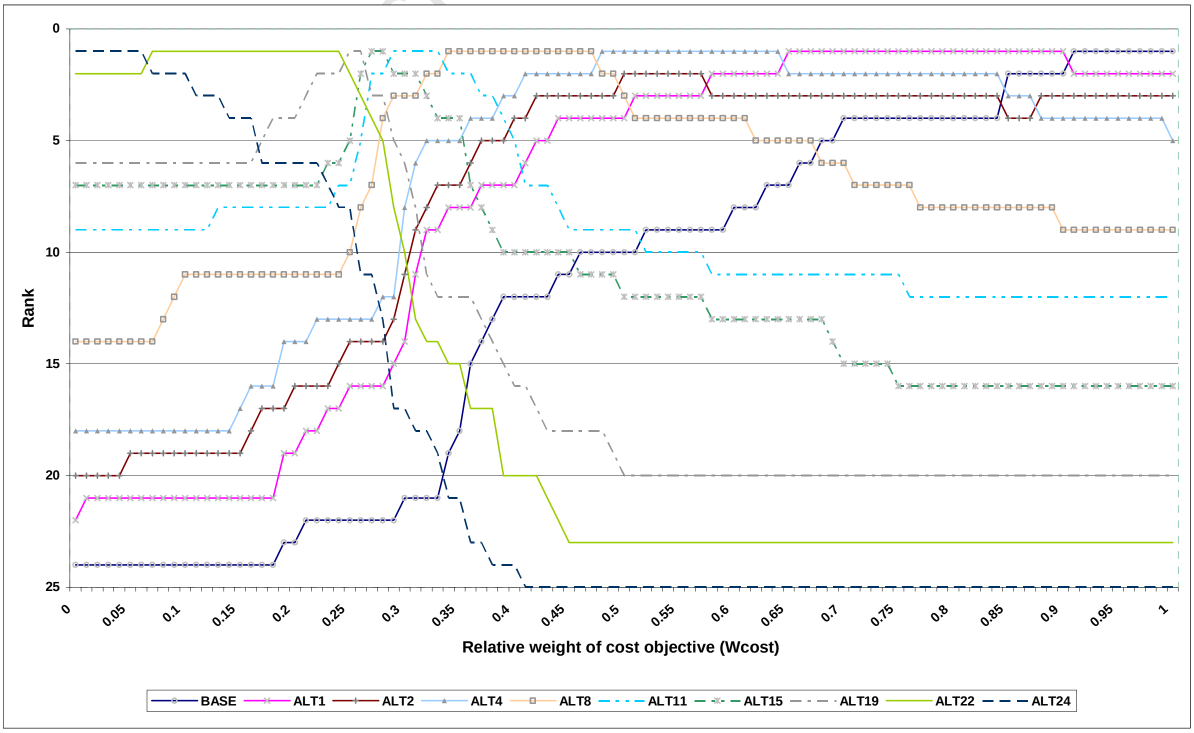

Figure 5-5 Excerpt of weighting sensitivity diagram to cost weighting

The effect that inter-criteria preference information has on the rank order of alternatives is illustrated in Figure 5-5 as a function of relative cost weighting. The ratio of the weighting of the other criteria relative to each other is kept equal, while the cost weighting is varied through its full range. The lower the ranking (Rank 1 is best), the higher the overall value score and therefore the more preferred an alternative is according to the preference information. Figure 5-5 demonstrates how the rank order changes significantly as the relative weight of cost changes in the overall value score. The effect of each of the other criterion weights can be generated in a similar manner (see appendix B for weighting sensitivity diagrams for non-cost criteria). This view differs from the SMAA methodology (Lahdelma et al., 1998; Lahdelma and Salminen, 2006) (see section 2.4.2 of chapter 2 for a more detailed description of the SMAA methodology) in that the full range of weights is examined for all the alternatives rather that focusing on only the alternatives that achieve the first rank.

This diagram can be useful in eliciting the sensitivity of the rank order to DM preference information. It can be seen that for certain ranges in relative cost weighing (e.g. 0.0-0.24) the lower rank order is relatively stable for the preferred alternatives while in other ranges (e.g. 0.25-0.33) the lower rank order is very sensitive to DM preference information. The unstable sections of the sensitivity diagram can be interpreted as the weight ranges for which alternatives have similar performance scores for that particular attribute and therefore small changes in weighting result in changes in the rank order. As the relative DM preferences change, so do the ranks of the alternatives. This is due to the fact that performance values across the attributes differ due to the technology mix of each of expansion alternative.

Once an initial set of preference information has been obtained from stakeholders by guiding them through a weighting procedure (such as described in section 5.3.1.3) it can be established where on the weighting sensitivity diagram their preferences lie and therefore how sensitive the overall results will be to the uncertainty in their preference choices. It can then be asked: “By how much would preference have to change in order to change the rank order?” Moving along the bottom of the sensitivity diagram (Rank 1), starting at a relative cost weighting of 0.07, ALT 22 is the preferred solution. ALT 19 becomes the preferred solution at a relative cost weighting of about 0.25, ALT 15 becomes the preferred solution at approximately 0.27, followed by ALT 11 at approximately 0.29. Of course it could be argued that such small changes in relative weightings are virtually impossible to discern from stakeholder interaction. The point to be made here is only that such small changes can have significant effects in overall ranking, and that demonstrating this to stakeholders can result in a more sharpened focus on the complexity of the decision situation – which is valuable in itself. If operating at a point on the sensitivity diagram that is close to a transition between different alternatives occupying the preferred rank (e.g. 0.26), then it can be said that the choice of the preferred alternative is highly sensitive to DM preference information and more attention needs to be paid to the differences between the competing alternatives at that point on the diagram and the preference information given by the DM. This information should be combined with detailed technology data for each of the preferred alternatives (along the "interesting" sections of the weighting diagram) to evaluate the degree to which the technology investment strategies change as the preferred alternatives change with preference information (discussed in more detail in section 5.3.2.4). The weighting sensitivity diagrams for each of the other criteria should be examined to determine the stability or sensitivity to DM preferences for each of the decision criterion.

While this approach helps to integrate the valuation model parameter uncertainty in preference information into the decision making process and build confidence in the results in relation to that information, it does not explicitly take technical uncertainty in the attribute data into account. This is considered in section 5.3.2.3.

5.3.2.3. Analysis of uncertainty for discrete futures

While a continuous evaluation of uncertainty can provide useful information as to the likely ranges in attribute performance for each alternative, a discrete evaluation of uncertainty, where different future scenarios are specified, and the performance of each alternative is evaluated for each future scenario (as discussed in section 2.5 of chapter 2) can yield insight into the distinguishability of alternatives for particular and specific futures. This approach is synonymous with typical scenario analysis in energy planning, The value of this type of analysis is that alternatives are compared for the same discrete futures, whereas, with a continuous evaluation, alternatives are compared over performance ranges, without reference to the individual scenarios that constitute those performance ranges. As an example, using a continuous analysis of uncertainty, it is observed that Alternative 3 and BASE overlap in performance for certain DM preferences. This is, however, not observed to nearly the same extent when using a discrete analysis of uncertainty as it is shown that the points where BASE and Alternative 3 overlap represent different futures (e.g. BASE performs badly due to a high gas price, and Alternative 3 performs well due to a low gas price). If these alternatives were compared on equivalent futures (e.g. a consistent gas price) it would be found that BASE almost always outperforms Alternative 3 (as can be seen in Table 5-3).

Such an exercise was conducted by accessing the overall value scores based on each discrete set of input parameters (from the sample of uncertain parameters) and then ranking the alternatives for each of those discrete sets of input data individually. Each discrete set of input parameters was considered a scenario, with the scenario set being made up of all the discrete scenarios representing individual samples of the uncertain parameters. From this data, the frequency at which alternatives obtain a given rank considering all the scenarios was calculated. The credibility[6] values (probability values based on the sample set) were calculated by determining the frequency at which each alternative occupied a given rank. The frequency at which particular alternatives occupy ranks can be used as an indication of the credibility associated with the rank order. This is illustrated in Table 5-2 and Table 5-3 for a sample size of 1000 at a relative cost weighting of 0.28 and 0.52 respectively. These relative cost weighting values were chosen to explore the credibility information for both a stable and unstable section of the weighting sensitivity diagram, with respect to the lower rank order (see Figure 5-5 above). This probabilistic information is displayed for all alternatives through the full rank order, based on the specific DM preference information considered (as reflected by the weights). This allows a comprehensive view of the performance information (in terms of rank and credibility)

[6] The concept of credibility has been used within the context of MCDA to describe the confidence that can be assigned to a rank order (Roy, 1986). In the context of this work “credibility values” specifically relate to the probability of an alternative achieving a given rank based on the sample set used.

of alternatives. A rank of 1 represents the most preferred alternative while a rank of 25 represents the least preferred alternative for a given set of DM preference weightings.

This methodology has parallels with the reference set and cross confidence intervals used in the SMAA methodology except that this methodology is based on the credibility levels of all alternatives rather than restricting the analysis to alternatives that achieve a rank of 1 alone. The benefits of doing this become clear when isolating a portfolio of preferred alternatives, as focusing only on alternatives that achieve a rank of 1 may exclude important alternatives from the portfolio set. This is demonstrated in section 6.3.4 of chapter 6. It must also be noted that the rank and credibility information of each alternative is based on a given set of DM preferences rather than on the central weighting vectors as in the SMAA methodology.
Table 5-2 illustrates that, for a relative cost weighting of 0.28, ALT 15 is the preferred alternative with a credibility level of 45 % for obtaining Rank 1, while ALT 11 ranks second best with a credibility level of more than 80 % for obtaining a rank of 2 or better (373/1000 for Rank 1 + 428/1000 for Rank 2). These ranks are followed by ALT 19 with a credibility level of 52.5 % for obtaining a rank of 3 or better (0/1000 for Rank 1 + 6/1000 for Rank 2 + 519/1000 for Rank 3). No single alternative emerges as the dominant solution with a high level of credibility (e.g. greater than 80 %) using this set of DM preferences and therefore a portfolio of alternatives may need to be isolated for further analysis (see section 3.2.4), such that a final decision can be made. The minimum credibility level that the preferred alternative would need to achieve would need to be defined by the DM. This value would be influenced by the DM's risk perception. However this being said, it is recommended that a portfolio of preferred alternatives be isolated such that a detailed analysis can be done to gain more insight into the preferred alternatives (this is done below).

Table 5-3 illustrates that, for a relative cost weighting of 0.52, ALT 4 is the preferred alternative with a credibility level of almost 70 % for obtaining Rank 1 while ALT 2 ranks second best with a credibility level of almost 50 % for obtaining a rank of 2 or better (195/1000 for Rank 1 + 303/1000 for Rank 2). These are followed by ALT 1, with a credibility level of 69 % for obtaining a rank of 3 or better (0/1000 for Rank 1 + 357/1000 for Rank 2 + 333/1000 for Rank 3). Although ALT 4 is the preferred alternative for almost 70 % of the discrete samples, this credibility level may not be high enough for the DM to confidently make a decision with this information alone. Therefore even in this situation it is suggested that a portfolio of alternatives be selected that satisfy minimum levels of performance and credibility levels, such that a small set of preferred alternatives may be compared on a more detailed technology investment based level, and a final decision can be made (discussed in more detail in section 5.3.2.4).

Table 5-2 and Table 5-3 can also be used to elicit the regret associated with each alternative. If for instance an alternative were to rank well for most of the samples but very poorly for some, it would indicate that that alternative was potentially risky for some futures although it performed well for most others (e.g. ALT 14 in Table 5-2 which achieved a rank of 1 for over 14 % of the samples but also ranked 10th for more than 30 % of the samples). The DM's attitude towards regret would be integrated into the process of isolating a portfolio of preferred alternatives by defining minimum levels of performance (in terms of rank or overall value score) within a specified level of credibility (this is discussed and demonstrated after Tables 5-2 and 5-3).

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Table 5-2 Frequency table for overall rank at a relative cost weighting of 0.28 using a sample size of 1000

	BASE	ALT 1	ALT 2	ALT 3	ALT 4	ALT 5	ALT 6	ALT 7	ALT 8	ALT 9	ALT 10	ALT 11	ALT 12	ALT 13	ALT 14	ALT 15	ALT 16	ALT 17	ALT 18	ALT 19	ALT 20	ALT 21	ALT 22	ALT 23	ALT 24
1	0	0	0	0	0	0	0	0	15	14	0	373	0	0	145	450	0	0	0	0	3	0	0	0	0
2	0	0	0	0	0	0	0	0	60	41	0	428	0	0	43	414	0	0	0	6	6	1	0	0	1
3	0	0	0	0	0	0	0	1	160	110	0	82	0	0	48	48	0	0	0	519	29	3	0	0	0
4	0	0	0	0	0	0	0	3	208	115	0	66	0	0	55	39	0	0	0	63	83	6	360	0	2
5	0	0	0	0	0	0	0	4	153	157	0	31	0	1	81	41	0	0	0	102	236	23	75	96	0
6	0	0	0	0	2	6	1	32	94	98	0	14	0	0	63	4	0	0	0	126	282	138	92	47	1
7	0	0	0	0	26	14	0	10	95	88	0	3	0	3	32	2	0	0	0	82	255	205	93	92	0
8	0	0	0	0	16	19	1	20	177	96	0	3	0	5	63	0	0	0	0	50	74	282	117	69	8
9	0	0	3	0	32	25	5	18	36	250	0	0	0	10	88	0	0	0	0	17	6	245	132	108	25
10	0	0	22	0	69	111	8	33	2	30	0	0	0	9	314	1	0	0	0	10	10	26	26	259	70
11	0	2	37	0	124	333	12	55	0	1	0	0	0	8	22	1	0	0	0	8	5	25	22	75	270
12	0	1	122	0	356	251	11	72	0	0	0	0	0	8	31	0	0	0	0	4	5	17	31	29	62
13	0	7	207	0	298	151	24	91	0	0	0	0	0	19	15	0	0	0	0	4	2	10	10	34	128
14	0	90	247	0	77	79	49	191	0	0	0	0	1	25	0	0	0	0	0	6	4	4	11	48	168
15	0	297	194	0	0	9	104	211	0	0	0	0	0	48	0	0	0	0	0	3	0	10	15	10	99
16	0	336	59	0	0	2	194	259	0	0	0	0	3	48	0	0	0	0	0	0	0	5	7	37	50
17	0	177	67	0	0	0	591	0	0	0	0	0	4	45	0	0	0	0	0	0	0	0	7	27	82
18	0	90	42	0	0	0	0	0	0	0	0	0	14	744	0	0	0	27	0	0	0	0	2	48	33
19	1	0	0	0	0	0	0	0	0	0	0	0	624	27	0	0	0	328	0	0	0	0	0	19	1
20	13	0	0	0	0	0	0	0	0	0	0	0	340	0	0	0	0	645	0	0	0	0	0	2	0
21	244	0	0	0	0	0	0	0	0	0	1	0	13	0	0	0	0	0	742	0	0	0	0	0	0
22	742	0	0	0	0	0	0	0	0	0	72	0	1	0	0	0	0	0	185	0	0	0	0	0	0
23	0	0	0	4	0	0	0	0	0	0	927	0	0	0	0	0	10	0	59	0	0	0	0	0	0
24	0	0	0	711	0	0	0	0	0	0	0	0	0	0	0	0	282	0	7	0	0	0	0	0	0
25	0	0	0	285	0	0	0	0	0	0	0	0	0	0	0	0	708	0	7	0	0	0	0	0	0

Table 5-3 Frequency table for overall rank at a relative cost weighting of 0.52 using a sample size of 1000

	BASE	ALT 1	ALT 2	ALT 3	ALT 4	ALT 5	ALT 6	ALT 7	ALT 8	ALT 9	ALT 10	ALT 11	ALT 12	ALT 13	ALT 14	ALT 15	ALT 16	ALT 17	ALT 18	ALT 19	ALT 20	ALT 21	ALT 22	ALT 23	ALT 24
1	0	0	195	0	699	0	0	0	106	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	357	303	0	200	0	0	0	140	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	333	398	0	101	0	0	0	168	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	310	104	0	0	59	10	0	517	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	896	31	5	51	16	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	37	415	28	13	507	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	8	434	385	5	88	0	80	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	102	495	0	389	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0
9	556	0	0	0	0	0	8	87	0	0	0	349	0	0	0	0	0	0	0	0	0	0	0	0	0
10	441	0	0	7	0	0	0	0	0	0	0	549	0	0	0	3	0	0	0	0	0	0	0	0	0
11	3	0	0	841	0	0	0	0	0	0	0	7	0	0	0	149	0	0	0	0	0	0	0	0	0
12	0	0	0	152	0	0	0	0	0	0	0	0	3	9	308	528	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	22	59	683	236	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	569	0	78	318	9	26	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	144	0	226	575	0	55	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	287	0	671	39	0	3	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	984	0	12	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	493	12	414	81	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	499	4	281	216	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	211	691	94	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	64	0	906	5	25	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	0	0	678	309	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	317	666	6	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	994	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1000

Creating a portfolio of preferred alternatives

The above approach allows a portfolio of preferred alternatives to be isolated from the larger set. This set should satisfy a minimum level of performance (in terms of rank and/or overall value score) within a specified level of credibility. The approach proposed here allows the DM to define acceptable levels of risk or regret by being able to specify the performance and credibility values that alternatives must achieve to become part of the portfolio. If for example, it was said that the portfolio must contain only alternatives that are expected to obtain a rank of 3rd or better within a 90 % credibility interval, only ALT 15 would satisfy this criterion (with a credibility level of 91.2 %) using a relative cost weighting of 0.28 and only ALT 4 would satisfy this criterion (with a credibility level of 100 %) using a relative cost weighting of 0.52. If however the confidence interval was dropped to 85 %, then the portfolio would include ALT 15 and ALT 11 for a relative cost weighting of 0.28 and ALT 4 and ALT 2 for a relative cost weighting of 0.52.

The performance and credibility criteria used to isolate preferred alternatives from the larger set need to be defined such that a sufficient number of alternatives are included in the set to allow for comparison, but not to confound the decision making process and overwhelm the DM. This choice depends on the number of alternatives that are competing for the top rank positions. In some cases, as demonstrated above, only one or two alternatives compete for the top rank positions with relatively high credibility levels; however there may be situations where many more alternatives compete, and therefore the values of the isolation criteria need to be more stringent to reduce the number of alternatives entering the portfolio set.

New alternatives can enter the preferred set of solutions by relaxing performance levels (in terms of rank or overall value score) and credibility levels individually. The SMAA methodology develops reference sets based on the confidence of alternatives being preferred (i.e. rank best) only. The additional freedoms of allowing alternatives that achieve ranks of below 1 give the DM the opportunity to differentiate between performance and credibility and to explore the effect that each have on the solution set individually. In this way a preferred set of solutions can be isolated from a larger set that would satisfy minimum performance characteristics within desired credibility intervals, thereby integrating technical empirical uncertainty into the multi-objective decision problem for a given set of DM preferences (once the sensitivity of the DM preferences has been evaluated using the weighting sensitivity diagrams). The frequency values (Table 5-2 and Table 5-3) should be re-examined at this point to elicit the potential regret (in terms of overall rank) associated with each of the preferred alternatives as outlined above. It may also be valuable to refer back to the performance results of the preferred alternatives at this point (as illustrated in Figure 5-3). This would enable the analyst to determine the likely ranges of individual attributes in each of the alternatives under consideration.

One of the advantages of this approach is that the portfolio set can be updated in real time once the frequency information has been generated. This allows for significant stakeholder interaction in the process of isolating alternatives as well as the opportunity for stakeholders to test different performance and credibility criteria, thereby increasing stakeholder confidence in the preferred alternatives.

5.3.2.4. Detailed analysis of investment plans

For this case study, each alternative represents an investment strategy spanning a time horizon of twenty years. DMs may be most interested in the initial steps that need to be taken in the short term to ensure that demand will be met, given their objectives, their current preferences and view of the uncertainties involved. This implies that once a set of preferred alternatives has been identified (based on the attribute performance scores of the alternatives over the entire time horizon), it is important to establish the similarities and differences between the alternatives such that the DM can understand the implications of choices in terms of the real actions that need to be initiated (in this case, investment into new technologies). This can be done by examining the short term investment strategies in terms of their specified technologies types and capacities for the preferred alternatives. This will be demonstrated for two values of relative cost weighting, representing different DM preferences and different sections of the weighting diagram (Figure 5-5 above). The short term investment strategies of all alternatives can be found in Table 4-11 in chapter 4 appendix 3.

Table 5-4 New short term capacity investment[7] (in MW) in selected technologies for preferred expansion alternatives

	Coal (pf)	Nuclear (ALWR)	Nuclear (PBMR)	OCGT	Pumped storage	FBC	CCGT (pipe)	CCGT (LNG)	Wind1	Wind2	Wind3
ALT 15	0	2493	3520	884	0	0	774	9654	987	100	50
ALT 11	1441	1555	3080	1273	0	0	774	9506	565	100	50

It can be seen from Table 5-4 that at a relative cost weighting of 0.28 both the preferred alternatives ALT 15 and ALT 11 both invest mainly in gas plants (combined cycle gas turbines (CCGT) using liquefied natural gas (LNG) and some pipeline gas) as well as nuclear plants (both advanced light water reactors (ALWR) and pebble bed modular reactors (PBMR)). The main differences between the alternatives are that ALT 15 invests in more ALWR, CCGT, PBMR and wind than ALT 11, while ALT 11 invests in a coal fired pulverised fuel (pf) station as well as investing in slightly more open cycle gas turbines (OCGTs). It also invests in slightly more capacity (about 120 MW) and therefore has a slightly higher reserve margin. The resulting attribute performance information (in terms of partial value scores) can be seen in Table 5-5 below:

Table 5-5 Mean partial value score results for preferred alternatives

Alternative	Cost	CO2-eq	SO2-eq	Water consumption	Overall value	Credibility level of attaining preferred rank
Weighting	0.28	0.24	0.24	0.24	1.000	
ALT 15	0.60	0.60	0.71	0.57	0.62	45.0 %
ALT 11	0.70	0.52	0.68	0.56	0.62	37.3 %

ALT 15 and ALT 11 performed similarly in terms of their partial value scores (where a score of “1” is best and “0” is worst) for SO_2-eq emissions and water consumption.

7 It must be noted that the model used in chapter 4 to generate the alternatives used linear programming, assuming all variables to be continuous rather than using mixed integer linear programming. The work done in chapter 7 extends this analysis such that investment would occur in technologically consistent blocks rather than continuously. This was not done at the time due to the inability to use stochastic programming and MILP simultaneously in MARKAL. This was NOT seen as a shortcoming in demonstrating the methodology presented here.

ALT 15 performed worse in terms of cost and better in terms of CO_2-eq emissions than ALT 11 resulting in the overall value function scores being the same (to 2 significant figures). These performance differences can be attributed to the levels of investment into the previously specified technologies. Ultimately the choice of a preferred alternative, given DM preferences, comes down to a trade-off between investing in more nuclear, gas and wind (ALT 15) at a slightly higher price resulting in better performance in terms of $CO_{2\ EQ}$ emissions or investing in a coal fired station and some more OCGTs and less nuclear, CCGT and wind, at a slightly lower price but with higher CO_{2EQ} emissions.

This example demonstrates that decisions relating to technology investment may need to be made even within a preferred set of alternatives with similar overall value scores and similar rank and credibility information. In a case such as this, the stakeholders would have to re-evaluate their preferences in relation to the specific trade-offs between the technologies at hand such that a preferred alternative can be identified.

Table 5-6 New short term capacity investment (in MW) in selected technologies for preferred expansion alternatives (Wcost=0.52)

	Coal (pf)	**Nuclear (ALWR)**	**Nuclear (PBMR)**	**OCGT**	**Pumped storage**	**FBC**	**CCGT (pipe)**	**CCGT (LNG)**	**Wind1**	**Wind2**	**Wind3**
ALT 4	4840	0	440	1561	0	2796	774	6945	714	100	50
ALT 2	5532	0	440	1719	0	2796	774	6287	538	100	50

At a relative cost weighting of 0.52 both the preferred alternatives (ALT 4 and ALT 2) invest in significant amounts of coal stations (both pf stations and fluidised bed combustion (FBC) stations) as well as CCGT, OCGT, wind and small amounts of nuclear (PBMR). ALT 4 invests in slightly less coal (pf), OCGT and slightly more CCGT (LNG) and wind than ALT 2.

Table 5-7 Mean partial value score results for preferred alternatives (Wcost = 0.52)

Alternative	**Cost**	**CO2-eq**	**SO2-eq**	**Water consumption**	**Overall value**	**Credibility level of attaining preferred rank**
Weighting	0.52	0.16	0.16	0.16	1.000	
ALT 4	0.88	0.26	0.51	0.66	0.69	69.9 %
ALT 2	0.88	0.22	0.52	0.68	0.69	19.5 %

The partial value scores are very similar for the preferred alternatives, both performing well in terms of cost (this would be expected with a relative cost weighting of 0.52), quite poorly in terms of CO_{2EQ} emissions (due mainly to the increased investment into coal fired power stations) and average performance in SO_2-eq emissions and water consumption. This results in ALT 4 obtaining the same overall value score (to 2 significant figures) as ALT 2 using this set of DM preference information.

Using a different set of DM preferences it can be seen that it is possible that the initial short term technology investment strategies can be so similar for different alternatives in a portfolio of preferred alternatives that the DM can proceed with the alternative that obtained the highest performance and credibility scores without revisiting their initial preference statements.

In this case, any hesitancy from the DM in choosing one preferred alternative over another based on insufficient credibility information (69.9 % credibility level of ALT 4 being the preferred alternative) can be easily countered. The short term technology investment data illustrates how both preferred alternatives invest in the same technologies, with only small differences in the capacities of those investments. The partial value scores also highlight the differences between the attribute performance values for the considered alternatives. This stresses the importance of evaluating preferred alternatives on the basis of technology investment, even after rank order and credibility levels have been established, in order to obtain a deeper understanding of the real investment decisions involved.

This case study has also highlighted how DM preference information can result in different alternatives becoming part of the preferred set or portfolio (ALT 15 and ALT 11 for a Wcost of 0.28 and ALT 4 and ALT 2 for a Wcost of 0.52) and how different the technology investment strategies and decisions can be for those portfolios and alternatives at the different preference values.

5.4. CONCLUSIONS

A MAVT approach was coupled with a sensitivity/robustness approach to address some of the uncertainties inherent in power expansion modelling. This methodology can be used to explore the robustness and sensitivity of each power expansion alternative to different types of uncertainty at various levels of aggregation, from partial value functions representing individual attributes, to the overall value function which represents the DM preferences to the criteria chosen, through a continuous analysis of uncertainty.

The weighting sensitivity diagrams representing inter-criterion preferences display valuable information regarding the stability of the rank order, given a range of preference weightings for each of the decision criteria. This continuous analysis of uncertainty can be used to increase stakeholder confidence in the results and to determine the sensitivity of the rank order to DM preference information.

Frequency tables based on the comparison of each alternative across a sample of discrete futures yield information regarding the credibility of alternatives in the rank with respect to the technical empirical uncertainties considered. While a continuous evaluation of uncertainty can provide useful information as to the likely ranges in attribute performance for each alternative, a discrete evaluation of uncertainty can yield insight into the distinguishability of alternatives for particular and specific futures.

This approach can also be used to elicit the regret associated with each alternative by evaluating the spread of each alternative across the rank order. It can then be used to isolate portfolios of alternatives with specified minimum levels of performance in terms of rank or attribute performance and credibility levels such that the DM can differentiate between performance and credibility and to explore the effect that each have on the solution set.

A more detailed analysis of the reduced solution set examined short term technology investment details and the attribute performance information. This analysis provided additional insight into the decision problem in terms of the actual technology choices being made, which could then be related back to real life actions. More specifically, the case study highlighted that decisions relating to technology investment may need to be made even within a preferred set of alternatives with similar overall value scores and similar rank and credibility information. In a case such as this, the stakeholders would have to re-evaluate their preferences in relation to the specific trade-offs at hand such that a preferred alternate can be identified. Conversely, it was also demonstrated that it is possible for initial short term investment strategies (for different alternatives in a portfolio of preferred alternatives) to be so similar as to not require any major decision in differentiating the technologies for implementation. The effect that DM preference information has on the alternatives that enter the preferred portfolio set was also highlighted in the case study.

5.5. APPENDIX B

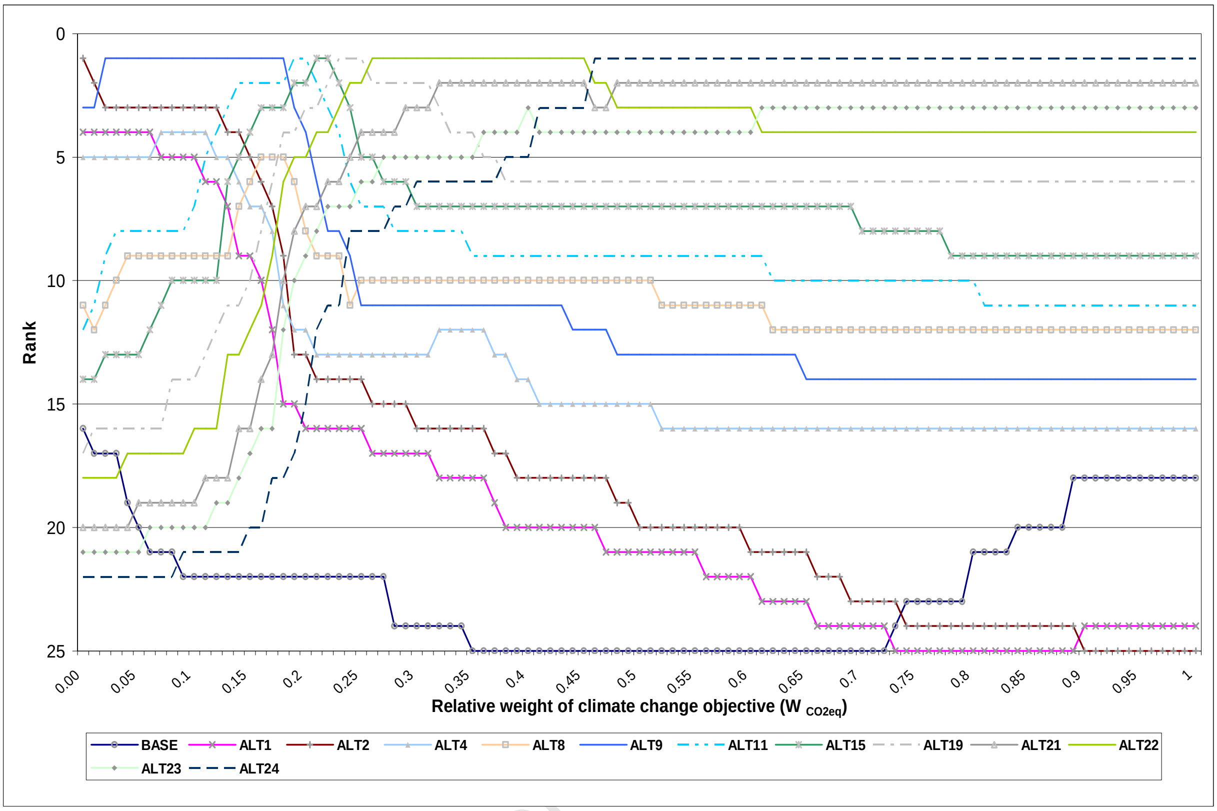

Figure 5-6 Excerpt of sensitivity diagram to CO_{2EQ} weighting

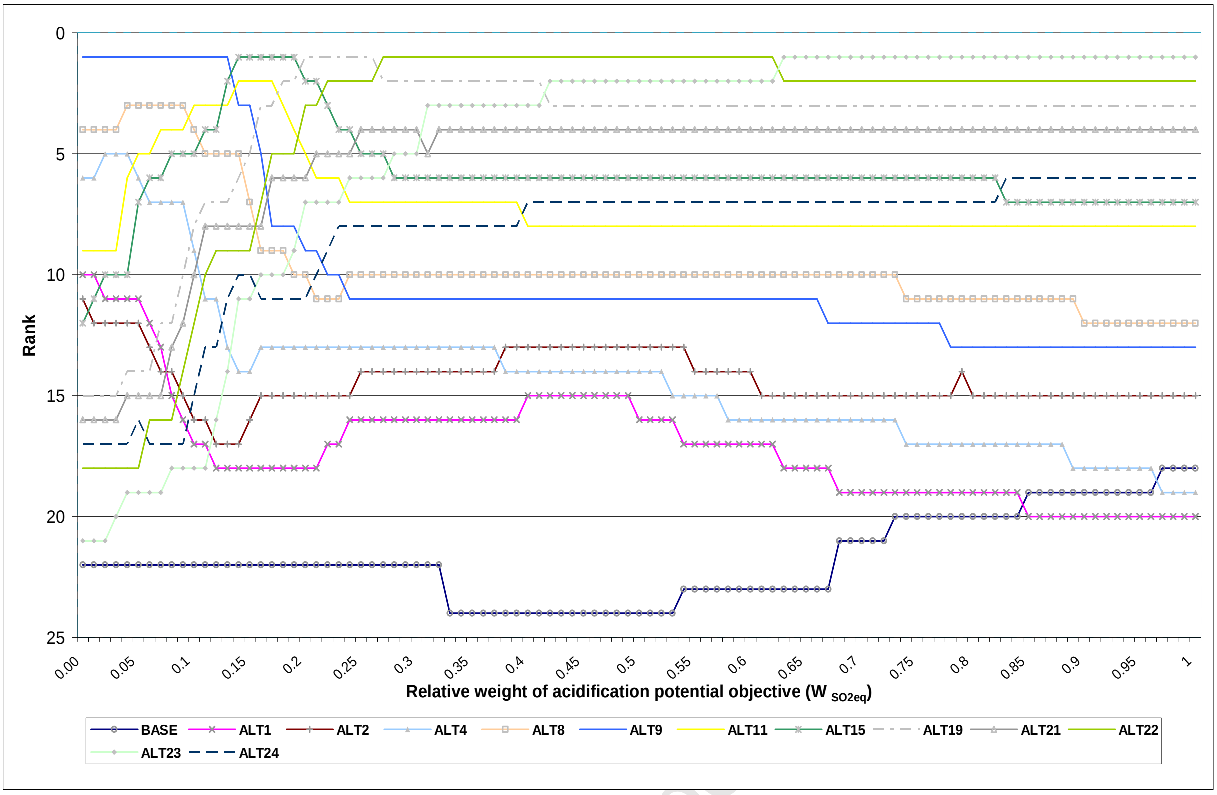

Figure 5-7 Excerpt of sensitivity diagram to SO_{2EQ} weighting

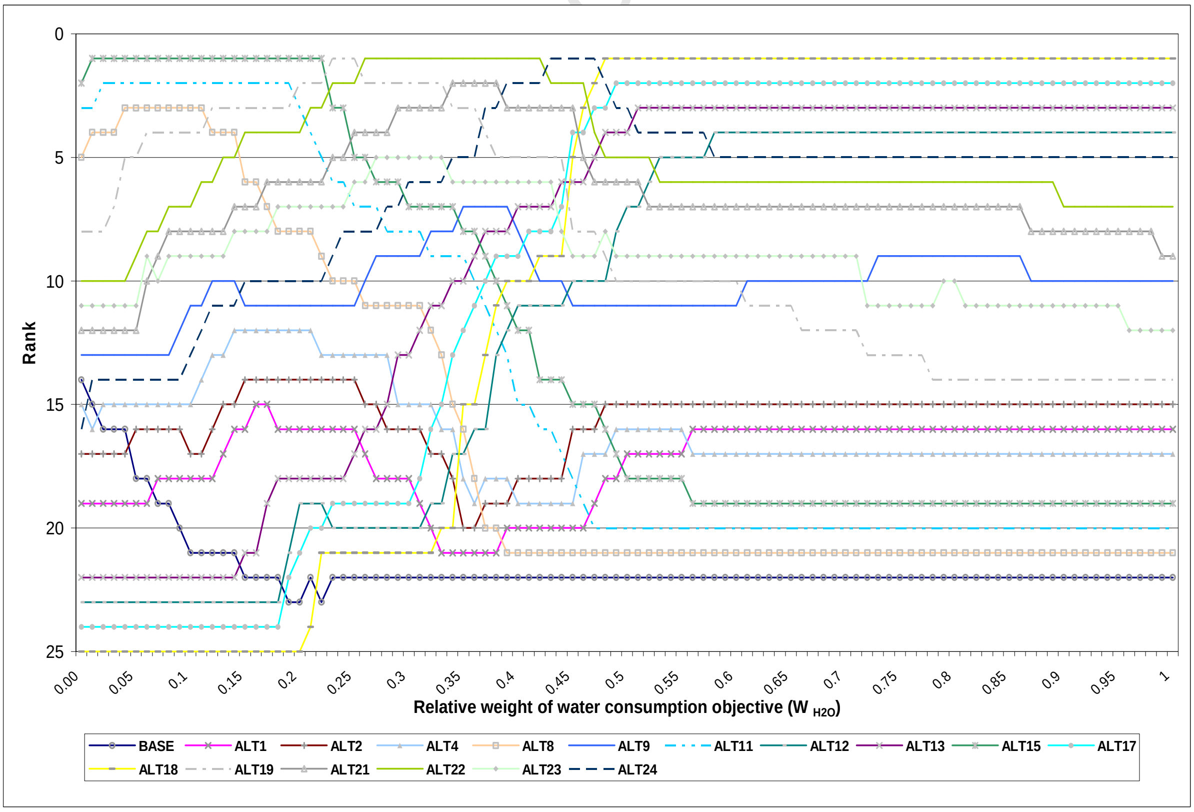

Figure 5-8 Excerpt of sensitivity diagram to H2O weighting

Table 5-8 Mean partial value score results for all alternatives

	Total cost	Total CO_2-eq	Total SO_2-eq	Water consumption
BASE	0.90	0.25	0.51	0.38
ALT1	0.89	0.22	0.49	0.68
ALT2	0.88	0.22	0.52	0.68
ALT3	0.88	0.43	0.56	0.06
ALT4	0.88	0.26	0.51	0.66
ALT5	0.85	0.24	0.52	0.71
ALT6	0.85	0.23	0.47	0.73
ALT7	0.83	0.26	0.48	0.74
ALT8	0.83	0.46	0.59	0.53
ALT9	0.79	0.33	0.56	0.72
ALT10	0.76	0.56	0.61	0.07
ALT11	0.70	0.52	0.68	0.56
ALT12	0.65	0.25	0.45	0.86
ALT13	0.63	0.32	0.47	0.86
ALT14	0.62	0.61	0.60	0.60
ALT15	0.60	0.60	0.71	0.57
ALT16	0.58	0.66	0.65	0.09
ALT17	0.55	0.24	0.51	0.91
ALT18	0.49	0.25	0.47	0.95
ALT19	0.30	0.73	0.78	0.69
ALT20	0.27	0.76	0.76	0.71
ALT21	0.22	0.77	0.77	0.73
ALT22	0.21	0.77	0.80	0.73
ALT23	0.18	0.77	0.81	0.71
ALT24	0.12	0.81	0.72	0.79

Table 5-9 Summary table for investment cost data for technologies and alternatives (kZAR)

	Coal (pf)	Nuclear (ALWR)	Nuclear (PBMR)	OCGT	Pumped storage	FBC	CCGT (pipe)	CCGT (LNG)	Wind1	Wind2	Wind3	Small landfill gas	Medium landfill gas	Large landfill gas	Hydro modifications and refurbishments
BASE	1.032E+07	0	1.112E+06	2.046E+06	3.504E+05	7.947E+06	8.658E+05	1.197E+06	1.775E+05	6.984E+04	6.894E+04	3.206E+04	3.420E+04	6.114E+03	2.065E+06
ALT1	1.036E+07	0	1.112E+06	2.090E+06	1.838E+05	7.990E+06	8.658E+05	1.194E+06	1.773E+05	1.287E+05	6.894E+04	3.206E+04	3.420E+04	6.114E+03	2.043E+06
ALT2	1.191E+07	0	1.194E+06	2.071E+06	0	5.823E+06	8.658E+05	1.391E+06	1.940E+05	1.315E+05	7.047E+04	3.393E+04	4.068E+04	7.273E+03	2.314E+06
ALT3	9.010E+06	3.208E+05	1.112E+06	1.913E+06	3.298E+05	7.947E+06	8.658E+05	1.402E+06	1.942E+05	1.322E+05	7.647E+04	3.206E+04	3.420E+04	6.114E+03	2.426E+06
ALT4	8.856E+06	3.081E+05	1.112E+06	1.817E+06	0	8.083E+06	8.658E+05	1.580E+06	2.361E+05	1.322E+05	7.647E+04	3.206E+04	4.068E+04	7.273E+03	2.470E+06
ALT5	1.110E+07	0	1.879E+06	1.242E+06	6.397E+03	6.942E+06	1.062E+06	1.688E+06	2.488E+05	1.260E+05	6.894E+04	7.886E+04	8.413E+04	1.504E+04	2.291E+06
ALT6	1.164E+07	0	1.112E+06	1.324E+06	2.434E+02	1.103E+07	8.581E+05	1.125E+06	1.073E+05	9.935E+04	6.620E+04	3.206E+04	3.420E+04	8.078E+03	1.951E+06
ALT7	8.927E+06	5.740E+04	2.634E+06	1.200E+06	0	1.128E+07	8.648E+05	1.494E+06	1.089E+05	1.176E+05	6.575E+04	7.886E+04	8.413E+04	1.504E+04	2.258E+06
ALT8	4.652E+06	4.864E+05	8.140E+06	1.735E+06	0	5.673E+06	1.378E+06	1.641E+06	2.232E+05	1.282E+05	7.047E+04	3.814E+04	4.068E+04	7.273E+03	2.523E+06
ALT9	4.355E+06	3.066E+06	8.314E+06	7.931E+05	2.874E+04	5.902E+06	1.482E+06	1.725E+06	3.699E+05	1.294E+05	7.200E+04	7.886E+04	8.413E+04	1.504E+04	2.346E+06
ALT10	0	5.826E+06	9.885E+06	6.586E+05	1.344E+04	8.134E+06	8.658E+05	1.765E+06	4.987E+05	1.407E+05	7.244E+04	7.886E+04	8.413E+04	1.504E+04	2.763E+06
ALT11	2.483E+06	6.400E+06	8.982E+06	1.153E+06	0	0	1.508E+06	3.209E+06	2.258E+05	1.438E+05	9.100E+04	7.886E+04	8.413E+04	1.504E+04	2.603E+06
ALT12	1.997E+07	0	1.112E+06	1.147E+06	3.038E+04	1.471E+07	8.658E+05	9.106E+05	9.382E+04	1.154E+05	6.302E+04	7.886E+04	8.413E+04	1.504E+04	1.756E+06
ALT13	1.180E+07	5.783E+04	7.171E+06	5.463E+05	5.719E+04	1.471E+07	8.666E+05	1.944E+06	9.382E+04	1.352E+05	6.927E+04	7.886E+04	8.413E+04	1.504E+04	1.809E+06
ALT14	0	8.707E+06	1.337E+07	5.463E+05	3.494E+04	1.018E+07	8.798E+05	1.507E+06	5.212E+05	1.407E+05	7.200E+04	7.886E+04	8.413E+04	1.504E+04	2.860E+06
ALT15	0	9.463E+06	1.337E+07	7.310E+05	0	0	1.385E+06	3.429E+06	4.365E+05	1.471E+05	8.045E+04	7.886E+04	8.413E+04	1.504E+04	2.750E+06
ALT16	0	1.204E+07	1.337E+07	5.463E+05	3.363E+04	8.327E+06	8.808E+05	1.410E+06	5.412E+05	1.407E+05	7.200E+04	7.886E+04	8.413E+04	1.504E+04	3.015E+06
ALT17	2.688E+07	0	1.879E+06	5.463E+05	5.975E+04	1.032E+07	8.658E+05	1.513E+06	9.401E+04	1.352E+05	6.927E+04	7.886E+04	8.413E+04	1.504E+04	1.777E+06
ALT18	2.786E+07	0	1.124E+06	8.482E+05	5.614E+04	1.471E+07	8.658E+05	1.155E+06	6.408E+04	1.194E+05	6.927E+04	7.886E+04	8.413E+04	1.504E+04	1.754E+06
ALT19	0	1.851E+07	1.337E+07	0	1.195E+05	0	2.967E+06	4.001E+06	1.951E+05	1.407E+05	7.200E+04	7.886E+04	8.413E+04	1.504E+04	2.393E+06
ALT20	0	2.473E+07	1.337E+07	0	2.891E+04	2.925E+06	2.967E+06	1.821E+06	5.283E+05	1.352E+05	7.200E+04	7.886E+04	8.413E+04	1.504E+04	2.525E+06
ALT21	0	2.721E+07	1.337E+07	0	5.975E+04	2.925E+06	2.967E+06	1.890E+06	1.769E+05	1.352E+05	7.200E+04	7.886E+04	8.413E+04	1.504E+04	2.334E+06
ALT22	0	2.473E+07	1.337E+07	0	5.975E+04	0	2.967E+06	3.499E+06	1.685E+05	1.335E+04	7.200E+04	7.886E+04	8.413E+04	1.504E+04	2.206E+06
ALT23	0	2.533E+07	1.337E+07	0	5.975E+04	0	2.967E+06	3.797E+06	7.082E+04	1.335E+04	7.200E+04	7.886E+04	8.413E+04	1.504E+04	1.705E+06
ALT24	0	2.932E+07	1.395E+07	0	5.975E+04	8.411E+06	2.967E+06	1.238E+06	1.455E+05	9.407E+03	1.860E+05	7.886E+04	8.413E+04	1.504E+04	2.298E+06

Table 5-10 Summary table for O&M cost data for technologies and alternatives (kZAR)

	Coal (pf)	Nuclear (ALWR)	Nuclear (PBMR)	OCGT	Pumped storage	FBC	CCGT (pipe)	CCGT (LNG)	Wind1	Wind2	Wind3	Small landfill gas	Medium landfill gas	Large landfill gas	Hydro modifications and refurbishments	Existing system
BASE	1.284E+06	0	1.356E+05	4.552E+05	4.931E+04	2.161E+06	3.522E+05	3.402E+05	1.012E+05	3.981E+04	3.930E+04	2.126E+04	2.342E+04	4.212E+03	8.602E+05	1.041E+08
ALT1	1.291E+06	0	1.356E+05	4.644E+05	2.586E+04	2.175E+06	3.522E+05	3.404E+05	1.011E+05	7.338E+04	3.930E+04	2.383E+04	2.642E+04	4.784E+03	8.518E+05	1.041E+08
ALT2	1.594E+06	0	1.482E+05	4.522E+05	0	1.513E+06	3.522E+05	4.169E+05	1.106E+05	7.496E+04	4.017E+04	5.717E+04	7.332E+04	1.367E+04	9.682E+05	1.041E+08
ALT3	1.153E+06	9.448E+04	1.356E+05	4.279E+05	4.641E+04	2.162E+06	3.522E+05	4.041E+05	1.107E+05	7.535E+04	4.359E+04	5.401E+04	6.163E+04	1.149E+04	1.017E+06	1.041E+08
ALT4	1.130E+06	9.075E+04	1.356E+05	3.941E+05	0	2.203E+06	3.522E+05	4.804E+05	1.346E+05	7.535E+04	4.359E+04	5.401E+04	7.332E+04	1.367E+04	1.053E+06	1.041E+08
ALT5	1.510E+06	0	2.537E+05	2.560E+05	9.002E+02	1.855E+06	4.386E+05	5.184E+05	1.418E+05	7.184E+04	3.930E+04	1.329E+05	1.516E+05	2.826E+04	1.074E+06	1.040E+08
ALT6	1.503E+06	0	1.356E+05	2.714E+05	3.425E+01	3.102E+06	3.488E+05	2.954E+05	6.116E+04	5.663E+04	3.774E+04	5.401E+04	6.163E+04	1.518E+04	7.895E+05	1.039E+08
ALT7	1.205E+06	1.691E+04	3.094E+05	2.457E+05	0	3.178E+06	3.517E+05	4.260E+05	6.207E+04	6.702E+04	3.748E+04	1.329E+05	1.516E+05	2.826E+04	1.021E+06	1.038E+08
ALT8	6.005E+05	1.433E+05	1.040E+06	3.771E+05	0	1.468E+06	5.783E+05	5.021E+05	1.272E+05	7.306E+04	4.017E+04	6.425E+04	7.332E+04	1.367E+04	1.108E+06	1.041E+08
ALT9	5.812E+05	1.082E+06	1.066E+06	1.637E+05	4.044E+03	1.538E+06	6.241E+05	5.208E+05	2.109E+05	7.377E+04	4.104E+04	1.329E+05	1.516E+05	2.826E+04	1.102E+06	1.039E+08
ALT10	0	1.998E+06	1.237E+06	1.364E+05	1.892E+03	2.218E+06	3.522E+05	5.510E+05	2.843E+05	8.020E+04	4.129E+04	1.329E+05	1.516E+05	2.826E+04	1.252E+06	1.039E+08
ALT11	3.088E+05	2.186E+06	1.134E+06	2.424E+05	0	0	6.353E+05	1.134E+06	1.287E+05	8.194E+04	5.187E+04	1.329E+05	1.516E+05	2.826E+04	1.168E+06	1.040E+08
ALT12	2.829E+06	0	1.356E+05	2.330E+05	4.275E+03	4.225E+06	3.522E+05	2.221E+05	5.348E+04	6.576E+04	3.592E+04	1.329E+05	1.516E+05	2.826E+04	8.668E+05	1.032E+08
ALT13	1.718E+06	1.738E+04	9.261E+05	1.121E+05	8.048E+03	4.225E+06	3.526E+05	6.228E+05	5.348E+04	7.708E+04	3.948E+04	1.329E+05	1.516E+05	2.826E+04	8.867E+05	1.033E+08
ALT14	0	2.997E+06	1.773E+06	1.132E+05	4.917E+03	2.843E+06	3.584E+05	4.415E+05	2.971E+05	8.020E+04	4.104E+04	1.329E+05	1.516E+05	2.826E+04	1.277E+06	1.035E+08
ALT15	0	3.149E+06	1.773E+06	1.517E+05	0	0	5.814E+05	1.230E+06	2.488E+05	8.383E+04	4.586E+04	1.329E+05	1.516E+05	2.826E+04	1.198E+06	1.038E+08
ALT16	0	4.478E+06	1.773E+06	1.132E+05	4.732E+03	2.277E+06	3.588E+05	4.150E+05	3.085E+05	8.020E+04	4.104E+04	1.329E+05	1.516E+05	2.826E+04	1.340E+06	1.035E+08
ALT17	4.086E+06	0	2.537E+05	1.121E+05	8.408E+03	2.884E+06	3.522E+05	4.820E+05	5.358E+04	7.708E+04	3.948E+04	1.329E+05	1.516E+05	2.826E+04	8.721E+05	1.030E+08
ALT18	4.236E+06	0	1.375E+05	1.736E+05	7.900E+03	4.225E+06	3.522E+05	3.354E+05	3.653E+04	6.807E+04	3.948E+04	1.329E+05	1.516E+05	2.826E+04	8.642E+05	1.028E+08
ALT19	0	6.756E+06	1.773E+06	0	1.682E+04	0	1.275E+06	1.481E+06	1.112E+05	8.020E+04	4.104E+04	1.329E+05	1.516E+05	2.826E+04	1.113E+06	1.031E+08
ALT20	0	8.780E+06	1.773E+06	0	4.068E+03	7.646E+05	1.275E+06	6.216E+05	3.011E+05	7.708E+04	4.104E+04	1.329E+05	1.516E+05	2.826E+04	1.202E+06	1.030E+08
ALT21	0	9.511E+06	1.773E+06	0	8.408E+03	7.646E+05	1.275E+06	6.572E+05	1.008E+05	7.708E+04	4.104E+04	1.329E+05	1.516E+05	2.826E+04	1.294E+06	1.029E+08
ALT22	0	8.780E+06	1.773E+06	0	8.408E+03	0	1.275E+06	1.306E+06	9.602E+04	7.610E+03	4.104E+04	1.329E+05	1.516E+05	2.826E+04	1.104E+06	1.030E+08
ALT23	0	8.957E+06	1.773E+06	0	8.408E+03	0	1.275E+06	1.437E+06	4.037E+04	7.610E+03	4.104E+04	1.329E+05	1.516E+05	2.826E+04	1.054E+06	1.029E+08
ALT24	0	1.007E+07	1.828E+06	0	8.408E+03	2.394E+06	1.275E+06	4.142E+05	8.291E+04	5.362E+03	1.060E+05	1.329E+05	1.516E+05	2.826E+04	1.281E+06	1.026E+08

Table 5-11 Summary table for fuel cost data for alternatives (kZAR)

	Coal	Uranium	Uranium PBMR	Diesel	Duff coal	Kudu gas	LNG
BASE	1.107E+08	7.097E+06	1.358E+05	2.767E+05	6.555E+05	1.748E+06	3.004E+06
ALT1	1.112E+08	7.097E+06	1.358E+05	2.939E+05	6.595E+05	1.748E+06	3.006E+06
ALT2	1.116E+08	7.097E+06	1.484E+05	1.266E+05	4.590E+05	1.748E+06	3.681E+06
ALT3	1.112E+08	7.155E+06	1.358E+05	2.781E+05	6.556E+05	1.748E+06	3.568E+06
ALT4	1.108E+08	7.152E+06	1.358E+05	7.192E+04	6.681E+05	1.748E+06	4.242E+06
ALT5	1.108E+08	7.097E+06	2.541E+05	6.768E+04	5.626E+05	2.176E+06	4.577E+06
ALT6	1.103E+08	7.097E+06	1.358E+05	7.551E+04	9.409E+05	1.731E+06	2.608E+06
ALT7	1.096E+08	7.107E+06	3.099E+05	4.973E+04	9.638E+05	1.745E+06	3.762E+06
ALT8	1.109E+08	7.185E+06	1.041E+06	6.606E+04	4.452E+05	2.870E+06	4.433E+06
ALT9	1.091E+08	7.762E+06	1.068E+06	3.660E+04	4.663E+05	3.097E+06	4.598E+06
ALT10	1.081E+08	8.324E+06	1.239E+06	3.244E+04	6.729E+05	1.748E+06	4.865E+06
ALT11	1.099E+08	8.440E+06	1.135E+06	4.292E+04	0	3.152E+06	1.002E+07
ALT12	1.093E+08	7.097E+06	1.358E+05	4.973E+04	1.282E+06	1.748E+06	1.961E+06
ALT13	1.075E+08	7.107E+06	9.274E+05	8.326E+03	1.282E+06	1.749E+06	5.499E+06
ALT14	1.067E+08	8.938E+06	1.775E+06	2.926E+04	8.624E+05	1.778E+06	3.898E+06
ALT15	1.081E+08	9.031E+06	1.775E+06	3.418E+04	0	2.885E+06	1.086E+07
ALT16	1.059E+08	9.848E+06	1.775E+06	2.926E+04	6.907E+05	1.781E+06	3.664E+06
ALT17	1.101E+08	7.097E+06	2.541E+05	0	8.746E+05	1.748E+06	4.256E+06
ALT18	1.092E+08	7.097E+06	1.376E+05	3.923E+04	1.282E+06	1.748E+06	2.961E+06
ALT19	1.048E+08	1.125E+07	1.775E+06	0	0	6.329E+06	1.308E+07
ALT20	1.040E+08	1.249E+07	1.775E+06	0	2.319E+05	6.329E+06	5.488E+06
ALT21	1.035E+08	1.294E+07	1.775E+06	0	2.319E+05	6.329E+06	5.803E+06
ALT22	1.039E+08	1.249E+07	1.775E+06	0	0	6.329E+06	1.153E+07
ALT23	1.037E+08	1.260E+07	1.775E+06	0	0	6.329E+06	1.269E+07
ALT24	1.019E+08	1.329E+07	1.830E+06	0	7.261E+05	6.329E+06	3.657E+06

Table 5-12 Summary table for CO_{2EQ} emission data for technologies and alternatives (kton)

	OCGT	FBC	CCGT (pipe)	CCGT (LNG)	Existing system	Coal (pf)
BASE	5.332E+01	2.354E+04	2.511E+03	2.697E+03	2.579E+06	5.023E+04
ALT1	5.774E+01	2.369E+04	2.511E+03	2.699E+03	2.598E+06	5.066E+04
ALT2	1.728E+01	1.649E+04	2.511E+03	3.305E+03	2.594E+06	6.258E+04
ALT3	5.234E+01	2.354E+04	2.511E+03	3.204E+03	2.485E+06	4.479E+04
ALT4	1.059E+01	2.399E+04	2.511E+03	3.809E+03	2.577E+06	4.436E+04
ALT5	1.060E+01	2.020E+04	3.126E+03	4.110E+03	2.579E+06	5.925E+04
ALT6	1.167E+01	3.379E+04	2.486E+03	2.342E+03	2.571E+06	5.899E+04
ALT7	1.069E+01	3.461E+04	2.507E+03	3.377E+03	2.566E+06	4.730E+04
ALT8	1.130E+01	1.599E+04	4.122E+03	3.980E+03	2.499E+06	2.357E+04
ALT9	6.727E+00	1.675E+04	4.449E+03	4.128E+03	2.570E+06	2.281E+04
ALT10	5.472E+00	2.416E+04	2.511E+03	4.368E+03	2.457E+06	0
ALT11	8.633E+00	0	4.528E+03	8.993E+03	2.487E+06	1.212E+04
ALT12	1.069E+01	4.602E+04	2.511E+03	1.761E+03	2.498E+06	1.110E+05
ALT13	0	4.602E+04	2.513E+03	4.937E+03	2.500E+06	6.742E+04
ALT14	4.512E+00	3.097E+04	2.555E+03	3.500E+03	2.425E+06	0
ALT15	5.996E+00	0	4.144E+03	9.748E+03	2.458E+06	0
ALT16	4.512E+00	2.480E+04	2.558E+03	3.290E+03	2.408E+06	0
ALT17	0	3.141E+04	2.511E+03	3.821E+03	2.467E+06	1.604E+05
ALT18	7.520E+00	4.602E+04	2.511E+03	2.659E+03	2.442E+06	1.663E+05
ALT19	0	0	9.092E+03	1.174E+04	2.381E+06	0
ALT20	0	8.328E+03	9.092E+03	4.927E+03	2.362E+06	0
ALT21	0	8.328E+03	9.092E+03	5.210E+03	2.352E+06	0
ALT22	0	0	9.092E+03	1.036E+04	2.361E+06	0
ALT23	0	0	9.092E+03	1.139E+04	2.356E+06	0
ALT24	0	2.608E+04	9.092E+03	3.284E+03	2.315E+06	0

Table 5-13 Summary table for SO_{2EQ} emission data for technologies and alternatives (kton)

	OCGT	FBC	CCGT (pipe)	CCGT (LNG)	Existing system	Coal (pf)
BASE	1.541E-01	4.831E+02	5.943E+00	6.382E+00	1.496E+04	1.873E+02
ALT1	1.674E-01	4.861E+02	5.943E+00	6.387E+00	1.505E+04	1.889E+02
ALT2	5.008E-02	3.383E+02	5.943E+00	7.823E+00	1.503E+04	2.333E+02
ALT3	1.514E-01	4.832E+02	5.943E+00	7.582E+00	1.467E+04	1.670E+02
ALT4	3.061E-02	4.924E+02	5.943E+00	9.014E+00	1.498E+04	1.654E+02
ALT5	3.071E-02	4.146E+02	7.399E+00	9.727E+00	1.494E+04	2.209E+02
ALT6	3.379E-02	6.934E+02	5.885E+00	5.543E+00	1.489E+04	2.199E+02
ALT7	3.089E-02	7.103E+02	5.935E+00	7.993E+00	1.486E+04	1.764E+02
ALT8	3.267E-02	3.281E+02	9.758E+00	9.421E+00	1.477E+04	8.787E+01
ALT9	1.947E-02	3.437E+02	1.053E+01	9.772E+00	1.491E+04	8.505E+01
ALT10	1.582E-02	4.959E+02	5.943E+00	1.034E+01	1.451E+04	0
ALT11	2.500E-02	0	1.072E+01	2.129E+01	1.470E+04	4.519E+01
ALT12	3.089E-02	9.445E+02	5.943E+00	4.167E+00	1.446E+04	4.139E+02
ALT13	0	9.445E+02	5.949E+00	1.169E+01	1.448E+04	2.513E+02
ALT14	1.311E-02	6.355E+02	6.047E+00	8.284E+00	1.438E+04	0
ALT15	1.732E-02	0	9.810E+00	2.307E+01	1.455E+04	0
ALT16	1.311E-02	5.090E+02	6.055E+00	7.786E+00	1.422E+04	0
ALT17	0	6.446E+02	5.943E+00	9.044E+00	1.429E+04	5.980E+02
ALT18	2.181E-02	9.445E+02	5.943E+00	6.293E+00	1.414E+04	6.199E+02
ALT19	0	0	2.152E+01	2.779E+01	1.409E+04	0
ALT20	0	1.709E+02	2.152E+01	1.166E+01	1.401E+04	0
ALT21	0	1.709E+02	2.152E+01	1.233E+01	1.395E+04	0
ALT22	0	0	2.152E+01	2.451E+01	1.398E+04	0
ALT23	0	0	2.152E+01	2.696E+01	1.393E+04	0
ALT24	0	5.351E+02	2.152E+01	7.772E+00	1.373E+04	0

Table 5-14 Summary table for water consumption data for technologies and alternatives (kton)

	OCGT	FBC	CCGT (pipe)	Existing system	Coal (pf)
BASE	2.511E+02	9.833E+03	2.185E+03	4.287E+06	9.689E+03
ALT1	2.719E+02	9.893E+03	2.185E+03	3.893E+06	9.772E+03
ALT2	8.137E+01	6.885E+03	2.185E+03	3.892E+06	1.207E+04
ALT3	2.465E+02	9.834E+03	2.185E+03	4.708E+06	8.641E+03
ALT4	4.986E+01	1.002E+04	2.185E+03	3.913E+06	8.557E+03
ALT5	4.991E+01	8.439E+03	2.720E+03	3.845E+06	1.143E+04
ALT6	5.497E+01	1.411E+04	2.163E+03	3.820E+06	1.138E+04
ALT7	5.033E+01	1.446E+04	2.182E+03	3.810E+06	9.124E+03
ALT8	5.320E+01	6.678E+03	3.587E+03	4.096E+06	4.546E+03
ALT9	3.168E+01	6.995E+03	3.871E+03	3.842E+06	4.400E+03
ALT10	2.577E+01	1.009E+04	2.185E+03	4.711E+06	0
ALT11	4.065E+01	0	3.940E+03	4.067E+06	2.338E+03
ALT12	5.033E+01	1.922E+04	2.185E+03	3.628E+06	2.142E+04
ALT13	0	1.922E+04	2.187E+03	3.636E+06	1.300E+04
ALT14	2.125E+01	1.294E+04	2.223E+03	4.007E+06	0
ALT15	2.824E+01	0	3.606E+03	4.052E+06	0
ALT16	2.125E+01	1.036E+04	2.226E+03	4.677E+06	0
ALT17	0	1.312E+04	2.185E+03	3.559E+06	3.094E+04
ALT18	3.541E+01	1.922E+04	2.185E+03	3.500E+06	3.207E+04
ALT19	0	0	7.911E+03	3.887E+06	0
ALT20	0	3.479E+03	7.911E+03	3.862E+06	0
ALT21	0	3.479E+03	7.911E+03	3.838E+06	0
ALT22	0	0	7.911E+03	3.839E+06	0
ALT23	0	0	7.911E+03	3.864E+06	0
ALT24	0	1.089E+04	7.911E+03	3.753E+06	0

Table 5-15 Probability distribution data [8]

Investment cost

Coal (pf)	triangular(0.956,1,1.044)
Nuclear (ALWR)	triangular(0.9126,1,1.0874)
Nuclear (PBMR)	triangular(0.9091,1,1.0909)
OCGT	triangular(0.9436,1,1.0564)
Pumped storage	triangular(1,1,1)
FBC	triangular(0.9546,1,1.0454)
CCGT (pipe)	triangular(0.9696,1,1.0304)
CCGT (LNG)	triangular(0.9659,1,1.0341)
Wind1	triangular(0.9297,1,1.0703)
Wind2	triangular(0.9297,1,1.0703)
Wind3	triangular(0.9297,1,1.0703)
Small landfill gas	triangular(1,1,1)
Medium landfill gas	triangular(1,1,1)
Large landfill gas	triangular(1,1,1)
Hydro modifications and refurbishments	triangular(1,1,1)

O&M cost

Coal (pf)	triangular(0.7612,1,1.2388)
Nuclear (ALWR)	triangular(0.8666,1,1.1334)
Nuclear (PBMR)	triangular(0.9091,1,1.0909)
OCGT	triangular(0.7606,1,1.2394)
Pumped storage	triangular(1,1,1)
FBC	triangular(0.6072,1,1.3928)
CCGT (pipe)	triangular(0.9166,1,1.0834)
CCGT (LNG)	triangular(0.9181,1,1.0819)
Wind1	triangular(0.9091,1,1.0909)
Wind2	triangular(0.9091,1,1.0909)
Wind3	triangular(0.9091,1,1.0909)
Small landfill gas	triangular(1,1,1)
Medium landfill gas	triangular(1,1,1)
Large landfill gas	triangular(1,1,1)
Hydro modifications and refurbishments	triangular(1,1,1)
Existing system	triangular(1,1,1)

Fuel cost

Coal	triangular(0.95,1,1.05)
Uranium	triangular(0.95,1,1.05)
Uranium PBMR	triangular(0.95,1,1.05)
Diesel	triangular(0.9,1,1.1)
Duff coal	triangular(0.95,1,1.05)
Kudu gas	triangular(0.95,1,1.05)
LNG	triangular(0.9,1,1.1)

[8] Triangular distribution (lower, mode, upper)   Uniform distribution (lower, upper)

Table 5-15 Probability distribution data cond.

CO2_eq emissions

OCGT	triangular(0.9,1,1.1)
FBC	triangular(0.643,1,1.643)
CCGT (pipe)	triangular(0.95,1,1.05)
CCGT (LNG)	triangular(0.95,1,1.05)
Existing system	uniform(0.951,1.034)
Coal (pf)	uniform(0.872,1.128)

SO2_eq emissions

OCGT	triangular(0.9,1,1.1)
FBC	triangular(0.2,1,3.2)
CCGT (pipe)	triangular(0.95,1,1.05)
CCGT (LNG)	triangular(0.95,1,1.05)
Existing system	uniform(0.849,1.122)
Coal (pf)	uniform(0.346,1.654)

Water consumption

OCGT	triangular(0.9,1,1.1)
FBC	triangular(0.828,1,1.172)
CCGT (pipe)	triangular(0.95,1,1.05)
Existing system	uniform(0.964,1.029)
Coal (pf)	uniform(0.828,1.172)

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CHAPTER 6 BIASES IN WEIGHT ASSESSMENT AND THE EFFECTS OF INTEGRATING TECHNICAL EMPIRICAL UNCERTAINTY INTO THE GENERATION PHASE

6.1. INTRODUCTION

Chapter 5 focussed on addressing technical empirical uncertainties in the selection phase due to the computational, time and data management burden of addressing these uncertainties in the generation phase.

One of the potential limitations of addressing uncertainty in the selection phase is that the operational characteristics of the system are not reoptimised for each discrete future (which is defined by a sample of the uncertainties involved) as would be the case in the actual ESI. If the operational characteristics of the system were optimised for each discrete future, the load factors for individual power stations would be reoptimised (within technical and contractual constraints) so as to best meet the overall system objectives given each discrete future even though the investment strategy would be fixed.

It was postulated in chapter 5 that as the power expansion alternatives were originally generated in an optimisation framework, this caveat would only result a slightly pessimistic view of the future. In other words, the higher end of the uncertainty range for each attribute in each alternative could be slightly higher than in reality, as in realty each alternative would have been reoptimised to meet the realised future. As some alternatives would be better positioned to adjust to those uncertainties than others, it would be possible that changes would occur in the rank order and only an indication of that would be captured by doing an analysis of uncertainty in the selection phase.

This chapter will evaluate whether or not there are significant differences in the absolute performance of alternatives in terms of their attributes when dealing with technical empirical uncertainties in the generation phase as opposed to the selection phase. It will then examine the rank order and frequency information obtained from dealing with technical empirical uncertainties in the generation phase and compares that to the rank and frequency information obtained from dealing with technical empirical uncertainties in the selection phase. Finally these differences will be analysed in relation to other uncertainties in the system (valuation model parameter uncertainty around DM preferences) to determine whether they are in fact significant or if they are "drowned out" by uncertainty in DM preferences.

This chapter will also focus on the normalisation process whereby attribute performance values are converted to value function scores in light of comparing the two data sets generated by dealing with uncertainty in the generation phase as opposed to dealing with uncertainty in the selection phase. The specific issue of weighting bias will be addressed.

6.2. APPROACH

The aim of this analysis was to evaluate the robustness of the "base case" or least cost solution and the 24 other non-dominated solutions that better satisfied the non-cost objectives generated in chapter 4.

As the purpose of this work was to compare the results obtained from doing the robustness analysis in the selection phase (hereafter referred to as approach A) as opposed to the generation phase (hereafter referred to as approach B), the same inputs or samples of the uncertain parameters were used. A description of the way in which the uncertainty sample sets were generated is described below:

6.2.1. REPRESENTING UNCERTAINTY

Uncertainty in technology cost data (investment, O&M) was incorporated into the model using data from the NIRP (NER et al., 2004), which formed the core data for the work done in chapter 4 and chapter 5. Estimated values based on available data for fuel price and emission coefficient uncertainty for each technology were included in order to demonstrate the capability of the model.

Triangular distributions were used to represent uncertainty in parameters where data was available (e.g. cost data from (NER et al., 2004)) while uniform distributions were used where only a minimum and maximum for a range were available (e.g. CO_2 emission factor ranges for pulverised coal fired stations (Notten, 2001) and (Eskom, 2001)).

An uncertainty distribution was then defined for each technology, for each of the uncertainty parameters (investment cost, O&M cost, fuel cost and emission factors). Sample sets of the uncertain parameters were generated using a median Latin hypercube sampling technique. The equivalent 1000 sets of input data were run in the model to match the analysis of uncertainty done previously in the selection phase.

Integrating uncertainty into the generation phase

In order to test the robustness of each of the 25 alternatives previously generated in chapter 4, the technology investment strategies were fixed in the options generator (MARKAL). Although the investment strategies were fixed, the operational parameters (power station load factors and related variables) were not and could therefore be reoptimised with the changing inputs (sets of uncertain parameters).

The model was then run for each of the 1000 sample sets of the uncertain parameters for each of the alternatives (totalling 25000 model runs). This was done by linking MARKAL to a framework developed by the United States Environmental Protection Agency (USEPA) called MIMS. MIMS provided a practical automated framework for running large numbers of MARKAL runs, with changing inputs.

The performance of each of the alternatives in each of the attributes (including uncertainty) could then be integrated into a preference model so as to evaluate the performance of the alternatives for the multiple criteria chosen.

6.2.2. PREFERENCE MODEL

The same methodology as used in chapter 5 was used to construct a value function model to evaluate the performance of the alternatives. However special attention had to be paid to the intra-criterion preference information. Although it has been shown that the weights obtained from different methods have been know to vary (as was shown in (Borcherding et al., 1991); cited in (Pöyhönen and Hämäläinen, 2000) and (Pöyhönen and Hämäläinen, 2001) in which the weights obtained using a range of weighting methods were compared), these studies and others have indicated that behavioral aspects are also responsible for differences in the weights (see (Weber and Borcherding, 1993) for a summary of these effects). Behavioral effects on weight elicitation are known as "weighting biases" with the two main types identified in (Pöyhönen and Hämäläinen, 2000) being discussed, namely the splitting bias and the range effect.

The splitting bias refers to a phenomenon that an attribute receives more weight if it is split into sub-attributes (i.e. weights may be influenced by the structure of value trees) (see (Stillwell et al., 1987; Borcherding and von Winterfeldt, 1988; Weber et al., 1988).

The range effect presented by (von Nitzsch and Weber, 1993; Fischer, 1995) occurs when the DM fails to adjust the weights as the ranges of attributes change. This problem is more pronounced with direct weighting methods than with indifference weighting or swing weighting methods but can occur if the attribute ranges are insufficiently considered in the weight elicitation process.

In the normalisation process whereby attribute performance values (for each sample of uncertain parameters) are converted to value function scores, the attribute values are typically normalised based on the highest and lowest values in each attribute such that the "worst" and "best" outcomes in each criterion are assigned values of 0 and 1 respectively. Equation 6.1 below demonstrates this normalisation procedure:

$$v_i(x_i) = \frac{(Max_i - x_i)}{(Max_i - Min_i)} \qquad (6.1)$$

Where: $v_i(x_i)$ is the value score of the attribute performance result X in attribute i and Max_i and Min_i are the maximum and minimum performance values for attribute i

While this approach works well in theory (especially in cases where only average values are used), the ranges can be easily skewed by highly improbable values at either extreme of the range when uncertainty is included. This would result in the entire range of values for a specific attribute being either artificially inflated or deflated depending on which extreme the outliers or improbable values lay. These artificially inflated or deflated value scores would result in an effective weighting bias whereby one criterion would be weighted more or less important relative to the other criteria. This effect is related to the range effect discussed above as it occurs when the weight range does not appropriately change with the attribute range at these extreme points. In order to eliminate this bias the true willingness to trade-off the attributes at these extreme points must be captured in the weight elicitation process and the shape of the value functions must be correct. Practically this means that the DM must be asked specific weighting questions for each part of each attribute range in order to correctly construct the value functions otherwise extreme values could "bunch" the remaining attribute values. (Stewart, 1993) demonstrated the use of piecewise linear value functions for capturing preferences across the full range of the attributes. This bias effect could become more pronounced when comparing data sets generated using different methods and therefore having different structural characteristics (as in the case of this work). This is demonstrated in section 6.3.1.

Assuming that the shape of the value function is not accurately represented and there are extreme values in an attribute range (i.e. the true willingness to trade-off the attributes at the extreme points is not accurately captured) then the weighting bias discussed above will occur. The obvious approach would be to discard outliers or improbable values and proceed to normalise the range based on the new minimum and maximum values. The problem with this approach is that decision makers may be interested in improbable values as they give an indication of the regret associated with each of the alternatives. If for instance an alternative performed well for most of the sample sets of uncertain parameters but performed very poorly for some, then the alternative would potentially be a risky choice (as discussed in section 5.3.2.3 of chapter 5). Therefore ideally all samples should form part of the data set for later analysis yet a methodology for normalising the attribute ranges that is not based on inflated minima and maxima is needed.

The approach proposed here is to normalise the attributes based on pseudo-minimum and pseudo-maximum values found by defining thresholds for the sample set. This can be done by stipulating the percentage of the data that the normalisation should be based on thereby ignoring outliers or improbable values when defining minimum or maximum values. For example, using 95 % of the data points, the upper and lower 2.5 % of the values would be neglected when defining the pseudo-minimum and pseudo-maximum values (but not discarded) and therefore the entire attribute range would be based on more "realistic" or probable values decided upon by the decision maker. This would however result in value scores that are greater than 1 and less than 0 for the values outside of the thresholds. While this may be counter-intuitive due to the convention of normalising data such that the lowest and highest values in each attribute are assigned scores of 0 and 1 respectively, it is not mathematically incorrect, and only the highly improbable values (for this case, 5 % of the data set) would have scores greater than 1 or less than zero instead of the entire range being skewed by inflated minima or maxima. The effects of using this methodology are demonstrated below using an example with 20 samples where 10 % of the samples are neglected when defining pseudo-minimum and maximum values (i.e. 1 data point at each end). This is contrasted against a standard normalisation using the actual maximum and minimum values to normalise the range.

Table 6-1 Example demonstrating pseudo-minima and maxima normalisation methodology

Sample number	Attribute A value	Partial value function score	
		Standard	Non-standard
1	97	0.029	0.005
2	100	0	-0.035
3	54	0.492	0.646
4	30	0.747	1
5	71	0.302	0.384
6	64	0.385	0.499
7	86	0.145	0.166
8	6	1	1.351
9	76	0.253	0.315
10	89	0.115	0.124
11	65	0.369	0.477
12	47	0.563	0.745
13	34	0.705	0.943
14	34	0.707	0.946
15	76	0.254	0.317
16	60	0.421	0.549
17	59	0.440	0.575
18	96	0.038	0.017
19	53	0.504	0.664
20	97	0.025	0

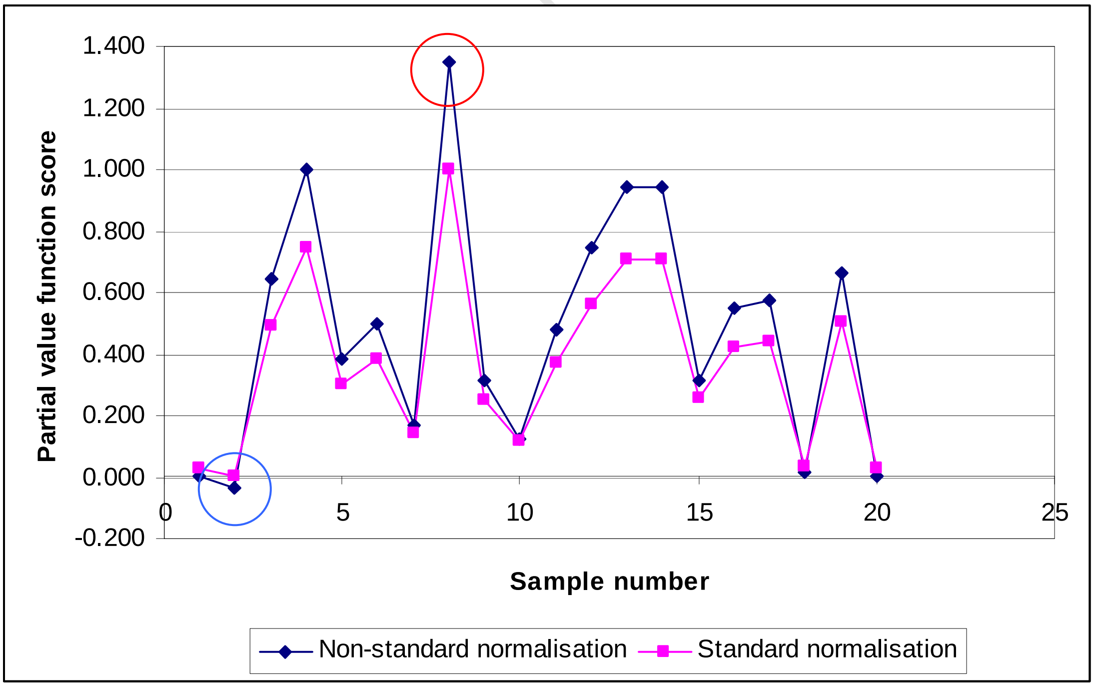

Figure 6-1 Graph of partial value function score for different normalisation methods

It can be seen in Figure 6-1 above that significant differences occur between the samples corresponding to higher partial value function scores when comparing the non-standard normalisation procedure to the standard normalisation procedure. This is due to the extreme value (sample no. 8, value 6) being left out when defining a pseudo-minimum value and the next lowest value of 30 being used as the pseudo-minimum value used to normalise the data range. Due to the fact that there is such a large difference between the actual minimum value (being 6) and the pseudo-minimum value (being 30) the samples that have high attribute performance values achieve higher partial value function scores than when using the standard normalisation procedure. In contrast, sample no. 2 (value 100) is left out when defining the pseudo-maximum value to normalise the data range and sample no. 1 (value 97) was used as the pseudo-maximum value. As there is very little difference between these two values, there is not much difference between the non-standard normalisation procedure and the standard normalisation procedure at the lower end of the partial value function range (as can be seen in Figure 6-1). Had sample no 8 (and sample no. 2) been dismissed as an outlier and the attribute performance scores been normalised based on the remaining range, the partial values scores would have been as reported by the non-standard normalisation procedure. The only difference is that now, the sample has not been discarded, it just achieves a very high partial value function score (see red circle on Figure 6-1) without skewing the partial value function scores of the entire range of data. In this way the partial value function scores are not skewed by improbable values and no data points are discarded (and can therefore be used later to determine regret).

In order to be consistent with this methodology, the weighting procedure for articulating stakeholder preferences has to be modified accordingly. This methodology is demonstrated using the indifference weighting method chosen previously in chapter 5. A technique based on indifference is described below:

In the case where a non-standard value function range is used so as to normalise the attributes based on pseudo-minimum and pseudo-maximum values, the original equation from section 2.4.2, equation 2-2 (repeated below) is still valid but Figure 6-2 is modified such that the actual extreme value scores are used (shown in Figure 6-3) instead of the typical 0 and 1 values:

$$w_i.v_i\left(x^*\right)+w_j.v_j\left(x_*\right)=w_i.v_i\left(x'\right)+w_j.v_j\left(x^*\right) \tag{6.2}$$

This equation represents the situation where on the LHS criterion i is at its best and criterion j is at its worst. The RHS of the equation then represents the situation where criterion i is at an acceptable level if criterion j were at its best. This equation can be seen to represent the indifference or trade-off question: "What sacrifice in terms of the best performance in criterion i would you be willing to make, to achieve an improvement from worst to best performance in criterion j?" The typical situation where the value score range between 0 and 1 is illustrated in Figure 6-2 and the non-standard situation where the value score range between less than 0 and greater than 1 is illustrated in Figure 6-3. The attribute performances in criteria i and j are represented by x_i and x_j respectively.

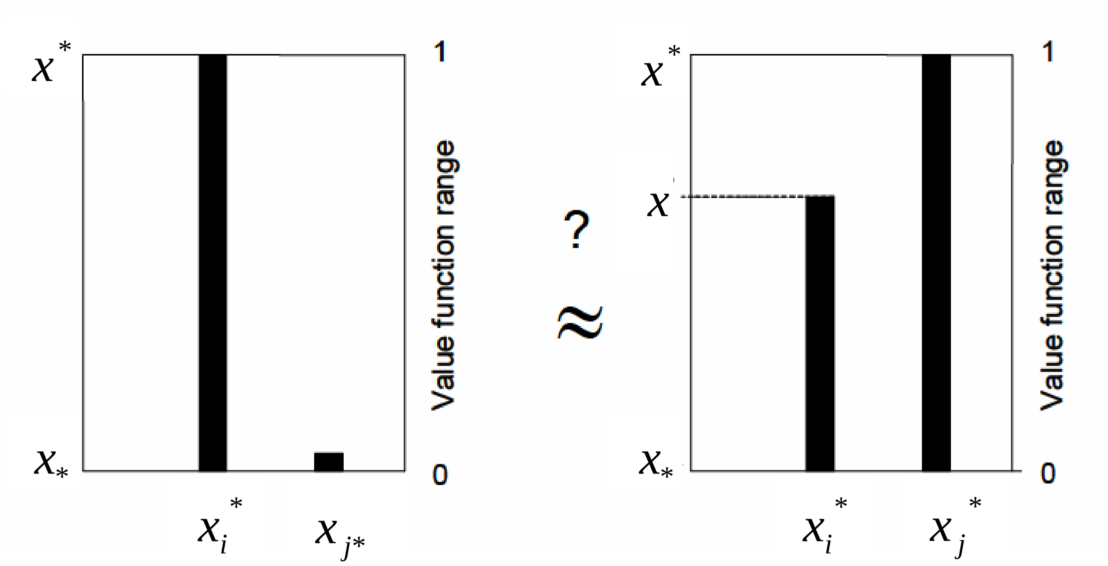

Figure 6-2 Indifference situation for typical 0-1 value function range (Basson, 2004)

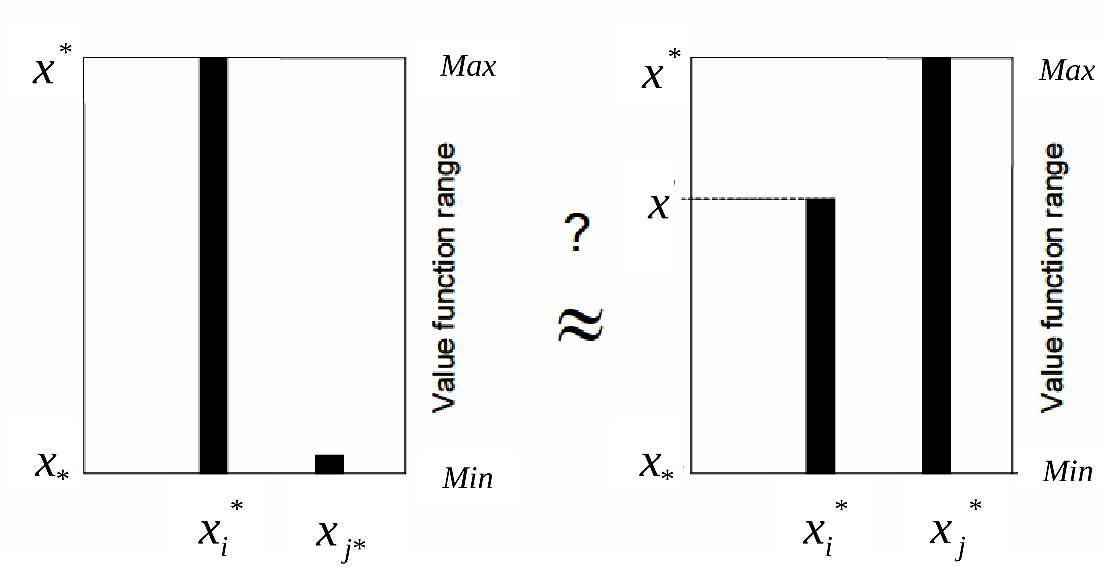

Figure 6-3 Indifference situation for non-standard value function range

Therefore the indifference equation in terms of the reference criterion α and the next criterion β is still:

$$w_\alpha.v_\alpha\left(x^*\right)+w_\beta.v_\beta\left(x_*\right)=w_\alpha.v_\alpha\left(x'\right)+w_\beta.v_\beta\left(x^*\right), \tag{6-3}$$

However this equation does not simplify to:

$$w_\alpha.1+0=w_\alpha.v_\alpha\left(x'\right)+w_\beta.1$$

$\dfrac{w_\beta}{w_\alpha}=1-v_\alpha\left(x'\right)=b$ as in section 2.4.2, equation 2-4, instead it becomes:

$$w_\alpha.Max_\alpha+w_\beta.Min_\beta=w_\alpha.v_\alpha\left(x'\right)+w_\beta.Max_\beta \tag{6-4}$$

$$w_\alpha.\left(Max_\alpha-v_\alpha\left(x'\right)\right)=w_\beta.\left(Max_\beta-Min_\beta\right)$$

$$b=\frac{\left(Max_\alpha-v_\alpha\left(x'\right)\right)}{\left(Max_\beta-Min_\beta\right)}=\frac{w_\beta}{w_\alpha}$$

The ratios relating the pairwise comparisons of the other criteria (b, c and d) can be calculated in a similar way. The individual weights can then be calculated in the same manner as in equation 6-3 above, with the weights being normalised to sum to 1.

In this way the indifference questions can be asked using the full range of each attribute, the entire data set can be used for further analysis and each attribute can be normalised on a more realistic or probable pseudo-maximum or pseudo-minimum thereby avoiding an effective weighting bias due to an artificially inflated or deflated value score range.

For the purpose of this analysis the two data sets were normalised using the same pseudo-minimum and pseudo-maximum values, defined using 95 % of the data in each attribute, with the upper and lower 2.5 % of the values lying outside the 0-1 value score range. The following results were then generated to compare the effect of normalising attribute performance values based on pseudo-minima and maxima as opposed to normalising them on their actual maximum and minimum values in terms of the rank order:

6.3. RESULTS

6.3.1. THE EFFECT OF NORMALISATION AND WEIGHTING APPROACH ON RESULTS

The results of normalising the attribute performance values based on pseudo-minima and maxima (with the appropriate indifference weighting procedure modifications) are compared to the results of normalising the attribute performance values based on the standard 0-1 value function range below.

The indifference situation was demonstrated using a representation of equal preference between criteria, where a situation in which an improvement of x % in a non-cost attribute at a sacrifice of the same percentage in cost was assumed to be indifferent to the situation in which cost was at its' best level of performance and the non-cost attribute was at its' worst. This is demonstrated below:

The weighting values change slightly when using the modified indifference weighting procedure even though the full range of each attribute is used in both cases. This is due to the Max_x and Min_x values being different for each attribute (instead of being 0 and 1 for all attributes) resulting in equation 6.4 above instead of equation 2.4 (also shown above).

Table 6-2 Value scores for minimum and maximum values in each attribute range

	Max_x	Min_x
Cost	1.044	-0.067
CO_{2EQ} emissions	1.101	-0.069
SO_{2EQ} emissions	1.119	-0.434
Water consumption	1.021	-0.049

Table 6-2 shows that the Max_x and Min_x values for cost and water consumption do not deviate much from the standard 0-1 range, however the values for SO_{2EQ} emissions, and to a lesser extent the values for CO_{2EQ} emissions, differ significantly from the standard 0-1 range. Using SO_{2EQ} emissions as an example, from Table 6-2 above it can be said that the maximum performance value for SO_{2EQ} emissions is almost 12 % above the pseudo maximum value, and the minimum value is more than 43 % lower than the pseudo minimum value. The sample data for this attribute can be seen in Figure 6-4:

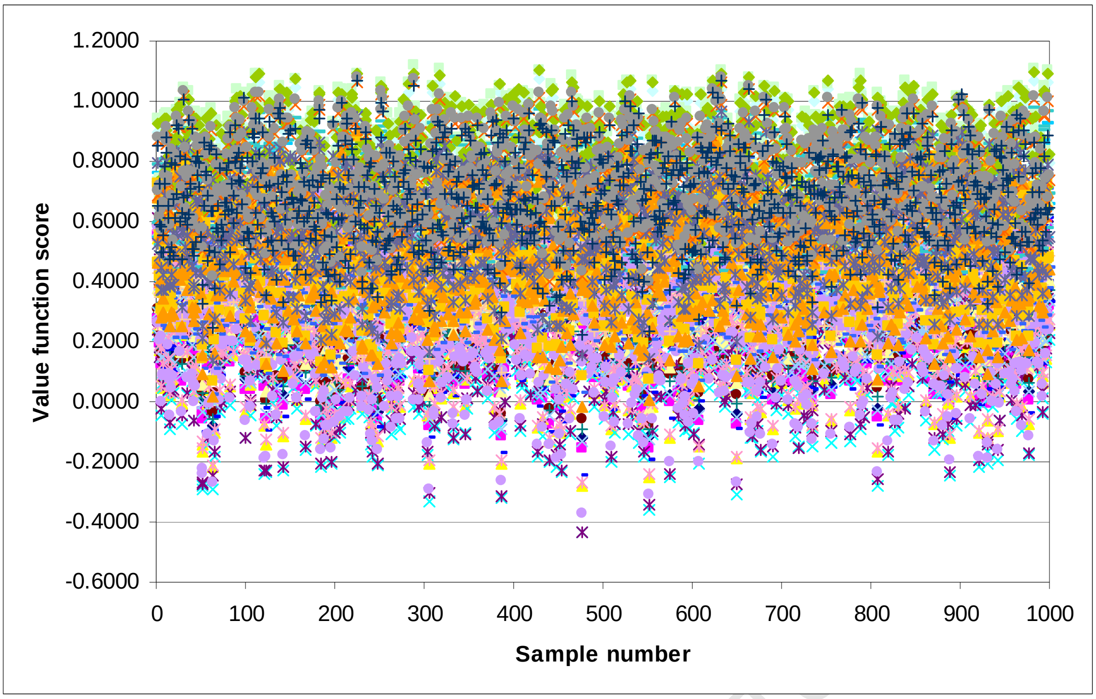

Figure 6-4 Value scores for all samples of SO_{2EQ} emissions

This data demonstrates that there are highly improbable values at each extreme of the performance range of this attribute that lie well away from the majority of the data points and that had these performance values been used to normalise the attribute performance range of SO_{2EQ} emissions, the entire range of value scores for this attribute would have been significantly skewed by these improbable performance values. Using pseudo minimum and maximum values defined using 95 % of the data to normalise the attribute performance range of SO_{2EQ} emissions reduces this effect significantly.

The pseudo minimum and maximum values from Table 6-2 above result in the weights derived from the modified indifference weighting procedure differing most for SO_{2EQ} emissions compared to the standard indifference procedure although the weighting value for CO_{2EQ} emissions also differs. The weighting value for cost therefore also differs substantially as it is calculated from the ratios of the other weights (see section 2.4.2, equation 2.6).

Table 6-3 Weights based on indifference procedure for equal preference between criteria

	Standard indifference procedure	**Modified indifference procedure**
Cost	0.306	0.344
CO_{2EQ} emissions	0.178	0.165
SO_{2EQ} emissions	0.325	0.219
Water consumption	0.276	0.272

Capturing these differences in the indifference weighting procedure calculations is an essential component of a consistent methodology that reduces the weighting bias caused by inflated minima and maxima as discussed above. As can be seen in Table 6-3 above, the modified weighting procedure does result in significant differences in weights, and therefore it is essential that the weighting procedure is modified to be consistent with the overall methodology. The effect of using pseudo-minima and maxima and the modified weighting procedure is shown below in terms of the overall value function scores and the lower rank order.

Table 6-4 Average overall value function scores and rank for top 5 alternatives using standard and non-standard normalisation methods for equal preference between criteria

Standard normalisation	**ALT 5**	**ALT 8**	**ALT 9**	**ALT 11**	**ALT 15**
Overall value function score	0.667	0.672	0.682	0.684	0.680
Rank	**5**	**4**	**2**	**1**	**3**
Non-standard normalisation					
Overall value function score	0.611	0.615	0.623	0.621	0.611
Rank	**4**	**3**	**1**	**2**	**5**

Table 6-4 demonstrates that for equal preferences between criteria, the lower rank order changes when using the non-standard normalisation and modified indifference weighting technique. This demonstrates that the effective weighting bias caused by inflated minima and maxima has significant effects on the lower rank order.

In light of the significant effects of demonstrated above, the modified normalisation and weighting procedure was used when comparing the performance results of Approach A with the performance results of Approach B in the rest of this chapter.

6.3.2. ABSOLUTE PERFORMANCE OF ALTERNATIVES

The performance results of Approach A were compared with the performance results of Approach B in order to test the postulation that not reoptimising the alternatives for each discrete future and dealing with uncertainties in the selection phase would result in a slightly pessimistic view of the future (see section 5.3).

Table 6-5 Excerpt comparing performance results of Approach A and Approach B

	BASE	**ALT 1**	**ALT 2**	**ALT 3**	**ALT 4**	**ALT 5**
Cost (kZAR)						
Approach B	2.605E+08	2.610E+08	2.623E+08	2.610E+08	2.609E+08	2.639E+08
Approach A	2.621E+08	2.626E+08	2.630E+08	2.631E+08	2.631E+08	2.649E+08
Difference (A-B)	1.627E+06	1.571E+06	6.908E+05	2.133E+06	2.186E+06	9.518E+05
Relative difference	**0.62%**	**0.60%**	**0.26%**	**0.81%**	**0.83%**	**0.36%**
CO_{2EQ} emissions (kton)						
Approach B	2.650E+06	2.668E+06	2.664E+06	2.551E+06	2.644E+06	2.659E+06
Approach A	2.641E+06	2.660E+06	2.661E+06	2.543E+06	2.635E+06	2.648E+06
Difference (A-B)	-8.770E+03	-7.896E+03	-3.292E+03	-8.499E+03	-8.950E+03	-1.120E+04
Relative difference	**-0.33%**	**-0.30%**	**-0.12%**	**-0.33%**	**-0.34%**	**-0.42%**
SO_{2EQ} emissions (kton)						
Approach B	1.569E+04	1.577E+04	1.528E+04	1.541E+04	1.572E+04	1.530E+04
Approach A	1.565E+04	1.574E+04	1.556E+04	1.535E+04	1.567E+04	1.557E+04
Difference (A-B)	-4.323E+01	-3.486E+01	2.785E+02	-6.028E+01	-5.270E+01	2.674E+02
Relative difference	**-0.28%**	**-0.22%**	**1.79%**	**-0.39%**	**-0.34%**	**1.72%**
Water consumption (kton)						
Approach B	4.300E+06	3.899E+06	3.914E+06	4.744E+06	3.922E+06	3.856E+06
Approach A	4.294E+06	3.902E+06	3.900E+06	4.713E+06	3.920E+06	3.855E+06
Difference (A-B)	-6.151E+03	3.327E+03	-1.421E+04	-3.081E+04	-2.466E+03	-1.127E+03
Relative difference	**-0.14%**	**0.09%**	**-0.36%**	**-0.65%**	**-0.06%**	**-0.03%**

PGPs (kZAR/kt)	**BASE**	**ALT 1**	**ALT 2**	**ALT 3**	**ALT 4**	**ALT 5**
CO_{2EQ} emissions	0	0	0	39	39	0
SO_{2EQ} emissions	0	0	6661	0	0	6661
Water consumption	0	16	16	0	16	47

Overall cost including PGPs (ZAR)						
Approach B	2.605E+11	3.219E+11	4.252E+11	3.597E+11	4.245E+11	5.466E+11
Approach A	2.621E+11	3.235E+11	4.276E+11	3.615E+11	4.263E+11	5.492E+11
Difference (A-B)	1.627E+09	1.622E+09	2.324E+09	1.804E+09	1.801E+09	2.680E+09
Relative difference	**0.62%**	**0.50%**	**0.54%**	**0.50%**	**0.42%**	**0.49%**

When the average performance results of each attribute, for each alternative of Approach A were compared with those of Approach B (see Table 6-5 above), it was found that for individual attributes (for some of the alternatives), Approach A did perform better than Approach B. The reason why alternatives in Approach A (which was not reoptimised) could outperform their counterparts in Approach B for individual attributes is that the reoptimisation was done for multiple objectives (as described in chapter 4). This enables the model to sacrifice performance in one or more of the objectives to better satisfy overall performance as defined by the overall objective function. In this case, as PGPs were used to force the model to better satisfy non-cost objectives, the overall performance could only be evaluated by taking the PGPs into account. Once this was done it could be seen that the Approach B outperformed Approach A for every alternative (including the alternatives not show in Table 6-5 but shown in Appendix C). It must be noted though that the relative differences were not large (all less than 1 %).

Therefore the postulation that not reoptimising the operational variables of the alternatives for technical empirical uncertainties would result in a slightly pessimistic view of the future was correct. The question of whether integrating technical empirical uncertainties into the generation phase as opposed to the selection phase significantly affects the rank order and credibility information of the alternatives remains unanswered. The next section will address that question.

6.3.3. Relative performance of alternatives

The effect that inter-criteria preference information has on the rank order of alternatives is illustrated in Figure 6-5 and Figure 6-6 as a function of relative cost weighting. The ratio of the weighting of the non-cost criteria relative to one another other is kept constant, while the cost weighting is varied through its full range. The lower the ranking (Rank 1 is best), the higher the overall value score and therefore the more preferred an alternative is according to the preference information. Figure 6-5 and Figure 6-6 demonstrate how the rank order changes significantly as the relative weight of cost changes in the overall value score.

For the purpose of this work it is interesting to compare the weighting diagrams for two approaches.

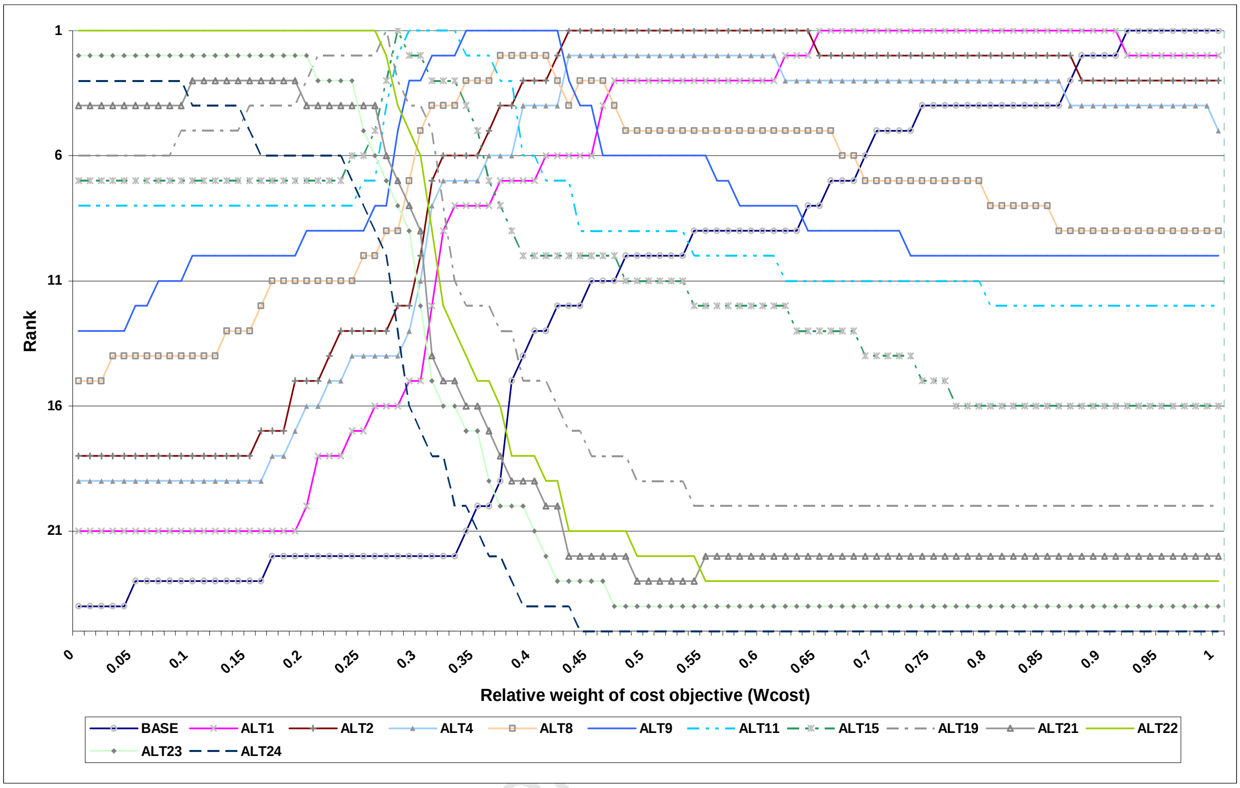

Figure 6-5 Excerpt of sensitivity diagram to cost weighting (Approach A)

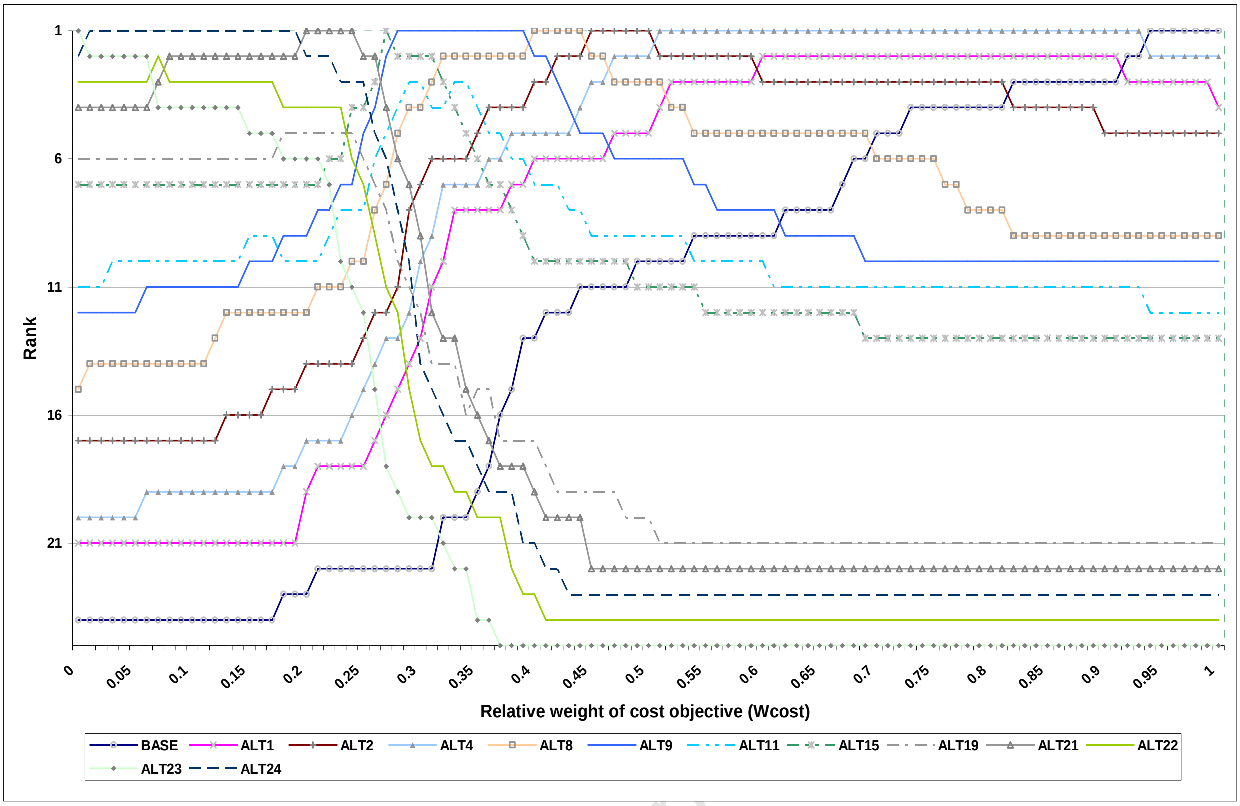

Figure 6-6 Excerpt of sensitivity diagram to cost weighting (Approach B)

While the weighting diagrams were similar for the two approaches, there were differences in the lower rank order at certain values of relative cost weighting.

Table 6-6 Summary of preferred alternatives in weight diagrams

Approximate weight range	Approach A	Approach B
0.01-0.19	ALT 22	ALT 24
0.20-0.26	ALT 22	ALT 21
0.27	ALT 19	ALT 15
0.28	ALT 15	ALT 9
0.29-0.33	ALT 11	ALT 9
0.34-0.39	ALT 9	ALT 9
0.40-0.42	ALT 9	ALT 8
0.43-0.44	ALT 2	ALT 8
0.45-0.52	ALT 2	ALT 2
0.52-0.64	ALT 2	ALT 4
0.65-0.91	ALT 1	ALT 4
0.92-0.93	BASE	ALT 4
0.94-1	BASE	BASE

Table 6-6 illustrates that the different approaches to dealing with uncertainty do in fact affect the sensitivity diagram and result in different alternatives occupying the preferred position (Rank 1) when moving along the relative cost weighting axis. There are however small sections of the sensitivity diagram where the same alternatives occupy the preferred rank in both methods for (e.g. ALT 2 in the W_{cost} range of 0.45-0.50).

While the weighting diagrams illustrate the differences between the results using the two approaches, they are primarily useful in integrating valuation model parameter uncertainty in preference information into the decision making process and building confidence in the validity of the results in relation to that information (see section 5.3.2.2). In order to compare the results of the two approaches in more detail, it is useful at this point to focus the analysis on specific parts of the sensitivity diagram and to examine the frequency information.

Relative cost weighting values of 0.34 (representing equal preference between criteria) and 0.61 (representing a stronger preference towards cost) were used to illustrate the results for an unstable and a stable section of the sensitivity diagrams in terms of the lower rank order.

Table 6-7, Table 6-8, Table 6-9 and Table 6-10 display the frequency at which each alternative obtained a particular rank for the set of discrete future scenarios at a relative cost weighting of 0.34 and 0.61 (representing equal preference between criteria and a stronger preference towards cost respectively), for each of the approaches to dealing with technical empirical uncertainty. The frequency at which particular alternatives occupy ranks can be used as an indication of the credibility associated with the ranking order. A rank of 1 represents the most preferred alternative while a rank of 25 represents the least preferred alternative for a given set of DM preference weightings.

Table 6-7 Frequency table for overall rank at a relative cost weighting of 0.34 (Approach A)

	BASE	ALT 1	ALT 2	ALT 3	ALT 4	ALT 5	ALT 6	ALT 7	ALT 8	ALT 9	ALT 10	ALT 11	ALT 12	ALT 13	ALT 14	ALT 15	ALT 16	ALT 17	ALT 18	ALT 19	ALT 20	ALT 21	ALT 22	ALT 23	ALT 24
1	0	0	0	0	0	0	0	4	2	591	0	403	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	1	0	27	124	1	56	189	201	0	197	0	0	0	204	0	0	0	0	0	0	0	0	0
3	0	0	44	0	134	107	2	34	253	203	0	81	0	0	0	142	0	0	0	0	0	0	0	0	0
4	0	0	76	0	152	188	8	32	387	5	0	37	0	0	0	110	0	0	0	5	0	0	0	0	0
5	0	3	340	0	108	272	31	55	93	0	0	39	0	0	2	24	0	0	0	33	0	0	0	0	0
6	0	13	303	0	134	256	52	65	46	0	0	52	0	0	3	54	0	0	0	15	0	0	7	0	0
7	0	151	161	0	356	39	41	77	7	0	0	25	0	0	10	89	0	0	0	37	0	0	7	0	0
8	0	592	51	0	58	14	51	91	22	0	0	10	0	2	7	32	0	0	0	53	1	0	16	0	0
9	0	169	17	0	21	0	116	324	1	0	0	104	0	25	31	44	0	0	0	114	2	0	25	7	0
10	0	42	7	0	6	0	367	106	0	0	0	32	3	37	73	173	0	0	0	36	10	0	94	14	0
11	0	17	0	0	4	0	121	54	0	0	0	17	10	56	453	52	0	0	0	113	41	1	25	36	0
12	0	6	0	0	0	0	73	15	0	0	0	3	22	302	177	50	0	2	0	170	64	11	74	31	0
13	0	7	0	0	0	0	28	29	0	0	0	0	208	82	58	20	0	16	0	163	187	45	132	25	0
14	0	0	0	0	0	0	34	39	0	0	0	0	90	30	57	6	0	150	0	92	324	35	112	31	0
15	0	0	0	0	0	0	30	19	0	0	0	0	59	59	58	0	0	55	49	102	176	213	93	87	0
16	2	0	0	0	0	0	45	0	0	0	0	0	46	40	71	0	0	63	22	46	126	278	106	155	0
17	12	0	0	0	0	0	0	0	0	0	0	0	58	241	0	0	0	161	32	20	60	153	134	105	24
18	32	0	0	0	0	0	0	0	0	0	0	0	146	105	0	0	0	242	30	1	9	199	85	80	71
19	88	0	0	0	0	0	0	0	0	0	0	0	204	14	0	0	0	199	60	0	0	60	65	203	107
20	294	0	0	0	0	0	0	0	0	0	0	0	88	7	0	0	0	90	137	0	0	5	22	101	256
21	383	0	0	0	0	0	0	0	0	0	0	0	66	0	0	0	0	22	152	0	0	0	3	84	290
22	189	0	0	13	0	0	0	0	0	0	21	0	0	0	0	0	0	0	484	0	0	0	0	41	252
23	0	0	0	721	0	0	0	0	0	0	270	0	0	0	0	0	0	0	9	0	0	0	0	0	0
24	0	0	0	266	0	0	0	0	0	0	709	0	0	0	0	0	0	0	25	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1000	0	0	0	0	0	0	0	0

Table 6-8 Frequency table for overall rank at a relative cost weighting of 0.34 (Approach B)

	BASE	ALT 1	ALT 2	ALT 3	ALT 4	ALT 5	ALT 6	ALT 7	ALT 8	ALT 9	ALT 10	ALT 11	ALT 12	ALT 13	ALT 14	ALT 15	ALT 16	ALT 17	ALT 18	ALT 19	ALT 20	ALT 21	ALT 22	ALT 23	ALT 24
1	0	0	4	0	0	0	2	3	9	889	0	39	0	0	25	4	0	0	0	3	10	7	1	1	3
2	0	0	3	0	23	142	1	45	467	95	0	200	0	0	2	13	0	1	0	0	3	2	0	0	3
3	0	0	48	0	97	243	0	58	302	12	0	156	0	0	4	75	0	0	0	0	3	0	0	0	2
4	0	0	194	0	123	201	1	57	145	1	0	99	0	0	3	170	0	0	0	0	2	3	0	1	1
5	0	0	193	0	128	282	4	51	56	1	0	128	0	0	6	147	0	0	0	0	3	2	0	0	1
6	0	22	360	0	109	86	19	75	16	0	0	110	0	0	8	187	0	0	0	2	1	0	0	1	2
7	0	133	134	0	329	35	31	60	2	0	0	55	0	0	64	90	0	7	0	41	14	3	0	2	0
8	0	368	60	0	130	9	89	103	2	0	0	43	0	0	65	58	0	9	0	25	29	5	0	0	5
9	0	310	6	0	48	0	81	208	0	2	0	78	0	10	103	68	0	8	0	32	32	5	1	3	4
10	0	112	0	0	12	0	282	148	0	0	0	48	1	13	135	120	0	27	0	29	60	7	0	1	5
11	1	36	0	0	1	1	230	78	1	0	0	29	2	87	259	48	0	48	0	81	76	11	1	4	5
12	1	15	0	0	0	0	92	49	0	0	0	9	26	233	109	16	0	86	2	121	202	20	6	3	9
13	0	1	0	0	0	0	64	19	0	0	2	3	135	121	52	3	0	157	1	116	222	65	19	5	16
14	3	2	0	0	0	1	40	19	0	0	0	1	119	97	30	0	0	181	12	116	171	121	43	9	35
15	3	0	0	0	0	0	17	16	0	0	1	1	105	77	28	0	0	188	11	100	92	225	68	13	53
16	35	0	0	0	0	0	17	7	0	0	0	0	102	76	19	0	1	144	20	79	48	185	105	37	123
17	95	0	0	0	0	0	17	4	0	0	1	1	80	68	27	0	0	76	37	52	12	175	136	57	161
18	175	0	0	0	0	0	11	1	0	0	5	1	78	84	28	0	0	44	48	42	2	78	140	82	181
19	217	0	0	4	0	0	1	0	0	0	12	0	102	95	8	0	0	19	93	34	3	50	131	91	139
20	250	0	0	33	0	0	0	0	0	0	66	0	123	32	9	1	3	4	104	30	3	16	114	93	117
21	194	0	0	58	0	0	0	0	0	0	116	0	107	5	6	0	19	0	183	11	6	8	85	123	79
22	18	0	0	140	0	0	0	0	0	0	304	0	17	1	4	0	69	0	262	24	2	4	24	89	41
23	3	0	0	313	0	0	0	0	0	0	337	0	2	0	1	0	145	0	88	45	0	3	32	25	5
24	1	0	0	351	0	0	0	0	0	0	138	0	0	0	1	0	281	0	65	17	3	1	86	52	5
25	3	0	0	101	0	0	0	0	0	0	18	0	0	0	1	0	482	0	72	0	0	3	7	307	5

Table 6-9 Frequency table for overall rank at a relative cost weighting of 0.61 (Approach A)

	BASE	ALT 1	ALT 2	ALT 3	ALT 4	ALT 5	ALT 6	ALT 7	ALT 8	ALT 9	ALT 10	ALT 11	ALT 12	ALT 13	ALT 14	ALT 15	ALT 16	ALT 17	ALT 18	ALT 19	ALT 20	ALT 21	ALT 22	ALT 23	ALT 24
1	0	193	529	0	278	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	488	97	0	415	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	319	374	0	307	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	880	36	0	84	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	118	318	2	562	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	2	445	180	172	201	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	3	0	0	0	0	0	196	454	182	162	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0
8	115	0	0	0	0	0	5	320	0	557	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0
9	875	0	0	0	0	0	0	40	0	80	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0
10	7	0	0	448	0	0	0	4	0	0	0	541	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	552	0	0	0	0	0	0	0	448	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	61	0	207	41	77	614	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	514	0	93	203	124	66	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	230	0	85	80	550	55	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	148	0	253	399	149	51	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	47	0	362	277	100	214	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1000	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	408	0	592	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	592	0	372	36	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	33	964	3	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	997	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	647	353	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	353	647	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1000	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1000

Table 6-10 Frequency table for overall rank at a relative cost weighting of 0.61 (Approach B)

	BASE	ALT 1	ALT 2	ALT 3	ALT 4	ALT 5	ALT 6	ALT 7	ALT 8	ALT 9	ALT 10	ALT 11	ALT 12	ALT 13	ALT 14	ALT 15	ALT 16	ALT 17	ALT 18	ALT 19	ALT 20	ALT 21	ALT 22	ALT 23	ALT 24
1	0	4	53	0	935	0	2	1	2	1	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0
2	1	558	377	0	62	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	1	420	555	0	3	10	0	0	7	1	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	14	13	0	0	633	1	0	337	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	3	3	0	0	0	278	40	85	589	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	2	0	1	0	0	53	255	591	35	61	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0
7	18	0	0	0	0	24	616	256	25	57	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0
8	352	0	0	0	0	0	76	44	3	522	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0
9	594	0	1	5	0	0	6	19	1	341	0	31	0	0	0	0	0	0	0	1	0	0	0	0	0
10	24	0	0	455	0	1	4	3	0	12	1	496	0	0	3	0	0	0	0	0	0	0	0	0	0
11	4	0	0	514	0	0	0	1	0	0	3	444	0	0	8	25	0	1	0	0	0	0	0	0	0
12	1	0	0	26	0	0	0	0	0	0	74	14	11	40	90	740	0	4	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	335	2	116	136	235	130	0	46	0	1	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	326	0	185	217	135	54	1	79	0	3	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	160	0	272	316	97	31	13	103	0	7	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	78	0	306	203	219	18	30	134	1	10	1	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	18	0	92	77	179	2	298	267	15	46	5	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	3	0	17	9	21	0	418	234	136	128	33	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	1	0	1	3	6	0	150	95	335	198	204	6	0	0	1
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	52	35	290	151	452	12	2	1	1
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	31	1	208	252	291	194	4	4	14
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	13	80	10	629	134	13	116
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2	103	4	91	453	68	278
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	60	382	236	302
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	25	678	289

Table 6-7 illustrates that for a relative cost weighting of 0.34 using Approach A, ALT 9 is the preferred plan with a credibility level of 59.1 % for obtaining Rank 1 while ALT 11 ranks second best with a credibility level of 60 % for obtaining a rank of 2 or better (403/1000 for Rank 1 + 197/1000 for Rank 2) followed by ALT 8 with a credibility level of 44.4 % for obtaining a rank of 3 or better (2/1000 for Rank 1 + 189/1000 for Rank 2 + 253/1000 for Rank 3). As no single alternative emerges as the preferred alternative with a high level of credibility (e.g. greater than 85 %) a portfolio of alternatives should be selected that satisfy minimum levels of stakeholder defined performance and credibility levels, such that a small set of preferred alternatives may be compared on a more detailed technology investment based level, and a final decision can be made (as was demonstrated in chapter 5 section 5.3.2.4).

Table 6-8 illustrates that for a relative cost weighting of 0.34 using Approach B, ALT 9 is also the preferred alternative with a credibility level of 88.9 % for obtaining Rank 1 but instead of ALT 11 ranking second best, ALT 8 does, with a credibility level of 47.6 % for obtaining a rank of 2 or better (9/1000 for Rank 1 + 467/1000 for Rank 2) followed by ALT 11 with a credibility level of 39.4 % for obtaining a rank of 3 or better (39/1000 for Rank 1 + 200/1000 for Rank 2 + 156/1000 for Rank 3). As ALT 9 emerges as the preferred alternative with a high level of credibility (88.9 %) it may not be necessary to isolate a small set of preferred alternatives, although there would be value in doing a more detailed analysis on technology investment based level, before a final decision is made.

At a relative cost weighting of 0.34, differences can be seen in both the rank and credibility of alternatives in the lower rank order. Although rank 1 is occupied by ALT 9 in both approaches, rank 2 and 3 are occupied by different alternatives in both cases. No single alternative emerges as the dominant solution with a high level of credibility at this value of relative cost weighting for Approach A although ALT 9 achieves a high level of credibility using Approach B. It would be valuable to compare Approach A and Approach B in terms of a portfolio approach using minimum levels of stakeholder defined performance and credibility levels. This is demonstrated in section 6.3.4 below:

Table 6-9 illustrates that for a relative cost weighting of 0.61 using Approach A, ALT 2 is the preferred plan with a credibility level of almost 52.9 % for obtaining Rank 1 while ALT 4 ranks second best with a credibility level of 69.3 % for obtaining a rank of 2 or better (278/1000 for Rank 1 + 415/1000 for Rank 2) followed by ALT 1 with a credibility level of 100 % for obtaining a rank of 3 or better (193/1000 for Rank 1 + 488/1000 for Rank 2 + 319/1000 for Rank 3). As ALT 2 is the preferred alternative for only 52.9 % of the discrete samples, the DM may not be able to confidently make a decision with this information alone. Therefore a portfolio of alternatives should be selected such that a small set of preferred alternatives may be compared on a more detailed technology investment based level, and a final decision can be made (as was demonstrated in chapter 5 section 5.3.2.4).

Table 6-10 illustrates that for a relative cost weighting of 0.61 using Approach B, ALT 4 is the preferred alternative with a credibility level of over 85 % for obtaining Rank 1 while ALT 2 ranks second best again with a credibility level of 63.9 % for obtaining a rank of 2 or better (53/1000 for Rank 1 + 377/1000 for Rank 2) followed again by ALT 1 with a credibility level of 78.0 % for obtaining a rank of 3 or better (4/1000 for Rank 1 + 558/1000 for Rank 2 + 420/1000 for Rank 3). Although ALT 4 achieves the preferred alternative with a level of credibility of over 85 % and it may therefore not be necessary to isolate a small set of preferred alternatives, there would be value in doing a more detailed analysis on technology investment based level, before a final decision is made.

At a relative cost weighting of 0.61, differences can be seen in the ranking and credibility values of the preferred alternatives although the top 3 ranking alternatives are the same using both approaches. At this point it would be interesting to isolate a portfolio of preferred alternatives from the larger set for more detailed analysis in order to compare Approach A and Approach B. These alternatives would be isolated based on satisfying minimum levels of performance within specified levels of credibility (see section 5.3.2.3).

6.3.4. Isolating portfolios of preferred alternatives based on performance and credibility

For demonstrative purposes portfolio sets of preferred alternatives were isolated based on achieving a rank of 3 or better with minimum credibility levels of 85 %.

At a relative cost weighting of 0.34, only ALT 9 matches these criteria for Approach A, and only ALT 9 matches these criteria for Approach B. If the selection criteria were relaxed to include alternatives with a credibility level of 80 %, ALT 8 would enter the portfolio for Approach B but not for Approach A.

At a relative cost weighting of 0.61 ALT 2, ALT 4 and ALT 1 match these criteria for Approach A, and ALT 2 and ALT 4 match these criteria for Approach B. The selection criteria would have to be relaxed to include alternatives with a credibility level of greater than 78 % in order for ALT 1 to enter the portfolio set using Approach B at this value of relative cost weighting.

This demonstrates that the different approaches to handling technical empirical uncertainty result in similar alternatives entering the portfolio of alternatives for detailed analysis for the values of relative cost weighting demonstrated above (representing equal preference between criteria and a strong preference towards cost).

What this also highlights is the impact that uncertainty in DM preferences can have on the decision making process. If preferences lie in an unstable section of the sensitivity diagram then small changes in preferences (less that 5 %) can result in switching between preferred alternatives in the rank order (as can be seen in Figure 6-5 and Figure 6-6) which can result in different alternatives entering the portfolio set. For similar reasons, the effects of using different approaches to dealing with other uncertainties (e.g. technical empirical uncertainties - as demonstrated in this chapter) are also more pronounced in this region. Therefore the computational, time and data management burden of doing a robustness analysis on technical empirical uncertainty in the generation phase as opposed to the selection phase may not be justified given that similar alternatives enter the portfolio set of preferred alternatives using both approaches and that any differences would likely be seen in unstable sections of the sensitivity diagram[1]. Considering that the effects of uncertainty in DM preferences are highest in this section of the diagram it is likely that they would have a greater effect on the results than technical empirical uncertainties would.

It must be noted that if this portfolio approach focused only on solutions that achieved a rank of 1 (the most preferred alternative) as when using the *cross confidence factors* and *reference sets* of the SMAA methodology (Lahdelma et al., 1998; Lahdelma and Salminen, 2006), the resulting portfolio set would be more sensitive to fluctuations in uncertain input parameters as the focus would be on a reduced portion of the performance space and therefore small changes would seem to have greater effects. For example if at a relative cost weighting of 0.62, the analysis was focussed only on solutions that achieved a rank of 1, with a minimum credibility level of 75 %, no alternatives would match these criteria using Approach A and only ALT 4 would match these criteria using Approach B. In fact, in order to obtain just two alternatives in the final portfolio of alternatives to be analysed further before final selection, the minimum credibility level would have to be relaxed to 27.8 % using Approach A and 13.1 % using Approach B. While focusing only on alternatives that achieve a rank of 1 has that advantage that fewer alternatives enter the portfolio set, and therefore final selection may be simpler, this approach may be less robust than focussing on a wider portion of the rank order. This is due to the fact that it is possible for an alternative to have the highest credibility level of all alternatives when looking only at rank 1, but when considering a minimum ranking of 2 or 3, other alternatives may have higher levels of credibility for obtaining those ranks. This is demonstrated below:

Table 6-11 Credibility values for preferred alternatives using approach A at a relative cost weighting of 0.61

Minimum rank	**ALT 1**	**ALT 2**	**ALT 4**
1	19.3%	52.9%	27.8%
2	68.1%	62.6%	69.3%
3	100.0%	100.0%	100.0%

[1] Greater differences in performance may have been seen by representing demand in higher resolution as this would allow for more sensitive optimisation of the power station load factors due to a greater number of time slices.

As can be seen of Table 6-11 above, ALT 2 has the highest credibility level of achieving a rank of 1, followed by ALT 4 and then ALT 1. However, when considering alternatives that achieve a rank of 2 or better, ALT 4 has the highest credibility level, followed by ALT 1 and then ALT 2. This means that ALT 4 is more likely to obtain a rank of 2 or better than ALT 2 (for the sample of uncertain parameters considered) and is therefore more robust than ALT 2 if the DM is willing to accept a minimum ranking of 2. This demonstrates that focusing only on alternatives that achieve a rank of 1 may in fact exclude important alternatives from the portfolio set. While it is not suggested that ALT 4 is a preferred alternative to ALT 2 at this value of relative cost weighting, it is argued that ALT 4 is worth comparing to ALT 2 in more detailed analysis (as demonstrated in chapter 5 section 5.3.2.4) and that ALT 4 would not be considered if only alternatives that achieve a rank of 1 were to be considered.

6.4. CONCLUSIONS

Using pseudo-minima and maxima to normalise attribute performance scores with a modified indifference weighting approach to articulate DM preferences reduces effective weighting biases by reducing the artificial inflation or deflation of value function scores based on improbable values without discarding those values for further analysis. Differences can be seen in the lower rank order of alternatives when comparing this method with the standard method of normalisation.

The assumption postulated in chapter 5 that integrating technical empirical uncertainty into the selection phase as opposed to the generation phase would only result a slightly pessimistic view of the future was proved correct based the overall performance results using the two different approaches.

The weighting diagrams illustrate that the different approaches to dealing with uncertainty result in different alternatives occupying the preferred position (Rank 1) at different values of relative cost weighting.

The additional effort and complexity of doing a robustness analysis on technical empirical uncertainty in the generation phase as opposed to the selection phase may not be justified given that similar alternatives make up the portfolios of preferred alternatives using both methods and differences would mainly seen in the unstable sections of the weighting sensitivity diagram where uncertainty in DM preferences would have the greatest effect on results.

Focusing only on alternatives that achieve the preferred rank may exclude important alternatives from the portfolio set and therefore from detailed analysis and final selection. Using a portfolio approach and focussing on a greater range in rank than just the preferred alternative increases the robustness of the selection process by reducing the effect of uncertainty in DM preferences and empirical uncertainties, allowing for a less intensive uncertainty analysis to be done (Approach A) prior to the detailed analysis of preferred alternatives.

APPENDIX C

Table 6-12 Attribute and overall value performance results of Approach A and Approach B

	BASE	**ALT1**	**ALT2**	**ALT3**	**ALT4**	**ALT5**	**ALT6**	**ALT7**	**ALT8**	**ALT9**	**ALT10**	**ALT11**
Cost (kZAR)												
Approach B	2.605E+08	2.610E+08	2.623E+08	2.610E+08	2.609E+08	2.639E+08	2.637E+08	2.643E+08	2.648E+08	2.683E+08	2.708E+08	2.716E+08
Approach A	2.621E+08	2.626E+08	2.630E+08	2.631E+08	2.631E+08	2.649E+08	2.649E+08	2.659E+08	2.661E+08	2.682E+08	2.700E+08	2.732E+08
Difference (A-B)	1.627E+06	1.571E+06	6.908E+05	2.133E+06	2.186E+06	9.518E+05	1.166E+06	1.640E+06	1.301E+06	-7.026E+04	-7.979E+05	1.636E+06
Relative difference	**0.62%**	**0.60%**	**0.26%**	**0.81%**	**0.83%**	**0.36%**	**0.44%**	**0.62%**	**0.49%**	**-0.03%**	**-0.30%**	**0.60%**
CO_{2EQ} emissions (kton)												
Approach B	2.650E+06	2.668E+06	2.664E+06	2.551E+06	2.644E+06	2.659E+06	2.663E+06	2.645E+06	2.541E+06	2.603E+06	2.457E+06	2.508E+06
Approach A	2.641E+06	2.660E+06	2.661E+06	2.543E+06	2.635E+06	2.648E+06	2.653E+06	2.638E+06	2.529E+06	2.601E+06	2.472E+06	2.494E+06
Difference (A-B)	-8.770E+03	-7.896E+03	-3.292E+03	-8.499E+03	-8.950E+03	-1.120E+04	-9.733E+03	-6.616E+03	-1.180E+04	-1.997E+03	1.491E+04	-1.393E+04
Relative difference	**-0.33%**	**-0.30%**	**-0.12%**	**-0.33%**	**-0.34%**	**-0.42%**	**-0.37%**	**-0.25%**	**-0.47%**	**-0.08%**	**0.60%**	**-0.56%**
SO_{2EQ} emissions (kton)												
Approach B	1.569E+04	1.577E+04	1.528E+04	1.541E+04	1.572E+04	1.530E+04	1.596E+04	1.591E+04	1.488E+04	1.505E+04	1.491E+04	1.445E+04
Approach A	1.565E+04	1.574E+04	1.556E+04	1.535E+04	1.567E+04	1.557E+04	1.593E+04	1.588E+04	1.514E+04	1.531E+04	1.504E+04	1.456E+04
Difference (A-B)	-4.323E+01	-3.486E+01	2.785E+02	-6.028E+01	-5.270E+01	2.674E+02	-3.031E+01	-3.225E+01	2.641E+02	2.627E+02	1.289E+02	1.138E+02
Relative difference	**-0.28%**	**-0.22%**	**1.79%**	**-0.39%**	**-0.34%**	**1.72%**	**-0.19%**	**-0.20%**	**1.74%**	**1.72%**	**0.86%**	**0.78%**
Water consumption (kton)												
Approach B	4.300E+06	3.899E+06	3.914E+06	4.744E+06	3.922E+06	3.856E+06	3.823E+06	3.813E+06	4.106E+06	3.825E+06	4.693E+06	4.093E+06
Approach A	4.294E+06	3.902E+06	3.900E+06	4.713E+06	3.920E+06	3.855E+06	3.835E+06	3.822E+06	4.097E+06	3.844E+06	4.707E+06	4.059E+06
Difference (A-B)	-6.151E+03	3.327E+03	-1.421E+04	-3.081E+04	-2.466E+03	-1.127E+03	1.180E+04	8.668E+03	-9.066E+03	1.918E+04	1.416E+04	-3.352E+04
Relative difference	**-0.14%**	**0.09%**	**-0.36%**	**-0.65%**	**-0.06%**	**-0.03%**	**0.31%**	**0.23%**	**-0.22%**	**0.50%**	**0.30%**	**-0.83%**

PGPs (kZAR/kt)

CO_{2EQ} emissions	0	0	0	39	39	0	0	39	39	39	193	0
SO_{2EQ} emissions	0	0	6661	0	0	6661	0	0	6661	6661	0	24424
Water consumption	0	16	16	0	16	47	47	47	16	47	0	16

Overall cost including PGPs (ZAR)	BASE	ALT1	ALT2	ALT3	ALT4	ALT5	ALT6	ALT7	ALT8	ALT9	ALT10	ALT11
Approach B	2.605E+11	3.219E+11	4.252E+11	3.597E+11	4.245E+11	5.466E+11	4.429E+11	5.453E+11	5.263E+11	6.484E+11	7.461E+11	6.883E+11
Approach A	2.621E+11	3.235E+11	4.276E+11	3.615E+11	4.263E+11	5.492E+11	4.446E+11	5.470E+11	5.288E+11	6.509E+11	7.482E+11	6.922E+11
Difference (A-B)	1.627E+09	1.622E+09	2.324E+09	1.804E+09	1.801E+09	2.680E+09	1.718E+09	1.790E+09	2.461E+09	2.501E+09	2.085E+09	3.892E+09
Relative difference	**0.62%**	**0.50%**	**0.54%**	**0.50%**	**0.42%**	**0.49%**	**0.39%**	**0.33%**	**0.47%**	**0.38%**	**0.28%**	**0.56%**

Table 6-12 Attribute and overall value performance results of Approach A and Approach B cond.

	ALT12	ALT13	ALT14	ALT15	ALT16	ALT17	ALT18	ALT19	ALT20	ALT21	ALT22	ALT23	ALT24
Cost (kZAR)													
Approach B	2.772E+08	2.781E+08	2.809E+08	2.771E+08	2.799E+08	2.843E+08	2.901E+08	2.989E+08	2.976E+08	3.048E+08	3.099E+08	3.173E+08	3.086E+08
Approach A	2.762E+08	2.774E+08	2.783E+08	2.790E+08	2.805E+08	2.821E+08	2.854E+08	2.963E+08	2.982E+08	3.010E+08	3.017E+08	3.031E+08	3.067E+08
Difference (A-B)	-1.015E+06	-7.005E+05	-2.603E+06	1.919E+06	6.393E+05	-2.208E+06	-4.724E+06	-2.554E+06	6.114E+05	-3.847E+06	-8.249E+06	-1.421E+07	-1.932E+06
Relative difference	**-0.37%**	**-0.25%**	**-0.94%**	**0.69%**	**0.23%**	**-0.78%**	**-1.66%**	**-0.86%**	**0.21%**	**-1.28%**	**-2.73%**	**-4.69%**	**-0.63%**
CO_{2EQ} emissions (kton)													
Approach B	2.651E+06	2.615E+06	2.425E+06	2.459E+06	2.415E+06	2.652E+06	2.652E+06	2.398E+06	2.366E+06	2.342E+06	2.350E+06	2.353E+06	2.334E+06
Approach A	2.645E+06	2.606E+06	2.447E+06	2.453E+06	2.423E+06	2.650E+06	2.645E+06	2.384E+06	2.368E+06	2.358E+06	2.363E+06	2.359E+06	2.338E+06
Difference (A-B)	-5.946E+03	-9.293E+03	2.219E+04	-5.886E+03	8.281E+03	-2.355E+03	-6.832E+03	-1.392E+04	2.336E+03	1.552E+04	1.252E+04	6.059E+03	4.306E+03
Relative difference	**-0.22%**	**-0.36%**	**0.91%**	**-0.24%**	**0.34%**	**-0.09%**	**-0.26%**	**-0.58%**	**0.10%**	**0.66%**	**0.53%**	**0.26%**	**0.18%**
SO_{2EQ} emissions (kton)													
Approach B	1.605E+04	1.593E+04	1.491E+04	1.428E+04	1.468E+04	1.508E+04	1.591E+04	1.371E+04	1.396E+04	1.383E+04	1.348E+04	1.329E+04	1.379E+04
Approach A	1.606E+04	1.592E+04	1.511E+04	1.437E+04	1.477E+04	1.564E+04	1.595E+04	1.394E+04	1.409E+04	1.403E+04	1.382E+04	1.378E+04	1.435E+04
Difference (A-B)	6.778E+00	-1.206E+01	2.046E+02	8.734E+01	9.178E+01	5.633E+02	4.404E+01	2.286E+02	1.284E+02	2.016E+02	3.412E+02	4.850E+02	5.610E+02
Relative difference	**0.04%**	**-0.08%**	**1.35%**	**0.61%**	**0.62%**	**3.60%**	**0.28%**	**1.64%**	**0.91%**	**1.44%**	**2.47%**	**3.52%**	**3.91%**
Water consumption (kton)													
Approach B	3.625E+06	3.617E+06	3.973E+06	4.064E+06	4.654E+06	3.570E+06	3.460E+06	3.916E+06	3.864E+06	3.801E+06	3.850E+06	3.860E+06	3.772E+06
Approach A	3.658E+06	3.658E+06	4.008E+06	4.042E+06	4.674E+06	3.593E+06	3.541E+06	3.881E+06	3.860E+06	3.836E+06	3.834E+06	3.858E+06	3.759E+06
Difference (A-B)	3.340E+04	4.121E+04	3.520E+04	-2.198E+04	2.038E+04	2.259E+04	8.138E+04	-3.482E+04	-3.610E+03	3.543E+04	-1.586E+04	-1.792E+03	-1.325E+04
Relative difference	**0.91%**	**1.13%**	**0.88%**	**-0.54%**	**0.44%**	**0.63%**	**2.30%**	**-0.90%**	**-0.09%**	**0.92%**	**-0.41%**	**-0.05%**	**-0.35%**

PGPs (kZAR/kt)	ALT12	ALT13	ALT14	ALT15	ALT16	ALT17	ALT18	ALT19	ALT20	ALT21	ALT22	ALT23	ALT24
CO_{2EQ} emissions	0	39	193	39	219	0	0	0	193	219	39	0	258
SO_{2EQ} emissions	0	0	0	24424	0	6661	0	36636	6661	6661	36636	44407	6661
Water consumption	73	73	16	16	0	73	83	16	16	16	16	16	16

Overall cost including PGPs (ZAR)

Approach B	5.422E+11	6.437E+11	8.120E+11	7.845E+11	8.092E+11	6.457E+11	5.776E+11	8.623E+11	9.085E+11	9.698E+11	9.548E+11	9.680E+11	1.061E+12
Approach A	5.436E+11	6.456E+11	8.142E+11	7.880E+11	8.117E+11	6.489E+11	5.796E+11	8.676E+11	9.104E+11	9.713E+11	9.593E+11	9.753E+11	1.064E+12
Difference (A-B)	1.427E+09	1.953E+09	2.238E+09	3.481E+09	2.455E+09	3.195E+09	2.038E+09	5.279E+09	1.862E+09	1.452E+09	4.488E+09	7.296E+09	2.708E+09
Relative difference	**0.26%**	**0.30%**	**0.27%**	**0.44%**	**0.30%**	**0.49%**	**0.35%**	**0.61%**	**0.20%**	**0.15%**	**0.47%**	**0.75%**	**0.25%**

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CHAPTER 7 INTEGRATING PLANT AVAILABILITY UNCERTAINTY AND RESERVE MARGIN INTO THE MULTI-OBJECTIVE FRAMEWORK

7.1. INTRODUCTION

In chapter 4 a partial equilibrium optimisation framework was extended to include multiple environmental objectives through the addition of PGPs introduced into the optimisation in the form of cost penalties. It was demonstrated that this was an efficient method for extending the analysis to multiple objectives as the solutions generated are non-dominated and are generated from ranges of performances in the various criteria rather than from arbitrarily forcing the selection of particular technologies. It was also demonstrated that this analysis could be extended to include uncertainty in demand growth through stochastic programming with recourse by splitting new power station investments into owner's development costs and equipment procurement and construction phases, thereby accounting for the concept of technology lead times in light of a decision node in the time horizon. The solutions generated then had built in flexibility towards demand growth uncertainty in light of the multiple objectives chosen.

In chapter 5 a methodology was developed for the ranking and selection of alternatives given multiple objectives and uncertainty in empirical and valuation model parameters. It was demonstrated how a continuous analysis of uncertainty using both the rank and credibility of alternatives could be used to isolate a portfolio of preferred alternatives. A more detailed analysis of the preferred alternatives, examining short term technology investment details and attribute performance information could then be used to provide additional insight into the decision problem, and related back to real life actions.

Chapter 6 examined the caveats identified in chapter 5 by exploring the analysis of technical empirical parameters in the generation phase instead of the selection phase. The findings of chapter 6 reinforced the value of the approach taken to model empirical uncertainty in chapter 5, as well as the importance of generating a portfolio of preferred alternatives based on minimum performance and credibility criteria.

The approach so far has been aimed at developing a transparent framework for the generation and selection of power expansion alternatives that comprehensively account for multiple objectives and have built in flexibility for and are robust to various types of uncertainty. One of the key uncertainties identified in chapter 3 that has not yet been integrated into framework developed thus far is plant availability uncertainty. It is imperative that preferred alternatives are robust to uncertainty in plant availability to prevent situations such as recent local blackouts in the Western Cape and South Africa as a whole due to unforeseen unit outage. This chapter will focus on integrating plant availability uncertainty into the multi-objective framework developed thus far such that the probability of events such as blackouts are minimised and their economic, social and environmental impacts are avoided.

7.2. BACKGROUND

Plant outage can be split into planned outage (planned, routine maintenance) and forced outage (unplanned maintenance). Plant outage is typically modelled using the derating method for planned outage and the derating method and/or reserve margin for forced outage. The derating method assumes that a station will be offline for a given period of time annually. This period is determined by the planned outage rate (POR) and the forced outage rate (FOR) by the following equation:

$$Availability = (1 - POR) \times (1 - FOR) \qquad (7\text{-}1)$$

This method effectively "derates" each station by their outage rate such that they cannot operate above this rate annually. This is enforced in the model using an annual constraint on the availability of each station which limits its operation to never exceed the annual outage rate, in any time slice[1]. While this approach may work for a very large system with many units, it is inadequate to represent outage in smaller systems. This is demonstrated below assuming a plant outage rate of 1/12:

[1] The year is broken down into various time slices to represent day/night, weekly and seasonal load characteristics.

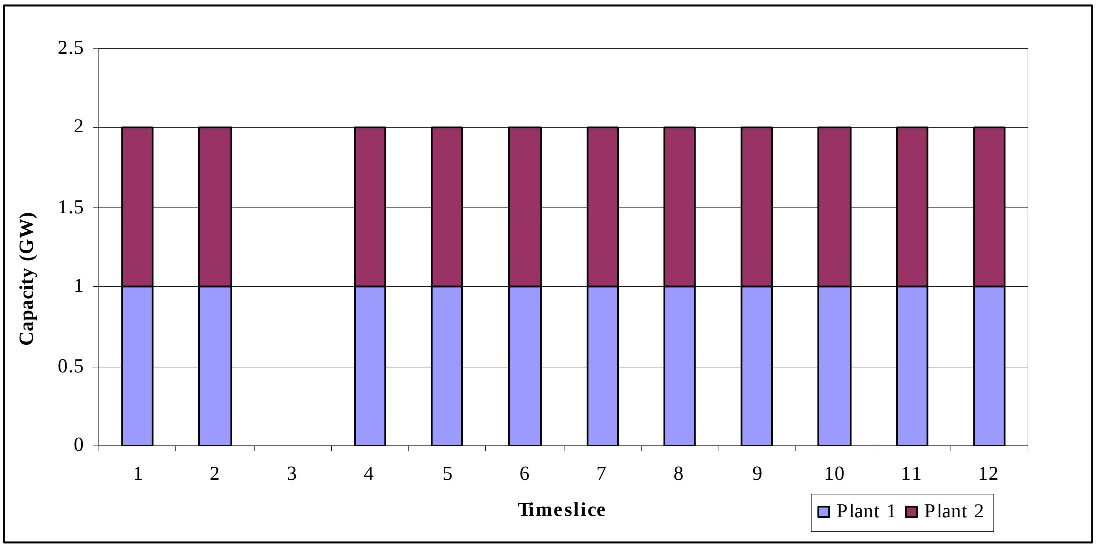

Figure 7-1 A system with 2 power plants each with an annual outage of 1/12

For the extreme case of a 2 plant system, if both plants had to go out at the same time no matter what reserve margin or demand was, demand would not be met.

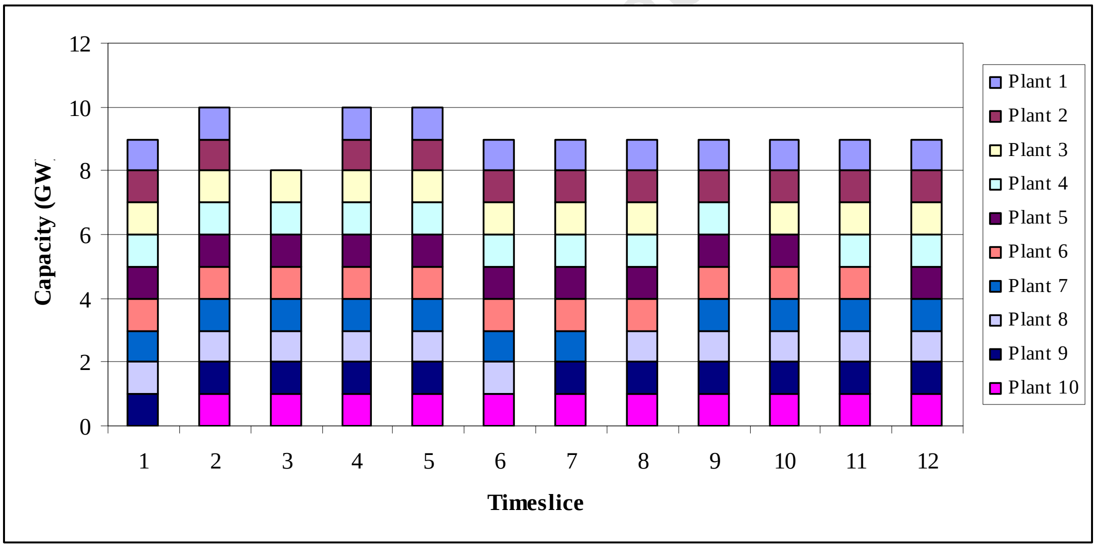

Figure 7-2 A system with 10 power plants each with an annual outage of 1/12

Examine the case of a 10 plant system, with each plant having a 1 GW capacity. If 2 of the plants had to go out at the same time there would be 8 GW of generating capacity left in the system and therefore a maximum demand of 8 GW could be met.

$$Reserve\ \ Margin = \frac{Total\ \ capacity}{Peak\ \ Demand} - 1 \qquad (7\text{-}2)$$

Assuming demand was 8 GW, the reserve margin would be 20 % (i.e. ${}^{10}\!/_{8} - 1 = 20\%$). This would be the minimum reserve margin needed to supply the required demand to this system if two plants went out simultaneously. A lower reserve margin would result in unserved energy as the generating power in the system would be less than the demand level if 2 plants went out at the same time.

This demonstrates how derating can only work in a system with a large number of plants and a high enough reserve margin.

While this methodology may be adequate for situations when stakeholders or planners have an in depth understanding of the relationship between the required reserve margin and plant outage, this is not usually the case. This relationship is highly dependant on the number of plants in the system and the modular size of the units due to the fact the units are usually forced out independently. This implies that a lower reserve margin would be required for a 10 GW system comprising 100 x 0.1 GW modular units than for a 10 GW system with 20 x 0.5 GW units due to the fact that less capacity would be forced out if a singe unit went offline. It also implies that a lower reserve margin would be required for a system of 10 GW with 10 x 1 GW units than for a system of 2 GW with 2 x 1 GW units (as demonstrated in the example above). Furthermore it can be shown using Jensen's inequality[2] that deterministic methods based on derating underestimate expected production costs relative to fully probabilistic methods (see for example Hobbs and Ji, 1995).

[2] Jensen's inequality relates the value of a convex function of an integral to the integral of that function.

7.2.1. More complex approaches to dealing with plant availbility uncertainty in ESI modelling

Forced outage

While the derating method in combination with a specified reserve margin has been widely used to model forced outage in ESI modelling, it does not specifically take unit size into account (as mentioned above), nor does it account for the fact that forced outage occurs in discrete blocks (i.e. a unit will go out for a period of 2 weeks straight, rather than two weeks over the period of a year). These caveats have led to more sophisticated approaches for accounting for forced outage whereby the reserve margin is an output of the modelling process rather than an input.

Production costing models deal with the optimisation of power station load factors based on the characteristics of each power station (capacity, planned and forced outage rates and operating constraints). The production model is either bundled with the investment model whereby all costs are annualized and the investment and production problems are solved simultaneously (as in the case of MARKAL and TIMES) or it is dealt with separately, typically after the investment problem has been solved (e.g. using the Benders decomposition method proposed by (Bloom, 1983)).

Using Benders decomposition, the *master-problem* is solved to generate an initial solution, and then the *sub-problem* is solved for the investment plan generated in the *master-problem*. The dual multipliers[3] of the *sub-problem* are then used to generate the next cut[4] for the *master-problem*. This procedure is repeated until convergence within a specified tolerance is achieved. This is an efficient and rigorous method for production costing and was implemented as part of the EGEAS framework. The benefit of this method is that the Benders cuts correctly represent the marginal effect of capacity additions upon the costs and therefore efficiently direct the master problem towards the optimal solution. A limitation of this is that the *master* problem

[3] Dual multipliers are equal to the marginal change of the primal objective function per unit increase of the corresponding constraint's right hand side. For a commodity balance constraint this value will thus represent the market price that should be attributed to this commodity. See for example (F.S. Hillier and Lieberman, 1990) for explanation on dual variables in linear programming.

[4] A cut is a constraint on the value of the solution of the master problem forcing it to reject the previous solution. This assumes that there is no primal degeneracy (no multiple dual solutions).

must be linear (no lumpy investments as is used in the proposed methodology in section 7.3) as the marginal costs are used as cuts. There are also limits in EGEAS for forcing stations to run when using this solution method and therefore take or pay contracts or minimum utilisation rates cannot be represented.

The most frequently used model of production costing is the load duration curve (LDC) method by (Baleriaux et al., 1967) and (Booth, 1972). The LDC is obtained by rearranging the chronological loads from the largest value to the smallest (shown below in Figure 7-3). It also gives the proportion of time during the year that the hourly load exceeds each level. The LDC method calculates the expected production costs by using the LDC rather than a chronological sequence of loads (see Figure 7-4 in section 7.3.2) and the deterministic outage of the generating units. First the generating units are ranked in terms of increasing cost, then the effective LDC facing each generating unit is calculated by convolving[5] the probability distribution of demand with the distribution of outages of less expensive generators, and finally the effective LDC is integrated over the appropriate domain to calculate the expected energy generated by the unit (see (Bloom, 1983) for a brief review of the LDC approach).

[5] Convolution is a mathematical operator which takes two functions and produces a third function that represents the amount of overlap between the first function and a reversed and translated version of the second.

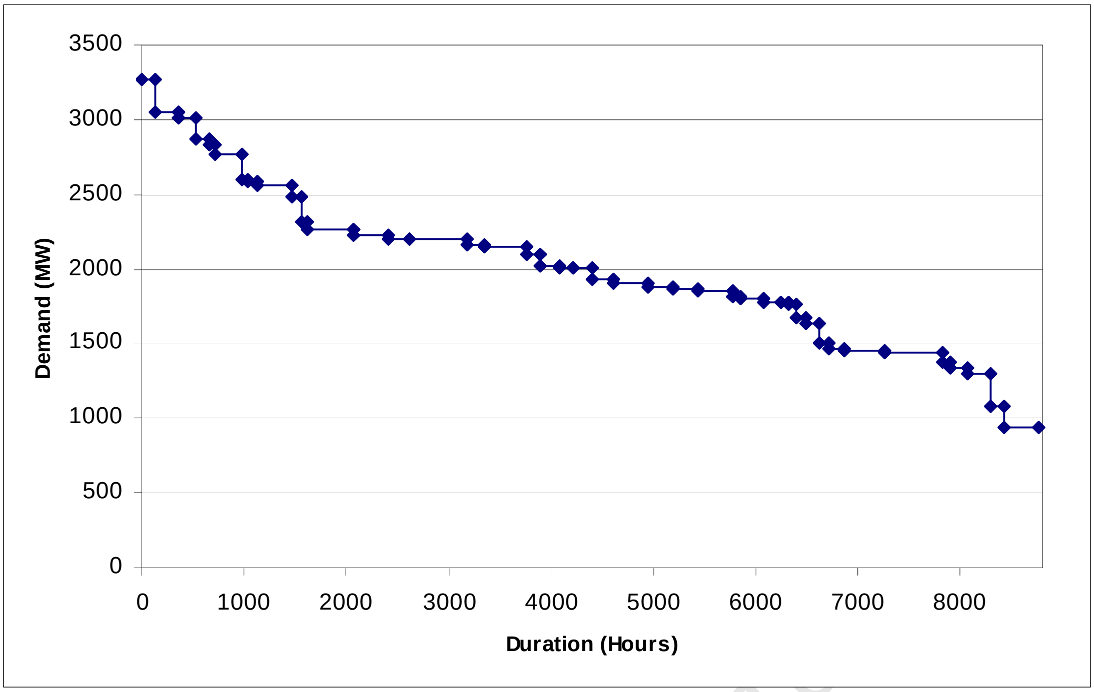

Figure 7-3 LDC representation of demand

The chronological information is lost in the LDC because loads are arranged in terms of their magnitude and duration, rather than when they occur and it therefore cannot simulate those aspects of production cost which are time dependent or chronological in nature. This shortfall is most prominent in multi-region models where different demands exist for each region with peaks occurring at different times (due to different customer demand profiles) and in single region models where detailed demand profiles exist for each sector (i.e. commercial, industrial, residential, etc.). There are distinct differences in peak load periods between each sector (i.e. the peak load period for industry electricity demand as opposed to that of the commercial sector). It is these peak and valley period deviations that provide a model that accounts for chronology in demand with the potential for reducing the system production cost, improving spinning and operating reserve as well as system stability enhancements.

As this need has been widely acknowledged, different methodologies have been developed to represent the chronological aspect of demand while simultaneously modelling the effect of random forced outage on system generating capacity.

The advantages and basic methodology of using Monte Carlo simulation in a power system reliability/cost worth analysis can be found in texts such as (Billinton and Li, 1994). Monte Carlo simulation has also been used within a production costing model to simulate the frequency and duration of forced outage while using a chronological simulation of demand (Mazumdar and Chrzan, 1995). The mean and standard deviation of production cost are reported for the Monte Carlo samples illustrating the difference between using an LDC approach and a chronological approach to representing demand as well as the differences between representing the frequency and duration of outage correctly rather than using aggregated forced outage rates.

Monte Carlo sampling has been used in combination with Benders decomposition to solve large-scale stochastic models (e.g. Dantzig and Infanger, 1992). This approach decomposes the original problem into a deterministic part and a stochastic part. The deterministic part is called the *master-problem* and in ESI modelling, this is the investment problem. The stochastic *sub-problem* is then the operational problem where elements such as plant availability and uncertainty in demand can be modelled probabilistically.

Danzig and Infanger (Dantzig and Infanger, 1992) demonstrated how this approach could be used to efficiently solve a large-scale stochastic linear program for a capacity expansion planning application. In this model 8 different stochastic availabilities for generators and transmission lines were used as well as 5 stochastic levels of demand. This model did not have a detailed representation of demand (only 1 demand value per period, with only 1,2 or 3 periods in the model) and therefore could not be used to accurately represent the frequency and duration of plant outages. This said, the idea of using sampling methods to represent uncertainty in plant operation within an operational *sub-problem* is an efficient method for feedback into the investment *master-problem.* It is from this point that an approach to model forced outage was developed and integrated into a framework that could model demand both chronologically and in high resolution such that both the frequency and duration of outage could be adequately represented, all within a multi-objective framework with a comprehensive analysis of system wide uncertainty. This approach is discussed in section 7.3 below:

7.3. Approach and demonstration

Using the methodology developed in previous chapters, a portfolio of preferred alternatives was isolated based on performance in terms of rank and credibility levels for a set of DM preferences. These alternatives have built-in flexibility towards uncertainty in demand growth and are robust to technical empirical uncertainty and uncertainty around DM preferences. The robustness of these alternatives towards uncertainty in plant availability needs to be ensured such that decision makers can be confident that their choices will be robust in terms of serving energy, as well as in terms of costs, emissions and valuation model parameter uncertainty. A methodology for doing this is outlined below:

7.3.1. Model refinements

In chapter 4 MARKAL was used to demonstrate how a single objective partial equilibrium framework could be extended to satisfy multiple objectives with built in flexibility toward demand growth uncertainty. Although MARKAL was suitable for this purpose, one of the disadvantages of using MARKAL was that demand could not be represented at a high enough resolution to accurately represent the duration and frequency of plant outage. For this reason another more recent model of the MARKAL family of models, **T**he **i**ntegrated **M**ARKAL-**E**FOM **s**ystem (TIMES), was used. With TIMES, energy systems can be represented, analysed and optimised on a flexible time and regional scale. In this way an equivalent model could be built to the one used previously in chapter 4, with higher resolution of demand, such that plant outage could be better represented[6]. A description of the way in which planned and forced outage was modelled follows below:

7.3.2. Model structure

The model was set up in TIMES to mimic the MARKAL model in chapter 4 except that demand was defined at a higher resolution and a "dummy" generation plant for unserved energy was included (discussed in more detail below). Using more time

[6] TIMES was not used initially (when the work for chapter 4 was being done) because the stochastic programming module and other aspects of the model were still being developed.

slices increases the accuracy of the demand representation but increases computing time significantly. Therefore a trade-off was made such that the key aspects of demand shape were captured while attempting to reduce the number of time slices. Seasonal variation in demand was defined by breaking the year into 3 seasons (summer, winter and an intermediate season). This was done to represent the characteristic differences in the demand profiles of these times of year in the South African environment. The week was split into weekdays and weekends and the day was divided into 7 parts such as to capture the morning and evening peaks. Using 3 seasons (s01, s02 and s03), 2 weekparts (w1 and w2) and 7 dayparts (h1-h7) resulted in the demand profile illustrated in Figure 7-4 .

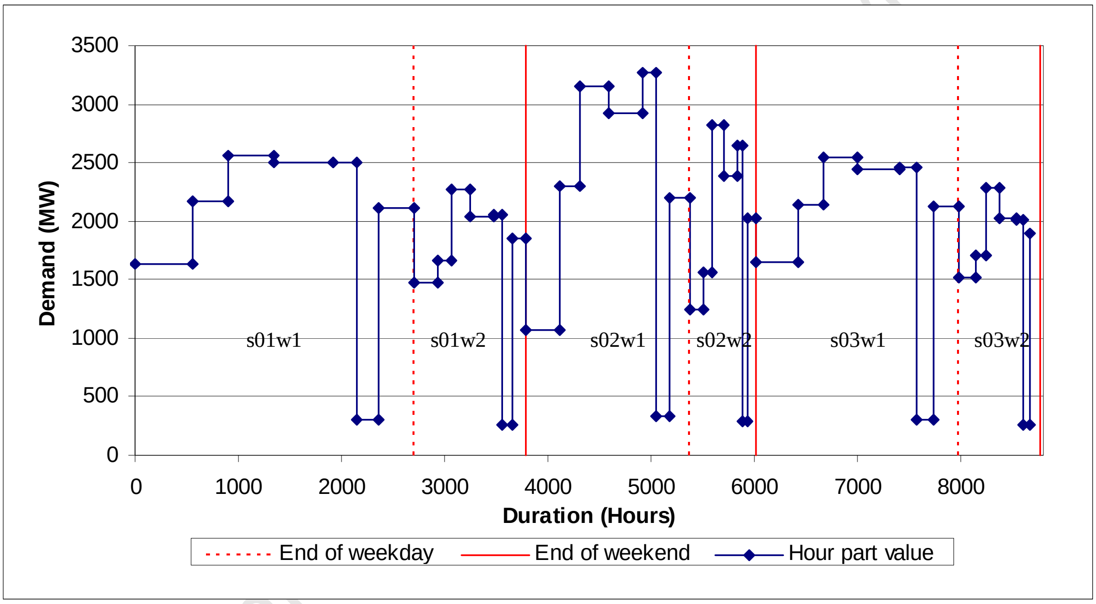

Figure 7-4 Chronological representation of demand

Figure 7-4 illustrates a chronological representation of demand whereby demand levels within each season and their weekday and weekend components are represented and each day is broken up into 7 parts to represent the morning and evening peak.

The unserved energy plant was included so that the model could decide, given the cost of not serving energy, whether it would be optimal to build new capacity or not serve energy. The cost of unserved energy is typically stakeholder defined and specific to the case study (see section 6.12 of (Wilson and Adams, 2006) for a discussion of the cost of unserved energy in South Africa). The trade-off between investment cost and the cost of unserved energy is particularly pertinent when demand is only marginally higher than supply capacity. This is because only a small amount of energy would not be served if new generation capacity was not built and therefore the cost of not serving this small amount of energy would be traded-off against the cost of building a new power station or unit.

The model was then separated into a *master* (investment) and *slave* (operational) problem so as to model uncertainty in plant outage. See Figure 7-5 below:

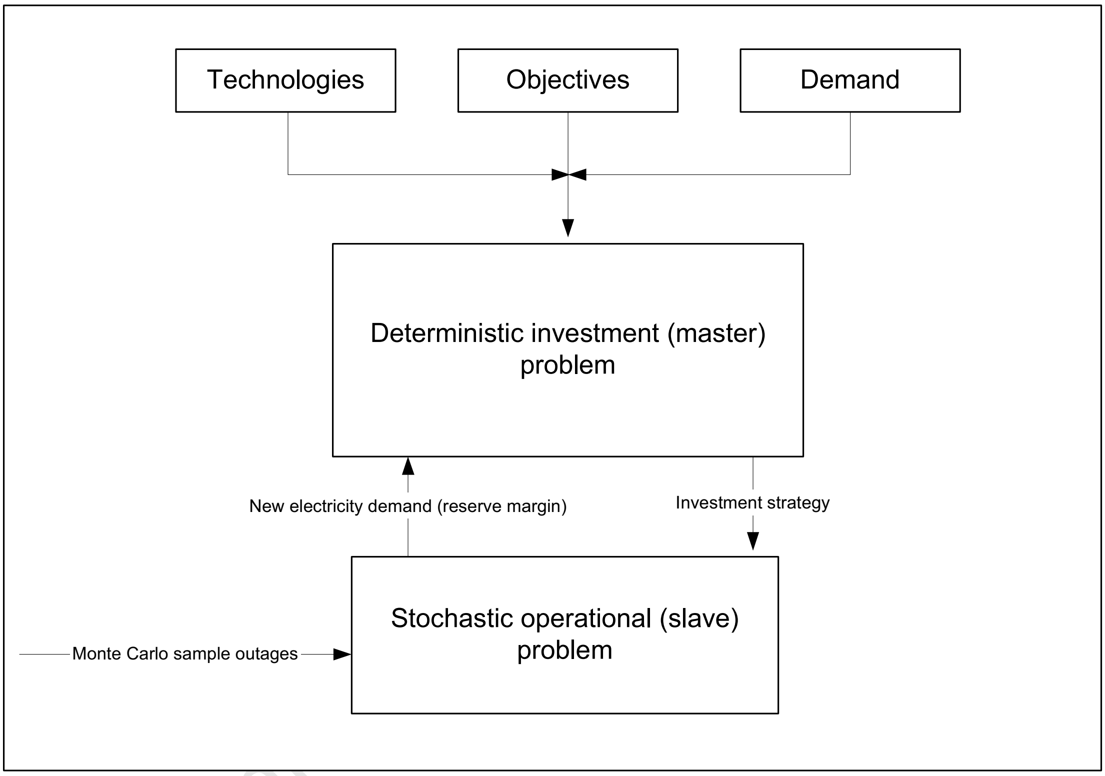

Figure 7-5 Representation of *master-slave* feedback for minimum reserve margin calculation

The *master-problem* is essentially a complete model in itself as TIMES is setup to solve both the investment and operation of the power plants for a specified demand simultaneously (similarly to MARKAL-described in chapter 4). However, in order to model uncertainty in plant availability an operational *slave* sub-model was created that uses the fixed investment "skeleton" from the *master-problem*.

The *master-problem* is solved to generate an initial solution (i.e. investment strategy) using a low reserve margin (i.e. 5 %), and then the *sub-problem* is solved for the investment strategy generated in the *master-problem* for each random sample of plant outages (described in section 7.3.4).

Unlike in the Benders decomposition method, the dual multipliers of the *slave* problem are not used as the new cuts for the *master-problem*. Instead, for each random set of outages generated using Monte Carlo sampling, the unserved energy of the system given the demand and the investment strategy from the *master-problem* is recorded. After the slave problem has been rerun for each of the Monte Carlo samples, the distribution of unserved energy over the sample set is calculated for each year in the time horizon and compared to the amount of unserved energy calculated in the *master-problem* for that year. If the amount of unserved energy in the *slave* problem is greater than the unserved energy in the *master-problem* (for a specified tolerance e.g. 95 %), then the demand level (see discussion below for comparison of using inflated demand rather than reserve margin) for that year in the *master-problem* is increased incrementally. This forces the *master-problem* to invest in more capacity in that year (if possible given the constraints of the model) which will in turn result in less energy going unserved in the *slave* problem. If the amount of unserved energy in the *slave* problem is less than the unserved energy in the *master-problem* then the demand level for that year remains unchanged[7]. This methodology is carried out iteratively until convergence is achieved in every year[8]. Total convergence in this case is not convergence on an optimal solution; it is merely a stopping point or upper bound on number of iterations of the *master-problem* to be carried out such that the solution space can be examined and the preferred solution selected (see Figure 7-8 and the surrounding discussion in section 7.4.2). The feedback mechanism of increasing the demand level only in years when the amount of unserved energy in the *slave* problem is greater than the unserved energy in the *master-problem* (for a specified tolerance) is the intelligent mechanism by which the solution space is explored. This is discussed further in section 7.4.2. Variance reduction methods could be used to make these methods more efficient by reducing the number of samples required (see for example Breipohl et al., 1990; Huang and Chen, 1993).

[7] This method only works if a low enough initial reserve margin is used.

[8] The master-slave problem would have to be set up separately for each alternative in the case where a portfolio of preferred alternatives exists. The initial investment strategy sent to the slave problem would then be the investment strategy of each of the preferred alternatives selected previously.

In contrast to the Benders decomposition method, the proposed methodology moves through the solution space directly exploring the relationship between unserved energy and total system cost (as it is the feedback between the *master* and *slave* problems). This allows a conscious trade-off to be made between cost and unserved energy (see section 7.4.3) thereby increasing the transparency in the decision process. The proposed methodology is also more accessible as it uses an existing and highly flexible energy planning model. The proposed approach also allows multiple objectives to be introduced into the problem formulation as demonstrated in Chapter 4.

A simpler way of exploring the relationship between levels of inflated demand and total system cost would be to increase the levels of inflated demand every year by an incremental amount. This method would however not be as efficient as demand would be increased in every year, without considering whether in fact it is necessary for capacity to be increased in that year. Using unserved energy as a feedback mechanism allows for demand (and therefore capacity) to be increased in years where it is needed.

Reserve margin or inflated demand?

The question of whether to use a minimum reserve margin or an inflated demand to increase capacity investment in the *master-problem* was considered. As mentioned in section 7.2.1, derating combined with a reserve margin is a common method used in ESI modelling. The problem with this method is in the way the model interprets a reserve margin. To the model, the minimum reserve margin represents a minimum capacity constraint that must be met. Therefore the model invests in plants that have lower investment costs than other plants; irrespective of their operating costs. This is due to the fact that these plants were built to meet capacity constraints, and will not actually be run in the model. In reality the excess capacity built to account for unforeseen unit outage will be run as other plants fail and therefore their running costs must be considered. One way of incorporating this into a model is to set minimum utilisation constraints forcing stations that are built to be run at a minimum utilisation rate (e.g. 5 % for OCGTs, 30 % for CCGTs) although this type of constraint is more often used to represent fixed take or pay fuel contracts especially for mid-merit stations like CCGTs.

Another way of doing this would be to use an inflated demand, thereby forcing the model to build stations for a hypothetical demand that must be met (instead of a capacity constraint). This method more closely resembles reality as running costs (as well as investment costs) are considered. A complication of this approach is that the operating or running costs calculated in the *master-problem* are inflated. However, using the approach presented here, the correct operating costs (taking plant outage into account) can be calculated from the *slave* problem.

A numerical experiment was performed to compare the results of using minimum reserve margins to those when using inflated demand by specifying minimum reserve margins in each year in the *master* problem and comparing the results to the equivalent run using inflated demand (the reserve margins generated from Plan 14 discussed in section 7.4.4 were used for this experiment). As expected the plan generated using minimum reserve margins built more OCGTs and less pumped storage and CCGTs than the equivalent run using inflated demand due to the lower capital cost components of the OCGTs relative to the CCGT and pumped storage units. The plan generated using minimum reserve margins with minimum utilisation rates on the OCGTs was almost identical to the plan generated using minimum reserve margins without minimum utilisation rates on the OCGTs except that it replaced slightly less CCGT with OCGT (due to the fact that it was forced to run them if they were built). The build plans generated in the *master* problem were then run in the *slave* problem and the costs and unserved energy results were compared.

Table 7-1. Costs and unserved energy for minimum reserve margin and inflated demand scenarios

	Fixed costs (Investement plus fixed O&M)	Activity costs (variable O&M plus fuel and unserved energy costs)	Total discounted system cost	Average total discounted unserved energy
	bZAR	bZAR	bZAR	GWh
Minimum reserve margin	101.4	117.1	218.5	8.9
Minimum reserve margin and minimum utilisation rates on OCGTs	101.8	116.7	218.5	8.7
Inflated demand	103.7	113.7	217.4	16.1

It was found that the plans generated using minimum reserve margins had lower fixed costs due to the lower capital cost of OCGTs relative to pumped storage and CCGTs but higher activity costs due to the much higher operating costs of the OCGTs. Using minimum utilisation rates on the OCGTs similarly resulted in lower fixed costs and higher activity costs relative to the inflated demand plan. The average total discounted unserved energy values were low for all three methods (but lower for the reserve margin methods due to more OCGTs being available to meet peak load) as both the reserve margin and the inflated demand levels used were at sufficiently high levels to ensure enough capacity to account for forced outage and minimise unserved energy (see section 7.4.3 for a discussion on the cost vs. unserved energy trade-off). The total discounted system cost using inflated demand was slightly lower than that when using the equivalent minimum reserve margin due to the fact that the model accounts better for operating costs in the master problem using this method. In light of the inflated demand method better accounting for operating costs in the *master* problem it was decided to use inflated demand as the feedback between the *master* and *slave* problems. It can be noted that the differences between the results using the different methods are minor when compared to other uncertainties in the system (e.g. uncertainty in DM preferences – see Chapter 5).

7.3.3. Planned outage

As mentioned in section 7.2, planned outage is typically modelled using the derating method, whereby an annual constraint on the availability of each station limits its operation to never exceed the annual outage rate, in any time slice. While this is a fair approximation that has been widely used in energy modelling (e.g. Loulou and Kanudia, 1998; Seebregts et al., 2001; NER et al., 2004), in reality planned outage is optimised such that maintenance occurs outside of the peak demand time periods. This can be modelled using constraints that specify an annual bound on activity for each station without a bound on the activity of each station in each time slice. In this way a station can run to its' full capacity when it is online, but can only be online for a specified amount portion of the year. One of the potential limitations of this approach is that outage will not necessarily occur in discrete blocks (i.e. a unit may go offline for two weeks over the period of a year rather than for a period of 2 weeks at a time). The model may therefore schedule planned maintenance at night, as it can break up the 2 weeks over the whole year. This would result in slightly too much capacity being available during the peak time slice and therefore the unserved energy in this period would be underestimated.

Another more computationally expensive alternative to modelling planned outage is to model planned maintenance such that the capacity of each station is derated for one season of the year, thereby forcing maintenance to occur within a fixed portion of the year rather than allowing it to be split over the whole year. This is an improvement over the annual derating approach as stations are only derated for 1 season rather than the whole year and in the other seasons their can run to full capacity. Within a model such as TIMES this would have to be done by using a number of dummy technologies for each station, representing generation on a seasonal basis, with constraints placed on these technologies such that the model could only run one of them at a time. This would increase the number of variables in the model significantly as well as the processing time. Therefore for the model presented in this chapter, planned outage was modelled by derating stations on an annual basis and allowing them to run to full capacity in any one time slice. While planned maintenance should be modelled using the more complicated and computationally expensive approach described above to generate defensible investment strategies, the simpler approach allows for the methodology presented in this chapter to be sufficiently demonstrated.

7.3.4. FORCED OUTAGE

Forced outage is more complicated to model than planned outage as it is random, and cannot be optimised in relation to the rest of the system (it can even occur in a time slice allocated to planned maintenance). The methodology adopted here was to simulate random forced outage using Monte Carlo sampling, such that a station/unit would either be available or out, for any given time slice, and that the total time that a station would be forced out in any year would be equal to its forced outage rate.

The starting point for the Monte Carlo sampling was to examine the probabilities of units going out. Table 7-2 below illustrates the probability of 0, 1, 2 or 3 units of a station going out (using a FOR of 0.05) as a function of the number of units in that station. Firstly, the number of combinations for which 0, 1, 2 or 3 units could go out given the number of units making up a station was calculated. Next the probability of the event of 0, 1, 2 or 3 going out was calculated. Finally by multiplying the number of combinations for each event by the probability of each event, the actual probability of 0, 1, 2, 3 or more units going out for each station could be calculated.

Using an example of a 10 unit station, the probability of 2 units going out simultaneously can be calculated by first calculating the number of ways in which 2 units can be chosen from 10 (45 combinations). Next the probability of the event of 2 units going out at the same time must be calculated. This is done by calculating the probability of 2 units going out $(0.05)^2$ and multiplying this by the probability of 8 units (10-2) not going out $(0.95)^8$. Finally this number is multiplied by the number of combinations in which 2 out of 10 units can go out, which yields the probability of the 7.46 %.

Table 7-2 Probability of unit outage as a function of number of units per station

Unit per station		No of combinations			Probability of event				Probability of combination				Probability of more than 3 units out
No. units out	**0**	**1**	**2**	**3**	**0**	**1**	**2**	**3**	**P_0**	**P_1**	**P_2**	**P_3**	
1	1	1	0	0	95.00%	5.00%	0%	0%	95.00%	5.00%	0%	0%	0%
2	1	2	1	0	90.25%	4.75%	0.25%	0%	90.25%	9.50%	0.25%	0%	0%
3	1	3	3	1	85.74%	4.51%	0.24%	0.01%	85.74%	13.54%	0.71%	0.01%	0%
4	1	4	6	4	81.45%	4.29%	0.23%	0.01%	81.45%	17.15%	1.35%	0.05%	0%
5	1	5	10	10	77.38%	4.07%	0.21%	0.01%	77.38%	20.36%	2.14%	0.11%	0%
6	1	6	15	20	73.51%	3.87%	0.20%	0.01%	73.51%	23.21%	3.05%	0.21%	0.01%
7	1	7	21	35	69.83%	3.68%	0.19%	0.01%	69.83%	25.73%	4.06%	0.36%	0.02%
8	1	8	28	56	66.34%	3.49%	0.18%	0.01%	66.34%	27.93%	5.15%	0.54%	0.04%
9	1	9	36	84	63.02%	3.32%	0.17%	0.01%	63.02%	29.85%	6.29%	0.77%	0.06%
10	1	10	45	120	59.87%	3.15%	0.17%	0.01%	59.87%	31.51%	7.46%	1.05%	0.10%
15	1	15	105	455	46.33%	2.44%	0.13%	0.01%	46.33%	36.58%	13.48%	3.07%	0.55%
20	1	20	190	1140	35.85%	1.89%	0.10%	0.01%	35.85%	37.74%	18.87%	5.96%	1.59%
30	1	30	435	4060	21.46%	1.13%	0.06%	0%	21.46%	33.89%	25.86%	12.70%	6.08%
50	1	50	1225	19600	7.69%	0.40%	0.02%	0%	7.69%	20.25%	26.11%	21.99%	23.96%
60	1	60	1770	34220	4.61%	0.24%	0.01%	0%	4.61%	14.55%	22.59%	22.98%	35.27%
70	1	70	2415	54740	2.76%	0.15%	0.01%	0%	2.76%	10.16%	18.45%	22.01%	46.61%
80	1	80	3160	82160	1.65%	0.09%	0%	0%	1.65%	6.95%	14.46%	19.78%	57.16%
90	1	90	4005	117480	0.99%	0.05%	0%	0%	0.99%	4.68%	10.97%	16.94%	66.42%
100	1	100	4950	161700	0.59%	0.03%	0%	0%	0.59%	3.12%	8.12%	13.96%	74.22%

It can be seen from Table 7-2 above that the probabilities of more than 3 units of a station going out simultaneously only become significant (i.e. greater than 1 %) for stations with more than 15 units. Therefore it could be said that provided the stations in the model have less than 15 units, only the probabilities of 0, 1, 2 and 3 units going out need to be taken into account when calculating forced outage. This enables some saving of computing time when doing thousands of model runs.

With this in mind a logical procedure was developed to decide the availability of each station in every time slice. By representing stations rather than units in the model, the number of technologies and therefore computational time could be significantly reduced. Therefore the procedure outlined below was used to set the availability of each station in the model based on a random draw, where P_0, P_1, P_2 and P_3 are the probabilities that 0, 1, 2 or 3 units of a particular station will be offline given the number of units in that station and the outage rates of those units.

- Draw a random number between 0 and 1
- If the number is less than P_0 then 0 units of that station are offline and availability =1 , else:
- if the number is greater than $(1- P_3)$ then availability of the station = 1-3/(number of units), else:
- if the number is greater than $(1- (P_3 + P_2))$ then availability of the station = 1-2/(number of units), else:
- the number is greater than $(1- (P_3 + P_2 + P_1))$ then availability of the station = 1-1/(number of units),

In this way the availability of each station for each time slice could be decided for a single model run. This is illustrated in Table 7-3 below for an example station with 6 units using a demand resolution containing 2 seasons (s01 and s02), 2 weekparts (w1 and w2) and 7 dayparts (h1-h7):

Table 7-3 Table of forced outages for an example of a 6 unit station

Time slice	2005	2006	2007	2008	2009
s01w1h1	1	1	1	1	1
s01w1h2	1	0.5	1	0.83	0.83
s01w1h3	1	0.67	1	1	1
s01w1h4	1	1	1	0.83	1
s01w1h5	1	1	1	1	1
s01w1h6	1	1	1	1	0.83
s01w1h7	0.83	1	0.83	1	0.83
s01w2h1	1	1	1	1	0.83
s01w2h2	1	0.83	1	1	1
s01w2h3	1	1	1	1	1
s01w2h4	1	0.83	1	1	0.83
s01w2h5	1	0.83	1	0.83	0.83
s01w2h6	1	1	1	0.83	1
s01w2h7	1	0.67	1	1	1
s02w1h1	1	1	0.83	1	1
s02w1h2	1	1	1	1	1
s02w1h3	1	1	1	1	1
s02w1h4	1	1	1	1	1
s02w1h5	1	1	0.83	1	1
s02w1h6	0.83	0.83	0.83	1	0.67
s02w1h7	1	1	1	1	1
s02w2h1	1	1	1	1	1
s02w2h2	0.83	1	1	1	1
s02w2h3	1	1	1	1	1
s02w2h4	1	0.83	1	1	1
s02w2h5	1	0.67	1	1	1
s02w2h6	1	1	0.83	0.67	1
s02w2h7	1	1	1	1	1

In Table 7-3 above, “1”s represent when the station is available to run and values less than 1 represent the degree to which the station is forced out or how many of the units of that station are forced out. This information is generated for each station given their forced outage rates using the procedure described above. This outage information is then fed into the operational *slave* problem and solved for the investment strategy generated in the *master-problem*. The solution represents the optimal operational strategy for the objectives defined. This process is repeated for the specified number of sample sets used to represent forced outage (varies depending on the size of the system and the number of samples necessary to adequately represent the outage for that system). The operational variables of each of the power stations as well as the amount of unserved energy for each sample set are recorded. The distribution of unserved energy over all the sample sets is then calculated and used as feedback to the *master-problem* as described previously in section 7.3.2. This methodology is demonstrated in section 7.4 below:

7.4. RESULTS

7.4.1. SAMPLE SIZE

Initially the sample size or number of runs needed for the *slave* problem needed to be determined. This number should be large enough to adequately represent plant outage and therefore unserved energy but should also be minimised to reduce computation time.

Figure 7-6 and Figure 7-7 below illustrate the average amount of unserved energy in each year as a function of sample size:

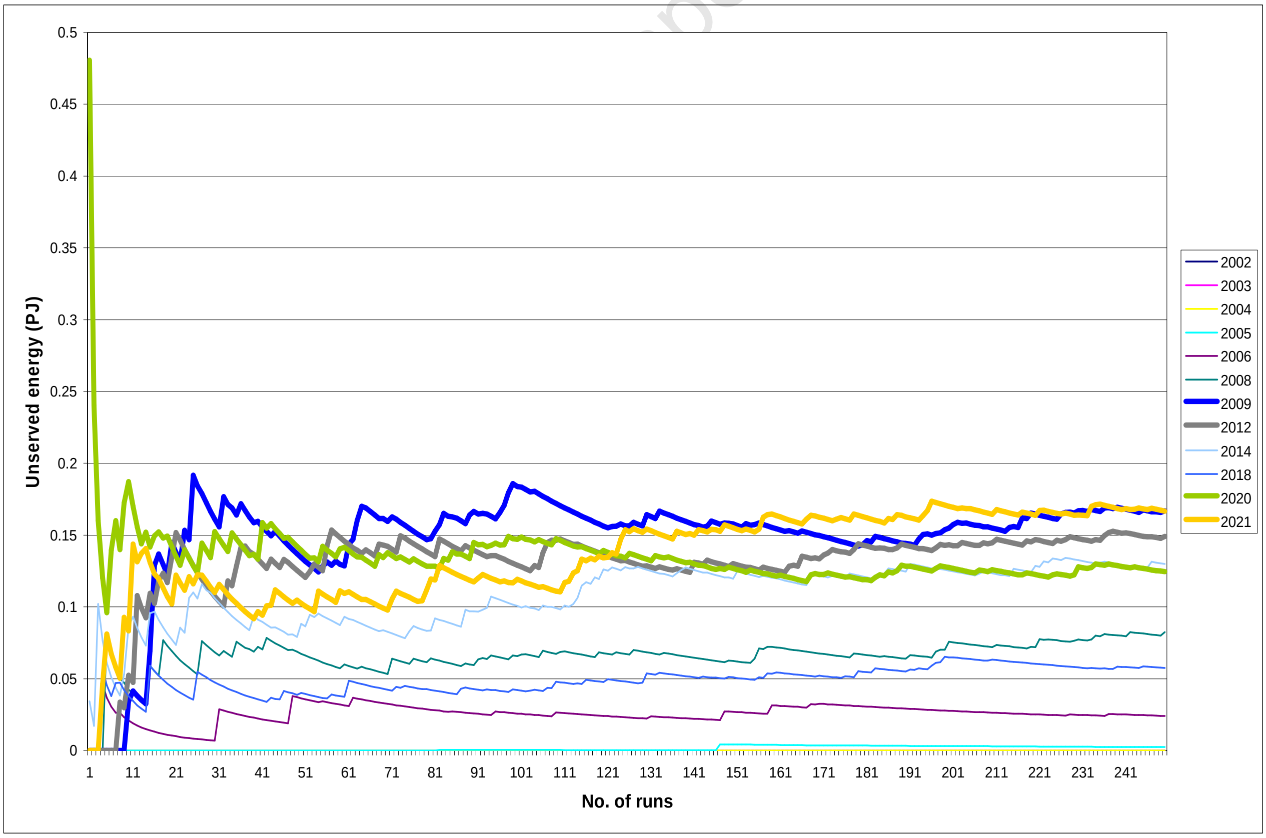

Figure 7-6 Graph of average unserved energy for selected years as a function of no. of runs of slave problem for a demand inflated by 5 %

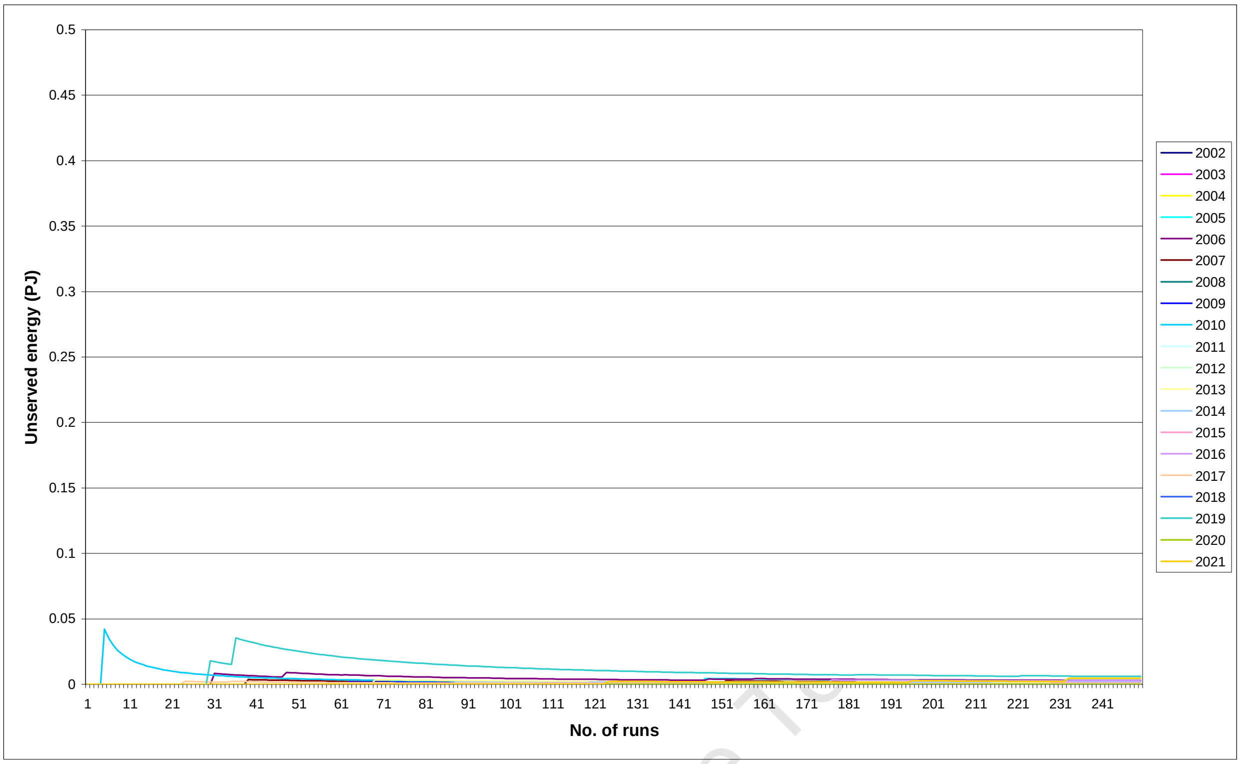

Figure 7-7 Graph of average unserved energy as a function of no. of runs of slave problem for a demand inflated by 10 %

It can be seen from the figures above that the amount of unserved energy decreases significantly from when a demand inflated by 5 % was used compared to that when a demand inflated by 10 % is used.

Using 2009 as an example, it can be seen from Figure 7-6 that the average unserved energy values stabilize (with minor fluctuations) from about 120 runs of the *slave* problem. The same can be said for other years where the average value of unserved energy is high, relative to other years (e.g. 2012, 2020, 2021).

It was therefore decided that running the *slave* problem 150 times for each iteration of the *master-problem* would be sufficient to represent plant outage and therefore unserved energy for this electricity supply system.

7.4.2. Exploring the solution space

The problem was then set up such that the initial demand level in the *master-problem* was 4 % above the actual projected demand. This number was used to reduce the number of *master* iterations necessary to explore the solution space. It was assumed that this level of inflated demand would be less than what would be required to account for the forced outage of the system (which proved correct given the results in Table 7-4). Another method that could have been used for obtaining a starting point for the model that is closer to the optimal investment strategy (correctly taking forced outage into account) would be to derate all stations by their FOR in every time slice and then run the *master-problem* using the actual level of demand. The minimum reserve margin of an ESI system approaches the average FOR of the stations in that system as the number of stations tends to infinity. Therefore derating each station by it's FOR would yield a good starting point for a system with a finite number of units as forced outage would be slightly underestimated, and the minimum reserve margin could then be found by increasing inflated demand. This said, derating all station by their FOR in combination with using inflated demand to model forced outage increases the number of parameters that are being adjusted to find the minimum reserve margin needed to account for forced outage. It was therefore decided to adjust inflated demand in the *master-problem* without derating all stations by their FOR.

The *master-problem* would then be run to obtain the investment strategy for that level of demand. This investment strategy would then be used in the *slave* problem where plant outage would be modelled as described in section 7.3.4 above using 150 model runs. The distribution of unserved energy for that investment strategy could then be calculated and compared to the unserved energy value reported in the *master-problem*.

To demonstrate this methodology the following convergence criterion was used:
The *slave* problem had to achieve unserved energy values equal to the *master-problem* within a 99 % confidence interval for each year; else the demand was increased by 0.5 % in the year/s where this criterion was not met. This process was repeated until this criterion was met in every year.

This is demonstrated for the base case scenario (BASE) as well as for ALT 11, which was generated using Pareto Generation Parameters (PGPs) so as to better satisfy non-cost objectives (see chapter 4 section 4.3 for methodology). These alternatives were chosen to demonstrate the methodology proposed in section 7.3 as they resulted in significantly different investment strategies and would therefore represent the preferred solutions for vastly different sets of DM preferences (discussed in more detail below). Figure 7-8 and Figure 7-9 demonstrate the results of using the *master-slave* approach on the total discounted system cost[9] (solutions circled in red are shown in more detail below). See Appendix D for detailed inflated demand, unserved energy and cost results of *master-slave* procedure for BASE and ALT 11.

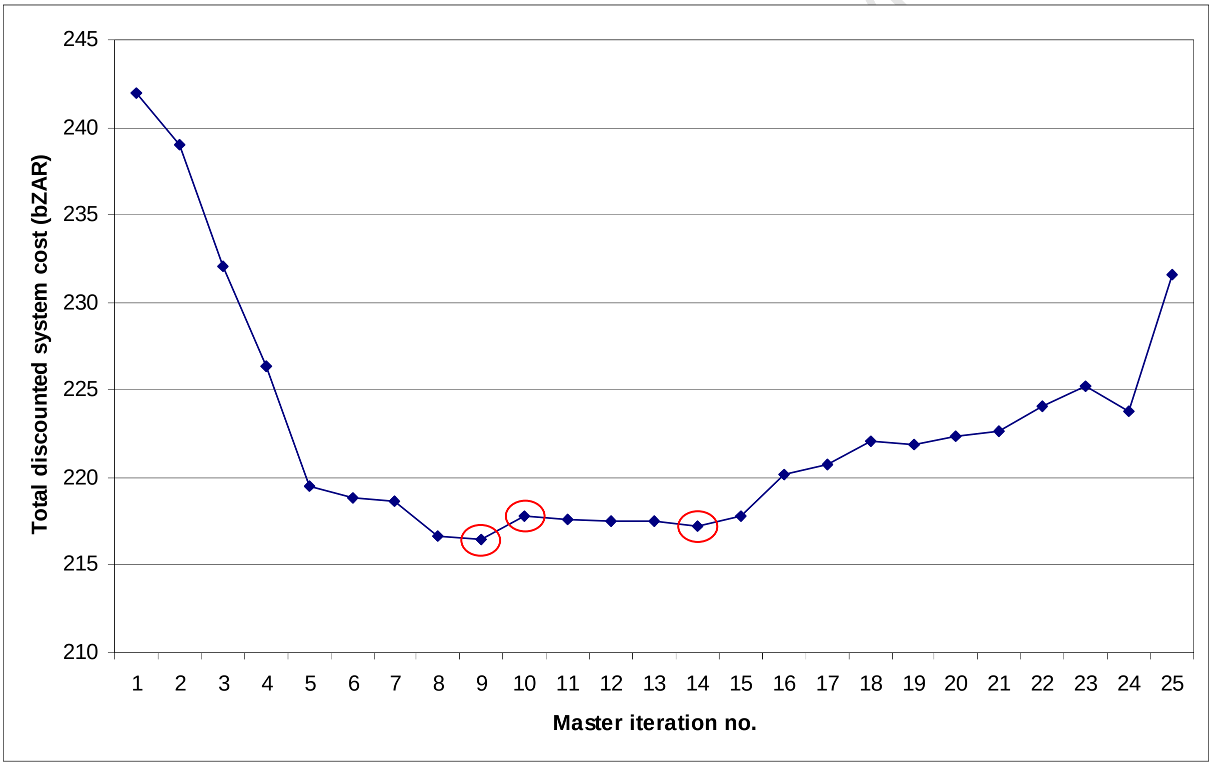

Figure 7-8 Graph of total discounted system cost as a function of *master-problem* iteration number (BASE)

[9] The total discounted system cost includes the investment and fixed costs from the *master-problem* as well as the average variable costs (e.g. variable O&M, unserved energy, variable fuel costs, emission taxes) from the *slave* problem.

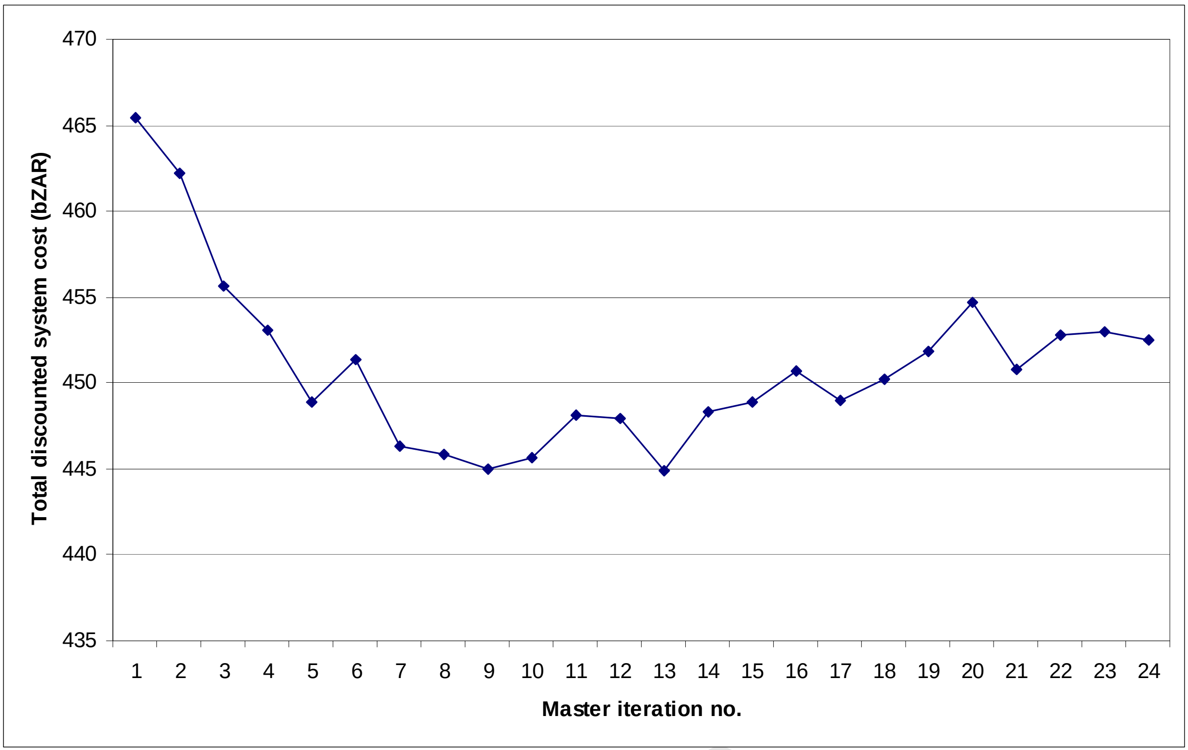

Figure 7-9 Graph of total discounted system cost as a function of *master-problem* iteration number (ALT 11)

Figure 7-8 and Figure 7-9 both show that total discounted system cost decreases as the demand is incrementally increased in years where the convergence criterion is not met. In both cases a minimum is reached before the stopping criterion is reached.

The shapes of Figure 7-8 and Figure 7-9 above are due to the trade-off between the avoided costs of unserved energy by building more capacity to account for plant outage and the investment cost and fixed O&M cost of that extra capacity. Up to the point where the minimum is reached, the avoided cost of unserved energy exceeds the extra investment and fixed O&M cost of the new capacity. Beyond that point it is more expensive to build the extra capacity than it is to not serve small amounts of electricity. This can be simplified to an example where in a particular year; the demand for electricity would be very slightly above the capacity to supply (e.g. 0.01 PJ or 2.78 GWh). In this case it would probably be cheaper to pay the high cost per unit of unserved energy and not supply that small demand than it would be to build a 120 MW gas turbine and run it for less than 1 % of the year. There is however a range of solutions in both Figure 7-8 and Figure 7-9 above that result in a similar average total discounted system cost after the minimum value has been reached in each case. This implies that the DM may have a choice between solutions that vary slightly in cost, but have different values of unserved energy. This is demonstrated using BASE in Figure 7-10 and Figure 7-11 below:

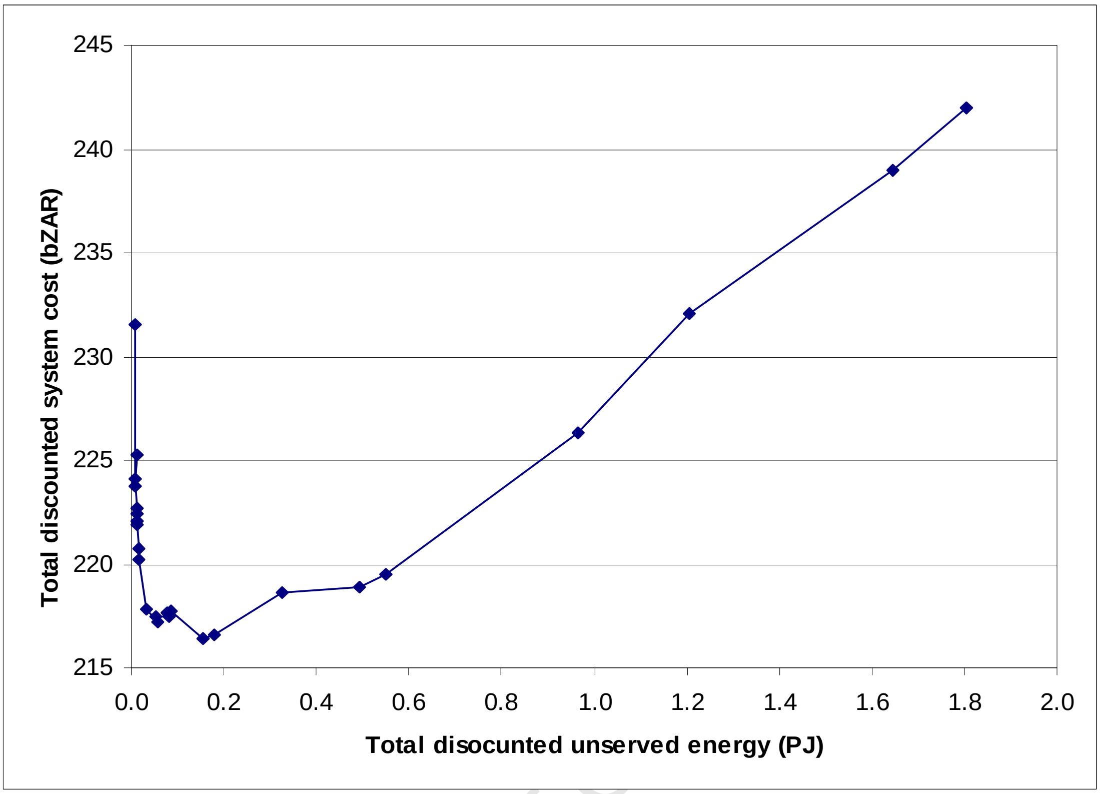

Figure 7-10 Relationship between total discounted system cost and total discounted unserved energy for BASE

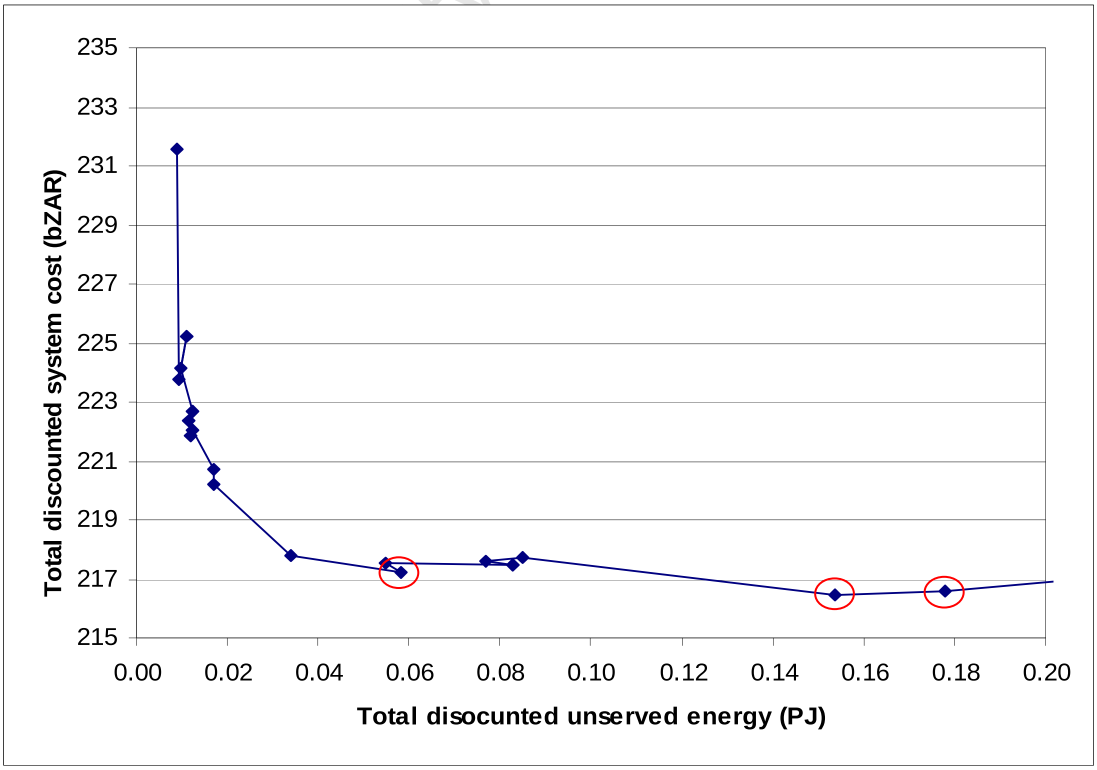

Figure 7-11 Closer view of solutions near optimum in Figure 7-10

Figure 7-10 demonstrates that total discounted system cost can be decreased significantly by reducing the amount of unserved energy in the system up to a point. From that point decreasing unserved energy becomes more expensive as the investment and fixed O&M cost outweigh the avoided cost of unserved energy. This said there may be a number of solutions near the optimum that have similar values of total discounted system cost, but with differences in the amount of total discounted unserved energy (as can be seen in Figure 7-11 for BASE). This trade-off between total discounted system cost and the amount of unserved energy is discussed further in section 7.4.3.

The reason for the differences in the values of Figure 7-8 and Figure 7-9 is that ALT 11 has emission taxes on $SO_{2\ EQ}$ emission and water consumption (PGPs). Therefore in each iteration of the *master* and *slave* problems the taxes are considered in the optimisation. This forced ALT 11 to invest in different technologies to BASE (as demonstrated in chapter 4 section 4.4.2). As each new technology has a particular unit size and forced outage rate, if two plans have invested in different technologies they will require different levels of inflated demand to account for forced outage. The magnitude of the difference between the levels of inflated demand required for each alternative is dependant on the extent to which the new and existing stations of those alternatives differ. As the existing system is the same in both cases, the levels of inflated demand would be similar, even for alternatives that have significantly different investment strategies (such as BASE and ALT 11). This is demonstrated in section 7.4.4 below. Obviously for new systems where there is not a significant amount of existing capacity, the levels of inflated demand required to account for forced outage would be almost entirely dependant on the new technologies built. Therefore in that case, the levels of inflated demand would have to be calculated separately for each alternative.

The "bumps" (slight oscillations) in Figure 7-9 and to a lesser degree in Figure 7-8 are due to the fact that the methodology used here increases the demand in each year where the criterion is not met, however, by increasing the demand in year *n*, year *n+1* is also affected as the capacity added in year *n* would still be in the system in year *n+1* and therefore increasing the demand in year *n+1* may not be necessary. This could be avoided by only increasing demand in the first year where the convergence criterion is not met, however this would result in many more iterations being needed to find the optimal inflated demand for the system and therefore far greater computing time. The modeller should be aware of this possibility and the results should be checked for the characteristic "bumps"[10].

7.4.3. Cost vs. unserved energy trade-off

As mentioned above in section 7.4.2, there may be a number of solutions near the optimum that have similar values of total discounted system cost, but with differences in the amount of total discounted unserved energy. A range of solutions were selected from Figure 7-8 and Figure 7-11 (shown using red circles) to demonstrate the relationship between unserved energy and total discounted system cost and the trade-off that the DM is faced with. The probability density functions for total discounted system cost of these solutions are shown below:

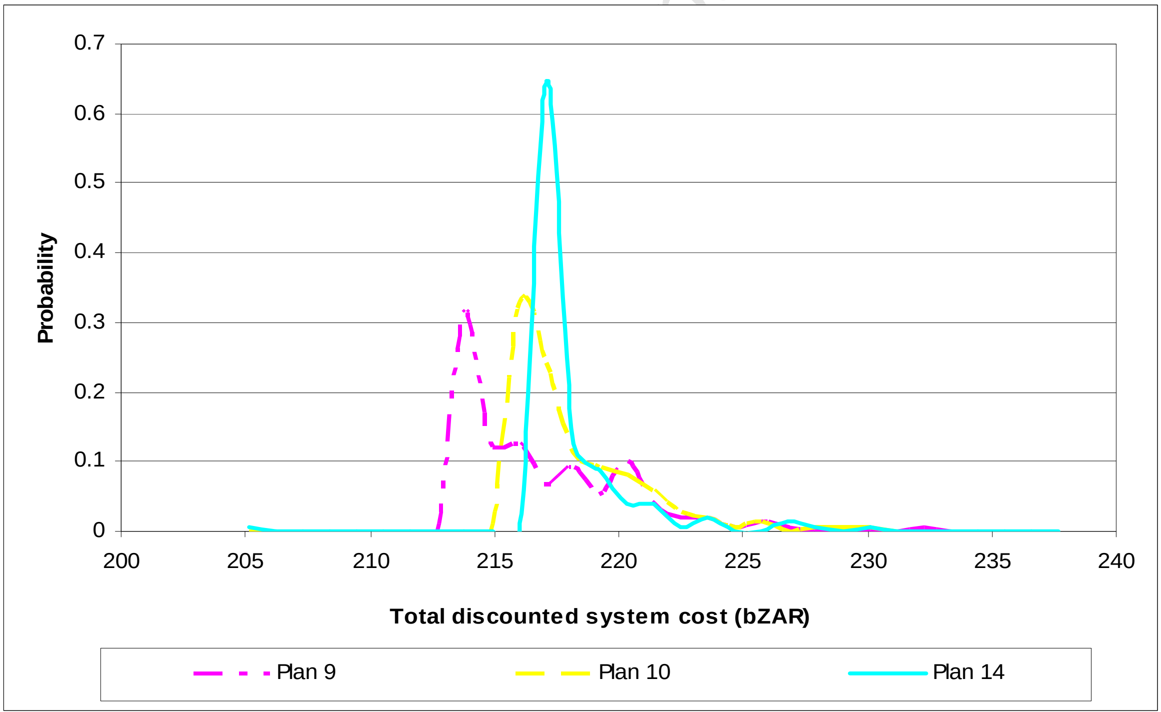

Figure 7-12 Probability density functions for total discounted system cost (BASE)

From Figure 7-8 above it could be seen that Plan 9 has the lowest average total discounted system cost (216.4 bZAR), however from Figure 7-12 it can be seen that

[10] "Bumps" can also be caused by the size of the modular constraints imposed on the model by using mixed integer programming relative to the magnitude of the demand and size of the model (in terms of the total capacity required to meet the demand).

this plan has a wide spread or relatively low probability of achieving its average value. This occurs because Plan 9 has a relatively low investment cost component and a relatively high unserved energy cost component compared Plan 10 and Plan 14 (see Table 7-8 in Appendix D for detailed unserved energy results). This causes Plan 9 to be extremely sensitive to the amount of unserved energy in the system and therefore it has very high costs for the *slave* runs when there is a large amount of unserved energy and very low costs when there is little unserved energy.

In contrast to Plan 9, Plan 14 has a higher average cost (217.4 bZAR, 0.45 % higher than Plan 9), but also has a much higher probability of achieving this cost due to a significantly lower unserved energy component. This means that this plan is less risky in terms of unserved energy than Plan 9 but will on average have a higher cost due to increased investment into generating technologies. Plan 10 has the highest average cost (217.8 bZAR) of the three plans as well as a wide spread, and would therefore be an inferior choice.

These results demonstrate the trade-off between unserved energy and total discounted system cost. Presenting this information to the DM allows for an informed choice to be made as to the inflated demand level required to ensure acceptable levels of risk towards unserved energy. Once an acceptable solution has been identified taking the trade-off between total discount system cost and unserved energy into account, the inflated demand level used to generate those solutions can be identified. This is demonstrated using Plan 14.

7.4.4. Analysis of selected solutions

The inflated demand level corresponding to Plan 14 from BASE is shown in Table 7-4 below. This demand level was then run in the model with the PGPs used to generate ALT 11 to determine the effect of using the inflated demand level obtained from the base case in an alternative generated to better satisfy non-cost objectives. Using the same inflated demand levels does not necessarily imply that the reserve margin would be the same for the two alternatives in every year, as reserve margin is calculated by equation 7.2 (shown in section 7.1).

As the availability of the power stations is not explicitly taken into account in the reserve margin calculation, two alternatives generated using the same inflated demand levels with different power stations would have different reserve margins due to the differences in the availabilities of the power stations. The minimum reserve margin corresponding to the inflated demand in Table 7-4 is shown for the base case and ALT 11 in Table 7-4:

Table 7-4 Table of demand level for *master* iteration corresponding to Plan 14 (BASE)

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Inflated demand level (PJ)																				
BASE	692	714	743	770	841	872	872	906	927	944	967	988	1003	1027	1050	1063	1077	1085	1093	1160
Inflated demand level (% above actual demand level)																				
BASE	4.00%	4.00%	4.00%	4.00%	8.77%	10.41%	8.23%	9.87%	9.87%	9.32%	9.32%	9.32%	8.77%	9.32%	9.87%	9.32%	8.77%	7.70%	6.63%	9.87%

Table 7-5 Table of reserve margin for *master* iteration corresponding to inflated demand levels from Plan 14 (BASE)

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
BASE	29.47%	25.92%	22.56%	19.89%	17.46%	18.54%	17.05%	16.77%	16.40%	15.68%	14.54%	13.58%	14.87%	12.75%	14.43%	13.93%	13.02%	13.90%	15.33%	11.32%
ALT 11	29.47%	25.92%	22.56%	19.89%	16.81%	18.63%	17.13%	17.11%	16.63%	14.14%	13.80%	13.56%	13.47%	13.53%	14.17%	14.04%	12.81%	13.38%	16.05%	12.22%

Table 7-6 Table of average unserved energy for *master* iteration corresponding to inflated demand levels from Plan 14 (BASE)

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total discounted unserved energy
Unserved energy (GWh)																					
BASE	0	0	0	0.1	1.7	2.1	3.2	4.0	2.4	2.2	1.6	2.1	1.5	0.7	3.0	0.8	6.2	1.1	0	3.6	16.1
ALT 11	0	0	0	0.1	4.5	1.5	3.2	2.8	2.4	2.3	2.7	2.2	1.5	0.9	2.7	0.3	6.8	2.0	0	4.2	18.1
Unserved energy (% of actual demand)																					
BASE	0 %	0 %	0 %	0.000%	0.001%	0.001%	0.001%	0.002%	0.001%	0.001%	0.001%	0.001%	0.001%	0.000%	0.001%	0.000%	0.002%	0.000%	0 %	0.001%	
ALT 11	0 %	0 %	0 %	0.000%	0.002%	0.001%	0.001%	0.001%	0.001%	0.001%	0.001%	0.001%	0.001%	0.000%	0.001%	0.000%	0.002%	0.001%	0 %	0.001%	

It can be seen from Table 7-4 above that the % above actual demand level is not the same for each year in the time horizon. It starts off at 4 % (being the starting value of the procedure) and only begins to increase in 2006 when additional capacity is needed to account for increasing demand and plant outage. In years prior to 2006 there is enough excess capacity in the system to account for plant outage. It can also be seen that the highest values for the % above actual demand level is 10.41 % in 2007.

Table 7-5 demonstrates that the reserve margin starts off very high in 2002 for both alternatives (29.47 %). This is due to the excess capacity in the system. The reserve margin drops gradually for both alternatives across the time horizon as demand increases. Theoretically, the more plants there are in the system, the lower the required reserve margin, as the smaller the effect of individual units going out. Another important factor is the difference between supply and demand in a particular year, as excess supply will offset the effect of plant outage. The reserve margin is very similar for both alternatives in almost every year in the time horizon. The marginal differences are due to ALT 11 having emission taxes on $SO_{2\ EQ}$ emission and water consumption and therefore investing in different technologies to BASE. Reserve margin reaches a minimum in year 2021 for both alternatives. It must be noted that when using the inflated demand corresponding to Plan 14 for the base case, the reserve margin is above 11.32 % in every year in the time horizon. Therefore using a minimum reserve margin of 10 % (as was done in the NIRP (NER et al., 2004)) would not be sufficient to account for forced outage uncertainty for this system.

The levels of inflated demand necessary to account for forced outage would not be the same across all DM preference situations, however due to the fact that the cost of unserved energy is very high, the situation where there would be large amounts of unserved energy would be avoided across most DM preference situations (see Table 7-5). Due to high cost of unserved energy combined with the fact that the existing system is the same for all the alternatives considered it is proposed that the levels of inflated demand obtained using the base case could be used to account for forced outage when generating solutions that better satisfy multiple objectives instead of repeating the *master-slave* procedure for each alternative.

In order to test this hypothesis the inflated demand levels for three solutions generated in BASE (Plan 9, Plan 10 and Plan 14) were run in the model with the PGPs used to generate ALT 11 (noting that these alternatives resulted in significantly different investment strategies – see chapter 4 section 4.4.2). The results are demonstrated in Figure 7-13 below:

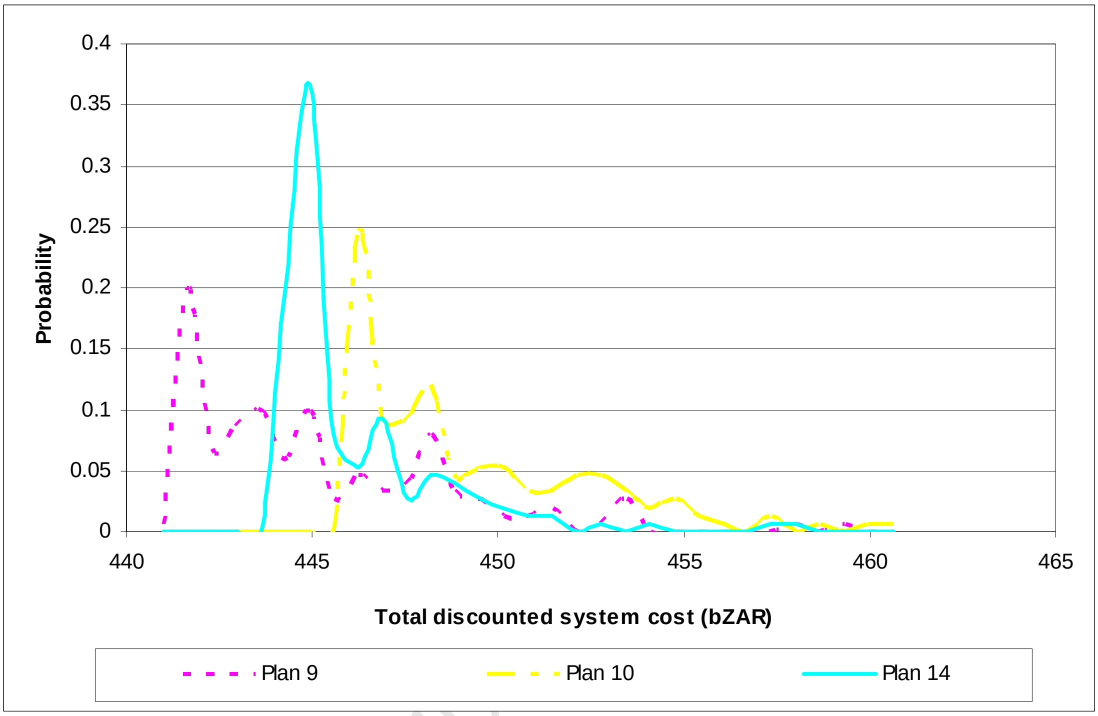

Figure 7-13 Probability density functions for total discounted system cost (ALT 11)

It can be seen in Figure 7-13 that using the inflated demand levels from Plan 9 of the base case yields the lowest average cost of 444.9 bZAR, which is almost identical to the cost of the solution in Figure 7-9 that achieves the lowest total discounted system cost. As in the base case (shown in Figure 7-12 above) this solution has a wide spread of costs or relatively low probability of achieving its average value due to the relatively low investment cost component and a relatively high unserved energy cost component of this solution.

Using the inflated demand levels from Plan 14 of the base case resulted in a slightly higher average cost (445.8 bZAR, 0.21 % higher than Plan 9) but also had a narrower spread and higher probability of achieving its average value due to the higher investment cost component. This solution is therefore is less risky in terms of unserved energy than Plan 9 but will on average have a higher cost due to increased investment into generating technologies. From Table 7-6 it can be seen that the amount of unserved energy when using this level of inflated demand for ALT 11 closely resembled that of the base case. Plan 10 once again has the highest average cost (451.8 bZAR) of the three plans as well as a wide spread, and would therefore be an inferior choice.

It must be noted that this approach does not guarantee that there will not be any unserved energy in system. It only attempts to model forced outage in such a way so that it may be integrated correctly into the planning process. This methodology is sensitive to the cost of unserved energy. However, the cost of unserved energy should be sufficiently high to avoid investment into power stations that are run at unreasonably low load factors. That said the results in Table 7-8 and Table 7-10 in Appendix D confirm that unserved energy decreases as inflated demand increases and more generating capacity is invested in.

Comparing the cost and unserved energy distributions of ALT 11 and the base case for the inflated demand levels corresponding to the plans shown above demonstrate that the levels of inflated demand obtained using the *master-slave* approach in base case can be used to account for forced outage when generating solutions that better satisfy multiple objectives instead of repeating the *master-slave* procedure for each alternative. If however the distribution of unserved energy was found to be unacceptable for a preferred alternative, the demand level could be inflated (thereby increasing the amount of investment for that alternative) until an acceptable solution was obtained using the methodology presented in this chapter.

7.5. CONCLUSIONS

Demand can be modelled both chronologically and in high resolution such that both the frequency and duration of forced outage can be adequately represented, all within a multi-objective framework with a comprehensive analysis of system wide uncertainty.

Using sampling methods to represent uncertainty in plant operation within an operational *slave-problem* is an efficient method for feedback into the investment *master-problem.* Plant outage and unserved energy can be adequately represented for a national system such as the South African ESI using 150 (or less) model runs in the *slave-problem*, and the level of inflated demand corresponding to the minimum total discounted system cost can be found in less than 10 iterations of the *master-problem*.

Given the size of the South African ESI, and the number of technologies considered in this study, the number of iterations needed to find the minimum reserve margin corresponding to the minimum total discounted system cost for other national systems should be similar (unless many more technologies options were included in the model). The number of iteration of the *master-problem* could be reduced by probing the solution space using larger steps and/or using a starting point closer to the minimum reserve margin corresponding to the minimum total discounted system cost.

Using unserved energy as a convergence criterion between the *master* and *slave* problems for each year in the time horizon is an effective method for exploring the solution space and identifying the levels of inflated demand required to account for forced outage. This method also highlights the trade-off between unserved energy and total discounted system cost, allowing the decision maker to make an informed choice around this trade-off.

The optimal inflated demand level varies little with DM preferences as unserved energy is minimised due to the high cost of unserved energy and the fact that the existing system is the same for all the alternatives generated. Therefore the *master-slave* routine used to determine the optimal level of inflated demand needed for each year in the time horizon can be carried out on the base case, and then used to generate further alternatives satisfying a range of DM preferences using the methodology presented in chapter 4. In this way forced outage uncertainty can be integrated into the multi-objective framework presented in this thesis without having to do large numbers of model runs for each alternative. If however the distribution of unserved energy for the preferred alternative was found to be unacceptable by the DM, the level of investment for that alternative could be increased using the methodology presented in this chapter.

7.6. APPENDIX D

Table 7-7 Inflated demand levels and cost for *master-slave* procedure (BASE)

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	
Actual demand (PJ)	666	687	715	740	773	789	806	825	844	863	885	904	922	939	956	972	990	1008	1025	1055	
Inflated demand level (PJ) - iteration no.																					**Average total discounted system cost**
1	692	714	743	770	804	821	838	858	878	898	920	940	959	977	994	1011	1030	1048	1066	1098	242.0
2	692	714	743	770	808	825	842	862	882	902	925	944	964	982	999	1016	1035	1053	1072	1103	239.0
3	692	714	743	770	812	829	847	866	887	907	929	949	968	986	1004	1021	1040	1059	1077	1109	232.1
4	692	714	743	770	816	833	851	871	891	911	934	954	973	991	1009	1026	1045	1064	1082	1114	226.3
5	692	714	743	770	820	838	855	875	896	916	939	959	978	996	1014	1032	1051	1069	1088	1120	219.5
6	692	714	743	770	824	842	859	879	900	921	943	963	983	1001	1019	1037	1056	1075	1088	1125	218.9
7	692	714	743	770	828	846	864	884	905	925	948	968	988	1006	1024	1042	1061	1080	1093	1131	218.6
8	692	714	743	770	833	850	868	888	909	930	953	973	993	1011	1029	1047	1061	1080	1093	1137	216.6
9	692	714	743	770	837	854	872	893	914	934	958	978	993	1011	1034	1047	1066	1080	1093	1142	216.4
10	692	714	743	770	841	859	872	897	918	934	962	983	998	1016	1039	1052	1072	1085	1093	1148	217.8
11	692	714	743	770	841	863	872	902	918	939	962	983	998	1016	1045	1058	1077	1085	1093	1148	217.6
12	692	714	743	770	841	867	872	902	923	944	967	988	1003	1016	1050	1058	1077	1085	1093	1148	217.5
13	692	714	743	770	841	872	872	906	927	944	967	988	1003	1021	1050	1063	1077	1085	1093	1154	217.5
14	692	714	743	770	841	872	872	906	927	944	967	988	1003	1027	1050	1063	1077	1085	1093	1160	217.2
15	692	714	743	770	841	872	872	906	927	944	967	988	1003	1027	1050	1063	1083	1085	1093	1160	217.8
16	692	714	743	770	849	880	881	915	937	953	977	998	1008	1032	1060	1068	1093	1091	1093	1171	220.2
17	692	714	743	770	854	885	886	920	941	953	977	998	1008	1032	1060	1068	1099	1091	1093	1171	220.7
18	692	714	743	770	858	885	890	920	941	953	977	1003	1013	1032	1060	1068	1104	1096	1093	1177	222.1
19	692	714	743	770	862	885	894	920	941	953	977	1003	1013	1032	1060	1068	1104	1096	1093	1177	221.9
20	692	714	743	770	862	885	899	920	941	953	977	1003	1013	1032	1060	1068	1104	1096	1093	1183	222.4
21	692	714	743	770	862	885	903	920	941	953	977	1003	1013	1032	1066	1068	1104	1096	1093	1183	222.7
22	692	714	743	770	862	885	908	920	941	953	977	1003	1013	1032	1071	1074	1110	1096	1093	1183	224.1
23	692	714	743	770	862	885	908	920	946	953	977	1003	1013	1032	1071	1074	1110	1096	1093	1183	225.2
24	692	714	743	770	862	885	912	920	946	953	982	1003	1013	1037	1071	1074	1110	1096	1093	1183	223.7
25	692	714	743	770	862	885	912	920	946	953	982	1003	1018	1037	1071	1079	1110	1096	1093	1183	231.6

Table 7-8 Unserved energy data for master-slave procedure (BASE)

Average unserved energy (GWh)																					
Iteration	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**Average total discounted unserved energy**
1	0	0	0	0.1	7.0	16.8	32.6	94.9	99.0	73.5	92.1	96.2	81.6	105.5	125.3	97.6	107.4	96.5	21.4	118.2	501.5
2	0	0	0	0.1	7.0	16.8	32.6	92.5	93.8	85.1	92.0	95.9	66.4	88.2	85.8	72.7	84.1	73.8	26.3	116.5	457.2
3	0	0	0	0.1	7.0	16.8	32.6	78.7	65.5	58.2	62.3	73.7	51.9	61.3	77.3	49.4	61.1	49.6	10.5	34.4	335.0
4	0	0	0	0.1	7.0	16.8	32.6	71.3	48.4	44.8	47.8	51.1	44.8	38.7	55.8	26.1	45.9	33.5	6.7	58.3	268.3
5	0	0	0	0.1	7.0	16.3	31.5	41.5	31.3	22.0	31.6	21.9	20.9	16.5	20.2	9.1	15.1	19.1	3.2	28.0	153.2
6	0	0	0	0.1	7.0	15.9	21.3	37.7	25.7	17.2	26.2	13.0	12.8	19.5	26.3	14.9	26.2	18.3	3.3	25.1	136.8
7	0	0	0	0.1	7.0	13.6	17.0	23.5	17.9	10.4	18.0	16.4	12.7	13.7	20.5	2.6	2.7	3.7	0	7.7	90.6
8	0	0	0	0.1	6.7	10.9	8.9	11.4	11.2	8.4	6.4	6.5	1.0	1.4	7.7	1.0	9.2	2.9	0	6.3	49.5
9	0	0	0	0.1	6.7	6.7	3.5	4.2	5.3	2.4	4.4	6.0	5.5	6.6	6.6	7.3	13.3	15.3	2.2	9.1	42.7
10	0	0	0	0.1	2.3	4.3	4.5	5.6	3.3	3.7	2.9	1.9	1.4	2.2	5.1	3.4	6.1	2.3	0	2.2	23.6
11	0	0	0	0.1	2.3	3.4	3.8	4.5	4.3	4.2	3.1	4.1	3.4	1.5	3.4	1.2	1.2	1.1	0	2.6	21.4
12	0	0	0	0.1	3.2	3.7	5.2	5.0	4.2	0.8	0.7	2.2	1.0	5.1	3.2	2.5	4.6	2.8	0	7.3	23.0
13	0	0	0	0.1	2.4	2.0	3.2	3.8	2.8	0	0.7	2.2	0.4	2.8	1.7	0	5.7	1.0	0	6.2	15.2
14	0	0	0	0.1	1.7	2.1	3.2	4.0	2.4	2.2	1.6	2.1	1.5	0.7	3.0	0.8	6.2	1.1	0	3.6	16.1
15	0	0	0	0.1	1.7	1.4	2.1	2.5	1.4	0.7	0.6	0.9	0.3	0.9	1.6	1.0	2.3	1.0	0	1.3	9.4
16	0	0	0	0.1	1.0	0.8	1.7	1.7	1.0	0	0.3	0.5	0	0	0.7	0	0.8	0	0	0.1	4.8
17	0	0	0	0.1	1.1	0.7	2.0	1.1	0.4	0	0	0.9	0.2	0	0.3	0	0.6	0.7	0	1.6	4.8
18	0	0	0	0.1	0.5	0.7	1.5	1.3	0.7	0	0.2	0.2	0	0	0.6	0	0.1	0	0	0.2	3.4
19	0	0	0	0.1	0.5	0.7	1.2	1.0	0.4	0	0.3	0.7	0.2	0	0.7	0	0	0.1	0	0.7	3.3
20	0	0	0	0.1	0.5	0.7	1.1	1.2	0.6	0	0.2	0.1	0	0	1.4	0.1	0	0	0	0	3.2
21	0	0	0	0.1	0.5	0.7	1.0	1.3	0.7	0	0.2	0.3	0	0	0.7	0.8	0.5	0	0	0	3.4
22	0	0	0	0.1	0.5	0.7	0.6	1.2	0.7	0	0	0.7	0	0.1	0.1	0	0	0	0	0	2.7
23	0	0	0	0.1	0.5	0.7	0.6	1.2	0.4	0	0.4	0.7	0.2	0.3	0.2	0	0.3	0.2	0	0.4	3.1
24	0	0	0	0.1	0.5	0.3	0.3	1.1	0.7	0	0	0.7	0.4	0.1	0.4	0.4	0.2	0.1	0	0.1	2.6
25	0	0	0	0.1	0.5	0.7	0.5	1.0	0.4	0.1	0.1	0.7	0	0	0.3	0	0	0	0	0	2.5

Table 7-9 Inflated demand levels and cost for *master-slave* procedure (ALT 11)

	2002	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	
Actual demand (PJ)	666	687	715	740	773	789	806	825	844	863	885	904	922	939	956	972	990	1008	1025	1055	
Inflated demand level (PJ) - iteration no.																					**Average total discounted system cost**
1	692	714	743	770	808	825	842	862	882	902	925	944	964	982	999	1016	1035	1053	1072	1103	465.4
2	692	714	743	770	812	829	847	866	887	907	929	949	968	986	1004	1021	1040	1059	1077	1109	462.2
3	692	714	743	770	816	833	851	871	891	911	934	954	973	991	1009	1026	1045	1064	1082	1114	455.7
4	692	714	743	770	820	838	855	875	896	916	939	959	978	996	1014	1032	1051	1069	1088	1120	453.1
5	692	714	743	770	824	842	859	879	900	921	943	963	983	1001	1019	1037	1056	1075	1093	1125	448.9
6	692	714	743	770	828	846	864	884	905	925	948	968	988	1006	1024	1042	1061	1080	1099	1131	451.4
7	692	714	743	770	833	850	868	888	909	930	953	973	993	1011	1029	1047	1066	1085	1104	1131	446.3
8	692	714	743	770	837	854	872	893	914	934	958	978	998	1016	1034	1052	1072	1091	1110	1137	445.8
9	692	714	743	770	841	859	877	897	918	939	962	983	1003	1021	1039	1058	1077	1096	1110	1142	444.9
10	692	714	743	770	845	863	877	897	918	944	967	988	1008	1021	1045	1058	1083	1102	1110	1148	445.6
11	692	714	743	770	849	867	881	897	918	949	972	988	1008	1021	1050	1058	1083	1102	1110	1148	448.2
12	692	714	743	770	849	867	881	897	918	949	972	988	1008	1021	1050	1058	1083	1102	1110	1154	448.0
13	692	714	743	770	849	872	886	902	918	949	972	988	1008	1021	1050	1058	1083	1102	1110	1160	444.9
14	692	714	743	770	849	872	886	906	923	949	972	988	1008	1021	1050	1058	1083	1102	1110	1160	448.3
15	692	714	743	770	854	876	890	911	927	953	977	993	1013	1021	1055	1063	1088	1107	1110	1165	448.9
16	692	714	743	770	858	876	894	915	932	953	977	998	1018	1027	1060	1063	1093	1113	1110	1171	450.7
17	692	714	743	770	862	876	899	915	937	953	977	998	1018	1027	1060	1063	1093	1113	1110	1177	449.0
18	692	714	743	770	862	876	903	915	941	953	977	1003	1023	1032	1060	1068	1099	1113	1110	1177	450.2
19	692	714	743	770	862	876	908	915	946	953	982	1003	1023	1032	1060	1068	1099	1113	1110	1183	451.9
20	692	714	743	770	862	876	908	915	946	953	982	1008	1023	1032	1060	1068	1104	1113	1110	1183	454.7
21	692	714	743	770	862	876	908	915	946	953	982	1008	1023	1032	1060	1068	1104	1113	1110	1189	450.8
22	692	714	743	770	862	876	908	915	946	953	982	1008	1023	1032	1066	1074	1110	1113	1110	1189	452.7
23	692	714	743	770	862	876	908	915	946	953	982	1008	1023	1032	1071	1074	1110	1113	1110	1195	453.0
24	692	714	743	770	862	880	908	915	946	953	987	1008	1023	1032	1076	1074	1110	1113	1110	1195	452.5
25	692	714	743	770	862	880	912	915	946	953	987	1008	1023	1032	1076	1074	1110	1113	1110	1195	454.5

Table 7-10 Unserved energy data for master-slave procedure (ALT 11)

Average unserved energy (GWh)																					
Iteration	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**Average total discounted unserved energy**
1	0	0	0	0.1	7.0	14.6	27.6	61.8	59.9	101.2	90.4	84.2	61.3	56.0	77.8	75.5	87.3	75.7	17.0	96.7	397.4
2	0	0	0	0.1	6.9	14.6	22.2	71.7	58.5	39.7	42.1	63.3	58.5	81.7	84.7	52.7	64.7	69.5	16.1	86.0	329.3
3	0	0	0	0.1	6.9	12.2	20.3	50.9	39.8	60.6	52.0	49.4	44.9	30.9	48.2	31.3	50.8	54.9	12.3	66.8	256.7
4	0	0	0	0.1	6.6	12.2	19.9	56.2	30	17.3	22.1	33.0	31.0	30	37.9	33.2	42.9	36.8	8.6	44.6	189.6
5	0	0	0	0.1	5.9	11.3	6.9	25.9	24.4	21.0	30.2	21.9	20.7	5.4	25.1	12.6	19.2	21.4	4.1	31.4	121.0
6	0	0	0	0.1	5.2	10.6	17.7	29.0	17.9	7.1	13.0	15.2	13.6	17.2	22.4	12.2	18.7	14.0	7.5	6.2	100.7
7	0	0	0	0.1	4.1	10.5	8.5	17.9	12.3	5.9	8.8	12.7	9.8	10.9	19.2	7.8	12.6	10.4	4.6	25.3	75.5
8	0	0	0	0.1	4.5	6.2	8.0	15.5	7.0	2.8	4.9	8.7	8.7	2.0	13.5	5.1	9.7	7.8	2.8	20.3	53.6
9	0	0	0	0.1	4.2	3.2	1.7	2.5	4.2	4.1	4.9	4.1	3.6	0	8.9	2.2	7.1	3.6	0	9.2	26.6
10	0	0	0	0.1	3.6	2.7	4.7	3.1	3.6	3.2	3.3	2.4	0.2	0	3.7	0.7	3.4	1.1	0	4.3	19.2
11	0	0	0	0.1	1.8	1.4	1.1	2.7	4.3	0.5	0.2	0.3	0	0	0.6	0	3.2	3.5	0	5.5	10.8
12	0	0	0	0.1	1.4	3.1	4.7	5.3	3.4	0.7	0.2	1.6	2.3	0.9	3.4	1.2	3.3	1.6	0	9.2	18.5
13	0	0	0	0.1	2.4	1.8	2.5	7.9	6.5	0	1.4	2.2	0.2	0.8	3.0	0.2	5.7	2.0	0	5.3	19.2
14	0	0	0	0.1	2.4	1.8	2.5	2.5	3.9	0.4	2.0	1.6	1.2	0.2	3.0	0.5	5.8	1.5	0	2.5	14.4
15	0	0	0	0.1	0.7	0.4	1.7	2.4	3.5	0.5	0.2	1.1	2.4	1.1	2.9	0.4	2.1	0.6	0	4.2	10.2
16	0	0	0	0.1	0.5	0.3	0.9	1.0	0.9	0	0	0	0	0	0.2	0	0.2	0.2	0	1.0	2.7
17	0	0	0	0.1	0.5	0.3	0.2	0.8	1.4	0.3	0	1.1	1.2	0.7	1.2	2.1	0.6	0.2	0	0.3	4.7
18	0	0	0	0.1	0.5	0.3	0.8	1.3	1.1	0	1.1	0	0.1	0	0.1	0	0	0.2	0	1.7	3.5
19	0	0	0	0.1	0.5	0.4	0	0.4	0.6	0	0.1	0.2	0.4	0	0.4	0	2.0	0	0	0.4	2.3
20	0	0	0	0.1	0.5	0.4	0	0.4	0	0	0	0	0	0	0.1	0	0.2	0.1	0	1.8	1.4
21	0	0	0	0.1	0.5	0.4	0	0.7	0.6	0	0.3	0.1	0.1	0.3	2.2	0.3	1.3	0	0	0.1	3.0
22	0	0	0	0.1	0.5	0.3	0	0.8	0.6	0	0	0	0	0	0.4	0	0.7	0	0	1.0	2.0
23	0	0	0	0.1	0.5	0.7	0	0.5	0	0	0.5	0	0	0.3	0.8	0	0.8	0	0	0	2.1
24	0	0	0	0.1	0.5	0.3	0.4	0.7	0.7	0	0	0	0	0	0	0	0.6	0	0	0	1.8
25	0	0	0	0.1	0.5	0.3	0	0.4	0.6	0	0	0	0	0	0	0	0.4	0	0	0.4	0

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CHAPTER 8 OUTLINE OF OVERALL METHODOLOGY AND CONCLUSIONS

8.1. INTRODUCTION

This chapter outlines the overall methodology for comprehensively integrating multiple objectives and uncertainty into ESI investment planning which has been developed in this thesis.

It will then reiterate the hypotheses presented in chapter 1 and relate the conclusions drawn from each chapter of this thesis in light of the hypotheses. The aim of this chapter is thus to provide a clear overview of this methodology as a whole. Finally, some recommendations for further work will be made.

8.2. OVERVIEW OF METHODOLOGY AND CONCLUSIONS

Appropriate Energy-Environment-Economic (E3) modelling provides key information for policy makers in the Electricity Supply Industry (ESI) faced with navigating a sustainable development path in both centrally planned, regulated markets as well as fully deregulated markets. Key challenges include engaging with stakeholder values and preferences, and exploring trade-offs between competing objectives in the face of underlying uncertainty as well as preserving the transparency of the decision process.

With this in mind the ESI problem can be broken down into two main phases, each with various inputs and outputs. The generation phase is where optimal solutions are generated in energy modelling frameworks to meet a projected electricity demand within a set of technical and practical constraints. A subsequent “alternative or selection” phase identifies preferred alternatives from within the set generated, based on DM preference information. Both of these phases can be explored against a set of policy making objectives, and both contain inherent uncertainties which relate to aspects of model definition, empirical quantities as well as valuation arguments. Figure 8-1 below outlines a representation of the ESI modelling problem.

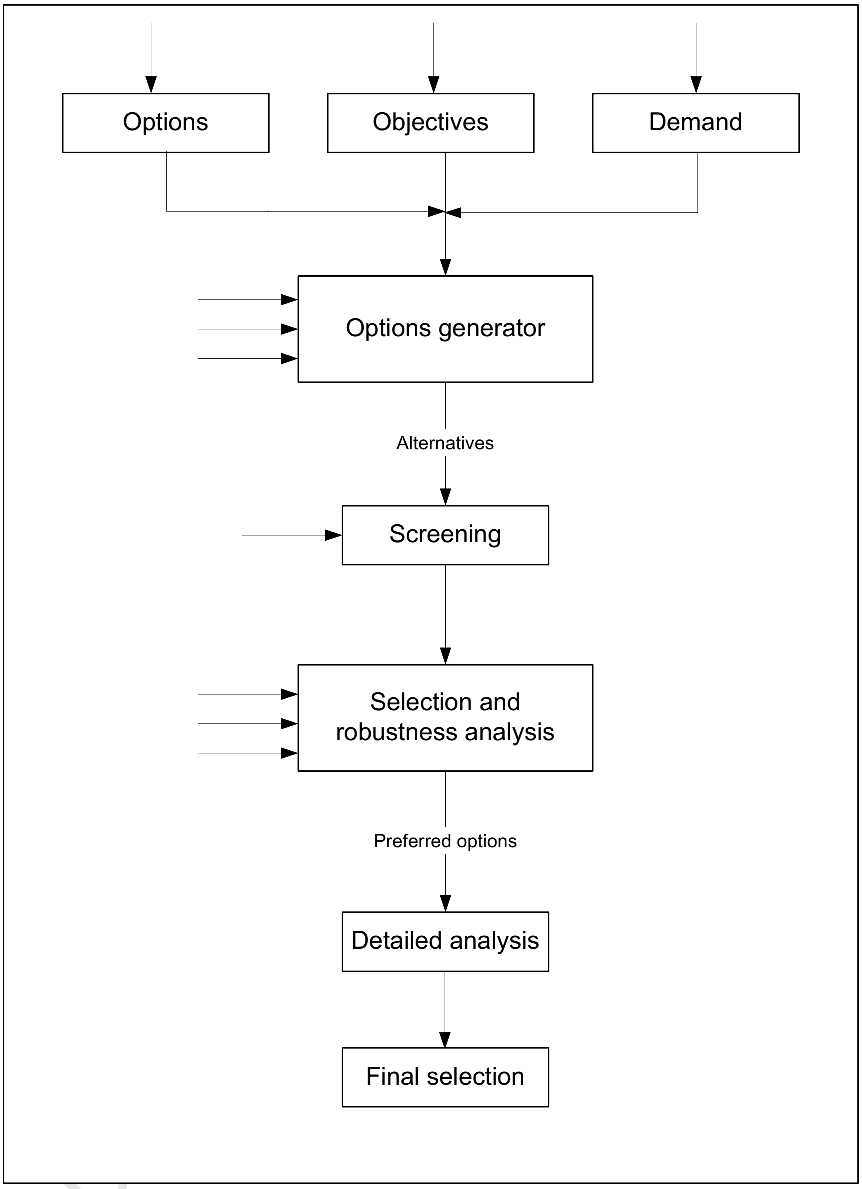

Figure 8-1 Flowchart representation of the ESI modelling problem

8.2.1. GENERATION FOR MULTIPLE OBJECTIVES UNDER UNCERTAINTY

Hypothesis 1: Multiple objectives representing policy maker preferences can be integrated into existing single objective energy modelling frameworks.

The initial research of this thesis aimed at developing a transparent methodology for the generation of solutions within an ESI modelling framework that considers multiple objectives, and includes aspects of flexibility to demand growth uncertainty into each solution.

The first step in the proposed modelling process was to develop a base case or "business as usual" scenario. A complete supply-side representation (including all costs and emissions coefficients) of all existing power stations in the system, as well as a range of technology options for future stations was compiled based mainly on the NIRP (NER et al., 2004). The base case scenario was then simply a least cost optimised solution for the represented power system attempting to meet the projected demand within the constraints defined by the modeller.

Once the optimal inflated demand level (corresponding to the minimum reserve margin required in the system to account for forced outage) had been calculated using the base case (see chapter 7), a range of alternatives could be generated to satisfy multiple objectives to varying degrees. This was done using a partial equilibrium framework which was extended to include multiple environmental objectives through the addition of Pareto Generation Parameters (PGPs) introduced into the optimisation in the form of cost penalties. This forces the optimisation routine to find solutions that attempt to satisfy multiple objectives. It is an efficient method for extending the analysis to multiple objectives as the solutions generated are non-dominated and are generated from ranges of performances in the various criteria rather than from arbitrarily forcing the selection of particular technologies. Extensive sections of the non-dominated solution space can be generated and later screened to allow further, more detailed exploration of areas of the solution space. MARKAL was chosen at the time this work was done as the framework to demonstrate this methodology, due to its wide usability, its capacity to include taxes on emissions as well as the two-stage stochastic recourse programming module available for this software.

Hypothesis 2: Flexibility towards future uncertainties can be built into each optimal solution for multiple objectives.

This work has also demonstrated that this analysis can be extended to include uncertainty in demand growth through stochastic programming with recourse. By splitting new power station investments into owner's development costs and equipment procurement and construction phases, the concept of technology lead times can be accounted for in light of a decision node in the time horizon. The hedging that is done in the recourse programming is automatically translated from purely financial to include whatever attributes the PGPs represent, due to the cost penalties that the PGPs impose on the solutions. The hedged solutions improve on the naïve solutions under the multiple criteria considered as well as better satisfy the non-cost objectives relative to the base case.

This methodology provides a framework for policy makers to generate a solution set for the power expansion problem that represents a range of solutions that each satisfies multiple objectives to a varying extent. The solutions also have built-in flexibility to demand growth uncertainty. The set of solutions generated in this manner can be used as part of a transparent decision making process in which policy maker preferences can ultimately inform the selection of a preferred solution. They also give policy makers an indication of the appropriate market signals necessary to influence the market towards a preferred state. This would be done retrospectively from the preferred solutions, through an analysis of the PGP values used to generate those solutions.

8.2.2. SELECTION FOR MULTIPLE OBJECTIVES UNDER UNCERTAINTY

Hypothesis 3: A comprehensive analysis of uncertainty can be integrated into the multi-objective selection phase to find robust solutions that best satisfy the multiple objectives chosen.

A Multi attribute value theory (MAVT) coupled with a sensitivity/robustness approach was developed in chapter 4 to address some of the uncertainties inherent in power expansion modelling. This methodology was used to explore the robustness and sensitivity of each power expansion alternative to different types of uncertainty at various levels of aggregation, from partial value functions representing individual attributes, to the overall value function which represents the decision maker preferences to the criteria chosen, through a continuous analysis of uncertainty.

The Weighting sensitivity diagrams representing inter-criterion preferences display valuable information regarding the stability of the rank order, given a range of preference weightings for each of the decision criteria. This continuous analysis of uncertainty could be used to increase stakeholder confidence in the results and to determine the sensitivity of the rank order to DM preference information. It can thus be used to identify where further information may be required to improve confidence in the results.

Frequency tables generated based on the comparison of each alternative across a sample of discrete futures yield information regarding the credibility of alternatives in the rank with respect to the technical empirical uncertainties considered. While a continuous evaluation of uncertainty can provide useful information as to the likely ranges in attribute performance for each alternative, a discrete evaluation of uncertainty can yield insight into the distinguishability of alternatives for particular and specific futures.

This approach was also used to elicit the regret associated with each alternative by evaluating the spread of each alternative across the rank order. It was then used to isolate portfolios of alternatives with specified minimum levels of performance in terms of rank or attribute performance and credibility levels.

Focusing only on alternatives that achieve the preferred rank may exclude important alternatives from the portfolio set and therefore from detailed analysis and final selection. Using a portfolio approach and focussing on a greater range in rank than just the preferred alternative increases the robustness of the selection process by reducing the effect of uncertainty around DM preferences and technical empirical parameters allowing for a less intensive uncertainty analysis to be done prior to the detailed analysis of preferred alternatives.

A more detailed analysis of the reduced solution set was done, examining short term technology investment details and the attribute performance information. This analysis provided additional insight into the decision problem in terms of the actual technology choices being made, which could then be related back to real life actions. More specifically, the case study in chapter 5 highlighted that decisions relating to technology investment may need to be made even within a preferred set of alternatives with similar overall value scores and similar rank and credibility information. In a case such as this, the stakeholders would have to re-evaluate their preferences in relation to the specific trade-offs at hand such that a preferred alternate can be identified. Conversely, this case study also demonstrated that it is possible for the initial short term investments for different alternatives in a portfolio of preferred alternatives to be so similar as to not require any major decision in differentiating the alternatives for implementation. The dominant effect that DM preference information has on the alternatives that enter the portfolio set was also demonstrated in the case study.

8.2.3. Normalising attribute scores

Hypothesis 4: Normalising attribute scores using a standard 0-1 value range can lead to an effective weighting bias due to inflated minima or maxima.

Using pseudo-minima and maxima to normalise attribute performance scores with a modified indifference weighting approach to articulate DM preferences reduces effective weighting biases by reducing the artificial inflation or deflation of value function scores based on improbable values. Differences can be seen in the lower rank order of alternatives when comparing this method with the standard method of normalisation.

8.2.4. The relative effect of specific uncertainties on the ranking and performance of expansion alternatives

Hypothesis 5: An analysis of the effects of using different approaches to dealing with technical empirical uncertainty can give insight into the relative importance of different uncertain parameters and the relative value of the approaches in light of this.

Integrating technical empirical uncertainty into the generation phase as opposed to the selection phase resulted in minor differences in the overall performance results.

The additional effort and complexity of doing a robustness analysis on technical empirical uncertainty in the generation phase as opposed to the selection phase may not be justified given that similar alternatives make up the portfolios of preferred alternatives using both methods and differences would mainly seen in the unstable sections of the weighting sensitivity diagram where uncertainty around DM preferences would have the greatest effect on results.

8.2.5. Integrating plant availability uncertainty and reserve margin into the multi-objective framework

Hypothesis 6: Plant availability uncertainty can be integrated into the multi-objective framework by finding the minimum required reserve margin for the system.

It was shown in chapter 7 that demand could be modelled both chronologically and in high resolution such that both the frequency and duration of outage could be adequately represented, all within a multi-objective framework with a comprehensive analysis of system wide uncertainty.

It was also shown that using sampling methods to represent uncertainty in plant operation within an operational *sub-problem* or *slave-problem* is an efficient method for feedback into the investment *master problem.* Plant outage and unserved energy can be adequately represented for a national system such as the South African ESI using 150 (or less) model runs in the *sub-problem*, and the minimum reserve margin corresponding to the minimum total discounted system cost can be found in less than 10 iterations of the master problem.

Given the size of the South African ESI, and the number of technologies considered in this study, the number of iterations needed to find the minimum reserve margin corresponding to the minimum total discounted system cost for other national systems should be similar (unless many more technologies options were included in the model). The number of iteration of the *master-problem* could be reduced by probing the solution space using larger steps and/or using a starting point closer to the minimum reserve margin corresponding to the minimum total discounted system cost.

Using unserved energy as a convergence criterion between the *master* and *slave* problems for each year in the time horizon is an effective method for exploring the solution space and identifying the levels of inflated demand required to account for forced outage. This method also highlights the trade-off between unserved energy and total discounted system cost, allowing the decision maker to make an informed choice around this trade-off.

It was shown in chapter 7 that the optimal inflated demand level varies little with DM preferences as unserved energy is minimised due to the high cost of unserved energy and the fact that the existing system is the same for all the alternatives generated. Therefore the *master-slave* routine used to determine the optimal level of inflated demand needed for each year in the time horizon can be carried out on the base case, and then used to generate further alternatives satisfying a range of DM preferences using the methodology presented in chapter 4. In this way forced outage uncertainty can be integrated into the multi-objective framework presented in this thesis without having to do large numbers of model runs for each alternative. If however the distribution of unserved energy for the preferred alternative was found to be unacceptable by the DM, the level of investment for that alternative could be increased using the methodology presented in chapter 7.

8.3. Concluding remarks

In summary, the research hypotheses have been met; a comprehensive framework that integrates multiple objectives and uncertainty into a transparent methodology that policy makers and planners can use to analyse and plan for investment in the ESI has been developed and demonstrated.

This work has been focused on developing a methodology that can be practically used in the ESI in both centrally planned regulated markets and in fully deregulated markets from the perspective of a regulator or policy maker. It has demonstrated how existing models and frameworks can be extended to account for multiple objectives and uncertainty and therefore the gap from research to practical application should not be overwhelming. That said modellers and planners have their own preferences and familiarities which may inhibit the adoption of new methodologies.

The benefits of comprehensively integrating multiple objectives and uncertainty into the planning process are significant. For example; correctly planning for forced outage uncertainty can significantly reduce the probability of blackouts. Poor environmental performance can be reduced by using a transparent methodology where decision makers are accountable for their choices and stakeholders outside of the decision making process can engage with those choices. The benefits of presenting decision makers with relevant information in a framework that they can engage with and understand would influence the decisions being made dramatically.

The gap between ESI modelling and policy making can lead to modellers focusing on issues that are not crucial to policy makers and policy makers making uninformed decisions due to lack of understanding of the technical issues. This thesis is an attempt to bridge that gap, such that key information can be transferred between the modeller and the policy maker and multiple objectives and uncertainty can be accounted for in the decision making process in a transparent and comprehensive manner.

This said the work done in this thesis could be extended in various directions. Some of these possibilities are discussed briefly below:

Chapter 4 presented and demonstrated a methodology for generating future expansion alternatives that satisfy multiple objectives to varying degrees and that have built in flexibility to demand growth uncertainty. This type of analysis, done in partial equilibrium frameworks, has provided policy makers with the “perfect market” response to future scenarios that are valid for both regulated, centrally planned power markets, as well as for efficient fully deregulated markets (when planning from the perspective of a regulator). Extending the methodology developed in this thesis to the perspective of an individual firm or investor in the market rather than from a global or regulatory perspective could be explored. This extension would add value to individual firms as although they may have different objectives and decision criteria to regulators and policy makers; they face similar investment decisions as well as a range of uncertainties which affect those decisions.

The ranking and selection framework presented in chapter 5 provided DMs with a structured methodology with which they could identify preferred future expansion alternatives, given their preferences and uncertainty in both the technical empirical parameters and valuation model parameters in terms of their preferences. This methodology was shown to be highly dependant on DM preferences and could therefore benefit through further research around the stakeholder preference elicitation process and the way in which stakeholders interact with the information they are given. This would further increase stakeholder confidence in the results and add value to the overall methodology.

Chapter 6 evaluated the value of integrating technical empirical uncertainty in the generation phase as opposed to the selection phase, given the computational, time and data burden of this approach. It would be interesting to repeat the analysis in both the generation and selection phase using a model such as TIMES, where demand could be represented in higher resolution (as was done in chapter 7). This would allow for more sensitive optimisation of the power station load factors due to a greater number of time slices and therefore it is possible that greater differences would be seen between the two approaches.

Chapter 7 developed a methodology for integrating forced outage uncertainty into the multi-objective framework of this thesis. This was demonstrated using a single node, national model. Further research could be done looking at multi-nodal ESI systems and how transmission affects forced outage uncertainty. In reality unserved energy does not occur simultaneously across an entire national network (rather occurring in parts of the network at one time). Therefore extending the work done in chapter 7 to model electricity transmission between nodes that each has their own demand would increase the value of the analysis.

As the electricity sector evolves and faces new problems, new methodologies will be developed. As personal computing power continuously increases the models used will be become ever more complex. Ultimately though, decisions are made by human beings with changing preferences, different ideals and opposing visions of where the future should go. The closer the gap between energy model and policy maker, the greater the chances of a sound plan being implemented. The more transparent the decision making methodology, the closer the gap between the policy maker and society.

8.4. References

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