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Decision Aid for Planning Local Energy Systems

Application of Multi-Criteria Decision Analysis

Doctoral thesis
for the degree of Doktor Ingeniør

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PREFACE

This thesis has been carried out at the Norwegian University of Science and Technology, Department of Electrical Power Engineering. The work started in February 2002 being funded through the project '*Analysis of energy transport systems with multiple energy carriers'* at SINTEF Energy Research. A significant part of this research has been carried out in collaboration with the research team from the project *Sustainable Energy Distribution Systems: Planning Methods and Models* (*SEDS*) at NTNU and SINTEF.

Acknowledgements

I would like to thank my advisors for initiating and supporting this research. First my thanks go to Professor Arne T. Holen for supporting my ideas of exploring the different disciplines that concerned this research. His optimistic attitude and guidance have helped me greatly these years. Special thanks to Dr. Bjørn H. Bakken at SINTEF Energy Research who has been my co-advisor. As project leader Bjørn has involved me in many meetings and discussions about the eTRANSPORT model, the final product of the project '*Analysis of energy transport systems with multiple energy carriers'*. I want to thank both my advisors for reading and commenting the material I have written during this research project.

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During the last year of research I spent two months at Helsinki University of Science and Technology, System Analysis Laboratory. There I had the chance to meet a hard working research team that inspired me. I am grateful to Professor Raimo P.Hämäläinen who made this visit possible.

I am very grateful to all my friends in Trondheim who supported me in the process of 'adaptation' and made life enjoyable. Also, all kafé-pause comrades are friendly acknowledged. Many thanks to Nancy Bazilchuk for assisting me in editing this thesis.

I would not have been able to come to an end of this thesis without the love, understanding and support of my family, my parents, my sister and my fiancé Jonas. It has been hard to be away from them all these years.

Maria,
Trondheim, March 2006.

SUMMARY

I. Background and motivation

Planning is what sustains an energy system. It is a process of analysis and ongoing decision making about what resources and energy technologies to use when supplying energy to society. This research focuses on integrated energy systems, i.e. systems that are comprised of several energy carriers – electricity, gas, hot water - and energy distribution networks. The planning of these kinds of systems is a complex process, influenced by many factors, among which the most important are the availability of energy resources and the competition between different energy carriers in satisfying energy demand.

During the last 10-20 years significant changes have taken place on the world energy scene, which have important implications for energy planning. Two main factors have triggered these changes.

The first factor is the immediate need to address environmental changes or more generally, to take measures that are sustainable in the long run. Sustainability can be defined in many ways and in relation to different issues such as economic and ecologic development, reduction of greenhouse gases, responsible use of natural resources, social equity, etc. In recent years, an increased awareness of these issues has been observed at all levels of the society.

The second factor is the deregulation of national energy sectors in more than 50 countries. This process brought changes in the ownership of different parts of the formerly integrated energy systems. New business opportunities were created in power generation, wholesale power/gas trading and energy retailing, while the energy infrastructures remained state owned or/and under regulatory control. The newly created energy markets (many of them international) have attracted both new players (power, oil and gas companies and financial institutions) together with the old ones (integrated utilities). In parallel with this vertical separation of national energy sectors, recent studies have shown a tendency for horizontal integration at the regional/company level. For instance, in order to reduce their overall business risk, companies prefer to participate in several segments of the energy value chain (in both regulated and non-regulated activities), and often across more than one fuel commodity, such as gas and electricity or district heating.

In this context, the competition between different energy carriers in satisfying the end-use energy demand became obvious in economic as well as in technological and environmental terms. Traditionally, in integrated planning, this competition did not play a big role, since the same state entity made decisions at both national and regional levels. However, in the post-deregulation era it is no longer obvious who the planner is. In many cases, planning decision at local levels involve at least three main interest groups: energy companies (and/or other investors), the state and the local community.

This thesis is motivated by the need to help planners to cope with the changes in concepts and values concerning the planning of *local* energy supply systems.

II. Aims

This thesis has two aims. The first aim is to improve the understanding of what planning of local systems implies and how such a process can be structured. The second aim is to contribute to the development of decision support methodologies and tools that can cope with the needs in planning. For this purpose, the use of energy modelling and Multi-Criteria Decision Analysis has been studied.

III. Earlier approaches

Planning for *single energy carrier* systems such as *electricity* or *gas systems* is a subject that has always received attention from both the research community and practitioners from industry.

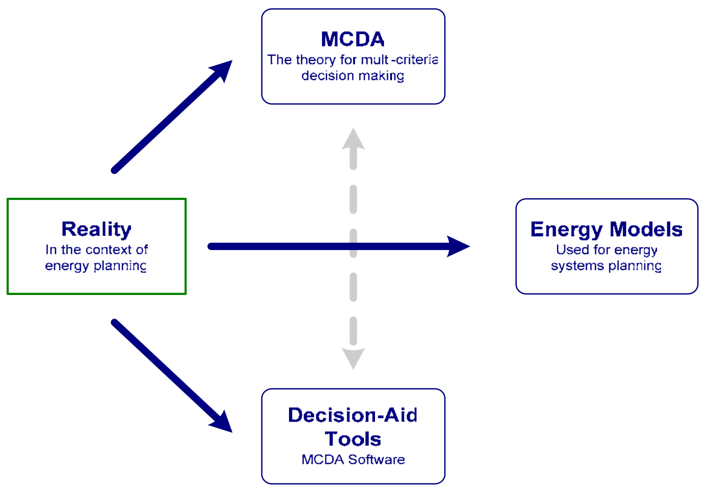
By comparison, less research has been done in the field of integrated energy systems, and in particular *local (or regional) systems*. Most contributions to this field consist of *models of the integrated energy systems,* which vary in details and scope, or of more *general analyses* where the energy system is seen as a part of a whole national system.

The process of decision making for planning has also received attention, and many energy related applications of MCDA (Multi-Criteria Decision Analysis) have been reported, but again, fewer applications of this approach have been used in the planning of integrated energy systems at local level.

In this context two areas where research is needed have been identified: 1) planning problem structuring and 2) improving the use of existing energy models to explicitly take into account uncertainties and multiple criteria.

IV. Contributions

The figure below shows the main components of this research. The main objective has been to propose an improved framework for problem structuring and modelling in local energy systems planning. Three different research directions have been explored: energy modelling, MCDA (Multi-Criteria Decision Analysis) and software for decision support.



The contributions of this thesis can be summarized as follows:

- *The process of planning local energy systems has been described.* The aim has been to unveil those aspects that add complexity to the planning process. MCDA concepts have been used to propose frameworks for problem structuring and analysis. This way of organising thinking is relatively new among energy planners. This thesis offers a basic conceptual framework that can be used by different decision-makers involved in the process of planning for local, integrated energy supply systems. These planners can be energy supply companies, local authorities or other entities. From another perspective, the type of problems proposed in this thesis offer new possibilities for application of MCDA.

- *The use of energy models in planning has been studied*. This research has been carried out in parallel with the development of a new energy system model called eTRANSPORT. Energy modelling is essential when dealing with problems involving large amount of data and uncertainties, thus any thorough system planning process should employ an energy model that can supply the relevant background data (impact modelling) based on which planning decisions must be made. However, despite these features, energy modelling is not sufficient to handle decision situations when multiple, quantitative and qualitative criteria have to be considered.

- *A classification of methods* for multiple criteria decision making and methods for decision making under uncertainty has been proposed. The purpose was to give an overview of the numerous methods and methodologies available, and to group them according to criteria that would matter to their selection in practical applications in energy planning.

- *Two strategies for extending the use of energy models in complex decision situations have been proposed.* The investigation concerned a *two-stage approach* and an *integrated approach* for the combined use of eTRANSPORT and MCDA. The focus has been set on investment planning problems, characterized by a small number of alternatives that must be judged in presence of several criteria and uncertainty. This type of problems appears at tactical and strategic planning.

- In the *two-stage approach*, the energy model is first used to generate quantitative information about how alternatives perform in terms of different criteria and scenarios, and then a MCDA method is used to help the decision-maker to analyse this information. The MAUT (Multi-Attribute Utility Theory) has been applied to a pilot case study, to test how this type of analysis can be conducted in the context of local planning. The participants in the experiment found this type of analysis useful and relevant to the type of problems applied. This application was valuable in terms of learning how to use of the method, i.e. how to design of the dialog with the decision-makers and how to interpret the results. The advantage with this *two-stage* approach is that practically several methods can be applied in combination with eTRANSPORT. Following the MAUT experiment, an application of the AHP (Analytic Hierarchy Process) has been conducted in the same problem setting, and the results could be compared.

An *integrated approach* for combining eTRANSPORT and MCDA into one computer-based decision-support tool has been also proposed. The idea has been to create a tool that can be used in both *problem structuring* and *preference elicitation*. With this tool, decision makers would be required to *define* both the energy model and the issues they are most concerned with (for example criteria like costs, environmental impact, noise, aesthetical impact, company's image), and then evaluate the alternatives accordingly. Moreover, the integrated tool would give its users full control over the simulations, thus contributing to the understanding of how different preferences influence the final recommendations. The proposal consists of guidelines for extending the eTRANSPORT model with an additional *advanced DA* module. Both the procedural steps for using the model and the mathematical background corresponding to these steps have been discussed. The model proposed has been inspired by earlier methods for *preference programming*, which support elicitation and decision procedures with incomplete preference information. Although the focus in this thesis has been the eTRANSPORT model, the concepts and the rationale presented can be used to extend other energy system models. The proposal for integration has not been yet implemented into the eTRANSPORT at the time this thesis was written. Accordingly no tests have yet been performed with real decision-makers to verify the approach's validity.

V. Thesis outline

The thesis is organized as follows:

Part A: *Problem definition* is comprised of one chapter (Chapter 1) in which the concepts and needs for planning local energy systems are stated.

Part B: *An overview of methods and tools for decision support* is comprised of three chapters that treat *energy modelling* (Chapter 2), *multi-criteria decision aid* (Chapter 3) and *decision making under uncertainty* (Chapter 4). Different classifications schemes are presented here, with the purpose of contributing to the understanding of how methods can be applied and in which contexts.

Part C: *Approaches to problem solving*, offers solutions for how the methods in *Part B* can be applied to problems in *Part A*. Two chapters form this last part of the thesis. The first chapter (Chapter 5) presents an investigation of different strategies for combining energy modelling and MCDA, while the second chapter (Chapter 6) proposes and approach to building an integrated decision-support tool for energy planning.

The last part of this thesis is dedicated to *Conclusions and suggestions for future research*.

In the appendices are added three conference papers that have been written during this research project (Appendices A, B and C) and additional material used in the applications reported in Chapter 5 (appendix D).

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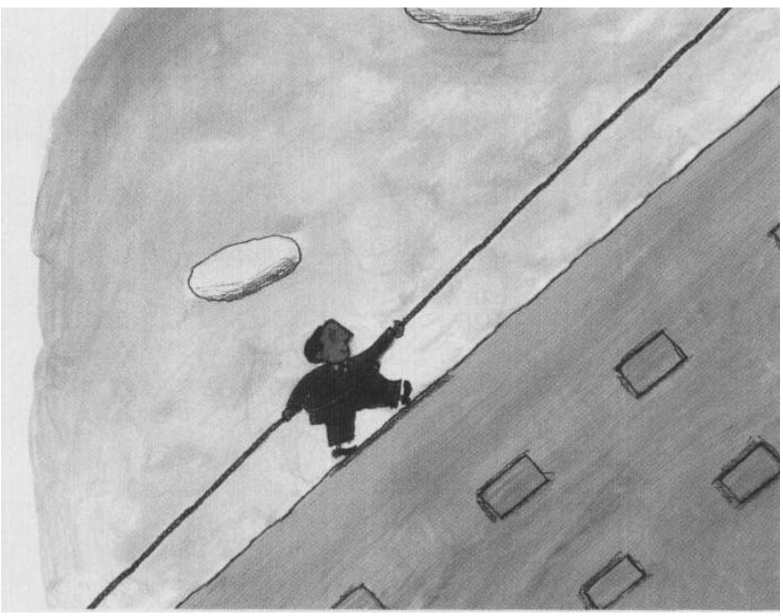
PART A

PROBLEM DEFINITION



Ralph L Keeney **Foundations for making smart decisions,** *IIE Solutions;* May 1999; 31, 5; ABI/INFORM Global, pg. 24.

Summary

This first part of this thesis presents the main issues concerning the planning of local energy supply systems. The section begins with a discussion about the fundamental changes in the thinking and approaches of energy planners over the last three decades. The present day energy landscape is characterized by deregulation, liberalization, increased competition on different energy markets and sustainability requirements. The future will be marked by the decreasing availability and the depletion of natural resources combined with the need to address environmental changes. Although many lessons can be learned from the past, planners will need to think differently in order to face the challenges predicted to come. New decision support tools and methodologies are needed, to ensure adequate planning of energy supply for the coming decades.

An approach to problem definition and structuring is proposed here. The process of local energy planning is first defined, after which the planners and their decision problems are identified and at the end the need for decision support is emphasised.

When addressing a planning problem, one very important issue is the definition of an energy system, i.e. its boundaries and respectively, its components. Three types of boundaries are proposed here: physical (geographical), impact and political boundaries. Depending upon the issues of concern, planning problems can be of different types: operative, tactical or strategic. The challenge for the local planners is to understand decision situations and identify the factors that may affect their decisions at different planning levels. Some of these factors are deregulation/regulation, the competition in different energy and emissions markets or the competition between different energy carriers in satisfying the total energy demand.

The problems identified here support the conclusion that there is a need to revisit the traditional methods and to look for new planning methodologies and tools, in order to propose solutions both for the short- and long-term. Traditional energy modelling procedures combined with multi criteria decision-analysis (MCDA) can be used in designing new decision-support frameworks.

Chapter 1 LOCAL ENERGY PLANNING

1.1 ENERGY SUPPLY

Energy and energy supplies have always played a central role in human society. The technological revolution of the last century, for example, would not have been possible without the invention and rapid spread of electricity distribution systems. In many parts of the world, as a result of this technological breakthrough, the standard of life improved dramatically - a direct consequence of the fact that the basic needs of heating, lighting and mobility became easily available to everybody.

Up until the energy crises in the 1970-1980, meeting energy needs was a routine problem where the solution was principally a matter of availability of resources and technology. However, the last 20-30 years have been marked by fundamental changes in thinking about the concepts of energy availability and energy supply.

The first, main factor that triggered this change was the dramatic increase in energy prices caused by the first oil crisis in the 1970s. At that point and at least in the Western world, the myth of plentiful, available and cheap energy was replaced by increasing concerns about the depletion of natural resources and the necessity for the efficient use of energy. At almost the same time, environmental considerations reflecting the need to cope with ongoing environmental degradation resulted in a reconsideration of values and a shift towards new, 'cleaner' technological solutions.

The 1990s added another dimension, that of decentralization and liberalization of the national energy sectors. This process affected more than 50 countries with more expected to follow suit. Decentralization has brought significant changes to energy system ownership. While systems were once nationally owned and integrated, now markets have been created with the idea that market mechanisms will have a better chance of balancing economic and social benefits and inducing increased efficiency in energy supply. Recent evaluations of different electricity markets show, however, that these goals have not entirely been met. Inadequate design of market mechanisms and the lack of appropriate regulations might have triggered suboptimal development of different energy systems and even shortages in energy supply, although this is difficult to prove. This same period was also marked by social movements that advocated embracing a culture of sustainability. The 1992 Rio de Janeiro Earth Summit ended with many industrialized countries signing an agreement, ***Agenda 21*** in which they agreed '*not to irresponsibly and irreversibly damage the ability of future generations to satisfy their own needs*'. Sustainability can be defined in many ways and in relation to different issues such as economic and environmentally sound development, reduction of greenhouse gases, responsible use of natural resources, social equity, etc. In recent years there has been an increased awareness of these issues and a recognition that necessary actions must be taken not only at the national, governmental levels but at the community level as well.

Future energy supplies will be characterized by decreasing availability and depletion of natural resources combined with the need to cope with environmental changes. Thus failure by planners to ensure an adequate energy supply for the coming decades may have tremendous consequences for national economies and the environment. New, systematic and comprehensive planning frameworks will be needed in order to anticipate, analyse and prepare for the future.

The focus of this thesis is planning the energy supply to communities. The local and regional energy supply systems analysed include several energy carriers and infrastructures. The rest of this chapter will introduce the main issues and needs in planning such systems.

1.2 PLANNING ENERGY SYSTEMS

1.2.1 General concepts

There is no generally accepted definition for the notion of *energy systems planning*. An *energy system* can be defined as the physically connected energy production (generation), transmission, and distribution facilities operated as an integrated unit. Based on this, *energy system planning* is the *process of choosing* the sources and technologies needed for energy generation, transmission and distribution, to satisfy community needs.

Depending upon the time horizon and the energy systems analyzed, variations of this definition are used to distinguish between different planning concepts. For instance, in a recent study [1] local energy systems planning is seen as *the path towards an economic and ecological sustainable local energy system while also taking into account limited financial and human resources as well as incomplete insight into the future development of economic technical and social conditions*.

Often the process of planning is seen as a process of decision-making, the only difference being that in general, the ‘output’ of decision making is a choice, while the ‘output’ of planning is a plan – meaning a description of what is to be done, when, by whom and what to do if uncertainties occur [2]. In addition, while a decision can, in principle, be localized in time and space and identified as a choice of a particular alternative, planning can be an ongoing process.

No matter which definition is used, a planning process essentially implies a *planner* and a specific *planning problem*. The next paragraph attempts to identify these two elements in the context of current energy systems planning.

1.2.2 The planner

Traditionally, the state (e.g. the state’s administrative structures) controlled the use of natural resources and assumed responsibility for planning the national energy supply. This situation remains unchanged in many countries, while in others the planners are not longer easy to identify. The deregulation and liberalization of the energy sector has made for new business opportunities in power generation, wholesale power/gas trading and energy retailing in more than 50 countries. These opportunities have attracted both new players, such as oil and gas companies and financial institutions, as well as the existing integrated utilities. A direct consequence of these changes at the local or regional level has been that different companies took responsibility for different energy distribution infrastructures. Thus instead of one, major planner (the national integrated energy company), several players now have a hand in the local energy system planning, making their roles no longer easy to distinguish.

Moreover, in each country, specific and differing rules, laws and institutional frameworks shape decision mechanisms and the roles different institutions may play in energy planning. In general, *two types of players* can be identified: 1) *decision-makers* - the ones that actually make planning (investment) decisions and 2) *stakeholders* – the ones that can be part of the initial decision making process and negotiations; they do not have power to make decisions but they may convince decision-makers to take into consideration issues that concern them. Stakeholders are in the end influenced by the final decision (decision-takers).

The number of decision makers and stakeholders involved in the planning of local energy systems depends on the specifics of each planning situation. As also discussed in *Paper 2 (see Appendix B)*, the different interest groups that may play a role in local energy planning can be:

1. Companies involved in the local energy supply;
2. The municipal or regional administrative authorities;
3. Regulatory authorities;
4. Political groups active in the local arena;
5. Industrial and private energy consumers;
6. Environmental groups and NGOs;
7. Other groups of interest such as technology vendors.

The first group is comprised of: companies owning local generation units, companies in charge with different distribution networks, and companies supplying customers with energy and energy services (energy retailers). In general, network companies and companies interested in investing in generating units are the main decision-makers in local planning. Often, different energy businesses (generation, distribution, and supply) may belong to only one company. Recent studies [3] have shown that in some parts of the world many companies want to participate in several segments of the energy value chain, and often across more than one fuel commodity, such as gas and electricity. This is because in general, by being multi-segmented and multi-commodity, companies can reduce their overall business and regulatory risks. Moreover, some of these companies can act at national or even at international level. Therefore, sometimes their interests and influence in local energy infrastructure planning might not coincide with the local goals although having great influence on the final decisions. However these companies are not the only decision-makers.

Governmental authorities and municipalities play also an important role in local energy planning. They can sometimes be decision-makers or stakeholders. From all groups involved in infrastructure planning, these authorities may be the only players that have an overview and can influence the economic and social situation in a region. For example, governmental authorities provide the rules and legislation concerning all energy related businesses. Their activity is in concordance with a national energy policy and they can influence the local planning process by providing incentives for the local energy companies to invest in new energy supply solutions (cleaner technologies, or making use of renewable energy resources). Municipalities can also influence the development of local energy systems because the construction plans of new houses and new infrastructures must be first approved by the local authorities. Moreover, in many countries it is common that local or regional authorities own the energy distribution companies (at least partly). Hence, these authorities can be in fact active decision-makers.

The last four groups of players are in general stakeholders. The end-users are crucial stakeholders in the system, since they are the consumers of the services that the energy networks deliver. However, some energy intensive industries may have enough local power to influence the structure of the energy system. For instance, some large energy intensive industries may own local generation capacities that can cover their demand for electricity or heat, and may supply, marginally, other consumers. Additionally, these industries may have flexibility as to the type of resources (electricity from the grid, gas) to use, so that the variation in market prices of these energy resources will not affect their production costs. If these consumers decide to change their energy consumption pattern depending on which energy resource is cheaper, or to use an energy carrier (or source) that is completely new to the region, then the local energy supply infrastructure may be greatly influenced. For example existing electrical or district heating networks might function below their efficient capacity or might be overloaded. The other stakeholders groups (political and environmental groups, technology vendors or NGO's) may have the chance to be present and make their opinions heard in the process of analysis and negotiations over the alternatives for energy supply, but usually they do not have decision power.

To conclude this discussion, in highly deregulated systems, the local planners may be business-focused companies (network companies, generators, large industrial consumers) that can make investment decisions, being however highly constrained by social, regulatory and political issues. In the short-term, a big challenge for these local planners is to understand the complexity the restructuring of the energy sector and the development of different energy markets, is adding to the decision-making process. Then, in the medium- and long- term, planners must take sustainable measures and add other, difficult to monetize criteria to their economic considerations. This is because a planning approach that reflects only technical or economic aspects and neglects environmental, social and political concerns may not be adequate and may fail because of lack of consensus.

1.2.3 The energy system planning problem

This paragraph provides an overview of the kind of planning problems local decision-makers may need to solve. As basis for discussion, some details of how an energy system can be defined (in terms of boundaries, components or energy flows) are first given.

1.2.3.1 The energy system

The energy systems analysed in this thesis consist of interconnected infrastructures for the generation (when needed), storage, transport and distribution of several energy carriers: electricity, heat, gas, biomass, etc. Such integrated energy systems can supply consumers with different types of end-use energy-based products and services. For instance households need electricity for lighting and electrical appliances, indoor heating and warm water (based on electricity, gas or wood), and energy for cooking (electricity or gas). Other types of energy consumers (industrial, commercial, administrative and office buildings) may have as well a diversified consumption pattern.

Energy planning cannot be successfully achieved if the system is not adequately defined. The planner(s) must have an overview of system's boundaries and of all types of interactions and flows within the system or between the system and its environment. For this purpose, it is meaningful to identify:

- The *physical components and boundaries* of an energy system. The system itself consists of different physical components (technologies) for energy conversion (generation) storage, transport and consumption. The physical boundaries usually coincide with the geographical borders of a region, town, community or locality. Within such boundaries, energy flows between different system components can be quantitatively measured, and the performances of the system (efficiency, reliability) can be estimated.

- The *impacts of a system* and its *impact boundaries*. Descriptively these should be the direct result of the existence and the operation of the energy system; a good example is the 'economic' boundaries and 'economic' (cash) flows between energy companies, and consumers. Environmental boundaries may be defined as well. This would enable a clearer understanding of the environmental impact caused by the system being considered. Within such boundaries, the impact of different pollutants can be estimated in quantitative terms and, more importantly, in terms of their effects on the ecosystem, on the health of the local population, etc. When establishing environmental boundaries, other issues must be as well clarified, such has: how to treat the emissions associated with the energy imports in a region. For example, how to take into account the CO_2 (or other pollutants) emissions for the electricity generated based on coal in Poland or Germany and consumed (or contracted) in a region in Norway? Such imports are primarily based on market agreements on quantities of energy a region in Norway would need, in certain conditions (weather dependent). The deficit of energy in Norway may or may not contribute to an increase of CO_2 emissions in other countries; therefore a clarification of these issues in every planning problem instance must be carefully carried out.

  Additionally, the identification of impact boundaries can be useful in the case of other, more difficult to quantify impacts (noise, aesthetical impact, customers' perception). Such impacts may be, in this way, easier to define and estimate. However, these issues have not received much attention; except the economic or environmental impacts, little guidance on how to define other impacts of an energy system or its impact boundaries can be found in the research literature. This is probably because their definition is highly dependent on the characteristics of each planning problem and on the decision maker (s) involved.

- The *political or administrative interactions and boundaries* that stem from the laws, regulations and institutional frameworks that directly or indirectly affect planning decisions at the local level. These are difficult to identify and highly dependent on factors such as the national energy strategy, the social policy or the overall national economy. For instance, the national policy regarding the use of certain primary resources can considerably influence the energy supply options and consequently the planning at the local level. On the other hand, local actions (such as success stories about the implementation of new energy technologies, solutions for improving the energy use, the efficiency and reliability of supply and so forth) may trigger reactions in other regions or at the national level.

Figure 1.1 offers a representation of the energy system within these main types of boundaries.

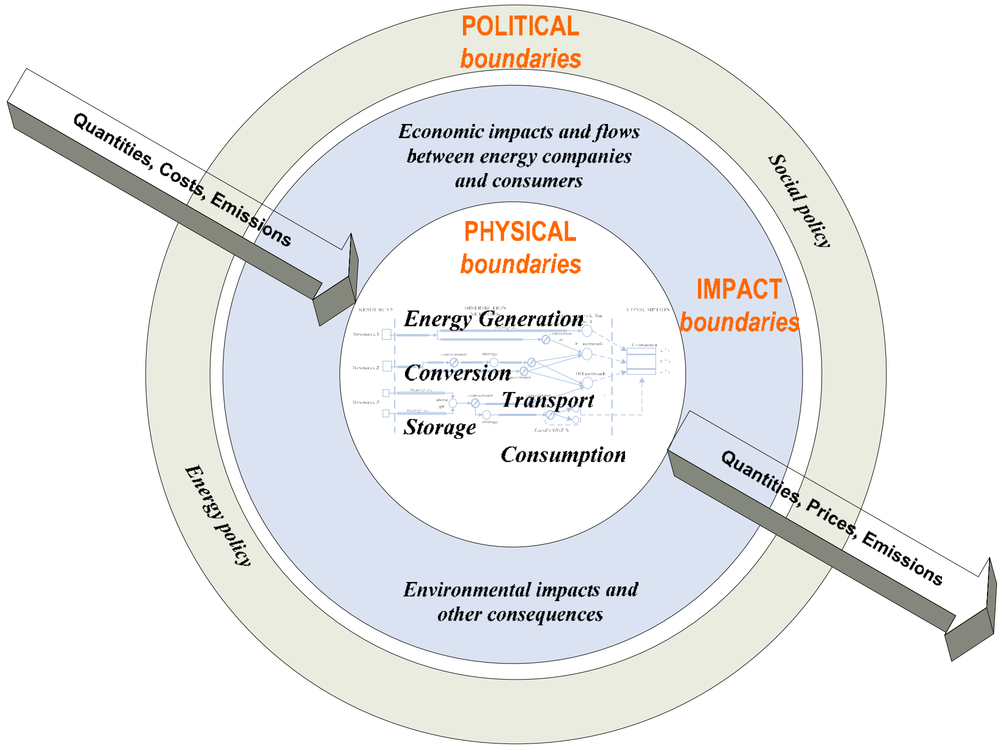


Figure 1.1 Energy system's boundaries

The *physical system* is represented in the centre and the *impact* and *political* layers build on it. For simplicity only the physical and measurable fluxes, between the system and its environment have been represented

The existence of different boundary types shows how complex the decision environment may be when planning. Planning problems can be of different nature and may require actions at different decision levels. The next paragraph is focussed on what kind of decisions local planners need to make.

1.2.3.2 Classification of planning problems

Decision problems for local energy systems planning vary with the decision-makers involved in the process and their target system. Furthermore, planning can take place at three main decision levels: operative, tactical and strategic.

Figure1.2 illustrates these planning levels in the case of building new energy infrastructure (for gas distribution in this case) in a region. This example is inspired by the situation in many towns and regions in Norway, country where most of the energy demand is covered by electricity (hydropower) as the main energy carrier. However, at local/regional level there is a great potential for using gas – an abundant energy resource in Norway- as an alternative to electrical based heating or cooking or for electricity generation.

Operational planning concerns the short-term operation of a given system. *Operative decisions* are decisions about how much energy to produce or to buy, and how to transport / distribute it in order to satisfy the needs of the end consumers. If there are different companies in charge with different infrastructures in a region, then each of them must make operative decisions.

DECISION LEVELS		
	Main actions	**Main factors influencing the decision**
STRATEGIC	**Build new energy infrastructure for gas distribution and sypply**	**Political and social factors:** - national energy policy - regulations
TACTICAL	**Create a gas market** - atract local consumers: households, municipality, industry - negotiate with other stakeholders	**Economic, environmental and social factors :** - % of the estimated gas market covered by an alternative - expected consumers costs, and their willigness to pay - the number of new jobs created, etc.
OPERATIONAL	**Analyse system's operation:** - simulate and analyse the operation of the system in possible configurations - identify uncertainties, construct scenarios to predict the evolution of prices and demands	**Economic, environmental and technical performances :** - operational and investment costs - emissions: CO_2, NOx, etc. - system's efficiency -reliability and quality of service, etc.

Figure 1.2 Decision levels at local energy planning

The planners of a new gas infrastructure would be interested to know how the integrated energy system would 'react' to the introduction of a new energy carrier in the region. Different supply alternatives should be simulated and compared based on comprehensive scenarios of how the different energy carriers and production capacities can be dispatched in order to cover the total energy demand, forecasted for different periods of the day, week, season or year.

Sometimes *large industrial energy consumers* may own local production capacities that can satisfy their own energy needs and marginally may supply other consumers. These companies may as well be interested in planning their operating activity in accordance with the rest of the system. These industries may influence heavily the operation of the integrated system because they have flexibility as to the type of end-use energy (electricity, gas, heat, etc.) to use so that the variation in prices for different end-use energies, in different markets will not affect their total costs.

Alternative strategies for operating different business must be analysed in an uncertain environment (uncertain prices, demands) and in terms of economic benefits and other objectives (achieve high efficiency, maximise reliability, minimise emissions, etc.).

Tactical decisions are mostly medium term decisions (intermediate decisions) that can prepare the system for strategic changes. For instance, suppose that the energy consumption in a region is expected to grow so that significant investments in the energy supply system will be needed. In these conditions local interest groups may identify a new, potential energy carrier – *gas* in this example - which can be used in the area. Building gas infrastructure is a significant decision with major implications in the region in the-long term. Thus, those who are willing to support the idea (the planners) must seek for approval from all other local interest groups.

Consumers are the major target for tactical planning. Obviously if this group does not accept the new solution, there will be no demand and without sufficient demand no infrastructure can be built. Of all consumers groups, the energy intensive industries in a region must be first attracted in order to ensure enough demand that could justify the construction of the new infrastructure (gas pipelines). Other groups of middle size energy consumers (office buildings, shopping malls, hospitals) may also count in this matter. The smallest consumers, households or residential buildings, may not have enough power to influence the building of new infrastructure. Moreover, depending on the population density in a region, the costs for extending the gas network to households can be significant. In Norway for example, such consumers are obliged to connect to district heating networks (if available) but no regulations in this respect exist for the case of gas distribution networks. To attract these smaller consumers in shifting appliances to those that use gas, temporary solutions may be proposed, before the actual gas infrastructure is built. For instance, a way to put the basis of a gas market in a region is to offer consumers the possibility to have access to gas storage tanks that can be refilled periodically.

A tactical planning process should be based on an analysis of what implications each relevant alternative for building new infrastructure may have on the local energy system and on the local community. In general a planner would need to know:

- how easy (or difficult) it would be to comply with relevant rules and regulations
- how the new solution will influence the existing system in terms of: competition with other energy carriers, costs, efficiency, economy of scale, etc.
- how consumers will accept the new solution in terms of costs or additional environmental impacts associated with the introduction of a new infrastructure.

A careful consideration of these issues would give the planner(s) sufficient support in documenting proposals for consumers and other stakeholders. It is essential to mention here that any tactical analysis must have at its core extensive operative analyses of the various tactical alternatives which may be identified.

Strategic decision problems target long-term technological and socio-economic development. For instance, the decision to build new gas infrastructure in a region is a strategic decision.

Strategic planning is a complex decision-making process that is in general difficult to structure and model: the process may be highly influenced by the national policy objectives that involve more than just the energy sector. For instance, a wide range of policy issues may have direct influence on local planning, because national programs and incentives may dictate the energy resources and energy technologies to employ, in order to minimize the negative impact on the environment and the local community.

Strategic planning implies massive investments, large uncertainties and long lead times. Decisions at this level must be supported by detailed analyses of all possible implications that may affect the future of society and the environment. In general, tactical analyses and operational scenarios are the main tools used in supporting strategic planning.

Many interest groups will affect and will be affected by strategic decisions. Strategic decisions are normally made after many sessions of discussions and negotiations with all parts involves. Discussions during these negotiations generally revolve around few main points: who (companies) will be allowed or charged with implementing the decision (carrying through the project), how new investments will be financed, and what will be the major implications for the local community.

Major investments in infrastructures must be approved and supported by state authorities. Governments are directly involved in the energy sector through the provision of the infrastructure (which is usually state-owned) and through regulation of transport and distribution of energy. In Norway for instance, NVE (The Norwegian Water Resources and Energy Directorate) assigns local area licensees to prepare, annually update and make public an energy plan for each municipality in the licensees area [4]. The energy plan should describe the current energy system infrastructure in the municipality, the expected energy demand in the municipality, broken down by the various energy carriers and user groups and it should identify the most relevant new energy solutions which may sustain substantial changes in energy demand.

1.3 DECISION SUPPORT FOR LOCAL ENERGY SYSTEMS PLANNING

The discussion so far emphasised a variety of decision situations related to local energy systems planning and the different groups of interest that can be involved in planning. This section addresses the main challenges posed by offering decision support to local planners.

The need for decision support in local planning varies with the decision level and the number of participants involved in the decision process.

Operational planning decisions are decisions about how much energy to produce or to buy, and how to transport / distribute it in order to satisfy the needs of the end consumers. If there are different companies in charge with different infrastructures in a region, then each of them must make operative decisions. Due to the competition of different carriers in satisfying the end-use demand, each planner must have a good overview of the activity in other networks. In fact this also applies to situations when only one planner is in charge of operating the whole system.

In mixed energy systems, the competition between different energy distribution networks is for the end-use energy demands that can be covered from different sources. Examples are where indoor heating can be provided by using gas, biomass, electricity or district heating.

Integrated system models that can centralize large amounts of information regarding the energy demand and energy availability (quantities prices) *are usually used for decision support in operative planning*.

Tactical and strategic planning are similar from the point of view of the complexity of the planning process because:

- several decision-makers and stakeholders (decision-receivers) may be involved in the decision-making process
- the different interest groups may have multiple, conflicting criteria when analysing the available options
- decisions must consider uncertainties over the medium and long term.

In these conditions, the first and most important step in providing decision support is to identify and structure the decision problem. This mainly implies the identification of all parts involved and their role and interactions in a decision process, along with the main strategic options and the main uncertainties.

The second step is to find tools that can offer decision support in the identified decision situations. *Integrated system models* can also be used to support tactical and strategic planning. For instance many energy models, that can be used in operative short term planning can also be adjusted to function in a repetitive mode (for different time periods, scenarios, etc.), to allow for medium and long term quantitative analyses of different investment alternatives [5-11]. However, more advanced procedures for decision-support would be needed in order to address more of the complexity described previously.

When several interest groups are involved in the decision process, they will most probably have different views and objectives regarding different strategic options (see also *Papers 1 and 2* in the *Appendices 1 and 2*). To help these groups to reach consensus, advanced decision-support tools are needed. One approach would be to allow each of the participants to use the same energy model as a common platform for analyzing different (investment) system alternatives. This idea is adopted also throughout this thesis.

Then, because different decision-makers might have a set of objectives in mind when analysing the available options, the decision-support tool should be flexible in order to allow each decision-maker to define and model his own concerns. A problem in this respect is that energy system models can provide only quantitative measurements of different objectives (costs, emissions quantities, etc.), while the decision-makers would need additional information about other, qualitative impacts that are not-so-easy to quantify. Examples for such impacts that can also be found in *Paper 2 (Appendix B)* are: noise or aesthetical impact, the impact on the health of the local population (pollution, etc.), the public image of the companies in charge with planning. However, in general the criteria for measuring the impacts may depend on the problem analyzed and on the energy system.

Assuming that all relevant criteria are identified, the tactical or strategic alternatives have to be judged accordingly by the planner(s). In problems with a small number of alternatives that must be judged against few, clearly defined criteria, a decision-maker may directly choose the alternative he or she considers the best. However, strategic energy planning problems are probably not so easily reduced to such size and thus, additional methodologies will be needed to help decision-makers to take explicitly into account different criteria.

Multi-criteria decision analysis (MCDA) has proved a valuable contribution to the successful resolution of various types of energy planning problems [12-17]. Most research however seems to address a large number of types of problems related with the planning of electricity systems, or of national integrated systems. By comparison, it is rather difficult to find applications of MCDA to the specific problems of planning *local, mixed energy* *systems*. The reason for this is perhaps that the basic local planning needs are still not very well recognized or expressed in many countries [1], and consequently the research community has not given enough attention to the process of local or regional planning of energy systems.

Thus, this thesis contributes to an emerging field, by addressing the issues of *problem identification and structuring* and of *improving the use of existing energy models to explicitly address complex planning problems involving uncertainties and multiple criteria*.

1.4 CONCLUDING REMARKS

The issues raised in this chapter can be summarized as follows:

1. The process of decision making for local energy systems planning is complex. Decentralization, the need to consider the interconnection between energy and emission markets, and the movement toward sustainability have changed the priorities of energy planners and policy makers. In many countries nowadays, instead of one major planner (the national integrated energy company), several players have a hand in the local energy system planning, making their roles no longer easy to distinguish. In order to adequately study the process of planning, an energy system can be defined within three types of boundaries: *physical*, *impact* and *political*.

2. Within the local planning context, three main types of planning levels can be identified: the operative, tactical and strategic levels.

3. The need for decision support in local planning varies with the decision level and the number of participants in the decision process. Operative planning decisions are supported by optimization and simulation models. Tactical and strategic planning problems are more complex because several decision makers with multiple, conflicting criteria are involved.

4. New research and dedicated decision-support tools are needed to help planners in structuring their problems and coping with uncertainties and multiple criteria.

5. This thesis contributes to an emerging field, by addressing the issues of *problem identification and structuring* and of *improving the use of existing energy models to explicitly address complex planning problems involving uncertainties and multiple criteria*.

Subsequent chapters present an investigation and an assessment of appropriate methodologies for aiding decision-making for local energy systems planning.

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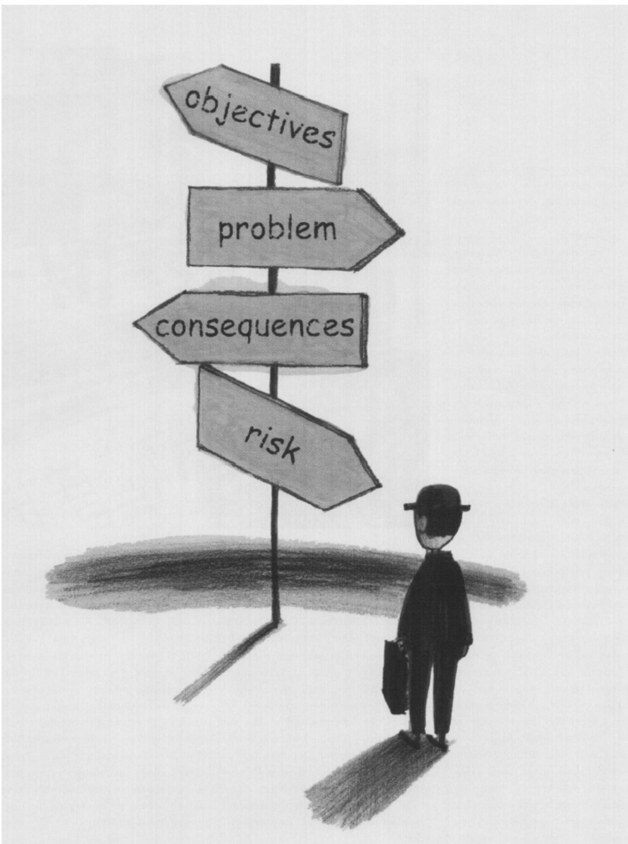
PART B

AN OVERVIEW OF DECISION SUPPORT TOOLS AND METHODS



Ralph L Keeney **Foundations for making smart decisions,** *IIE Solutions;* May 1999; 31, 5; ABI/INFORM Global, pg. 24.

Summary

The purpose of this section is to give an overview of approaches that can be used for decision support in energy planning. This part of the thesis is comprised of three chapters (Chapters 2, 3 and 4). The chapters focus on different facets of the decision-support process: energy modelling, multi-criteria decision making and uncertainty in decision-making.

Energy modelling was and still remains the main approach in solving energy planning problems. Chapter 2 begins with a discussion of the purpose of and opportunities for modelling energy distribution systems. Some well- known energy system models are first reviewed. The remainder of the chapter consists of a presentation of a new energy model, ***eTRANSPORT****, which occupies a central role in this research.*

Chapter 3 provides a study of Multiple Criteria Decision Aid (MCDA) as a discipline that can help decision makers make 'better' decisions when judging their alternatives with respect to different criteria. MCDA is a good candidate for solving complex energy planning problems. The approach has been proved useful in many energy-related decision problems, although there are few reports of the use of this approach in the field of concern for this thesis (planning mixed energy distribution systems).

MCDA can improve problem solving when applied to the 'correct' decision situation. MCDA does not provide 'the right answer', as some mathematical or engineering methods would be expected to do, but instead provides recommendations or advice regarding which decision to make based on the information available in a given decision situation. An MCDA application is successful when the decision-maker gains a better understanding of the decision-problem and accepts the final recommendation. The basic concepts defining this discipline are first discussed, while the remainder - the largest part - of the chapter is dedicated to describing methods under the MCDA umbrella. Before applying MCDA, a user must have a good understanding of how and in which situations different methods can be applied. This chapter offers and extensive evaluation and classification of methods from a practical perspective.

The last chapter in this section, Chapter 4, treats decision-making under uncertainty and risk. Uncertainty is a basic, structural feature of the environment in which energy planners must make decisions. It affects a wide range of short- and medium- term decisions and it is critical in strategic planning problems. Recognizing the uncertainties in a decision context, accepting them, and making the effort to structure and understand these uncertainties, are the main steps in dealing with uncertainty and in making it part of the decision process. This chapter offers a review of the main approaches in dealing with these issues. An integrated view of on how uncertainty can be captured with both energy system (impact) and multi-criteria (preference) models is offered.

Chapter 2 MODELLING THE ENERGY SYSTEM

2.1 ABOUT ENERGY MODELLING

A major goal of energy modelling is to create tools for decision support in energy planning and policy making. Energy models are generalized descriptions of the physical energy systems. Depending upon the purpose for modelling, the level of detail needed and the assumptions made, the components of a system can be modelled by taking into consideration physical characteristics and phenomena as well as complex relations between system parameters.

Energy modelling has been and still is the most basic approach in aiding energy planners. Energy models can be used to represent, simulate and reveal the issues that matter in a decision context. Such tools help by facilitating an understanding of the problem being analysed. For example, models can reveal new facets of the problem or courses of action which might not otherwise be evident, by allowing the initial conditions for the analysis to be varied. Complex analysis would be impossible without such models, because of the way they help in processing and modelling large amounts of data.

The insights that are gained by decision-makers when using the model should be at least as important as the numbers the model produce. In fact a model can be successfully used for decision support only if decision-makers accept it as a relevant tool in a particular decision situation.

The discussion in Chapter 1 showed that the decision making process in energy planning may be fairly complex, involving many decision levels where problems can be formulated in many ways. Integrated energy systems are complex structures where different energy carriers have to compete in satisfying the end-use energy demand. In essence there are two main dimensions of this 'competition':

A technical dimension - which energy technologies and energy flow paths to use considering:

- the energy resources available in a region
- the evolution of demand for different end-use energy types: electricity, ambient heat, hot water, energy for cooking, etc.
- the available technologies for energy conversion, transport or storage.

A decision-making dimension - which energy supply solution to adopt, considering:

- the economic impact on society: utilities, consumers etc.
- the impact of the energy system on the environment
- the political and social implications etc.

Theoretically, the physical (technical) systems can be modelled in many different ways, depending upon the needs for decision support. A model, once built, can be used in different planning situations (applied to different local systems) to support decisions at different levels (operative, tactical or strategic). Energy models can offer information about costs, emission quantities, losses etc. Although these are basic criteria in any analysis, in many real decision situations local planners weigh many other aspects when making decisions, as has been shown. These are, for example, the opinions of local interest groups, the national energy policy, social values, or other criteria that are not obvious or simple to measure. Thus, it is often true that the energy model provides only a part of the picture in a decision situation. For a better decision-support, in addition to energy modelling, supplementary time and effort must be dedicated to the process of bringing forward and modelling such issues, if possible.

The reminder of this chapter is comprised two main parts. The first part is dedicated to a short review of existing models for integrated energy systems. The main characteristics and the use of these models for decision support will be discussed. The last part of the chapter is dedicated to the description of a new model called eTRANSPORT. This model plays an important role in the present research, as a large part of the investigation in this thesis is directed towards improving the model's use in complex decision settings.

2.2 A SHORT REVIEW OF ENERGY MODELS

The development of energy models started 40 – 50 years ago [1] in response to severe energy problems. The scope for model development and application has shifted over the years to reflect the continuously changing environment for decision making. The energy models developed in the 1960s focused mainly on supply and demand for a single energy form or fuel, such as electricity, oil or natural gas. Then, these models became no longer useful at the beginning of the 1970s, during the first oil crisis, because they could not adequately describe inter-fuel substitutions related to changes in energy prices, technological development or environmental considerations related to energy use. Since then, integrated energy modelling was developed to solve national (even international) or regional energy problems.

Network representations are usually used to calculate energy balance and flows from the primary energy resources through conversion processes to the end-use of various fuels and energy forms. There is no available information about on how many energy models have been developed so far, although different classifications exists [1, 2]. The following discussion aims to give an overview and a short classification of some of the most well known integrated energy system models, according to their scope and applicability.

Energy system models can be distinguished by their level of aggregation/detail in modelling the system and its components, as well as by their spatial and time resolution.

In highly aggregated macroeconomic models, or *top-down* models, the energy system is represented with very little detail - more or less as a black box. These models can be econometric or parametric and are used to describe the relationships and synergies between the energy sector and other sectors of the economy [2]. They are mainly used in energy policy making, technology assessment, predicting future market developments through historical energy-economy interactions and customers behaviour in reaction to changes in prices. Scientific reports about this type of models abund in scientific journals oriented towards energy- policy making; see for instance [1], [2], [3], [4]. This study does not target such *top-down* models, but they are worth mentioning as possible alternatives in helping in decision making for local energy planning.

Of interest to this research are the *bottom-up* models - usually called energy system models, engineering models, or even energy system optimization models. These models allow a fairly detailed representation of different technologies and components of the energy system. In general, large amounts of information are required to describe such systems.

Bottom-up system models are in general large scale linear programs that provide solutions for optimal allocation of resources and energy carriers given a set of technical, economic or environmental constraints. Reviews and discussions about the available energy system models can be found for example in [1, 2, 5, 6]. In general, these models differ according to:

- *The size of the energy system modelled* (geographical coverage):
    - Models describing an entire national energy system: MARKAL, MESSAGE, EFOM, TIMES, BESOM etc.
    - Models for local or regional energy systems: MODEST, PERSEUS, etc. plus other large scale models that can be adapted for local or regional systems modelling.
- *The way uncertainties are modelled*:
    - Static, deterministic optimization models, which are especially suited to calculate least-cost strategies under certain boundary conditions
    - Dynamic, interactive models where uncertainties (future prices, loads and so forth) can be represented stochastically, or by using fuzzy logic, or through scenario simulations, etc.
- *The time horizon allowed for analysis*:
    - Models describing the short-term operation of the system –usually describing, with sufficient details, a fixed technical system and a given socio-economic framework;
    - Long-term simulation models used in strategic planning – used in the analysis of long-term technological and socio-economic developments.

The concept of integrated system modelling is continuously evolving; many of the existing models have been improved or new models have been created [7, 8]. Two main directions for improvement have been observed. The first is to develop models that can accommodate more details in the description of the energy system, as for instance in the representation of:

- Different technologies for conversion, storage transport and distribution of energy - including models for new, emerging technologies
- Energy demand and energy procurement at the level of hourly forecasts.
- Market-related issues: spot prices, hourly purchased quantities etc.

Secondly, improvements have been observed in the usability of these models: the tendency nowadays is to create tools that can be used not only by their developers (experts) but by planners as well. This has been achieved by:

- more transparent, comprehensive and easy-to-follow optimization procedures
- and better representation of the results – through illustrative graphical-user interfaces.

However, because a significant amount of time and effort must be spent to set up and use such tools, it is still realistic to assume that the real decision-makers may not be willing to use these models directly. Future generations of energy models should be built so as to diminish the gap between the decision-makers and the tools they use to support their decisions. If decision-makers were be able to at least partly use a model, decision-support through energy modelling could be significantly improved.

The remainder of this chapter presents a new energy system model that has been developed in parallel with the research for this thesis. This model, named eTRANSPORT has been built in several steps, with each iteration of the prototype tested with different case studies. The research in this thesis has benefited from the experience gained with the model because its development process added progressively new insights into the actual needs for decision support. In turn, the model will also benefit from this research. The last part of this thesis is oriented towards proposing a framework for extending the model with an '*advanced decision-support module*'.

2.3 eTRANSPORT - A NEW ENERGY SYSTEM MODEL

2.3.1 General characteristics

eTRANSPORT is an energy model developed to provide support for the planning of local or regional integrated energy distribution systems. It is a deterministic linear model, and describes in sufficient detail the various types of technical components of an energy system [9, 10]. The model determines the cheapest way - from a socio-economic point of view - to satisfy end-use energy demand. eTRANSPORT is flexible, in that it is applicable to relatively small systems (local/municipal regional), but it can be extended to large systems as well. It can be used for short-term operation planning, but also for long-term (investment) analyses. In analyses using this model, uncertainty can be taken into account by simulating scenarios using forecasted values of various important parameters (energy costs, prices, demand levels, etc.).

The novelty of the eTRANSPORT model is that the component types for different energy infrastructures are included in one optimization model for the whole energy system in a region, and that geographic details and the competition between different energy types are accounted for [11]. The long-term goal is to develop a robust and flexible tool to be used by private and governmental energy planners on a regular basis.

2.3.2 The structure of the model

The model consists of two main parts, as shown in Figure 2.1: the *operational* and the *investment* modules.

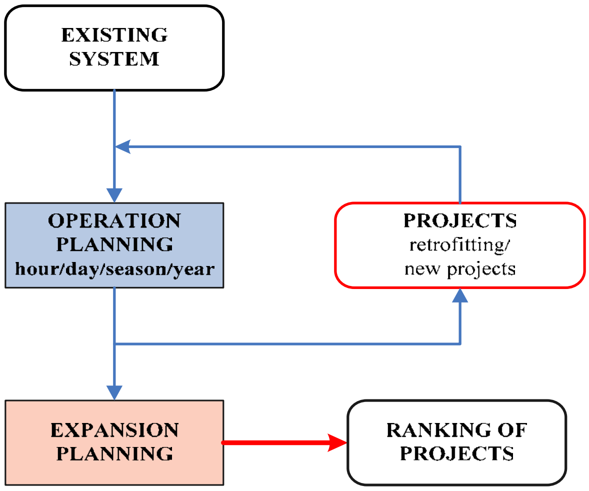


Figure 2.1 Simplified flowchart of the eTRANSPORT model

A. The operational module

The *operational module* calculates the optimal energy flow for a fixed system configuration and for given loads and price profiles. Three different *types of technologies* are modelled within the operational module:

- *Conversion technologies*: converting one energy carrier to another at a specific geographic location
- *Transport technologies*: transporting a given energy carrier over a defined geographic distance
- *Storage technologies*: storing a given energy carrier over time at a specific geographic location

Structurally, eTRANSPORT includes three *classes of components* that are linearly modelled:

- *Energy sources*, or input nodes;
- *Network components*: conversion, transport and storage;
- *Sinks* or end (output)-nodes: end-use loads and markets.

The actual location of each physical component is accounted for. Each class of components comprises several sub-component types, as shown in the Table 2.1.

SOURCES	NETWORK COMPONENTS		SINKS
	Conversion units	Transport /storage units	
▪ Electricity ▪ Gas ▪ Oil ▪ Waste ▪ Biomass	▪ AC/DC converter ▪ Warm water tanks ▪ Gas plants: (CHP, GE, CC) ▪ Boilers ▪ LNG station ▪ LNG re-gasification	▪ Electric net. ▪ DH net ▪ Gas pipe ▪ Gas ship ▪ LNG ship ▪ Storage	▪ Electricity ▪ Heating ▪ Warm water ▪ Gas

Table 2.1 The components of the operational sub-module

The table shows the sub-components currently implemented, although the model is continuously evolving.

The time division in the operational model reflects the variation in time-dependent parameters of the energy system with sufficient accuracy. The estimation of time-dependent parameters in an integrated energy system depends on the ability to model each particular energy network. These parameters also depend on the ability to measure and forecast different end-use energy demands or prices. For example, electricity specific data are usually obtained hourly. Thus a time step of 1 hour is typically used when modelling the electrical network. This is the smallest time-step in the model. Because other network parameters may vary or may be measured in larger time periods – daily, weekly and so forth- the model can be used in making calculations for different time periods.

The objective for the operational model is to minimize the total operational costs for the studied energy system. The overall cost function to be minimized sums up the cost objectives corresponding to each component/classes of components in a given configuration of the system. The connection between model components is made through variables defining energy flows.

The restrictions in the model concern both these energy flows but also sub-model specific restrictions such as: technical and physical limitations for the studied components, (capacities and efficiencies), restrictions on the available quantities of primary resources, and, most important, the obligations of covering the end-use energy demand. Parameters that need to be predefined are: loads, costs, prices, and different technical and economic efficiency specifications.

B. The investment module

The *investment module* consists of a sequential algorithm in which the *operational module* is used to evaluate the operation of the system in different configurations (expansion alternatives or plans) and time spans. The mathematical optimisation problem is modelled as a linear problem and has been successfully solved with linear programming. Recently, dynamic programming has been implemented as an alternative to the initial algorithm. However, the formal mathematical optimisation problem is independent of the technique used to solve it [11].

The *investment module* identifies the expansion alternative with the least total cost (the sum of investment costs and operational costs) for the whole planning period for a predefined set of investments and a given evolution in demand. Each expansion alternative typically consists of many different physical components/investments. An expansion plan shows which investments should be selected, if any, and when investments should be made.

The investment algorithm can be represented as shown in Figure 2.2. First the operational model is solved for a given configuration (state) of the system, in different time-segments within a year (typically 1-4 seasonal segments). These time-segments must be predefined and usually are directly correlated with the variation of different end-use energy demands and energy prices. For example, the number of days and weeks corresponding to different seasons/segments (summer and winter, as an example) can be derived by observing the variation in patterns of different energy demands. The annual operational cost is then calculated for all relevant configurations of the energy system being studied, and for all periods in the planning horizon.

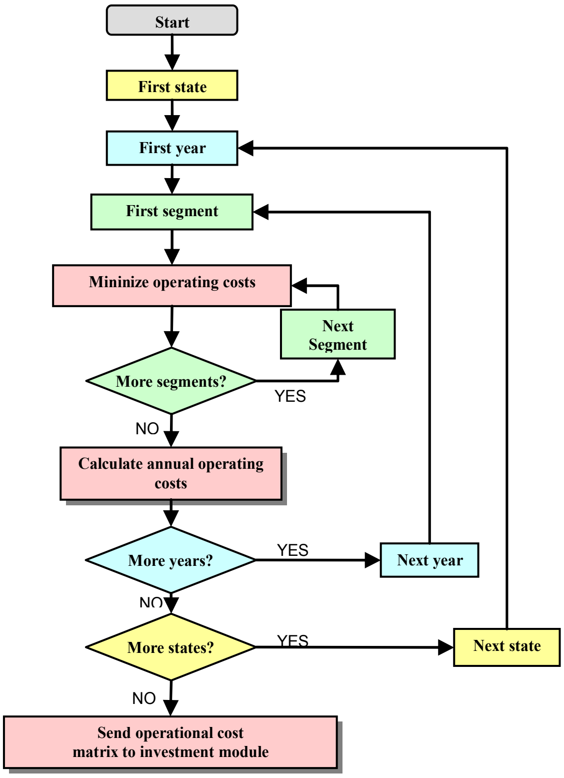


Figure 2.2. The investment sub-model [10]

An investment analysis usually has a horizon that is a few decades in the future (20-30 years or more). To simplify the effort needed for data estimation and forecasting, the investment algorithm in eTRANSPORT can be set up to run on different time periods during which it can be assumed that the energy demand will not change considerably. For example, a planning period of 20 years can be grouped into four sub-periods, each of which is 5 years long. For each sub-period, specific annual operational costs are calculated.

A predefined set of relevant investments for a given energy system is assumed to be known. Each of these investments refers to different system components (power plants, networks, etc.). The investment algorithm searches combinations of different components that may lead to the optimal system configuration. Some of these system configurations are in fact the alternatives that may be relevant in a decision situation. The algorithm produces a ranking of all predefined investment alternatives. Because it can be time consuming to evaluate all possible optimal combinations and configurations, the model allows the user to specify additional information about which investments that are mutual exclusive from an economic and technical point of view.

During the investment analysis some of the new investments will be made in replacing existing infrastructure. Within the model calculation, this replacement is a result of the specific lifetime of different components. Most of the *restrictions* in this model describe how investments and scrapping of invested components affect the state of the energy system and therefore the operational costs for different years.

2.3.3 Using the eTRANSPORT model

eTRANSPORT has been developed in a project that linked research institutions and industries. This collaboration enabled the testing of the model, at different steps during its development period [9, 10, 12, 13]. Most of the case studies have analyzed how the construction of new local power plants could be optimised with respect to size and location and subject to economic, technical and environmental constraints. These first applications were conducted by researchers (or their collaborators) who were in charge of constructing the model. Recently, a ready-to use prototype of the model has been distributed for testing by all parties involved in the project.

The following discussion shows the features of this prototype when used in practical applications. Figure 2.3 shows a snapshot from an application session with the model. The graphical user interface consists of three main parts: The *Component Library* to the left, the main *Drawing Area* and the *Results Window* at the lower part of the screen.

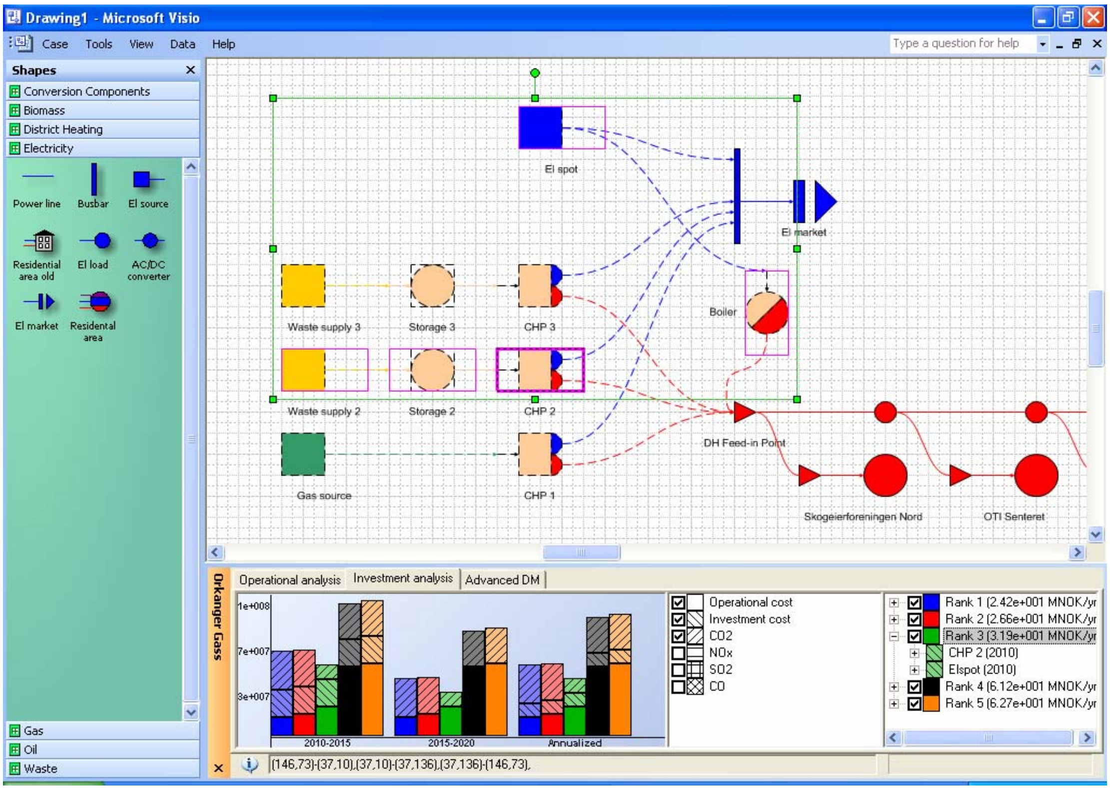


Figure 2.3 Main screen with drawing area, component libraries and result window [11]

eTRANSPORT as a decision-support tool is flexible and easy to use. There are three main steps to follow:

Step 1: Draw the system, by dragging-dropping system components from the library. It is also possible to copy, open, modify and use an already existing model.

Step 2: Input specific data for each system component. Edit windows such the ones shown in Figure 2.4 make this possible. Some component-specific default parameters are already available

Step3: Run the optimization by specifying the system components that should be included and the ones that are to be scrapped in each alternative during the time period set for analysis. Interest rates must also be specified to discount the future costs.

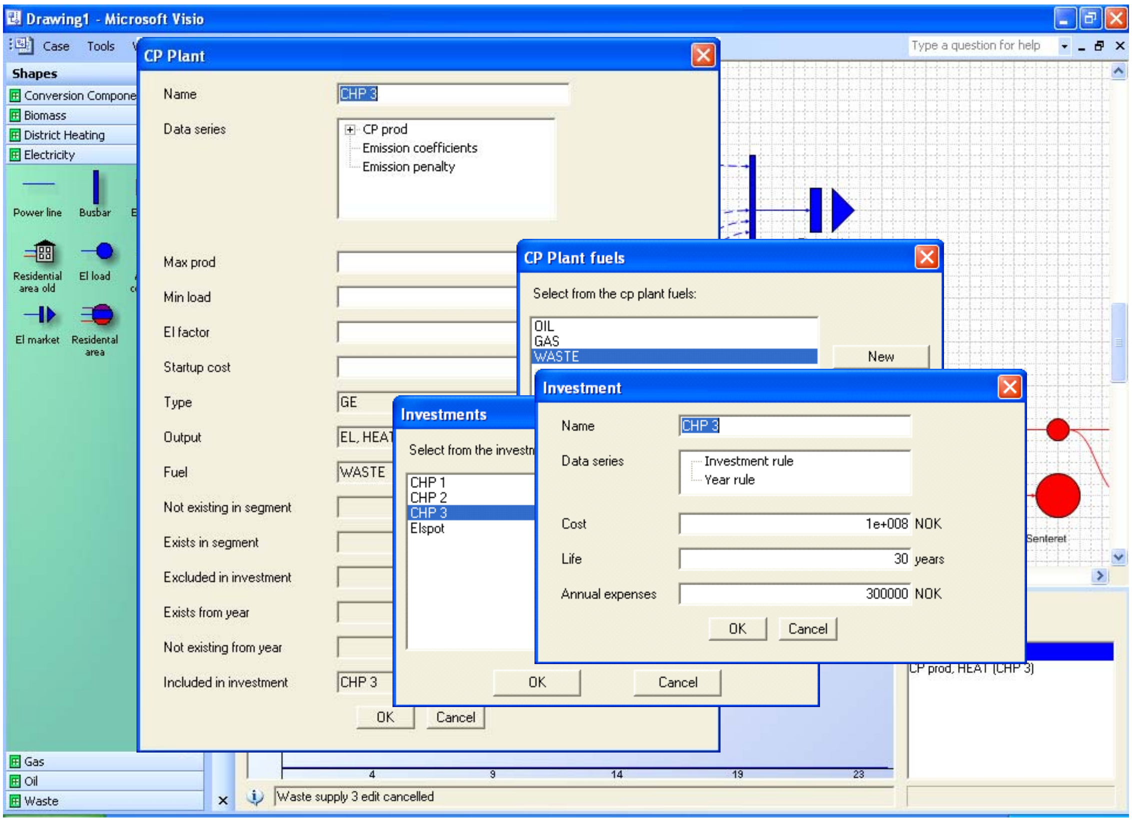


Figure 2.4 Main screen with edit windows [11]

eTRANSPORT provides suggestive representations of results The user has three modes of analysis to choose from: *operational* or *investment analysis,* and *advanced decision aid*. The first two modes correspond to the modules already described in the previous paragraphs. The advanced decision aid module has yet to be implemented.

Figure 2.5 shows an example of using the model in the *investment-analysis mode*. Relevant alternatives (the list in the right column) are ranked from the lowest to the highest annualized sum of operational and investment costs. The values for total costs are shown to the right of each ranked alternative. By expanding the rank’s investment tree the user can see details about the components included in and alternative as well as the optimal time to invest in new components.

The graph at the left of this window allows the user to compare the cost components (the middle column) for different alternatives that must first be selected from the right column. In this prototype emission results can be displayed as well.

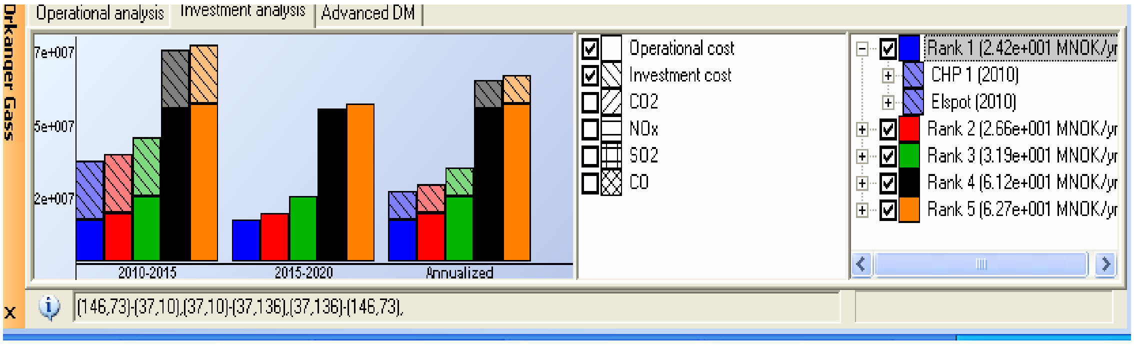


Figure 2.5 The *investment analysis* mode [11]

These are emissions (measured in tonnes) corresponding to the *min cost* for operation the system in a given configuration. The idea is to show, in a suggestive way, that emissions may count considerably, in some situations, to the ranking of alternatives.

eTRANSPORT can be easily set to simulate if/how the ranking of alternatives changes when some of the relevant input data are modified: costs, prices, demands profiles, or the restrictions set on emissions (quantities / taxes). These simulations contribute significantly to the understanding of correlations and synergies between the many issues that matter in planning decisions. The model allows for uncertainty modelling in terms of scenarios.

The current version of the model provides static results, however, in the sense that the results in different simulations cannot be displayed together, for a comparative analysis. Spreadsheets or other tools have been used in assembling all simulations and finalizing the decision aid process.

The *operational analysis mode* allows for in-depth analyses of each of the alternatives considered. The decision-maker can check how the different components in a given system configuration (or investment alternative), can be operated optimally during different periods of analysis. When selecting a component, a graph will appear in the lower window, which shows the hourly operation of each component. An illustrative example is shown in the Figure 2.6.

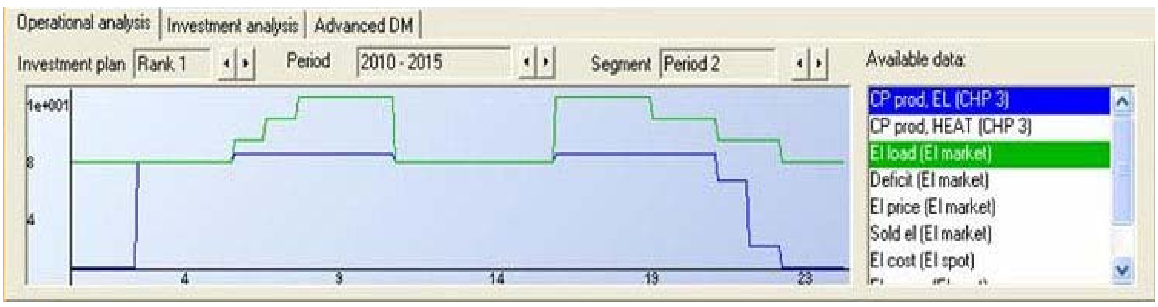


Figure 2.6 The *operational analysis*-mode

In this way, changes in energy demands, prices and so forth can be tracked to the level of detail of every single system component, allowing planning at the most basic operational level.

The various possibilities for analysis and decision support, make the eTRANSPORT model a valuable tool in many decision situations:

- *The model can be used by different decision-makers* such as companies in charge of different parts of the system, municipalities, large industrial consumers or even other types of small consumers. The operational mode allows each of these users to check how they can optimize and run their business in relation to the entire energy system. Moreover, the investment mode allows them to check how to expand their activity, or how to find new energy supply solutions, which can be integrated into a given system. For an optimal and relevant analysis, however, the main requirement is that each user has sufficient information about the whole target system. This information might not be always available, because it might concern not only decision-maker's own activity but the activity of other players as well.

- *The model can be used to support planning at both an operational and investment level*, thus allowing for basic analysis and decision support in most of the decision situations described in Chapter 1.

Gathering information about large energy systems is a difficult and time-consuming task. This is the reason why many energy models are not actually used by the final decision-makers, but rather by analysts who report to these decision-makers. Sometimes, the practical relevance of such tools might be reduced because the tools are only useful in decision support if they are easy to use and trusted by the beneficiaries of their results.

Because it is fairly easy to use, and because it provides results in a suggestive way the eTRANSPORT tool may be attractive for the ultimate decision-makers, especially once most of the information for the model has been assembled (by others). Future developments of the model (such as the *advanced decision aid module*) will be directed towards providing decision-makers with the ability to compare simulation results or to extend the analysis to additional qualitative issues, which so far cannot be done within the model.

2.4 Concluding Remarks

This chapter has focused on the subject of modelling energy systems. In short, the following issues where discussed:

1. The purpose of energy modelling is to create tools for decision support in energy planning and policy making. *Due to the large amount of information that must be studied and processed, an energy model should be the basis for any energy system planning decision*.

2. When modelling integrated energy systems, the competition between different energy carriers can be represented both in technological and in decision making dimensions.

3. The challenge of modelling energy systems can be tackled using many different approaches and methodologies. The choice of an approach depends on the needs for

decision aid: long- or short-term analyses of local or national energy systems, where uncertainty may or may not be included.

4. A new energy model, eTRANSPORT, has been developed to provide support in investment planning and operation of integrated energy distribution systems. This tool has been developed in parallel with the research for this thesis, thus contributing to a better understanding of the needs for supporting decision making in energy planning.

5. eTRANSPORT is a user-oriented flexible and easy-to-use tool to support decision making. Energy systems can be easily modelled within the tool, and a variety of analyses can be performed. For instance, the model can be used by different kinds of decision-makers to support planning at both the operational and investment levels.

6. eTRANSPORT can be used in providing basic *information* about the *impact* decisions may have at any planning level. However, as discussed in Chapter 1, most decision situations concern many important issues that cannot be practically resolved with this tool in its current form. Future developments of the model (the *advanced decision aid module*) will be directed towards providing decision-makers with the ability to compare simulation results or to extend their analyses to additional qualitative issues, which so far cannot be done with the model.

The discussion in the following chapters will be driven by the goal of finding good ways of extending the use of the eTRANSPORT model to complex planning situations.

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Chapter 3 MULTI-CRITERIA DECISION AID

3.1 THE SCIENCE OF DECISION AID

For centuries philosophical or mathematic theories have been centred on different explanations about the thinking behind decision making and the acceptance of the consequences of the decision. For example, the science of calculating probabilities emerged as an attempt to define instruments through which the contingencies of life and human behaviour could be explained using mathematical concepts [1]. Scientists believed that through a scientific analysis the mystery behind human deliberation and decision making could be understood. Thus the field of social mathematics converged in a set of methods and techniques for making rational decisions. Social and political sciences are among the first domains where these techniques have been applied. Then, after the World War II the science behind reasoning decisions took shape under the name of **M**anagement **S**cience with two main streams: **O**perations **R**esearch (**OR**) and **D**ecision **A**id (**DA**).

The concepts of **OR** and **DA** have been extensively discussed by Roy [1] in his quest to establish the validly and viability of methods models and procedures related to this field, and to distinguish between '*decision science*' and '*decision-aid science*'. Roy uses a definition from Miller and Starr who in 1969 defined **OR** as '*applied decision theory… requires the use of scientific, mathematical or logical means to structure and resolve decision problems. Construction of an adequate decision model is crucial*'. Then **DA** is consequently defined as '*the activity of one who, in ways we call scientific, helps to obtain elements of answers to questions asked by actors involved in a decision-making process, elements helping to clarify this decision in order to provide actors with the most favourable conditions possible for that type of behaviour which will increase coherence between the evolution of the process on the one hand and the goals and/or systems of values within which these actors operate on the other*'.

Within Roy's framework, **DA** relies on both **OR** as well as on other disciplines and other approaches. Roy also stresses that not every contribution from **OR** will necessarily be related to **DA**, insofar as certain purely mathematical studies that bear the **OR** label are not directly oriented towards decision aid.

More than forty years ago a new discipline emerged as a result of the need for formalized methods to support decision making with multiple criteria. This discipline is called **MCDM** (**M**ultiple **C**riteria **D**ecision **M**aking) or **MCDA** (**M**ultiple **C**riteria **D**ecision **A**nalysis or **M**ultiple **C**riteria **D**ecision **A**id). There is no clear distinction between the different terms scientists use when they refer to this discipline. During the years, a number of different (often called 'divergent' [2]) schools of thought have emerged, each of them using a different nomenclature.

The term **MCDM** is used commonly used in relation to the set of *descriptive methods for building models of the behaviour of the decision maker*. These methods and models are then assumed to be applicable to different types of problems.

In a similar approach, the philosophy behind **MCDA** is to develop *frameworks and methods for decision aid*, to help the user to understand the problem and his own contribution to the decision making process [2]. Thus **MCDA** is more of *a process* that starts with the identification of the problem and the multi-criteria method that best fits the problem, and ends with the assessment, interpretation and validation of the results.

The scope in this chapter is to offer an overview of the main concepts, methods and techniques belonging to this discipline. Thus, when referring to it throughout the chapter, the term **MCDA** will be used, as it somehow captures both the idea of identification of the problem and the methods used to solve it.

3.2 How Can MCDA Help?

Why and how can an analysis based on multiple criteria help in a decision making process? Wouldn't the process of analysis and modelling in terms of different criteria complicate the actual decision making process? Why shouldn't we use the traditional, well grounded economic theory that allows for monetary evaluations of almost any aspect and criterion? The following discussion is an attempt to answer to these questions. For a deeper understanding, the reader can consult the MCDA literature, which abounds with arguments related to these issues.

Decision-making is a human managerial task which can never be totally automated with tools, techniques or algorithms [3]. *The concepts, methods and procedures used for decision aid, unlike their counterparts in the physical and natural sciences, can scarcely claim to describe realities that would be independent of both the observer and other human actors* [1].

Thus, for a decision aid process to be successful, the description and the interpretation of reality in a decision situation should be compatible with the way the decision maker thinks. Naturally, people take decisions with more than one criterion in mind. Consequently, decision support procedures that can help decision-makers to explicitly account for all criteria that matter to them, may provide a better (or at least as good) description of reality than the 'traditional', single criterion methods. Few arguments will be given further to support this affirmation.

Unlike many approaches that allow for modelling and finding solutions, *when the problem is given*, MCDA contributes to problem identification and structuring and provides the theoretical background for model building. Methods belonging to this discipline can help in organizing and synthesizing information that is complex and conflicting and that often reflects differing points of view and which additionally may change over time [2]. In fact, it is not only the 'reality' that is independent of the decision-maker(s) that is modelled by MCDA but also part of his subjective contribution to the decision making process. MCDA's ultimate goal is to lead to more 'qualified' decisions in the sense that the decision-maker involved would gain a better understanding of the problem and his own thinking (preferences) as these contribute to the decision making process.

The **MCDA** process was described by Belton and Stewart [2] as in Figure 3.1. In theory, the decision aid process should start with the identification and structuring of the complexity that undoubtedly exists in a decision process. In other words, all important aspects of a decision should be identified and clarified: the main key issues, alternatives, uncertainties, divergent goals, values, constraints or issues related to the external environment and other stakeholders. In order to understand at this point how decision-makers might proceed, their main goals and values should be the main factors in the identification of the key issues and the available alternatives with respect to all constraints, uncertainties and other parts involved in the decision-making process.

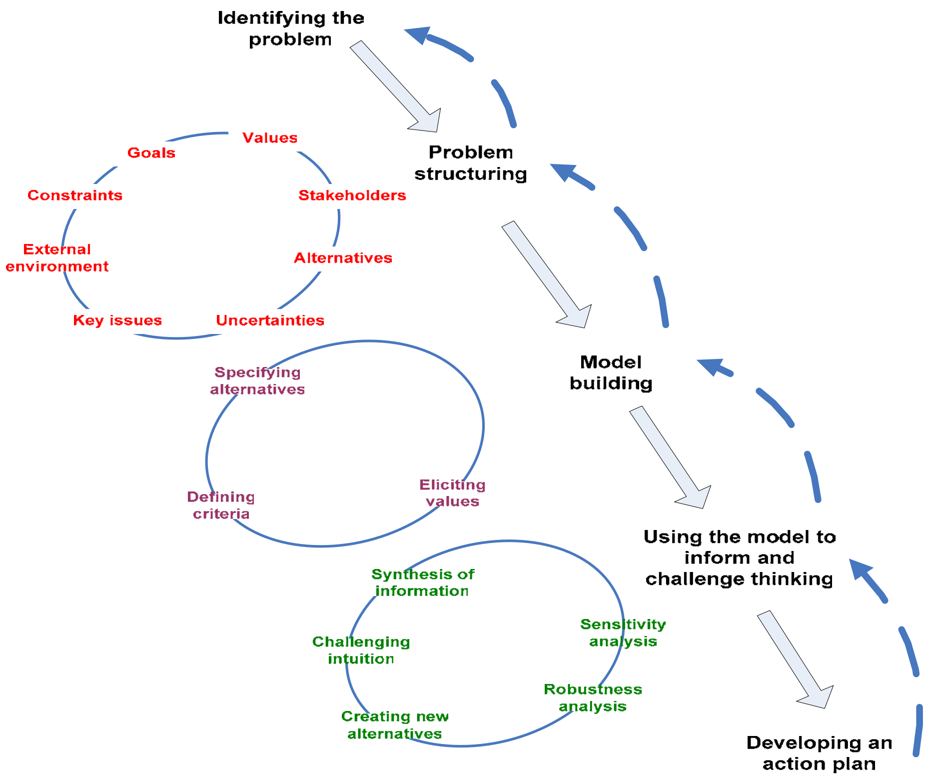

Figure 3.1 The MCDA process, as based on [2]

Next, the model building phase must reflect a more convergent mode of thinking, a process of extracting the essence of the problem from the complex representation in a way which supports a more detailed and precise evaluation of possible ways to move forward. The model will then be used to synthesise the information and to inform the decision-maker about his options. Sensitivity and robustness analyses may challenge the decision-maker to identify or create new alternatives. The ultimate goal in the process is to help the decision-maker in developing the action plan to be implemented. It is possible that the outcome of each of these phases would be a return to the previous phase or even a return to divergent thinking, as a result of the need to think creatively about other options or aspects of the decision situation.

From a practical point of view, it is necessary to reflect on the different situations in which MCDA may be applied. The 'traditional' methods have the advantage of being accepted, used and verified. This is not necessarily the case with multi-criteria methods. Since this discipline appeared, almost forty years ago, scientists are still debating to which established discipline these new concepts, methods and applications ought to belong [4-6]. Moreover the diversity in philosophies and models makes it difficult for both new researchers entering in the field and for practitioners or potential users of **MCDA** to get a clear understanding of which methodologies are appropriate to use in their particular context [2]. Additionally, although a large number of applications have been reported in the literature, little has been written about the empirical validation and testing of the various approaches [3].

To summarise the above discussion, **MCDA** provides the theoretical background for advanced decision-aid which can contribute to:

- a more detailed analysis of the decision problem by identifying and structuring both the reality independent of the decision-maker as well as his way of thinking (preferences);
- 'better' and 'justifiable' decisions, in the sense that the decision-maker better understands his problem and his own contribution to the solution and is thus capable of justify and defend it to others.

However **MCDA** methods might discourage some potential users due to the complexity of the procedures, as well as the time and resources these methods often require. Nevertheless ***MCDA** can help in practical applications* ***if*** *decision-makers consider it necessary,* and ***if*** *they understand the methodology applied and accept the results.*

3.3 CONCEPTS AND DEFINITIONS FOR MCDA

3.3.1 Multi-criteria problems

A multi-criteria problem reflects a decision situation where the available options have to be judged against several criteria. Roy first defined [2] four types of multi-criteria problems:

- **choice problems**: when a simple choice must be made from a set of possible actions (or decision alternatives)

- **sorting problems:** when actions must be sorted into classes or categories such as 'definitely acceptable', 'possibly acceptable but needing more information', and 'definitely unacceptable'

- **ranking problems**: when actions must be ranked according to some sort of preference order, which might not necessarily be complete

- **learning (descriptive) problems**: when actions and their consequences must be described in a formalized manner so that decision-makers can evaluate them. These are essentially learning problems [2] in which the decision maker seeks simply to gain a greater understanding of what may or may not be achievable

To these, Belton and Stewart [2] have added two more types:

- **design problems**: which imply searching, identifying or creating new decision alternatives to meet the goals and aspirations identified through the MCDA process. Keeney [7] also supportd this way of thinking which he calls 'value focused thinking' and which he claims is the most appropriate for real-life decision situations

- **portfolio problems**: when a subset of alternatives must be chosen from a large set of possibilities, taking into account not only the characteristics of the individual alternatives but also the manner in which they interact and the positive or negative synergies between them.

3.3.2 Criteria and alternatives

The above definition of the problem makes use of two fundamental concepts: criteria and alternatives.

What is a criterion?

The dictionary defines *'criterion'* as 'a means or standard for judging'[8]. A *criterion* can also be seen as a tool constructed for evaluating and comparing potential actions according to a (as much as possible) well-defined point of view [9].

When referring to the same concept, different MCDA schools of thought often use different terms for the methodologies they develop. These terms are: *goal*, *objective* or *attribute*.

Goals (or targets) are seen as priority values or levels of aspiration.

In connection with a goal or a criterion, an *objective* is something (usually measurable) that should be pursued to its fullest.

For example, if a criterion in an energy planning problem is *environmental impact of* NO_x (which means that decision-makers care about this in the analysis) then a goal would be *not to exceed a certain limit of pollution with* NO_x, within the general objective to *minimize the emissions of* NO_x. Following this line of reasoning, the only way these actions can be possible is to define an attribute that *provides the means of evaluating the levels of achievement of a criterion (or objective or goal).*

Attributes are often called *performance (or achievement) levels* for alternatives, according to the different criteria. *Attributes* can be performance parameters, characteristics or properties. Thus they need to be defined on a scale that fits with the issues of concern in the problem being analysed. One of the most important steps in a aiding in decision making is choosing, accepting and understanding the meaning of these measurement scales. Several types can be distinguished [9]:

a) purely *ordinal scales*, often called *qualitative scales*: when the actual difference between two achievement levels does not have a relevant meaning. This is the case with *verbal scales* and *numerical, ordinal scales*

b) *quantitative scales*, also called cardinal or ratio scales: numerical scales defined by referring to clearly defined and meaningful quantities for each achievement level. Such scales should be defined by an origin (absence of quantity, 0) and a unit of measurement

c) other types of scales which are described in [9] as intermediate scales, when any of the two types of scales discussed above is not suitable for use in a particular MCDA application.

Since criteria are the main tools in making a decision, it is important to know that they are indeed the main concerns of the decision-maker involved in the process and that these criteria measure what they are supposed to measure, i.e. that the scales of measurement for these criteria are meaningful to the decision-maker.

Careful consideration of these issues is necessary in most real-life applications because the criteria a decision-maker has are usually very general, abstract and often ambiguous. In fact, *part of the art of solving a decision problem is choosing criteria and ways in which to measure them, and thus the attributes*.

There are several techniques to address the definition of criteria in a decision problem. First, when criteria are too general, the way to clarify it is to find families of sub-criteria that best describe the main criteria. In this way, a *hierarchy of criteria* can be constructed. A tree-shape structure is usually used to represent the hierarchy of criteria. In complex problems with broad or fuzzy criteria, the hierarchy can spread to many levels.

Second, if it is very difficult to find an attribute (measurement scale) for one criterion, a solution can be to choose one that captures most of the idea in that criterion and that best suits to the possibilities at hand: in other words, an attribute that is easy to obtain information about and to calculate. These attributes are usually called ‘proxy’ attributes.

It is theoretically impossible to find exact representations of criteria, fact supported by the observation that it is impossible to model ‘all reality’. It is thus very important to know when to stop in developing new levels in the criteria hierarchy or in searching for ‘less-proxy’ attributes [2]. It is also relevant here to mention the work by Kenney [7]. He offers suggestions about how to direct the search and the thinking about values as the main driving force in identifying the true ‘criteria’.

What is an alternative?

Alternatives or more generally, *potential actions*, designate the object of the decision or that which the decision aiding is directed towards [9]. An action is qualified as potential when it is possible to implement it or when it is relevant in a specific decision context. Usually the term *alternative* is used to denote actions that are mutually exclusive.

Alternatives may be *explicitly defined and discrete*, or *implicitly defined and continuous* as described in mathematical programs.

The alternatives in a decision problem must be compared using different criteria. In some decision situations, several alternatives may be obvious while others must be discovered. Thus the set of potential actions or alternatives at a given stage in a decision problem is not necessarily stable; it can evolve throughout the decision process. Again, according to Keeney [7], it is the fundamental criteria that usually lead to the discovery of new and possibly better alternatives.

3.3.3 The parties involved in the decision process and their role

Virtually all decision aid theories were developed to help *decision-makers*. The term *decision-maker* designates the person (or persons) that is (are) confronted with a problem and is (are) in charge with solving it making a decision regarding it.

Decision-maker (s) can be [2]:

- *a single individual* with sole responsibility for a personal decision or for a decision that might affect others (companies, organizations, etc.)
- a relatively *small and homogeneous group* of individuals sharing more-or-less common goals
- *a larger group* representing different points views within the same organization
- highly *diverse interest groups* with very different agendas. This group may share corporate responsibility for a decision, it may have the task of investigating an issue with the goal of making a recommendation to a decision making authority, or it may have been assembled for the explicit purpose of exploring alternative perspectives without any executive power.

Individuals or small homogenous groups can carry out a multi-criteria analysis, providing that they have good knowledge and understanding of the method adopted. However, in complex decision situations, when large amounts of information must be processed and modelled, the multi-criteria analysis is usually conducted under the guidance of *one or more expert facilitators* (or *decision analysts*).

Thus, while the *decision-maker* has responsibility for the decision, the *analyst* guides and assists the decision-maker in reaching a satisfactory decision [2].

An analyst must have a broad overview of the existing multi-criteria methods and experience with their practical implementation. Only then will the analyst be able to direct the decision making process and propose a framework and a method that suits the problem at hand. Since the *analyst* may have an important contribution throughout the decision process (structuring the information, formulating the decision-problem and supplying information about the alternatives, etc.) it is required *that this person plays a neutral and objective role* [10]. Otherwise he can easily 'manipulate' the decision making process by influencing the decision-maker's final choice – consciously or not.

3.3.4 The basic formulation of a multi-criteria problem

A decision-maker needs to select from a set of feasible alternatives ***A*,** an alternative a, that complies best with his set of criteria ***C***. The levels of achievement in all criteria considered, over the set of alternatives can be measured, and these are $\boldsymbol{C_k}$, where $\boldsymbol{k}$ is the number of criteria considered, $\boldsymbol{k} \in [1,..n]$.

Then, the basic decision problem can be formulated as:

$$\underset{s.t.a\in A}{Max}\, F[C_1(a), C_2(a), ...C_n(a)] \qquad (3.1)$$

where **F** is decision-maker's unknown *preference function* [10].

The assumption that a *preference function* can be estimated is central to a multi-criteria analysis.

What this function actually does is to bring all criteria to a common measurement scale ('sum up') through the perception of a decision maker. Then, what remains is to analyse the different alternatives according to where they are situated on this scale.

It is important to remember that such a function does not (necessary) exist in the mind of a decision-maker. Moreover it is not necessary to explicitly define the function in order for a decision-maker to make decisions which are consistent with his underlying values [10]. Such a function can represent part of the subconscious preferences a decision-maker has regarding different criteria in the problem analysed. It is, in a way, a measure of the awareness and understanding gained by the decision-maker during the decision making process. This preference function is what conceptually distinguishes multi-criteria methods from other methods because it explicitly introduces the decision-maker's contribution into the analysis.

3.4 A Taxonomy Of Methods For Multi-Criteria Decision Making

So far, the basic concepts for multi-criteria decision making have been introduced. The remainder of this chapter presents an overview of the main methodologies and methods belonging to the MCDA discipline. The intention here is not to give detailed descriptions of different methodologies or mathematical formulations although some of the most important method concepts will be discussed. The purpose is rather to discuss and group methods according to characteristics that would matter to their selection for practical application.

The following classification is based on a number of books and research papers dedicated to different MCDA methods. For an integrated and at the same time fairly detailed description of methods, the reader may wish consult for instance [6] which contains the latest published MCDA survey.

Practitioners often claim that the problem of developing a classification scheme for MCDA is a multiple-criteria problem in itself [10]. Accordingly, in this thesis, the criteria used for classification have been derived from the author's experience – as a newcomer in this field - in searching for methods. This search had been primarily directed towards finding methods to be used in addition to energy modelling, in solving the energy planning problem. In this view, two main factors have been considered in the grouping multi-criteria methods:

- *the possibilities for modelling alternatives in a decision situation*, which relates more or less to the type of problem analysed

- *the interaction between the analyst and the decision-maker* in each method.

The success of decision-support in practice depends considerably on the method chosen. The method should conform to the opportunities for its application and the abilities of the individuals involved in the process, to use it. In general, the analyst is usually the person who has an overview and the practical experience with different methods while the decision-maker decides at the end of the process to apply and use the results produced by a specific method. In a decision situation, the use of a method will probably depend on the degree of involvement of these two parties in the initial phase of problem structuring, but also in subsequent steps in the decision support process. These are the underlying assumptions and considerations that drive the following discussion.

The chapter is further divided in two parts, as there are two main criteria for classification. The first part provides a short introduction to the most well known approaches to solving multi-criteria problems. This introduction includes: a general problem formulation, descriptions of various solution concepts and listings of the most commonly used methods in each approach.

The second classification is focussed on the use of different methods and the interaction between the analyst and the decision-maker. No new method concepts will be presented here. The methods already mentioned in the first part will be re-grouped in classes dictated by the second factor for classification.

Classification of methods according to the way in which alternatives are modelled

The set of alternatives in a decision problem may be *explicitly defined and discrete*, or *implicitly defined and continuous* as described in mathematical programs. Accordingly, methods and methodologies for multi-criteria decision making can be divided in two groups:

MADM (Multi-Attribute Decision Making) - methods dealing with problems in which *the set of alternatives is discrete* (and finite).

MODM (Multi-Objective Decision Making) - methods dealing with problems in which *the set of alternatives cannot be explicitly defined or given*.

3.4.1 MADM methods

3.4.1.1 General formulation of a multi-attribute problem

Methods for solving multi-attribute problems require the decision-maker needs to analyse a set of discrete, finite set of (predefined) alternatives $\boldsymbol{A} = \{\boldsymbol{A_1}, \boldsymbol{A_2}, \ldots \boldsymbol{A_m}\}$. The problem may be to choose, rank or sort alternatives according to a set of criteria $\boldsymbol{C} = \{\boldsymbol{C_1}, \boldsymbol{C_2}, \ldots \boldsymbol{C_n}\}$ that best reflects the decision-maker's concerns.

A multi-attribute problem can be easily represented in a matrix format, as illustrated in Figure 3.2. In this matrix, $\boldsymbol{a_{ij}}$ are attributes - levels of achievement in each criterion, corresponding to each alternative – which are *supposed to be known* (possible to estimate).

$$
\begin{array}{c|cccc|}
 & \multicolumn{4}{c}{\underline{\textbf{Criteria}}} \\
 & \mathbf{C_1} & \mathbf{C_2} & & \mathbf{C_m} \\
\mathbf{A_1} & a_{11} & a_{12} & \cdots & a_{1n} \\
\mathbf{A_2} & a_{21} & a_{22} & \cdots & a_{2n} \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
\mathbf{A_m} & a_{m1} & a_{m2} & \cdots & a_{mn}
\end{array}
$$

Alternatives

Figure 3.2 Matrix representation of a MADM problem

In the case of small problems, this matrix can be also translated into a graphical representation. For example, consider a two-criterion problem, where four alternatives must be evaluated according to two measurable (minimizing in this case) criteria – for example, cost and emissions. This problem can be represented graphically as shown in Figure 3.3.

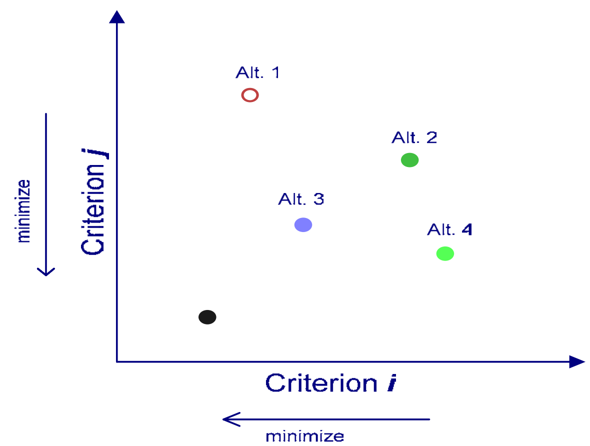

Figure 3.3 Graphical representation of a MADM problem

There are several steps in solving MADM problems. First, the idea is to *reduce the set of alternatives* to the efficient ones. This task consists in eliminating *dominated alternatives* by checking how alternatives perform simultaneously in different criteria. In the example presented above the objective is to minimize in both criteria. The point closest to the origin could represent the best, *ideal alternative*. In practical applications such alternatives do not exist but an ideal point may help in classifying the alternatives available.

An alternative is *dominated* if another alternative exists (in the same set), which is at least as good in all criteria and strictly better in one. For example in Figure 3.3 *alternative 2* is dominated by *alternative 3*.

There might be still alternatives left to analyse after the dominated ones are identified. These are the *efficient* alternatives (called also non-inferior or Pareto-optimal) which are not dominated by any other feasible alternative. In this example, *alternatives* 1, *3* and *4* are efficient. Note that at this point the differentiation of alternatives is independent of the decision-maker's preferences.

The second step in solving multi-attribute problems is when the decision maker has to evaluate and make further selections from the set of efficient alternatives. In large, complex decision problems, the selection can be facilitated by some sort of modelling or quantification of the decision-maker's values and preferences regarding the criteria that are specific to the decision-problem. There are several methodological concepts for solving multi-attribute problems or modelling decision-maker's contribution. Two methods, commonly used in practice, the *trade-off analysis* and the *MAVT* (multi-attribute value theory), will be discussed here.

3.4.1.2 Different solution concepts for multi-attribute decision making

a) Trade-off analysis

Trade-off analysis is a simple, straightforward method to help decision-makers to analyse the set of efficient alternatives.

An efficient alternative is not better than other efficient alternatives: when choosing one of them the decision-maker will gain in one criterion but in the same time will lose in another one. For instance, *alternative 3* is better than *alternative 4* in criterion ***i*** but worse in criterion ***j*** and vice versa. If the decision maker is mostly concerned with alternatives that perform well in criterion ***i,*** then he will choose alternative *3* (or vice versa).

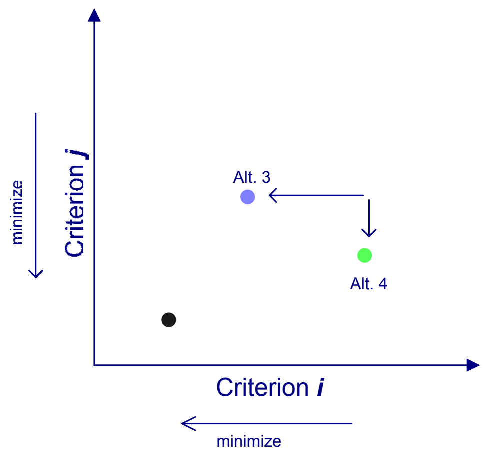

Figure 3.4 Making trade-offs

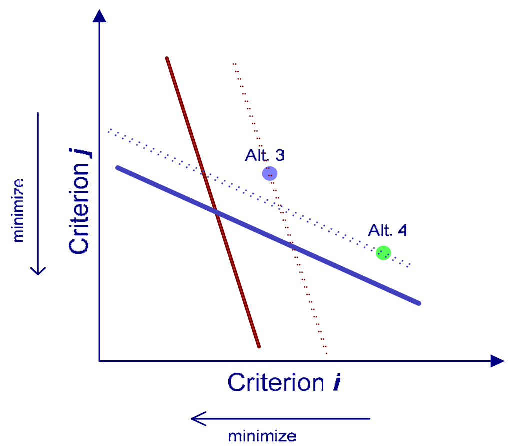

Figure 3.5 Representing trade-offs

Making a trade-off means deciding which of the criteria is preferred and, in essence, how much the differences in attribute levels (when moving from one efficient solution to another) matter for the decision-maker. If the decision-maker's preferences are constant in a given problem setting, then the trade-off can be represented linearly as shown in Figure 3.5 or mathematically through a formula: $f(C_i, C_j) = C_i + \alpha\, C_j$.

Trade-off curves are also called *indifference curves*, meaning that the decision-maker would be indifferent to any alternative that performs accordingly. Such trade-off functions, once determined, can theoretically be used to select between any alternatives judged in the decision space defined by the two criteria. For instance, if in a given problem context a decision-maker can specify a constant trade-off between two criteria (the red or the blue lines in Figure 3.5) then the preferred alternative(s) will be the ones that first meet the indifference curve, i.e. the horizontal translation of the trade-off indifference curve (in this example it is assumed that the marginal rate of substitution depends on criterion C_j and not on C_i). Thus, *alternative 3* will be chosen given the 'red' trade-off, while *alternative 4* will be chosen given the 'blue' trade-off.

Trade-off functions are not necessarily linear, and this happens when the trade-offs between two criteria are not constant within specific intervals of variations of attributes. For instance, a decision-maker may be willing to trade less and less for an increase in a criterion as the value in that criterion increases.

Trade-off curves have long been used to aid in the understanding of the environmental dimensions of energy choices. However, a typical multi-criteria problem in this field may have more than two attributes for which trade-offs may be difficult to establish in a relevant way. For example, assessing all pairwise comparisons in graphical form may be impossible when there are more than three or four attributes. Many applications look at costs versus other attributes [11].

Moreover, the tradeoffs can be applied (graphically) when criteria can be measured in quantitative terms, which is not necessarily the case in all energy system related decisions. Thus, the trade-off method may not be suitable for complex analyses characterized by more than two criteria, which may not be well defined and measured.

b) Multi-attribute value theory - MAVT

Compared to the trade-off analysis, multi-attribute value theory is a more advanced approach. This approach assumes that it is possible to construct a means of associating a real number with each alternative in order to produce a preference order for the alternatives, consistent with the decision maker's value judgements [2]. In other words, each alternative ***A*** has value ***V(A)*** for the decision-maker, and this value can be expressed numerically.

In principle, values measure preferences when taking all criteria into account. Then, based on these values alternatives can be differentiated. For example, if alternative A_1 is preferred to A_2 ($A_1 \succ A_2$) then $V(A_1) > V(A_2)$. Additionally, when the decision-maker is indifferent to the difference between alternative A_1 and A_2, ($A_1 \sim A_2$) then $V(A_1) = V(A_2)$. The existence of such values stems from the following assumptions regarding the decision maker's preferences:

- *Preferences are complete*: for any pair of alternatives either one is strictly preferred to the other or there is indifference to the choice of either of them
- *Preferences and indifferences are intransitive*: for any three alternatives A_1, A_2, A_3 if $A_1 \succ A_2$ (or $A_1 \sim A_2$) and $A_2 \succ A_3$ (or $A_2 \sim A_3$) then $A_1 \succ A_3$ (or $A_1 \sim A_3$).

Value functions are in particular appealing for quantitatively oriented managers or management scientists because the functions give a feeling of objectivity to the decision-making process and certainly help to focus the decision process on those aspects that matter. In principle, once determined, value functions automatically lead to the optimal alternative.

Important theoretical and practical issues for the assessment of value functions will be briefly outlined further. The discussion here is aimed to explaining and revealing common practices in constructing value functions/preference aggregation, without going too much into details.

Constructing value-functions

A value function can be constructed by using different procedures/methods. All these methods seek in one way or another, to synthesize preference information reflecting:

- The values a decision-maker would assign to the performances of each alternative in each of the criteria considered, or *intra-criterion evaluations.*
- The relative importance of criteria for the decision-maker, or *inter-criteria evaluations.*

The first step in traditional value function methods is *the assessment of the 'marginal' (or 'partial') value functions*, $v_k(a)$ or scores. A partial value function can be estimated for each criterion k and it measures, theoretically, the relative importance a decision-maker assigns to different performance levels (attributes) in that specific criterion (a_{ik}).

The partial value function can be defined in the same way as a value function, i.e. in terms of preservation of preference ordering. Such a function 'translates' each of the criteria analysed, measured on its own scale, into value scales (usually normalized). A partial value function may be linear or not, as shown in Figure 3.6:

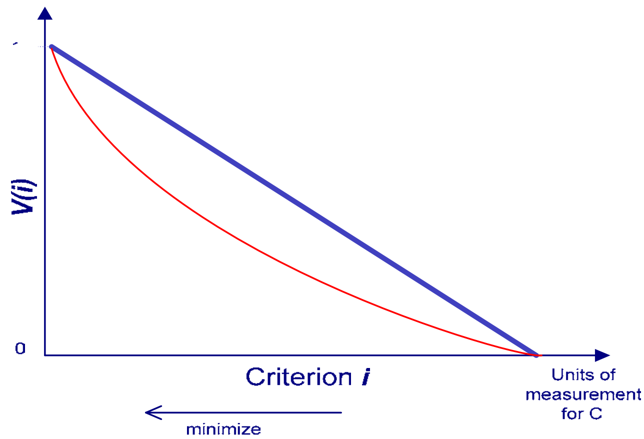

Figure 3.6 Partial value functions

The shape of the partial value function should reflect the way a decision-maker thinks in terms of an attribute. Theoretically, the accuracy of partial value functions estimations improves considerably if the decision problem is well structured, i.e. if the criteria are clearly represented and measured to reflect, incite and trigger the right thinking strategy 'inside' the decision-maker [2]. The usual procedure for estimating the shape of a partial value function is to first check if certain assumptions are valid in a given problem setting. This is done through a preliminary questionnaire that emphasises essential characteristics of the decision-maker's values, such as:

- If the partial value function is monotonically increasing or decreasing against the 'natural' scale, i.e. if the highest value of the attribute is preferred against lower levels or vice-versa
- If the partial value function is non-monotonic, i.e. an intermediate point on the scale defines the most preferred or least preferred point.

After verifying these properties, the analyst can assume a certain shape for the partial value function. A linear representation is commonly used in practical applications It has been demonstrated that the linearity assumption is usually valid in well-structured decision problems. However, experimental simulations cited in [2] warn against the over-simplification of the problem by the inappropriate use of linear value functions. It has been shown that the results of a multi-criteria analysis may be very sensitive to such assumptions, thus leading to bad recommendations.

Practices for deriving partial value functions differ in the way criteria are represented and measured. Belton and Stewart [2] give detailed methodological explanations of different approaches. They distinguish between *direct assessment methods* which first assume certain characteristics of the value function over a measurable criteria, as discussed above, and *indirect methods* that require construction of measurement scales when 'natural' measurement scales for criteria do not exist or can be given only qualitatively.

The second step in building value models consists of the assessment of *the relative importance of different criteria* considered in the decision process. When multiple criteria are considered in decision making, not all of them are equally preferred, judged in the same way or *have the same weights*. As is true for partial value functions, theoretically, these weights w_k, corresponding to each criterion, C_k ($k \in [1..n]$) can be estimated through a new questionnaire. The purpose with this questionnaire is establishing an order of criteria: in terms of importance or indifference (equal preference). Ideally, the decision-maker should be also able to characterise his preferences, i.e. how much more (and why) he prefers one criterion than another.

Many methods for weight elicitation focus on *swing weights*, i.e. weights that 'compensate' values against criteria. Swing weights can be determined only when the scales for measurement in each criterion are clearly defined. On these scales, a worst and a best value in each criterion can be identified and the decision maker is asked to assess which swing (interval step) from the lowest levels (usually) gives the greatest increase in value. For instance, if a swing from worst to best on the highest rated criterion is assigned a value of 100, what would be the value of a swing from worst to best in the second ranked criterion? In practical applications, swing values can be derived using any two reference points on a criterion scale. Thus, instead of the worst and the best levels, 'neutral' and 'good' reference points can be defined if the decision-maker consider that this helps in comparisons.

In practical applications it is important to know that *weights are dependent on the scales used for scoring* as well as on the *intrinsic importance of criteria* (swing weights capture these issues very well). For instance, if an important criterion does not differentiate much between alternatives, i.e. if the minimum and maximum points on the value scale correspond to similar achievement levels, then that criterion might be ranked quite low [2].

Another issue to be emphasized is that in practical applications, where decision problems are defined over hierarchies of criteria, the determination of weights can become difficult [12, 13]. In these situations, the simplest way out would be to consider only the criteria in last level in the tree for the weights-revealing questionnaires. However many methods have been developed for dealing with hierarchical value tree analysis [13].

Preference aggregation in MAVT

So far, the main steps in the construction of multi-attribute value functions have been discussed. The purpose in determining the *scores* (partial values) and *weights* is to contribute to good approximations of the overall value functions ***V(A)***, according to which the alternatives can be evaluated.

Overall value functions can be constructed by some sort of aggregation of scores and weights. In practical applications, the additive aggregation is mostly used. Thus, supposing that for any alternative $\boldsymbol{A_i}$ ($i \in [1..m]$)and criterion $C_{\boldsymbol{k}}$ ($k \in [1..n]$), the scores $\boldsymbol{v_k(a_{ik})}$, and the weights $\boldsymbol{w_k}$ can be assessed, then the overall value function can be written as:

$$V(A_i) = \sum_{k=1}^{n} w_k v_k(a_{ik}) \tag{3.2}$$

This additive aggregation form is widely used in practice because it is easily explained and understood by decision-makers from a wide variety of backgrounds [2]. The use of additive value functions is, however, restricted by several conditions which must be verified before every application.

The first requirement is *that criteria should be preferentially independent*. This means that the decision-maker is able to compare alternatives in terms of a specific set of criteria, without thinking about how these alternatives would perform with respect to the rest of criteria. Moreover, theoretically, the existence of an additive representation is also implied by three main properties: the corresponding *trade-offs,* the *interval scale property* and the property that *weights* can be interpreted as *scaling constants for values*. For a detailed discussion and illustrative examples on these issues, the reader can consult [2] or [14].

In cases when the additivity conditions are not valid, the common advice is to first go back to the problem identification and structuring process [2]. The alternative would be to use other forms of aggregation of preferences [15], as for instance multiplicative value functions:

$$V(a) = \prod_{k=1}^{n} [v_k(a)]^{w_k} \tag{3.3}$$

The details for using multiplicative aggregation are thoroughly described in [14], in connection however with utility theory. While value theory can be applied in conditions of certainty, utility theory is its equivalent in uncertainty conditions. This theory will be briefly discussed in the next chapter.

To conclude this discussion, Figure 3.7 shows an illustration of the main procedural steps in modelling multi-attribute value functions. For instance, suppose that a decision-maker has to analyse and choose between a finite and clearly defined set of efficient alternatives that must be compared in terms of several, relevant criteria. This choice depends on the underlying values the decision maker has in this decision situation and in principle, the alternative with the highest value should be chosen.

The theory provides us with the means of constructing models for the decision-maker's preference values. The main components in a value model are the *scores* and the *weights*. The *scores* reflect the preferences a decision-maker has for different achievement levels under each criterion considered (achievements in different alternatives), while the *weights* reflect the preferences for the different criteria. The *scores* result from comparisons of attribute levels in each criterion while *weights* result from inter-criteria comparisons.

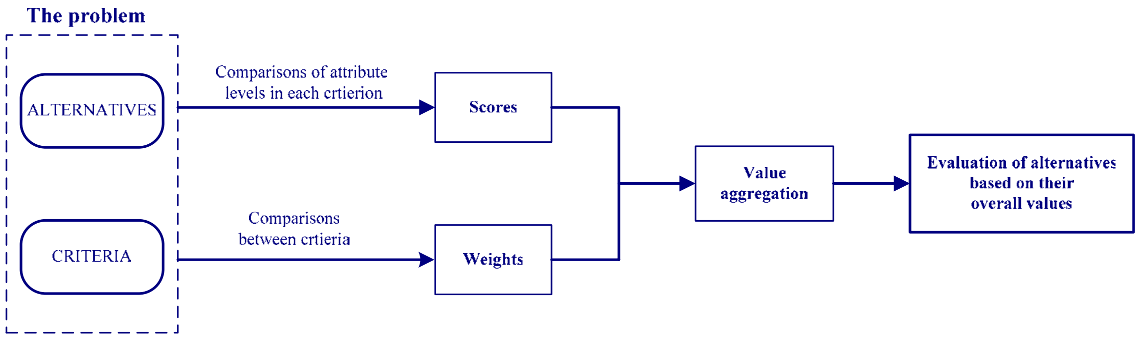

Figure 3.7 The steps in assessing value functions

When aggregating the *scores* and the *weights* (additive, multiplicative or any other form of aggregation), overall values - for each of the alternatives considered - are obtained, and the alternative with the highest value is recommended.

3.4.1.3 Methods for multi-attribute decision making

The main concepts from the trade-off analysis and the multi-attribute value theory are used by the largest part of methods and techniques developed to help with solving multi-attribute problems. These methods can be organized into three classes, according to the nature of information that can be obtained and analysed in a decision-making process.

The **first class** contains those *methods that assume that the decision maker is able to specify precise (complete) answers to a wide range of preference elicitation questions*. Examples are: *methods for direct trade-offs*, *value functions (SMART [16], SWING, etc.)*, *utility functions and the AHP (Analytical Hierarchy Process) method*.

The AHP method is not usually included in the group of value function methods group. This issue has been openly debated, for example in [17], [18]. AHP differs procedurally from the basic value function method by the fact that it accepts linguistic labels (*equally preferred*, *strongly preferred* etc.) to express judgements about relative preferences. Then these linguistic scales are 'translated' into numerical ratio scales (and not interval-scales as is done in MAVT), which are used for the further ranking alternatives. In [2] the debate has been summarized around three main points of concern: *the interpretation of criteria weights* (the relationship between scores and criteria weighs – which is different than in MAVT); *the properties of the ratio scale of preferences* (for example the meaning of the pairwise comparisons and the numerical interpretation of the semantic scale); and *the rank reversal problems* (which may occur with the addition or deletion of alternatives). However, apart from this controversy, AHP seems to be widely applied in practice by itself and even in combination with many other decision support methodologies such as linear or integer programming, data envelopment analysis, genetic algorithms or neural networks [19]. The method is appealing because it is transparent, intuitive and easy to use, *provided that the decision-maker understands the relevance of the questions posed*.

The second class of methods is comprised of those that allow for more *imprecise representations of criteria and the decision-maker's preferences*.

Regarding the way *criteria* can be emphasized, decision problems can be: *ill-structured* problems (where criteria are represented both in qualitative and quantitative terms) and *unstructured problems* (where criteria are given only qualitative descriptions).

Value function methods (and the AHP) [2] can be applied to ill-structured problems, with some modifications in the preference elicitation questions: the decision makers will be asked to compare alternatives on both qualitatively and quantitatively defined criteria.

For dealing with unstructured problems, *Verbal Decision Analysis* was proposed [20]. This approach is based on valid mathematical principles, and takes into account peculiarities of the human information processing system. The problems of this type are unique in the sense that each problem is new to the decision-maker and have characteristics not previously experienced (such as problems for policy-making and strategy planning in different fields). In these problems, the evaluation of alternatives against qualitative criteria can be obtained only from experts (the final decision-makers) through their subjective preferences.

In the second class are methods that deal with imprecise (incomplete) *representation of decision-maker's preferences*. The reality is that in many decision situations, complete preference information is closely to impossible to obtain, and even if possible the costs to obtain it would be very high. Thus methods were developed to allow decision-makers to express preference specifications in which they feel most confident with.

In principle, *all MADM methods that incorporate interactive procedures* actually deal with imprecise preferences (once the decision maker decide to revise his statements), even though these preferences are taken into consideration as numerical, fixed values.

Another set of approaches that deal with incomplete preference information are those included under the umbrella of *preference programming*. These approaches were first developed to accommodate incomplete information in hierarchical weighting methods such as value tree or AHP [21]. The principle underlying preference programming is, again, to find a value function, or a family of value functions which is consistent with the incomplete preference information. Incomplete information can be expressed as: ordinal statements, semantic categorizations or interval statements. With preference programming, preferences can be synthesised in terms of value intervals for the alternatives, weight intervals for the attributes and dominance structures and decision rules for the comparison of alternatives (if the resulting intervals do not allow the determination of the best alternative). These results are obtained as solutions to LP problems where the relevant objective functions are solved subject to the constraints imposed by the decision-maker's judgements.

Principles derived from preference programming form the basis for implementation of a range of decision-support software such as: *Web-HIPRE*, *RICH*, *Smart Swaps*, *WINPRE*, *PRIME-Decisions* [22], etc. These decision support tools allow for interactive preference elicitation procedures that usually provide more detailed results as the decision-maker gradually approaches a more specific preference description.

Here the *MACBETH* approach (Measuring Attractiveness by a Categorical Based Evaluation Technique) must be also mentioned. The method requires *only qualitative judgements* about differences of values to help an individual or a group quantify the relative attractiveness of options. The *MACBETH* software which was developed using this approach, has been reported to be successful in many public and private multi-criteria applications [23].

The third class of methods is comprised of *outranking methods (approaches)*. Unlike the methods listed above, *outranking approaches are not based on an underlying value function*. The output of an outranking analysis is not a value for each alternative but an outranking relation on the set of alternatives [2]. These methods are applicable to discrete choice problems; thus, they focus on pairwise comparisons of alternatives but require less precise inputs in terms of the description criteria or preferences. For instance, an alternative ***A*** is said to outrank another alternative ***B*** if, taking into account al available information regarding the problem and the decision-maker's preferences, there is a strong enough argument to support a conclusion that ***A*** is at least as good as ***B***, and no strong argument to prove the contrary. The comparisons are made in terms of indifference thresholds, weak preference, veto thresholds, incomparability situations and other complementary concepts (concordance and discordance).

Outranking methods have been developed by scientists belonging to what is called the 'European/French school'. The following groups of outranging methods are mostly used in practical applications: the *ELECTRE* family (*ELECTRE I, IS, II, III, IV, TRI*, etc) and the *PROMETHEE* and *GAIA* methods, etc. Other outranking methods exist (some derived from these main groups), with a detailed description provided in [24].

The implementation of *ELECTRE* and *PROMETHEE* methods in real world decision problems is achieved through different software packages: ELECTRE IS, ELECTRE III-IV, ELECTRE TRI, IRIS, SFR, and the DECISION LAB software (for *PROMETHEE* and *GAIA)*

Because outranking methods are not based on restrictive assumptions as is true for the value-based approaches, they may capture more faithfully the way in which decision-makers think. However, a major drawback seems to be due to the many non-intuitive inputs required, such as: concordance and discordance thresholds; indifference, preference and veto thresholds; and the preference functions of PROMETHEE. Also, the algorithms themselves tend to be complicated and time consuming for decision-makers who are inexperienced with the approach to fully understand and use. Thus, outranking methods seem to be more appropriate for 'backroom' analyses by analysts and/or by support staff for the final decision-makers [2].

3.4.2 MODM methods

3.4.2.1 General formulation of a multi-objective problem

In multi-objective decision problems, alternatives are not explicitly known in advance. These problems reflect situations where practically a nearly infinite number of options are feasible. Mathematical programming is used to model this type of problems and solutions can be determined through a set of mathematically defined constraints. The scope for modelling here is to seek for solutions rather than extracting and interpreting the decision-makers preferences [25].

A multi-objective problem can be formulated as following:(3.4)

$$\max \boldsymbol{F(x)}$$

$$st.: \boldsymbol{G(x)} = 0 \qquad \boldsymbol{H(x)} \le 0 \qquad \boldsymbol{x} \ge 0$$

where:

$\boldsymbol{x}$	vector of decision variables (may include integer or binary variables)
$\boldsymbol{F(x)}$	vector of objective functions
$\boldsymbol{G(x)}$	set of equality constraints
$\boldsymbol{H(x)}$	set of inequality constraints

The concept of solution in multi-objective problems will be illustrated through an example[1]. As in the MADM case, consider a simple problem with two objectives to minimize, $\boldsymbol{F_1}$ and $\boldsymbol{F_2}$ and five constraints, as defined and represented graphically in Figure 3.8. The coloured area in this figure represents the space (the set) of *feasible solutions*, i.e. solutions (pairs of decision variables) that satisfy all constraints in this problem.

The problem can be further translated into the attribute (or criteria) space (Figure 3.9) to show how alternative solutions perform in terms of the two objectives chosen. In fact, the MODM problem representation in Figure 3.9 is equivalent with the MADM representation Figure 3.3.

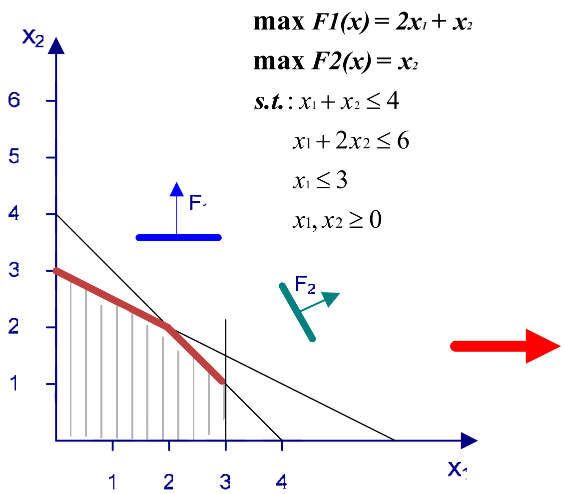

Figure 3.8 Decision space

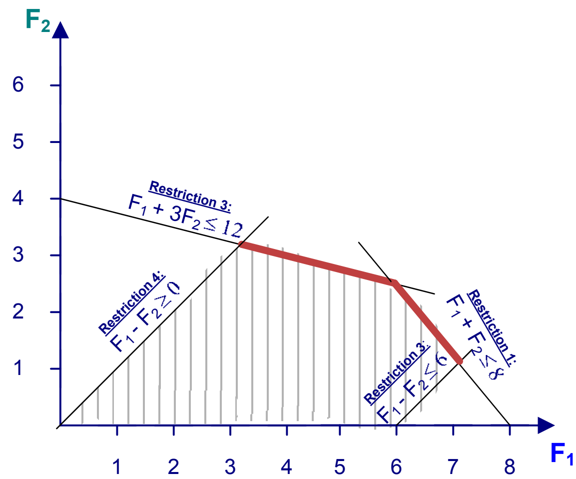

Figure 3.9 Attribute space

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[1] This example was presented by Prof. Manuel Matos, from INESC-Porto in the '*Tutorial on the application of risk analysis and multicriteria models in energy planning*', Trondheim, 6-9 October 2003

One can clearly observe how the space of solutions is continuous (and infinite) in the MODM case, as compared to the MADM case.

As with MADM, the next step is to select the *efficient solutions (non-dominated solutions, Pareto-optimal solutions)* belonging to this set. This set of efficient solutions for the MODM problem is found at the frontier of the feasible set (the red lines in Figures 3.8 and 3.9), since both objectives must be maximised.

There are different *mathematical procedures for solving multi-objective problems* [26]. Briefly, current *practices* can be divided into *exact* and *heuristics*. The Simplex algorithm is for example an *exact procedure*. Then, heuristic procedures are usually used in large combinatorial problems (large mix-integer problems), where the conventional (*exact*) solution algorithms do not lead to a final solution. In essence, a *heuristic search procedure* associates heuristics with a search algorithm for exploring the space of feasible solutions. *Genetic Algorithms*, *Tabu Search*, and *Simulated Annealing* are examples of heuristics procedures for solving large combinatorial problems. A large number of optimization packages and decision support software have been developed to allow for different practices [27].

Depending on the nature (and the size) of the problem analysed, different *methods for multi-objective decision making* may require specific procedures for finding the efficient solution. The purpose of this chapter is not to go into the details of mathematical optimization but to give an idea of what kind of resources MODM requires in practical applications.
MODM *methods* differ with the way in which objectives are assessed and when and how the intervention of a decision-maker is needed. The classification continues further with four main groups of MODM methods: aggregation methods, generation methods, interactive methods and goal programming.

3.4.2.2 Different method concepts for multi-objective decision making

a) Aggregation methods
The basic idea in aggregation methods is to transform the multi-objective problem into a single-objective problem for which one has already good approaches for solving it. This 'transformation' is equivalent to summing up (converting) all objectives into one.

Value functions or weight parameters can be used for aggregation. These *values or weights are inputs* into the optimization problem. Thus, here, the value elicitation procedure and the optimization must be carried out separately. When searching for values to be employed in multi-objective applications it is preferable to have knowledge about possible intervals of variation in the different objective functions. This will guarantee that the preference values will refer to the actual problem analysed, although some theories suggest that general values can also be employed.

The following figure summarizes the procedural steps in aggregation methods:

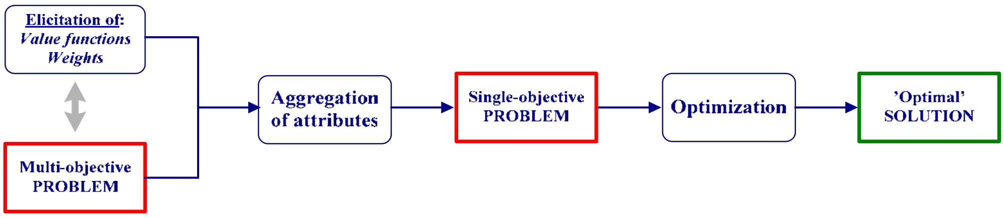

Figure 3.10 The steps in aggregation methods

The single-objective optimization problems obtained though aggregation are solved and the resulting solution is ‘optimal’ in the sense that it complies with the decision-maker’s values (as expressed at the beginning of the process) and with the constraints in the optimization problem.

b) Generation methods

The idea with these methods is to first generate a list of efficient alternatives and then let the decision-maker to select among them. Such a list can be very large and a decision-maker might not be able to make a selection directly. In those situations, a value model may be constructed separately and then used to order the alternatives. The procedure here can be similar to the one described above, only that this time, the decision-maker analyses the *consequences* obtained through optimization.

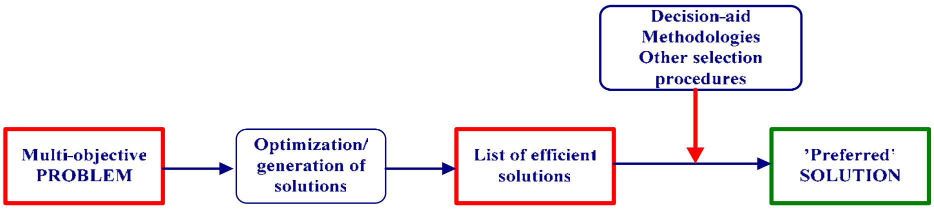

Figure 3.11 The steps in generation methods

There are three main procedures for generating the efficient set of solutions: *multi-objective Simplex algorithm*, *parametric variation* and *constrained optimization*.

Multi-objective Simplex can be used in a procedure described as in Figure 3.11. The other two generation methods are characterized by different procedural steps.

Parametric variation is based on finding an optimal solution for an auxiliary problem that is at the same time the optimal solution for the original problem. The objective function of the auxiliary problem is constructed as a parametrical sum of the initial objective functions:

$$\max F(\mathbf{x}) = \sum_{k=1}^{n} \lambda_k F_k(\mathbf{x}) \tag{3.5}$$

The parameters used are only instrumental and they are varied so that a set of possible solutions is generated. The decision maker must analyse and select solutions obtained in this way, which in fact are ‘optimal’ given the selected parameter values. Once a choice is made, the parameters that contribute to that particular solution can be validated as the ‘true’ decision-maker’s values.

Another approach for generating efficient alternatives is the *constraint approach.* Here the idea is to optimize in one criterion while constraining the remaining ones. Thus, in this approach, all objectives functions exept one, are transformed into constraints by imposing minimum requirements on their value. The problem becomes then to solve a set of ordinary, single criterion optimization problems of the form:

$$\begin{aligned} &\max_F \boldsymbol{F_1(x)} \\ st.: &F_2(x) \geq \varepsilon_2 \\ &F_3(x) \geq \varepsilon_3 \\ &\ldots\ldots\ldots \\ &F_n(x) \geq \varepsilon_n \end{aligned} \tag{3.6}$$

where $\varepsilon_2 \ldots \varepsilon_n$ are minimum requirements imposed on the *n-1* criteria. The decision-maker then must analyse the alternative solutions obtained through repetitive optimizations (when varying the limits ε_i) and to choose one (or stop the search) that best reflects his requirements.

This method is has been used long before MCDM was crystallized as discipline [10]. OR practitioners called it 'soft' optimization. The technique was usually used to relax the solution to a traditional 'hard' optimization problem, based on the principle that in order to be satisfactory an alternative does not need to be the best but to fulfil certain minimum requirements. This approach has been successfully used when 'traditional' mathematical tools or models are already available for decision support (such as in energy planning). However, an important observation is that although the procedure is intuitive and easy to use, it is very difficult to set limits on different attributes.

c) Interactive methods

Interactive methods allow the decision-maker to intervene at different stages in the process of searching for solutions. The idea is that if the decision-maker is not satisfied with the solution (s) presented to him, he will change some of the assumptions that lead to that solution, i.e. he will influence the process of generating solutions.

For instance, in an interactive procedure with *parametric variation*, the decision-maker will be allowed to change the parameters by himself, and then check how the final solution (s) has changed (illustrated by the first dashed line in the Figure 3.12).

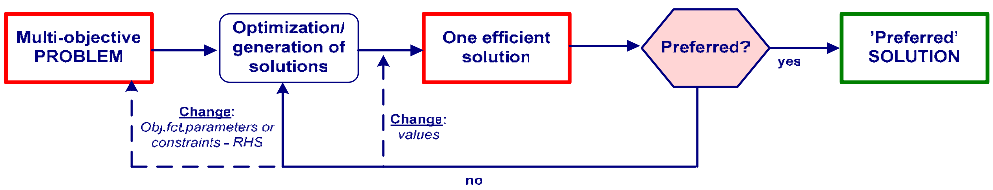

Figure 3.12 The steps in interactive methods

Similarly, when thinking in terms of *constrained optimization*, if a first initial efficient solution is not preferred by the decision-maker, then he should decide which criteria he wants to improve and which criteria he accepts to worsen and the direction of change (how much to improve or worsen). Alternatively, the decision-maker will also be allowed to change his preferences (values), in a procedure that assumes analysis of consequences (the right dashed line in the Figure 3.12).

Interactive approaches are natural ways to solve multiple criteria decision problems, because the decision-maker is always an essential part of the solution; he is learns step by step about the decisions he needs to address.

In practical applications, attention should be given to the following factors, which can affect the success of the interactive methods [27]:

- How preference information is gathered: if the information gathering process is complicated, the decision-maker might be unable to give reliable information and consequently, the algorithm will interpret this information erroneously.
- How information is used to generate new alternatives for the decision-maker to evaluate: unrealistic interpretation of the decision-makers preferences will lead to solutions that are not consistent with his wishes.
- How the system generates alternatives: the decision-maker should have the ability to evaluate all efficient alternatives, not just a part.

There is anyway a risk with applying interactive methods: the decision-maker may loose an overview of the problem particularly when more than two objectives have to be considered (‘one might not see the forest if one focuses on the trees!’).

Many interactive methods have been proposed for solving multi-objective problems. Different classifications and evaluations of these methods have been published –see for example [28]. Some of the classic interactive methods are: *STEM (STRANGE)*, *Zionts-Wallenius*, *Interval Criterion Weights*, *Pareto race*, *Trimap*.

d) Goal programming
Goal programming is a popular method, well established within the OR discipline. This method can be described in terms of the target levels to be achieved rather than quantities to be maximized or minimized.

Decision-makers may express goals ranging from idealistic attribute levels towards which to strive, to non-negotiable bottom lines that allow for no further concession. Obviously, in multi-objective problems ideals cannot be achieved. *Goal programming models can help the users to achieve their goals as nearly as possible, by minimizing a weighted sum of deficiencies (or deviations from the goals).*

There are different procedures (or norms) for implementing goal programming [2]. The *Archimedean goal programming* is a procedure that is mathematically equivalent to the use of an additive value function built on decision-maker’s preferences regarding the levels of deviation in different objectives.

For problems concerning a large number of goals, *preemptive goal programming* is normally used [29]. It is based on a classification of goals into priority classes, where each class may consist of one or more goals. Following this prioritization, the minimization of the weighted sum of deviations is restricted initially to the first priority class only. Once this solution is obtained, deviations from goals in the second priority class are minimized subject to the additional constraint that the weighted sum of deviations from the first priority class should not exceed that obtained in the first step. The process is then continued with each priority class in turn.

Although the *Archimedean* and *preemptive goal programming* are usually presented in most management science books, other forms of goal programming exist such as *compromise programming*, *reference point methods* and *interactive methods*. Initially, goal programming was formulated in the context of linear programming problems but the same principles can be applied in nonlinear, non-convex and discrete problems [2].

Goal programming procedures have been proved to be valuable tools for individual decision-makers. However, these procedures (especially the interactive ones) might be difficult to use in complex decision problems, that involve several decision-makers. This is because in such situations it might be difficult to keep track of different goals and dissatisfaction levels for each of the participants, in order to be able to document and justify the final result.

Classification of methods according to the interaction between the analyst and the decision-maker

As discussed previously most multi-criteria applications involve one analyst (or more) and one decision maker (or more). The decision-maker (DM) is the one who is in charge of the decision and who needs support to solve it, while the analyst (AN) is the one who can help the decision-maker with his problem. When the analyst proposes a method to be used in the decision-making process, he should be aware of how and when in the decision-aid process the intervention of the decision-maker is needed. This intervention as well as the actual interaction between the decision-maker and the analyst, are crucial issues that may lead to the success or to the failure of the decision aid process. The following classification is based on when (and how) in the decision aid process the contribution of the decision-maker is allowed and prescribed with different methods.

The basic design issues when organising the interaction between the analyst and the decision-maker are [10]:

1) The timing in the decision aid process, when the set of alternatives and the preferences of the decision-makers are investigated. Two possibilities exist:

   a. a *phased* arrangement, when the investigation of alternatives and the investigation of preferences are performed in two different phases, or
   b. an *iterative* approach, consisting of a sequence of alternating investigations: constantly examine and modify the set of alternatives that are relevant for a given set of preferences or vice versa.

2) Who directs the investigation, accumulates the information and makes the final choice:

   a. the decision-maker, or
   b. the analyst.

Based on these considerations, four overall organization modes of the DM-AN interaction in multiple criteria applications can be summarized as shown in figure 3.13. These organization modes will be used as criteria for a new classification scheme. No new methods will be introduced further, but the ones already discussed will be re-grouped based on the above mentioned principles.

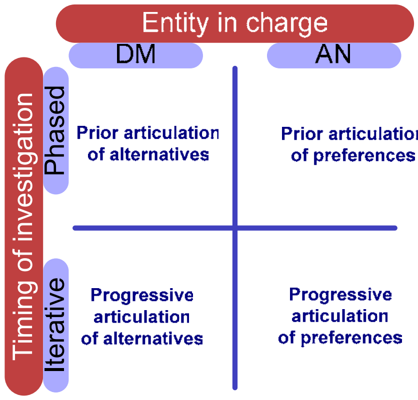

Figure 3.13 Organization of the interaction between AN and DM, based on [10]

3.4.3 Methods allowing for prior articulation of alternatives

Methods for *prior articulation of alternatives* are governed by the decision-maker and consist of two main steps:

1. The set of efficient alternatives is first identified by the analyst and then submitted to the decision maker for analysis
2. The decision-maker analyses the proposed alternatives, clarifies his preferences and makes a decision.

These procedures have evolved from the traditional, single objective, economic (cost/profit) decision problems. In fact, this style of structuring of the decision support process is still encountered in hierarchical organizations, where routine tasks are handled by rules, programmes and traditions, or in the context of public planning where advisors (consultants) perform analyses for political decision-makers.

Methods allowing for prior articulation of alternatives do not require explicit preference information from the decision maker. In fact, these methods do not describe precisely how the final selection of alternatives should be made.

The analyst has an important role here in being the one who first validates and reduces the possible number of alternatives to a concrete, promising set. It is thus important that the analyst master the method used to produce this final set of solutions so that the decision-maker will not miss important opportunities.

Methods in this group are mainly *multi-objective methods* such as: ***generation methods*** (*constrained optimization*, *parametric variation*, etc) and ***goal programming***.

3.4.4 Methods allowing prior articulation of preferences

The application of these methods requires the following steps:

1. First, the construction of a model of the decision-makers preferences by studying his behaviour in previous contexts, by interrogating him in relation to general choice contexts. This model should be based on a thorough investigation of the set of relevant criteria and alternatives in a specific problem context.
2. The 'application' of the preference model to the set of feasible alternatives in an attempt to select the most preferred alternative or to at least reduce the set of alternatives from which the final selection will be made by the decision-maker.

In these methods the preference model represents a surrogate decision-maker, the analyst is in charge with conducting the process, and the determination of a most preferred alternative is reduced to optimization. However, the methods entail demanding assumptions that must be met in practical applications:

- The decision-maker's preferences must be internally consistent and stable
- Preferences must be completely represented by a series of criteria / objectives
- The decision-maker must be able to perform a preference evaluation for any relevant set of criteria.

Prior articulation of preferences requires considerable time and effort from both the analyst and the decision-maker in the assessment of decision-maker's preferences. The process of preference investigation may be of greater value for the decision-maker (in terms of gaining insight and learning about his preferences) than its actual result i.e. the preference model.

In these procedures the decision-maker is involved only at the beginning of the decision-support process, while the final recommendation will depend only on the analyst and the optimization model used. For a successful application, both parties involved should be aware of this fact.

In practical applications, careful consideration has to be given to the recommendations that result from such procedures. This is because the preferences of a decision-maker might not be stable: they may change over time while he learns more about his underlying values and preferences, or while the initial assumptions about the problem change.

Methods belonging to this group are mostly *multi-attribute value methods*: ***trade-offs***, ***MAVT***, ***MAUT*** (which can be applied to both discrete or continuous sets of alternatives) and ***outranking methods*** [10].

3.4.5 Methods allowing for progressive articulation of alternatives

These methods prescribe several rounds of interaction between the decision-maker and the analyst. In each round, the decision-maker poses a question about the set of alternatives and the analyst provides an answer. Next, the decision-maker evaluates the answer and decides whether or not to stop the search. If the decision-maker feels comfortable with one of the alternatives identified so far he might choose to use that as a compromise solution.

Otherwise, he can either abandon this form of investigation or continue the search, in which case a new round of interaction is initiated.

The decision-maker does not need to clarify his preferences beforehand since real alternatives become successively available. Thus, whatever is known about alternatives can be used to clarify and reduce what needs to be known about preferences. Also, the analyst does not need to investigate the alternatives without guidance, as interesting search directions may be derived from the decision-maker's wishes.

The iterative procedures are directed by the decision-maker. He has great freedom in making a choice since he can form and change his wishes in whichever manner he likes. However, the analyst has a difficult task: he must answer to the decision-maker's questions and must be able to identify feasible and/or optimal alternatives. Depending upon the size of problem, this search for solutions may require innovation and creativity.

In theory, the methods belonging to this group are the *interactive versions of the prior articulation of alternatives approach* discussed above: ***interactive generation methods*** (the constraint method, the parametric variation method) and ***interactive goal programming***.

3.4.6 Methods allowing for progressive articulation of preferences

Methods in this group are also iterative and interactive. The analyst directs the search this time. In each round, he poses questions to the decision-maker about his preferences and the decision-maker answers. If the analyst has sufficient knowledge regarding the decision-makers' preferences, he makes a final recommendation in terms of which alternative(s) should be chosen. Otherwise, the questioning process continues until the preferences become clearer.

This group of methods can be easily described in comparison with to the previous ones.

First, as methods for *progressive articulation* of preferences, they are interactive and do not assume that the decision-maker has explicitly defined or unique preferences.

Second, *both* methods for *prior* and *progressive articulation of preferences* are founded on the implicit assumption that the decision-maker has internally consistent preferences. However, these methods have quite distinct goals: the *prior* approach presumes that consistent preferences pre-exist and seeks to make these preferences explicit, while the *progressive* approach seeks to develop the preferences during the decision-aid process. It has been often argued [10] that the latter procedure more realistically reflects the decision-maker's preferences because all demands and assumptions that need to be verified for mathematical value functions might not be consistent with what the decision-maker thinks.

In these procedures, the analyst has the easier task while the decision-maker has to do the difficult job of thinking and answering repeated preference elicitation rounds. There is a wide spectrum of procedures for organizing the interactive dialog for obtaining the decision-maker's preferences. These procedures differ in the computational duties of the analyst and in the type of information requested from the decision-maker. Usually, two main groups of procedures can be distinguished:

- The decision-maker is asked about his ***substitution wishes*** (how much is he willing to give up in one objective in order to improve another one).
- The decision-maker is asked to evaluate ***existing substitution possibilities*** (compare the relevant alternatives directly).

The procedures for incorporating ***substitution wishes*** are usually used in a *multi-objective context*, i.e. when the set of relevant alternatives is not explicitly given, but must be found through an extensive search of the feasible space. Practically, the information obtained gradually from decision makers is used to define search directions for standard non-linear programming algorithms.

The earliest progressive articulation of preferences procedure is the *Geoffrion-Dyer-Feinberg* (GDF) procedure, described also in [10]. In this procedure, the decision-maker can successively express his substitution wishes when confronted with different feasible alternatives. First a feasible alternative is presented to the decision maker (with the corresponding achievement levels in all criteria considered). The decision-maker is then asked to analyse the alternative and to declare if he accepts it or not. If not, he would need to specify which achievement levels he would definitely like to improve (and how much) and which of the other achievement levels he would be willing to worsen. Based on the decision-maker's answers, a new alternative will be identified in the feasible set and subsequently presented to the decision-maker for evaluation. The procedure stops when the decision-maker finally does not want to move away from a given proposal, either because it cannot be improved upon, or because he does not consider possible improvements worth the effort.

Another *procedure* proposed by *Zionts and Wallenius* [3], [10] is used when the decision-maker has to evaluate some ***existing substitution possibilities***. Here the term '*existing substitution possibilities'* generally means identifiable (but not optimal) trade-offs between objectives. The procedure aims at *generalising the value-function concept* in the sense that the components of the value model are not explicitly determined in advance (such as for prior articulation of preferences) but they are incorporated in a linear-optimization routine. The preference function is assumed to be linear such that the unknown aspects are the weights assigned to the different criteria. The decision-maker is required to evaluate substitution possibilities and the answers are used as constraints on the feasible set of weights. For example, the analyst presents a set of trade-offs to the decision-maker; asking him if he is willing to accept a combined changed in several criteria, with some criteria improving and some worsening. The answer can be in terms of *yes*, *no* or *indifferent*. Extensions to the *Zionts – Wallenius* procedure were later proposed by different researchers, among them Stewart and Korhonen et.al [3].

Although these procedures appear to be simple and efficient to implement, there is relatively little practical implementation reported in the literature [3]. The main inconvenience with these methods, from a practical point of view, is that the decision-maker might not be willing to pursue such a time and effort consuming processes. He cannot be expected to have the patience – or the ability to remain consistent – that would be necessary to conduct the in sophisticated dialogues regarding substitution wishes and possibilities. However, these procedures are supported by well established and approved mathematical algorithms.

3.5 CONCLUDING REMARKS

The scope of this chapter has been to offer an overview of the main concepts, methods and techniques in the MCDA discipline. The discussion can be summarised as follows:

1. MCDA techniques can be used for aiding decision making, by providing a sound theoretical background for:
   - Conducting detailed analyses of complex multi-criteria decision problems;
   - Identifying and structuring both the reality independent of the decision-maker as well as his way of thinking (preferences); and in essence
   - Helping decision-makers to 'justify' their decisions, through a better understanding of decision problems and of their own contribution to the solution.

3. MCDA methods can help in modelling decision-makers' contribution to the decision. With the purpose of understanding the possibilities for *preference modelling,* a classification scheme for MCDA methods has been proposed. The main criteria for classification were *how alternatives in a decision problem can be identified* and how different methods prescribe the *interaction between the analyst and the decision-maker*.

4. The classification presented in this chapter included a large variety of methods, procedure, methodologies or techniques for supporting multi-criteria decision-making. This review of methods has been undertaken with the purpose of showing how MCDA can be applied for aiding decision making. In particular, methods have been evaluated in the view of their integration with energy planning tools – in this case the eTRANSPORT model.

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Chapter 4 DEALING WITH UNCERTAINTY IN DECISION MAKING

4.1 UNCERTAINTY AND RISK IN DECISION MAKING

Uncertainty is a basic, structural feature of the environment in which energy planners must make decisions. The purpose of this chapter is to show how risk and uncertainty can be explicitly taken into account in *decision making*. The goal is to give an idea about which methods may be used in specific decision situations where uncertainty is an important factor. The discussion here covers more issues than the usual engineering approaches for dealing with uncertainty, because it is particularly focussed on the uncertainty that inherent in a *decision making* process.

The first part of this chapter presents a brief discussion of the basic concepts of uncertainty and risk and lists the main sources of uncertainty in decision making. The last and largest part of the chapter is dedicated to an overview of the techniques that can be used in modelling uncertainty.

4.1.1 Basic concepts

Decision situations have been conventionally divided into three categories: *certainty*, *uncertainty* and *risk* [1].

Certain is something that is unconditionally known. At the other extreme, *uncertain* is something that is not definitely known or decided, subject to doubt or question. At a fundamental level, *uncertainty* relates to a state of the human mind, i.e. the lack of complete knowledge about something [2].

Strictly related to the concept of *uncertainty* is the concept of *risk*. *Risk* is usually defined in relation to the decision environment as '*a chance of something bad happening*' or in relation to the decision-maker as '*the degree of desirability of uncertain outcomes*' [2, 3]. In fact, this *degree of desirability of uncertain outcomes* measures the attitude of a decision-maker in risky (uncertain) situations. *Risk seeking,* risk *adverse* or *risk indifferent* behaviours can greatly influence the decision making process and the final decision. Thus while uncertainty can be seen as a general feature of the decision environment, risk is in general something measurable, something that can explicate and model (part of) this uncertainty.

Significant research has been dedicated to the study of uncertainty inherent in decision-making. However, dealing with uncertainty is not an easy task: it first requires *recognizing* the various sources of uncertainty in a given decision context, to *accept* it, then to make the effort to *structure* and *understand it* and finally to *model* it and make it part of the decision-support process.

4.1.2 The main sources of uncertainty in a decision making process

Many techniques for *modelling* uncertainty and imprecision have been proposed but there are only few authors who are mainly preoccupied with identifying and structuring uncertainty. Among these, French [4], is concerned with *the reasons* for modelling uncertainty, *if* it can be modelled, *how much* of it can be modelled, *where to stop* in modelling, and *how to* treat the uncertainty introduced by the model used, etc. He identifies for instance, several sources of uncertainty in all the main steps of the decision aid process: *the uncertainty in modelling, uncertainty expressed during the exploration of the model* or *uncertainty in the interpretation of results.*

Motivated by practical needs for modelling, other authors [2] have reduced the classification to two main types of uncertainty:

- *External uncertainty*, related to the nature of the environment and the lack of knowledge about the consequences of a particular course of action, which may be *outside of the control of the decision-maker*
- *Internal uncertainty* which is present in the process of identification, structuring and analysis of the decision problem – process *depending on the decision-maker*.

The assumption further is that part of the *external uncertainty* can be modelled with *impact models* which were described in Chapter 2, while part of the *internal uncertainty* can be resolved with *preference models*, which were described in Chapter 3.

4.2 MODELLING UNCERTAINTY

4.2.1 Dealing with uncertainty in '*impact models*'

The energy system models discussed in Chapter 2 are deterministic. However, a great deal of the data used in energy modelling is uncertain by nature. It is generally possible to model part of this uncertainty, by extending these deterministic models (and their use).

Many sources of *external uncertainty* can be identified when modelling an energy system. Various parameters in the model have a highly uncertain nature: electricity prices, the levels of hourly demand for different end-use energies, the reliability of the system, etc. Thus uncertainty can affect a wide range of short- and medium-term decisions and it might be critical in long-term, expansion planning decisions.

There are a number of approaches in the literature about how to represent uncertainties in an impact model. The following discussion concerns only techniques for data representation and modelling since a separate sub-chapter will be devoted to data analysis (*preference modelling*). Two main groups of methods will be reviewed: probabilistic techniques and fuzzy methods.

4.2.1.1 Probabilistic techniques

These techniques can be described in three steps: the first is to find descriptions of possible *future states of the world*, next decision-makers need to assign *probabilities* to the likelihood that any one of these states my happen, and if the decision problem involves a large amount of information, finally to use a model (such as an energy system model) to *simulate* the set of *probable* outcomes.

There are different methods for *estimating future states of the world*, i.e. forecasting how different input parameters will vary over time. The most common types of forecasting are *time series*, *regression methods* and *qualitative methods* [5].
Time series is a category of statistical techniques that uses historical data to predict future behaviour. *Regression* (or causal) methods attempt to develop a mathematical relationship between the item being forecasted and the factors that cause it to behave the way it does. *Qualitative methods* use management judgement, expertise and opinions to make forecasts. The qualitative methods are actually the most common type of forecasting, such as in strategic planning.

After the possible evolutions of different parameters are determined, the next step is to estimate the probabilities with which any of these futures will happen. A distinction can be made between *objective* and the *subjective probabilities* [5]. *Objective probabilities* can be divided into *classical* or *a priori* (probabilities stated prior to the occurrence of an event) and *relative frequencies* (probabilities stated based on observations of past occurrences). *Subjective probabilities* are estimates based on personal beliefs, experience or knowledge of a situation [6].

Modelling techniques for solving problems under uncertainty differ in the way they allow the description of unknown parameters ('*forecasted*' values) and probabilities. For instance, when a *finite* set of possible evolutions of certain parameters in the future can be estimated, and if a probability can be assigned to each of these possible states, then ***scenario simulations*** can be used to evaluate the model outcomes. Then, if it is difficult to identify a discrete set of forecasts, *random* values can be assigned to the uncertain parameters. Continuous random values can be defined within intervals or ranges. Assigning a unique probability to every value of the random variable would require an infinite number of probabilities. Usually, *continuous probability distributions* are used to describe these random values. ***Stochastic programming*** stands for a set of modelling techniques that deal with random variables and continuous probability distributions. Several techniques can be used in solving stochastic problems, most of which are adjustments of methods known from deterministic programming, such as *stochastic linear programming*, *stochastic integer programming* and *stochastic non-linear programming* or *stochastic dynamic programming*.

In the literature, *scenario simulations* are often presented together or as a basic form of *stochastic analysis* [7]. However these techniques lead to different solution concepts. For instance, scenario simulations are closer to deterministic situations, than stochastic analysis. This is because scenario simulations are in fact separate optimizations problems solved with the same model – but using as inputs the scenario-specific uncertain parameters. Thus in essence scenarios are extensions of the classical deterministic analysis, fact that made them very popular in practical applications. Decision-makers have here a more participative task, in that they must analyse how different alternatives would perform in different possible 'futures' and choose one that conforms attitude towards risk. The different techniques for decision support under uncertainty will be discussed further, in paragraph 4.2.2.

The use of *stochastic programming* is conceptually different than scenario simulations. Consider for example, a model in which the alternative (the solution) associated with a problem can be specified via a vector of decision variables. The objective function in such a model may be composed of two parts: one part corresponding to the 'fixed' parameters and another one that corresponds to the stochastic parameters (usually a recourse function).

Then the scope would be to maximize the overall *expected value* (of the objective function) subject to a set of probabilistic (chance) constraints. Since the problem is solved for uncontrollable parameters - modelled using random variables, then the solution can also be viewed as random [8]. A *stochastic programming* model is not necessarily static. It can incorporate dynamic formulations to accommodate (sequential) decisions over time. In this context, the most important restriction imposed in a *stochastic programming* formulation arises from the assumption that randomness is exogenous and cannot be affected by (previous) decisions [8]. In certain design problems, such an assumption may not be valid, and in these cases, the models outlined above are inadequate. Nevertheless, there is a large class of applications where randomness is exogenous (e.g. weather, loads, prices of financial instruments, market demands etc.), and *stochastic programming* models provide a sound approach in this situation.

A fundamental observation made in [7] can be also used to distinguish between these two approaches: while a scenario solution may be valid after the fact (it will always be such that one of the scenario solutions turn out to be the best choice), the stochastic solution is normally *never* optimal after the fact, but nevertheless it is hardly a bad solution! In other words: 'if you base your decisions on *stochastic models,* you will normally *never do things really well,* while if you base your decisions on *scenario solutions, there is a certain chance that you will do well*'.

In practical energy system planning applications, scenario analysis is mostly used to support decisions for long-term (strategic planning) decisions while stochastic analysis is mostly used to support short term decisions (for instance bidding on the day-ahead electricity market, unit commitment, etc.).

4.2.1.2 Fuzzy methods

Fuzzy methods have been developed to overcome problems in representing the uncertainty in mathematical models – such as the 'impact' (energy system models) that are discussed in this thesis. All methods discussed so far have employed *crisp* numbers (real numbers, assumed to be known) in the definition of uncertainty. However, in real world problems, there are cases when expert knowledge is not sufficiently developed as to specify the parameters in the form of real numbers. *Fuzzy methods* are an alternative to the *stochastic* or *probabilistic methods* and have a particular application in those cases where it is difficult to rely on proper estimations of the probability distributions or parameters. Such cases may appear when:

- Historical data for some parameters cannot be obtained easily, especially in the case of parameters never employed before, and
- Subjective probabilities cannot be specified easily when many parameters exist.

Fuzzy numbers (sets) capture the notion of *possibility* which is conceptually broader than the notion of *probability*: if something can happen (it is *possible* to happen) then it is also *likely to happen* with a certain probability. A *fuzzy set* is an estimation of an uncertain parameter that can *vary between possible ranges*, while a *probabilistic* estimation implies a *forecasting of the probable* values.

The difference between *crisp* and *fuzzy* sets can be simply illustrated graphically. For instance, *a crisp set* (**A**) can be defined by saying if an object is or not an element in **A**.

Enumeration, analytical representation of the object, or a membership function (taking the value of 1 if the object is in the set, or 0 if not) are alternative ways to represent a crisp set.

On the other hand, a *fuzzy set* is a set of pairs composed by the object and its degree of membership in the set- the possibility of belonging to the set, or the 'true value' of the statement '**x** is in **A**' [9].

Figures 4.1 and 4.2 show the differences between representing an uncertain parameter (an electrical load *P* of *800 kW*) in a crisp or a fuzzy way [10].

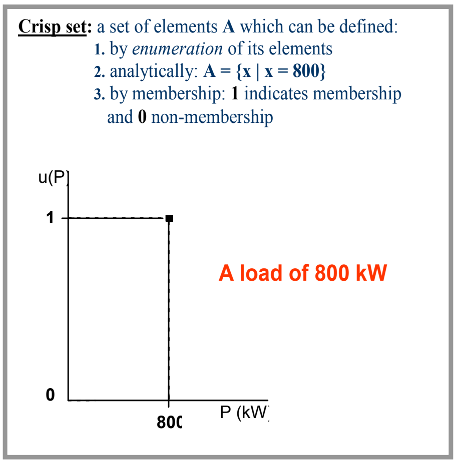

Figure 4.1 The representation of a crisp set

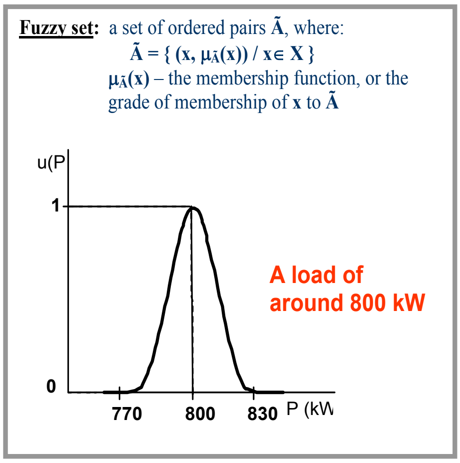

Figure 4.2 The representation of a fuzzy set

It is not certain how the load will evolve in the future: it is *probable* that it will reach a value of *800kW* (crisp) but it is also *possible* that this value can be *around 800kW* (fuzzy). In the first case the probability that this value (of *800kW*) will be reached must be estimated, while in the second case it is necessary to specify how much 'around' this value the load is expect to be (for example, between 770kW and 830kW).

Issues concerning the distinction, the competition and the co-existence of fuzzy sets and probabilistic representations have been often raised by some authors [11]. While subjectivists manipulate fuzzy events as symbols, objectivists can benefit from the concept of fuzzy events (defined as measurable membership functions) to enlarge the calculus of probabilities [12]. Only the characteristics and the possibilities of obtaining the necessary information in a given problem context, can dictate which method should be chosen.

In comparison with probabilistic analysis, fuzzy analysis may require increased effort in implementation from both the decision-maker and the analyst modelling the fuzzy procedure. There are several steps in modelling and solving problems in which uncertainty is described through fuzzy parameters:

1. *Find linguistic descriptions* for all elements of the model which cannot be modelled other than through fuzzy descriptions. A conventional mathematical model, normally represented through crisp parameters, variables and constraints, can *theoretically* accommodate fuzzy representations for all these model components [3, 13]. For instance:

- the ***constraints*** - equalities or inequalities - can be fuzzy, when represented through statements such as: '*…approximately smaller than…RHS* (the right-hand side of the constraint)'; '*…approximately equal to…RHS*', etc.
- the ***parameters*** can be fuzzy; both the coefficients in the objective function and in the constraints or the RHS ('*the load is around…*')

2. *Find models to represent these fuzzy descriptions* (*fuzzifications*). As shown in figure 4.2, a fuzzy parameter can be represented in general as a fuzzy set defined by two elements: the possible range of variation of the parameter and a membership function. These are the translations of the verbal, imprecise statements, and are essential in modelling with fuzzy parameters. In the example above, a triangular representation for the fuzzy set '*a load around 800kW*' has been used. Other shapes of the membership function can also be considered, depending upon the type of information that is modelled. For instance a parameter expressed as '*the load is at least 770kW but not larger than 830kW*' can be modelled through a trapezoidal membership function. Often in applications, the shape of the membership function appears to be chosen more or less arbitrarily rather than modelling decision maker's preferences directly [9]. For convenience linear functions are usually used.

3. *Define the operations with fuzzy numbers* - both conceptually and in terms of mathematical equations as well. Addition, subtraction, multiplication, division or inverse are operations that can be defined for fuzzy numbers. The crisp optimization algorithms must be modified to accommodate the interdependences and interactions among the fuzzy elements (operations with fuzzy numbers, fuzzy rules, fuzzy functions [14, 15]).

4. *Interpret the results of the fuzzy optimization (de-fuzzification)* – obviously if fuzzy representations are used for the input parameters in a given problem context, then the result of the optimization will be fuzzy. A fuzzy decision may be viewed as an instruction whose fuzziness is a consequence of the imprecision in the given gaols and constraints. A maximizing decision can be defined, for instance, as a point in the space of alternatives at which the membership function of a fuzzy decision attains its maximum value [16].

The primary difficulty in using fuzzy logic is that the analyst (the programmer) must first thoroughly understand the intricacies of and be able to precisely define a problem, and then he must be able to evaluate and fine-tune the results. If a model involves a large number of parameters and goals, it might be impossible for the decision-maker to have an active part in the process.

However, fuzzy set theory is a better means for modelling imprecision arising from mental phenomena that are neither random nor stochastic. Since the 1960s, when the approach was first proposed, fuzzy logic has created a revolution in the thinking of scientists in many research areas: mathematics, engineering, economy, management sciences, medical science, to name just a few. This fact is reflected in the large number of journals and books having as central point fuzzy theory. The newest applications of this theory are in the field of *soft computing.* This discipline is a combination of fuzzy logic and other mathematical tools (such as neural networks, genetic algorithms or chaos theory). It can offer solutions for complex industrial management problems by providing a *means for reproducing human-*

like intelligence towards creating automated, intelligent systems [17]. *The human brain can reason with uncertainties, vagueness and judgements. Computers can only work with precise valuations. Fuzzy logic is an attempt to combine the two!*

In conclusion, this discussion has shown that many techniques can be theoretically be used to model uncertainty in an impact model. The choice of a method must primarily depend on the final scope of modelling, primarily the 'target' problems and the individuals involved in the decision process.

The research for this thesis has been focussed on extending the use of an existing model whose applicability has been already established (see Chapter 2). From this perspective, probabilistic techniques are the first choice when dealing with uncertainty in the impact modelling for an energy system. Nevertheless, fuzzy techniques can be an alternative to probabilistic modelling of uncertainties in energy planning, if in the future additional research would be addressed to this issue.

4.2.2 Dealing with uncertainty in '*preference models*'

So far, the main approaches for uncertainty representation in *impact models* - *energy system models*, have been discussed. In general, the outputs from such a model (assumed to be either certain or uncertain) are not 'optimal' from a decision making point of view. At the final stage of the decision-making process, a short list of the most relevant alternatives will be revealed. Most probably, one of these alternatives will be finally selected by the decision-maker; and this will be the optimal alternative in the given decision context. The process of choosing an alternative is not simple: all options must be judged in presence of uncertainty and against several criteria.

Methods for multi-criteria decision making have been already reviewed in Chapter 3. In this chapter the discussion on this topic will be re-engaged, with the purpose of emphasising how uncertainty is dealt with in different MCDA methods.

The main assumption when designing a decision aid process is that the decision maker is able to express judgements about different decisions alternatives. As mentioned previously, considerable uncertainty resides in the way the decision-maker states these judgements, i.e. in how well he understands the implications of different decisions and how well he manages to express his main concerns. For instance, when judging different courses of action (decision alternatives) in terms of several criteria a decision maker may have clear preferences (*complete*) for some attributes – i.e. high cost alternatives, above a certain limit, will be never preferred - while for others preferences may not be so easy to express (*incomplete*), - i.e. how much to pay to reduce environmental impacts. Moreover, situations when decisions must be made in uncertain outcomes (expressed probabilistically or fuzzy) induce additional 'indecision' in the process.

Figure 4.3 emphasises the main groups of methods designed to deal with the uncertainty consistent with different frameworks for modelling decision-maker's preferences:

- Procedures for the complete assessment of certain outcomes - **Area *1***
- Procedures for the complete assessment of risky situations - **Area *2***
- Procedures for the incomplete assessment of certain outcomes - **Area *3***
- Procedures for the incomplete assessment of risky situations - **Area *4***.

Area *1* corresponds to the deterministic case, when it is supposed that the decision-maker has clear preferences over certain outcomes. This assumption, rather unrealistic in decision-making, has served well in developing basic mathematical, quantitative models of the reality. For instance, most of the methodologies and methods described previously in Chapters *2* and *3* can primarily address deterministic situations.

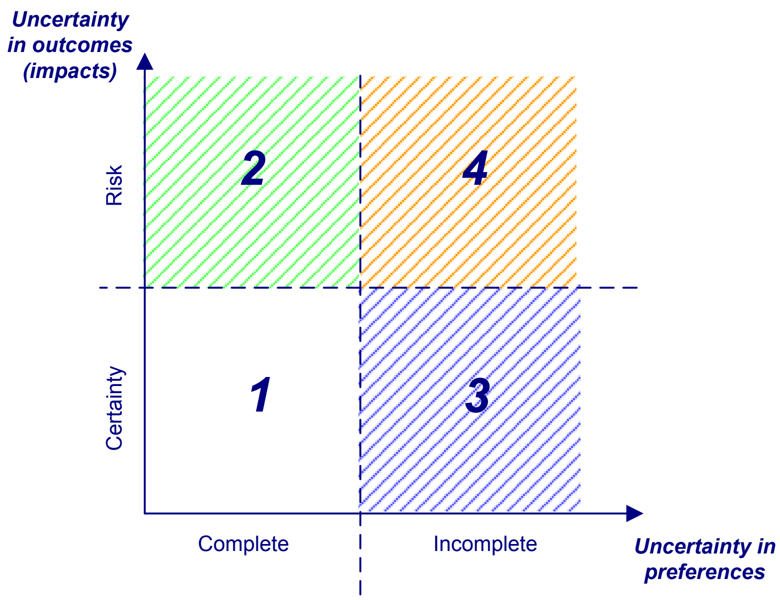

Figure 4.3 Uncertainty in preference models

Nevertheless, significant research is dedicated to MCDA under uncertainty. Some techniques encompassed by *Area 1*, for instance, may also take into account risk as an additional criterion – provided that relevant risk assessment procedures are available. In general, many of the deterministic methods for preference elicitation have been extended to account for different types of uncertainty. In addition to these, other techniques have been developed to particularly address the imprecision in human judgements regarding both certain or risky situations.

The discussion will further focus on different approaches for dealing with uncertainty in decision making, which can be classified according to the marked areas (2, 3 and 4) in Figure 4.3. The purpose here is to give an overview of the kind of techniques that can be used in different circumstances in modelling decision problems.

4.2.2.1 Procedures for the complete assessment of risky situations

Procedures described in this paragraph can be applied when the decision-maker(s) is able to *completely* specify judgements when analysing uncertain decision alternatives.

Recall that in most MCDA methods described in Chapter 3, the decision-maker is required to assess how alternatives perform in each criterion and also to specify the importance of each criterion in a decision situation. The term *complete* is used here to characterize preferences that can be given in terms of *fixed numerical values* or *yes* or *no declarations*.

Risky situations are characterized by the lack of knowledge about the consequences of different courses of action, *outside of the control of the decision-maker* as described in paragraph *4.2.1.1.* The discussion here will be limited to only those methods for assessing decision-maker's values for probabilistic outcomes – *scenario analysis*- although some of these methods can deal with fuzzy representations in a similar way (fuzzy scenarios).

Scenario analysis has been widely used to support decision making, especially in strategic planning. Scenarios are constructed independently and usually prior to the construction of alternatives. A scenario may describe the current and other, plausible future states of the world. In general at least two scenarios are required to reflect uncertainty, but more than four have been proved to be impractical [2]. Scenarios must be relevant to the decision-maker's concerns and must provide a useful, comprehensive and challenging framework against which the decision-maker can develop and test strategies and action plans.

Scenario planning can contribute to a deeper understanding of the effects of external uncertainties in MCDA. Figure 4.4 shows a basic representation scheme for a multi-criteria problem when scenarios can be generated to capture uncertainty in attributes:

		Criterion 1	Criterion 2	Criterion 3	...	Criterion n
ALTERNATIVE A	SCENARIO 1					
	SCENARIO 2					
	SCENARIO 3					
	. .					
	SCENARIO m					

Figure 4.4 Data representation in multi-criteria scenario analysis

Each alternative (A) is described in terms of how it may perform in different futures, in terms of different criteria. When constructed, each scenario is usually assigned a probability of occurrence. Once all alternatives have been described in this way, the decision-maker must analyse them and make a decision as to which alternative to implement; in essence, the validity of a decision alternative depends on how well it will perform in the future.

Although scenario analysis and MCDA have been widely applied in strategic decision making, it seems that little has been written about procedures that can integrate these two approaches [2]. A scenario-based approach to MCDA under uncertainty is sustained by the following observation: standard assumptions of MCDA imply that it should be possible to obtain preference orderings for any given set of achievement levels (attributes) for each individual criterion, *whether or not these attributes refer to real (deterministic case) or hypothetical (uncertain) alternatives*. Several authors [2], [10], [18] have proposed different approaches for integrating MCDA and scenario analysis.

Figure 4.5, inspired by a similar figure presented in [10], summarizes some of the strategies often mentioned in research or practical papers for combining scenario analysis and MCDA. Thus, supposing that in a decision situation each alternative, A (from the set A_1, A_2..A_m) must be judged in presence of several criteria C (from the set C_1, C_2…C_n) and several scenarios with associated probabilities p (p_1, p_2,…p_s) then several possibilities (models) for further decision support can be adopted:

Model 1:
This model is in fact an extension, to the multi-criteria case, of the classical scenario-based analysis. Thus, first the uncertain outcomes (attributes) in each criterion are *aggregated* based on a decision *paradigm* the decision-maker should specify. Examples of decision paradigms are: *Expected Value*, *Minimax Regret, Maximax*, *Maximin*, *Minimax*, etc. As in scenario analysis, such decision paradigms help in reducing the dimensions of the problem being analysed to something similar to the deterministic case: reducing the ($s_{scenarios} \times n_{crtieria}$) possible outcomes to n aggregated outcomes in each alternative. In principle, many of these decision paradigms also capture the *attitude towards risk* a decision maker may have [5]. For example, the *Minimax Regret* paradigm (often referred to as robust analysis) reflects a risk-adverse attitude, *Expected Value* reflects a risk-neutral attitude while the *Maximax* reflects a risk-seeking attitude.

After the attributes have been aggregated, from mathematical and modelling (engineering) points of view there are no restrictions in applying any *standard MCDA value measurement* procedure to the problem of comparing the alternatives in terms of the aggregated attributes - given that the decision-maker always keeps in mind what these aggregated attributes stand for. However this approach may reduce the value of decision support under uncertainty, i.e. the calculation of scores and weights determined based on the aggregated attributes may disqualify relevant alternatives. Moreover decision-makers may encounter difficulties when comparing expected values, regrets, etc. in order to be able to answer to the scores and weights elicitation questions.

A value model on the aggregated attributes would then transform the multi-criteria problem into a mono-criterion optimization problem that involves choosing the alternative with the *highest value*.

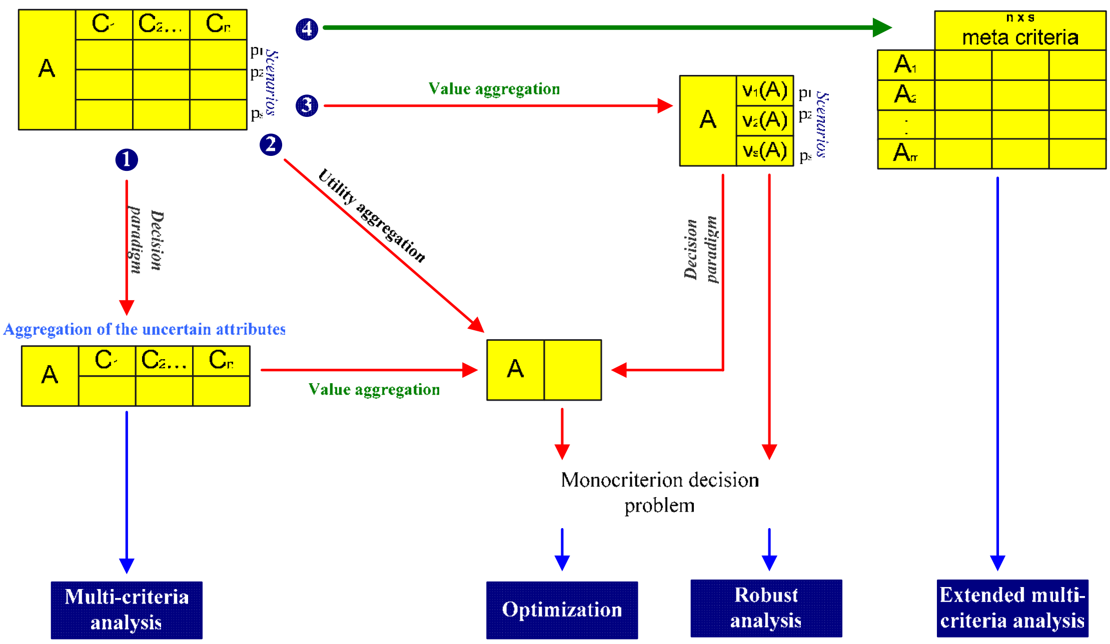

Figure 4.5 Models for integrating MCDA and scenario analysis

Model 2:
This model is based on *utility theory* for finding decision-maker's preferences over all uncertain attributes corresponding to the C (C_1, $C_2 \ldots C_n$) criteria. *Multi-attribute utility theory (MAUT)* explicitly models risk preferences. As in MAVT (described in Chapter 3), MAUT seeks to construct a *utility function* that can be used in establishing a preference ordering of the alternatives. The procedures for building utility functions are similar to those used for finding value functions, in the sense that single and inter-criteria evaluations are needed. The main difference consists in the way individual utility functions (single criterion evaluations) are constructed: in MAUT the decision-maker's risk attitude is captured through a series of lottery questions for each criterion analysed. In essence, these lotteries aim at establishing *the attribute level* at which the decision-maker would be indifferent between to getting this value as certainty or getting a lottery with given chances (constructed probabilities) for obtaining the maximum or minimum possible values for that specific criterion. Several axioms and theoretical procedures support the use of MAUT. The reader can consult [3, 19], [20], [21] for qualified theoretical descriptions.

The analytical hierarchy process (AHP) has been also proposed for solving multi-criteria problems under uncertainty based on an approach similar to utility aggregation. Recall that in AHP the decision-maker should be able to compare all pairs of criteria and decision alternatives using a ratio scale. The accuracy of such comparisons depends on the information available to the decision-maker as well as on how well he understands the problem under consideration. The presence of risky situations, i.e. alternatives whose outcomes can be defined in terms of scenarios with probabilities, affects the pairwise comparisons between alternatives, thus affecting the results. In [18] *a risk adjustment procedure* with AHP has been proposed. This procedure is an AHP of the certainty monetary equivalent, recognized also in utility theory. The idea is therefore similar: ask the decision-makers to compare risky projects with their risk-free versions. Based on these comparisons, decision-makers should either specify the attribute levels at which they are indifferent to the outcomes of risky and certain situations or say how much more the certain outcome is preferred. This procedure allows for variance, regret and risk aversion adjustments.

Similar to the pervious model, utility aggregation would also transform the multi-criteria problem into a mono-criterion optimization problem of choosing the alternative with the *highest value*.

Model 3:
The strategy here is to construct a *value model* across all possible attributes values (for the given alternatives and scenarios). This value model can produce a numerical scoring (values) indicating the level of performance of each alternative under the conditions of each scenario. The problem can thus be solved either as a standard mono-criterion problem under uncertainty (solved through robust analysis for example) or as an MCDA problem with aggregate performances under each scenario (or decision paradigm) playing the role of 'criteria'. The final step would be then to recommend the solution that is either robust under uncertainty or that best satisfies these 'criteria'. However, this second level MCDA problem poses many challenging questions for the MCDA community as described in [2].

Model 4
The last strategy would be to treat all criterion-scenario combinations as metacriteria and apply some form of MCDA to the problem of comparing *m* alternatives in terms of the $n \times s$ metacriteria, as discussed in [2]. Here each *metacriterion* represents the desire of the decision-maker to achieve a satisfactory target for each particular criterion under a particular scenario.

An important observation, that distinguishes this procedure from the previous one, is that preference structures (weights and scores) may differ across scenarios, i.e. the relative trade-offs between criteria (weights) and intensities of preferences for different increments in the performance of any criterion may differ from scenario to scenario. When using such an approach, it is thus important to determine whether the same range of outcomes in one criterion would have the same impact on the final decision, in one scenario than another.

4.2.2.2 Procedures for the incomplete assessment of certain outcomes

Methods in this group deal with the uncertainty residing in the *imprecision in human judgements* in certainty conditions. This imprecision resides in the way decision-makers think or are able to express preferences regarding different aspects of a decision situation. For instance, in many real decision situations only incomplete, imprecise or approximate preferences can be stated, in the form of semantic categorizations (qualitative/verbal), ordinal statements, interval statements or numerical values that can be modified interactively. As examples, consider that a decision maker may reply when asked if '*alternative **a** is preferred to alternative **b***' with: '*yes and no*', '*I do not know*', '*I am not sure*', '*maybe*', '*yes, perhaps it is 2-3 times more preferred',* etc.

Methods allowing for *qualitative/verbal statements* differ in the degree of freedom a decision-maker has in expressing judgements and in the way recommendations are derived. The AHP is one such method that allows decision-makers to express their preferences in qualitative terms such as: *weakly* preferred, *equally* preferred, etc. This verbal scale is 'predefined' by the AHP method, which afterwards translates decision-makers' answers into numerical values, using different numerical scales. Although the verbal scale in AHP covers many alternative answers that a decision-maker may possibly give, the method does not accept additional statements, other those that have been predefined. Moreover, it has been proven that the final recommendations with AHP may depend on the numerical scaling used to translate the verbal statements. Another approach, *MACBETH* (Measuring Attractiveness by a Categorical Based Evaluation Technique) is built on similar principles, although its developers have been more concerned with finding value scales that are meaningful in both qualitative and quantitative ways [22]. Outranking methods fall also in this category, although their underlying philosophy is to find an outranking relation (and not a value function) on the set of alternatives based on grades of preferences (strong, weak, high, low, etc) [9].

Incomplete preference information expressed in terms of *ordinal or interval value statements* can be addressed in with what is generally called *preference programming*. In essence methods for preference programming have been developed from the classical deterministic MCDA methods (starting with the AHP method and continuing with other value function elicitation methods [23]). These approaches allow the decision-maker to specify interval statements about all elements of a value model. In modelling terms, such interval statements correspond to linear constraints in a series of LP problems that serve in the calculation of corresponding value intervals. Principles from preference programming are the basis for a variety of decision-support software: *Web-HIPRE*, *RICH*, *Smart Swaps*, *WINPRE*, *PRIME-Decisions*, etc (see for example [24]). Most of these decision support tools allow for interactive preference elicitation procedures which usually provide more detailed results as the decision-maker gradually enters a more specific preference description.

Fuzzy numbers can be also used when translating verbal statements into numerical values, as explained in an earlier paragraph. The theoretical background and examples on how to use fuzzy measurements in relation to different multi-criteria methods are given in [26].

In general, if a decision maker decides to revise preference statements, then this means that the initial statements can be qualified as imprecise. In this respect, *all methods incorporating interactive procedures (MADM or MODM)* deal in fact with incomplete preferences, expressed in numerical terms.

Although many decision situations may naturally trigger imprecision in judgements, it is important to be aware of the fact that more effort dedicated to problem structuring can contribute to a better clarification of preferences.

4.2.2.3 Procedures for the incomplete assessment of risky situations

In reality the process of decision-making, is often based on incomplete judgements regarding the uncertain outcomes that different decisions may have in the future. Some procedures attempt to come closer to modelling this reality by employing for instance: fuzzy preference models over fuzzy impacts, incomplete preference modelling over probabilistic scenarios, outranking methods, verbal decision analysis or other strategies [3].

An alternative way to tackle decision problems that are highly affected by uncertainty is to reduce, if possible, this uncertainty through better problem structuring. If problem structuring is refined, then those decision-support procedures (such as value or utility theory) which are based on more restrictive assumptions about reality (and uncertainty) can be used.

Ultimately, the goal for decision-support is to help decision-makers in understanding decision situations and in making a choice according to their values. Since constructing a model from reality always requires abstractions, in principle any method can be applied if it has a good chance to successfully fulfil its purpose.

4.3 CONCLUDING REMARKS

The purpose of this chapter was to discuss how uncertainty can be explicitly taken into account in decision making. Several important points should be emphasized:

1. *Recognizing* the uncertainty in a decision context, *accepting* it, making the effort to *structure*, *understand and model* it, are the main steps in dealing with uncertainty and in making it part of the decision process.

2. Several sources of uncertainty are inherent in the process of decision support. For instance, uncertainty can appear during modelling, during the exploration of the model and also during the interpretation of results.

3. Two types of uncertainty are usually modelled. The first type is *the external uncertainty*, which is related to the nature of the environment and the lack of knowledge about the consequences of a particular course of action, which may be *outside of the control of the decision-maker*. The second is the *internal uncertainty* which is present in the process of identification, structuring and analysis of the decision problem – process *depending on the decision-maker.*

4. Methods can be evaluated in terms of the way uncertainty is addressed. Part of the *external uncertainty* can be modelled through *impact models* as described in Chapter 2, while part of the *internal uncertainty* can be resolved through *preference modelling*, described in Chapter 3.

5. Uncertain parameters can be represented using an impact model, probabilistic or fuzzy. When using the energy system model eTRANSPORT for decision support, the simplest way to account for uncertainty, is to use probabilistic techniques.

6. Three groups of procedures for dealing with the uncertainty consistent with different frameworks for modelling the decision-makers preferences have been discussed: *procedures for the complete assessment of risky situations*, *procedures for the incomplete preference information over certain outcomes* and *procedures for the incomplete assessment of risky situations*.

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PART C

APPROACHES TO PROBLEM SOLVING

Ralph L Keeney **Foundations for making smart decisions,** *IIE Solutions;* May 1999; 31, 5; ABI/INFORM Global, pg. 24.

Summary

This section of the thesis presents an investigation of possibilities and a proposal for combining energy modelling and MCDA in one, integrated tool. The idea is to solve the problems described in Part A by combining the approaches discussed in Part B. This section consists of two chapters: Chapters 5 and 6.

Successful decision-support relies on effective facilitation by the analyst or on the ability of individual users to learn how to make effective use of a model. In many cases, impact energy models can be used directly, without explicit preference modelling - the decision-maker simply analyses the information the model provides and makes a decision based on it - while preference models can be used as an additional decision-support when the impact data is difficult to assess.

Chapter 5 presents an investigation of different strategies for combining the two main approaches to decision support discussed in the second part of the thesis: energy modelling and MCDA. The study is focussed on extending the use of the eTRANSPORT model towards offering advanced decision aid. So far, this model does not provide support in decision situations when multiple criteria have to be considered.

Two strategies for combining impact and preference modelling have been studied. The first idea was to use the two models separately; to test the applicability of some MCDM methods on the type of data eTRANSPORT can provide. The second idea was to find a good way for integrating the two models, by adding a new module (advanced DA) to the eTRANSPORT model, to allow for preference elicitation and advanced decision aid.

In a two-stage approach, Multi-Attribute Utility Theory (MAUT) and afterwards the Analytical Hierarchy Process (AHP) have been applied to a pilot case study, where the impact information has been provided by the eTRANSPORT model. The experience gained from these applications contributed to the evaluation of the possibilities to integrate impact and preference modelling in one stand-alone decision support tool. The search for a design scheme for the advanced DA module in the eTRANSPORT model has followed two main criteria: flexibility in defining the decision problem (i.e. decision criteria) and ability to deal with incomplete preference information.

The PRIME technique has been chosen as the model for building the advance DA module of the eTRANSPORT. This method allows imprecise preference statements to be modelled and is thus suitable for decision support in planning and negotiations, where the issues of concern are perhaps more difficult to assess. Moreover, PRIME has a strong mathematical foundation and had already been successfully implemented in decision-support software, called PRIME Decisions.

The approach proposed in Chapter 6 takes uncertainty into account. This is the uncertainty which stems from the incomplete preference information the decision maker is allowed to provide in the analysis of alternative decisions. If uncertainty in impacts is to be as well considered in terms of scenarios, some sort of aggregation of attributes has to be carried out before the advanced DA module is used.

Chapter 5 STRATEGIES FOR INTEGRATING ENERGY MODELLING AND MCDA

5.1 BACKGROUND

The process of decision making for local energy systems planning is complex. Decentralization, the interplay between different energy and emission markets, and the movement toward sustainability have changed the priorities of energy planners and policy makers. They may be confronted nowadays with new tasks and must make decisions in situations they may never before have encountered. Consequently, new planning tools must be developed to meet their needs for decision-support effectively.

One goal of this research has been to study how the use of an existing energy model, eTRANSPORT can be extended in order to offer decision support in complex decision situations when multiple criteria and the uncertainty inherent in many decision situations have to be taken into account. This chapter presents an investigation of possible strategies for combining the two main approaches to decision-support discussed in the second part of the thesis; these are energy modelling and MCDA.

5.1.1 eTRANSPORT: characteristics of the existing tool

Before discussing its possibilities for extension it is important to provide a brief review, of the main features of the eTRANSPORT model.

eTRANSPORT is currently composed of two sub-models (modules): the *operational module* and the *investment module*. The *operational module* can be used to find the optimal allocation (*cost-based* optimization) of resources and technologies to supply a certain energy demand, under a relevant system configuration (system alternative). The model is demand-driven; the energy demand can be for heat, electricity, gas, hot water or other end-use energies and it can vary during a day, a week, a season or a year.

Different events may result in considerable changes in the level and the structure of the total energy demand of a region: the construction of a residential area, the construction of a new industrial site, a change of the energy demand profile of an existing industrial customer, the possibility of using a new energy source (or energy carrier) in that region, and so forth. eTRANSPORT can be used to study and plan these changes. For example, the model can be used to compare and rank different relevant supply alternatives in terms of operation and investment-related performances. This comparison (which is *cost-based* at the moment) is made within the *investment module*: in each of the relevant alternatives, the operation of the system is first optimized (*operational module*) then the investment cost is added to the optimal operation cost, and in the end alternatives are ranked according to their total cost. Figure 6.1 shows a graphical representation of this algorithm.

Because of this structure, eTRANSPORT can be used for decision support at different decision levels: in operational, tactical or strategic planning.

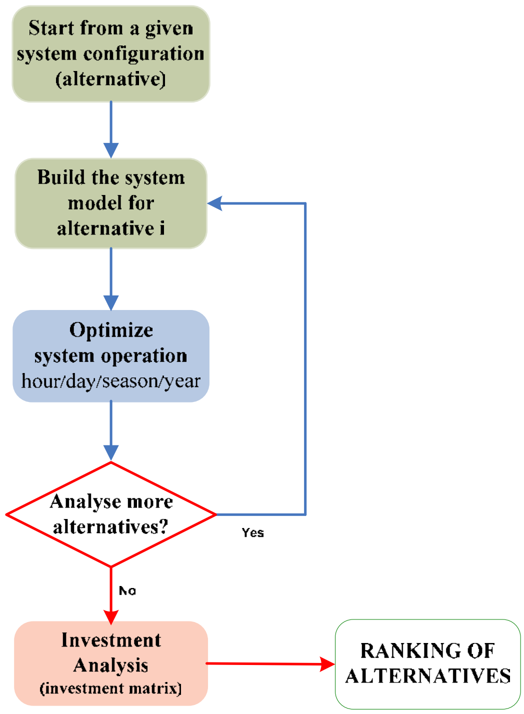

Figure 5.1 The structure of eTRANSPORT

So far, eTRANSPORT has been used in facilitated (involving an analyst) cost-based analyses. However, the model is flexible and fairly easy to use (provided that all data necessary to set up the model is available), thus it is possible from a practical standpoint, for individual decision-makers to carry out independent analyses as well.

5.1.2 Accounting for multiple criteria

System planners may think in terms of different criteria when analysing their options and making decisions. In many situations the economic, environmental or social impacts of different decisions must be carefully estimated and evaluated. eTRANSPORT can offer basic impact information about the operational and investment costs, the quantity of pollutants emitted when operating the system as well the energy losses. The traditional analysis technique is to assign monetary values to all these criteria and to compare alternatives according to their economic performances. However, monetary values for important criteria (environmental or social impacts, for example) are difficult to estimate and in addition, their true impacts may be more important to decision-makers than their monetary equivalents. Thus, instead of adding up criteria using monetization, the decision-maker may want to compare alternatives in terms of their 'true' impacts, i.e. compare costs to the tons of emissions, or to the number of new jobs created.

MCDA offers a theoretical basis for making these comparisons possible through adequate decision-support. MCDA methodologies can help in structuring decision problems and in building models that can capture how decision-makers think when challenged to compare decision alternatives in terms of several criteria and when the outcomes of those alternatives are uncertain. However, *preference models* can only be constructed when relevant impact information is already available. From this point of view, although the eTRANSPORT model can provide relevant quantitative information, this may not be sufficient to support complex, high-level (tactical or strategic) decisions. In these situations, additional impact information may be considered, such as: company's image, aesthetical impact, or other such qualitative criteria.

From the perspective of extending the use of the eTRANSPORT model in complex multi-criteria energy planning, another observation must be made: *the operation and the investment analyses have to be treated separately* because the issues of concern at these two planning levels are not the same. The same is true for modelling possibilities.

For example, the *operational problem* can be extended to a *multi-objective optimization problem* (MODM) while the investment problem can be seen as a *multi-attribute* problem. When solving only the *multi-objective operational problem*, it is necessary to have some kind of *prior preference information* (goals, value functions or other values that can be refined through interactive procedures) regarding the operation related criteria. The *investment multi-attribute problem*, on the other hand, requires the decision-maker's input *after obtaining the relevant impact information* (including the operation-related data).

In principle, many MCDA methods can be used in combination with eTRANSPORT. It has been shown in Chapter 3 that MCDA decision support frameworks differ with the way preferences can be articulated, i.e. the time in the process when the intervention of the decision-maker is accounted for. When choosing an MCDA method for extending the eTRANSPORT model it is therefore important to keep in mind the difference between the operational and investment problems, and to carefully design the algorithm that connects the two modules when multiple criteria are accounted for. For instance, if any form of multi-criteria aggregation is performed at the operational level, then the data that is forwarded to the investment analysis is already '*optimal*' from the operational point of view.

So far, eTRANSPORT has been used for decision support in investment (expansion) planning. Therefore, the research and the case studied for this thesis have also been focused on these types of problems. Nevertheless, further research would be useful in addressing the operation-planning problems, and the implications that a multi-criteria evaluation performed at this stage might have on decisions made at higher levels.

5.1.3 Modelling uncertainty

Uncertainty affects decisions and therefore should be considered at operative, tactical and strategic planning levels. As discussed in Chapter 4, in the process of decision aid it is important to differentiate and try to model both *external* [2]and *internal*[3] uncertainty

The impact model eTRANSPORT in its current form can be used to account for *external* uncertainty at operational level. The *operational module* can be easily used to simulate the optimal system operation based on different sets of input data. Thus eTRANSPORT can be used to quantitatively simulate the performances of different energy system alternatives in different scenarios.

[2] uncertainty regarding the nature of the environment and the consequences of a particular course of action.
[3] uncertainty related to the process of problem structuring and analysis.

Several key issues can contribute to the definition of scenarios at the operational level. eTRANSPORT is demand-driven, which means that the energy system must operate such as to meet the demand for different end-use energies at all times. Demand variations may influence the way the system can be operated. In particular, variations of that part of demand that may be met by different energy carriers are critical. For example indoor heat in private houses may be provided either by electrical heaters, gas boilers, district heating or wood stoves. If at least two substitution possibilities exist, then the choice of the consumers (probably influenced by weather conditions or prices of different energy carriers) about which heating solution to use can considerably influence the demand for these end-use energies and respectively the operation of the different supply networks. Thus scenarios can be defined in terms possible evolutions of the energy demand and, accordingly the operation of the integrated system (in alternative configurations) can be studied. eTRANSPORT can then provide quantitative information about costs, emission levels or energy losses in each alternative and scenario.

Another important factor that can influence the operation of an integrated system is the variation in prices of different energy resources or carriers. As discussed in Chapter 2, a local energy system is neither isolated nor self sufficient in terms of covering the energy needs. Electricity is usually a resource that is imported to the region. The variation of electricity prices may trigger important changes in the cost local energy suppliers would have during some periods. A simple example is when a CHP (combined heat and power plant) delivering both electricity and district heating (or cooling), is operated at full electrical capacity in order to export electricity in periods with high market prices. Because during some of these periods the demand for heat might not be high enough to absorb the output from the combined generation, this heat will be dumped with an effect on the environment. Thus scenarios can be also defined in connection with electricity prices. Depending on the system analysed, the prices of other energy resources (gas, wood, biomass, hydrogen) and energy carriers may affect as well the operation of the system. Furthermore, it can be possible to define combined scenarios (demand-prices) and also to assign probabilities of occurrence of each scenario.

At *tactical* and *strategic* levels uncertainty has to be taken into consideration in a different way. Decisions at these levels are usually yes/no decisions about large investments in technologies with long life time. The uncertainty that might affect the selection of alternatives at these levels comes from the way the system (in each alternative) can be operated or from other reasons. Quantitative figures such as costs or emissions provided by eTRANSPORT can definitely give a picture of how different alternatives could perform in different futures, *if* built. However, it has been discussed that at higher decision levels alternatives can be judged in terms of other, qualitative criteria more difficult to define and measure. Scenarios can be emphasised in terms of these criteria as well. Consider for example the aesthetical (or noise) impact of a new plant (for instance a small scale cogeneration plant). Uncertainty in this case arises from spatial and time related factors. For example, in the moment when planners decide to build this plant outside a town there may be nobody really affected by it, but at some point in the future it might be possible that new houses will be built in the neighbourhood. If, in the moment of the decision the planners have information about this possible event, then they can consider different scenarios.
An important observation is that it might not be possible to define uncertainty factors that can affect all alternatives. For instance, the factor described above (the construction of new

houses near the plant) might not have any influence on other investment alternative with which the first one is compared.

In the applications presented further in this chapter, the external uncertainty was modelled through *quantitative* scenarios (uncertainty in prices, demands, etc.). Other external uncertainty issues can be explicated through more advanced problems structuring techniques, and this can be an interesting direction of further research.

The *internal* uncertainty related to the process of problem structuring and analysis can also be taken into consideration when integrating eTRANSPORT and MCDA. However, this is as well a complicate issue. In complex decision situations the information provided by the eTRANSPORT model might not be enough to support thorough analyses. This model, in its current form does not give the user much freedom in structuring and modelling the *decision* problem. Although it has an important strength in processing the large amount of data necessary in calculating the impacts of the different alternatives, additional decision-support procedures (MCDA) or impact models have to be used, in complex situations because eTRANSPORT does not offer enough information about alternatives.

Thus, when extending the use of eTRANSPORT it is important to identify what type of decision-aid 'needs' the new tool (or procedure) can resolve: how the multi-criteria analysis can be carried out and how much of the uncertainty can be modelled. The strategies for integrated eTRANPORT and multi-criteria analysis proposed in this chapter will address these isssues.

5.2 A Two-Stage Approach For Combining eTRANSPORT And MCDA

5.2.1 The decision support procedure

In this paragraph a two-stage decision support procedure is proposed to solve multi-attribute investment problems, specific in tactical and strategic planning. The setting is as following: the eTRANSPORT model is used first to generate information (costs, emissions, losses) about possible alternatives and then an MCDA procedure is applied to help decision-makers to compare alternatives in terms of all these quantitative criteria.

The advantage when adopting this strategy is that practically several MCDA methods can be applied in combination with eTRANSPORT. This would give the opportunity to test and compare how different MCDA procedures can be used for decision support when decision-makers have to analyse the information obtained with this energy model. Moreover, the testing of MCDA methods on energy planning problems, either in laboratory settings or in real life applications would increase their acceptability among planners and energy experts.

In this approach, the decision aid process is facilitated by an analyst who will have the following main roles:
- gather information about possible system alternatives
- set up and use the eTRANSPORT model
- choose the information (and the format) to present to the decision maker during the decision support process
- choose a method for multi-criteria decision making and designing the dialog with the decision-maker, i.e. the preference elicitation procedure, and

- present the final recommendations to the decision-maker, in an comprehensive way.

This two-stage procedure can be summarised by the algorithm described in Figure 5.2. The first step consists of collecting all necessary data and setting up the eTRANSPORT model for each relevant system alternative. The operation related attributes (costs, emissions, losses) are calculated within the operational module. Then investment related attributes are added to the investment matrix. The research in this thesis captures an incipient stage of application of both the eTRANSPORT energy model and MCDA. Therefore in the first applications, only the investment cost has been considered as an additional criterion to the operation-related criteria. Moreover, in the first round of applications, a traditional, rationalistic (engineering) approach to uncertainty modelling has been adopted: scenarios (with probabilities) analysis.

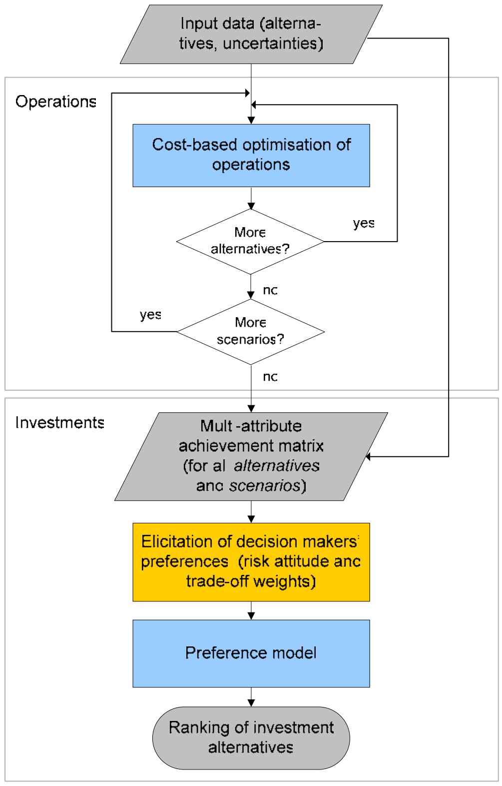

Figure 5.2 The algorithm used for generating impact data

In this setting, decision-maker's main contribution comes in the last part of the decision support process, when the multi-criteria method is used for building the preference model.

MCDA theory also prescribes that decision-makers should be involved as much as possible in the problem structuring process i.e. in identifying relevant decision alternatives and criteria and establishing important assumptions for analysis (such as how to take into account the uncertainty).

5.2.2 Applications

Two applications have been developed (see *Paper 3* in *Appendix C* and [1]) to test the use of two multi-criteria methods (the Multi-Attribute Utility Theory (MAUT) and the Analytical Hierarchy Process (AHP)) for decision aid where the impact information has been provided by the eTRANSPORT model.

These applications have been carried out in laboratory settings. *Five people* (*decision-makers A, B, C, D and E*) with a background in energy economics have participated in these applications. They were asked to imagine themselves to be the decision makers in charge of making important investment decisions in a local energy distribution system.

The energy system expansion planning problem presented to the five respondents has been set up based on a previous case-study in which eTRANSPORT has been used for cost-based analysis [2]. Thus, the input data used in simulations with eTRANSPORT has been derived from this initial case study. The constructed decision problem posed in these applications differed from the initial case, such that it required decision-makers to analyse alternatives in terms of several criteria and not only in terms of cost. Moreover, uncertainty has been considered in this new setting, i.e. scenarios of variation in electricity prices and emissions have been simulated and eTRANSPORT has been used to derive impact information in each alternative and scenario.

In these applications, the author of this thesis contributed with the formulation of the decision problem and the design of interview session with MAUT. The author has also been involved in conducting the MAUT application (playing the analyst's role) and in the interpretation of results.

The AHP experiment has followed the MAUT experiment. The same respondents have been asked to consider the same decision problem only that at this time the method for multi-criteria analysis was different. The author of this thesis has not been involved directly in this second experiment. The AHP application is discussed in this thesis because this method can be an alternative to using MAUT on the information eTRANSPORT provides. For a more detailed description of the AHP application and the initial comparison of results obtained with the two methods the reader can consult [1].

5.2.2.1 The decision problem

The participants in the two-stage application have been asked to imagine themselves as the top managers of an integrated energy company that supplies electricity, gas and heat to both residential and industrial energy consumers in a region (or town). A potential lack of supply capacity in this region has been forecasted once a new residential area is built in the town. This situation obliges the local energy company, as the only supplier in this town, to find new energy supply solutions. In addition to the new residential consumers, a possibility existed that a large industrial customer would want to be supplied with heat. This industrial consumer had previously been able to generate itself the heat needed in its industrial processes. However the managers of this company could consider replacing this solution because the generating unit (a diesel boiler) was economically and environmentally inferior to other alternatives.

This increase in energy demand in the region can be considered an opportunity for the local energy company to gain more customers and expand its business. However, this increase may affect significantly the local energy supply infrastructure and may trigger high investments, especially because this demand is concentrated partly inside the town and partly outside.

Several investment alternatives for covering the possible increase in energy demand have been identified. These alternatives vary with the energy resources and energy technologies used. Figure 5.3 illustrates the issues discussed above and emphasises the possible investment alternatives.

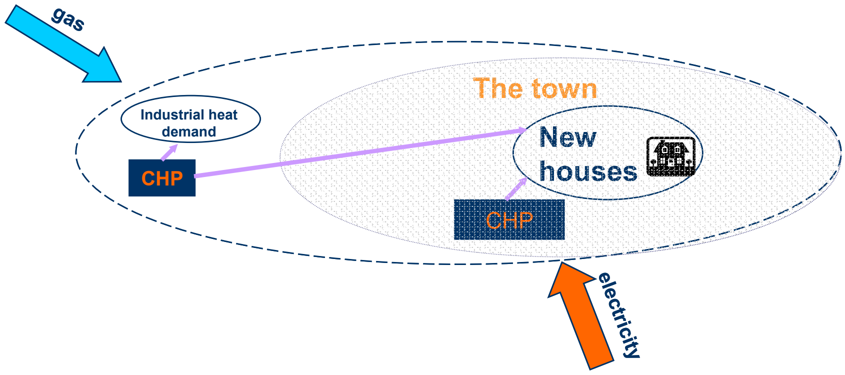

Figure 5.3 Possible alternatives for extending a local energy supply infrastructure

The first alternative (*'The base case'*) consists of reinforcing the electricity grid with a new supply line to the area, so that one can continue to rely on electricity to supply the local stationary energy demand. A district heating network and a CHP (Combined Heat and Power) plant is built in the other three alternatives, to serve the heat demand for the customers in the residential area. In addition, a gas boiler is built to meet the peak demand for district heating.

In the *second alternative* (*'3,6MW near the industrial site'*), the district heating network also covers the industrial demand outside the residential area. The CHP plant (with a capacity of 3,6MW) is placed at the industrial site, and can also meet the heat demand there, currently supplied with the diesel boiler. In *alternatives three* (*'3,6MW near the town'*) and *four* (*'5MW near the town'*) the CHP plant is placed nearby the residential area. The only difference between these alternatives is the size of the CHP plant. The CHP plant has a larger capacity (5MW) in alternative four, facilitating the generation of more electricity, which can be sold to the electricity market when it is profitable. A consequence of higher electricity generation might be excess heat from the CHP plant, which is dumped to the local surroundings, thus causing possible environmental damage.

The details regarding the four alternatives are summarised in Table 5.1.

Alternative	**New el line**	**DH network**	**CHP plant**	**Gas boiler**
1. *The base case*	yes	no	no	no
2. *3,6MW near the industrial site*	no	large	3.6 MW	5.0 MW
3. *3,6MW near the town*	no	small	3.6 MW	5.0 MW
4. *5MW near the town*	no	small	5.0 MW	5.0 MW

Table 5.1 Possible alternatives for extending a local energy supply infrastructure

To generate impact data regarding each system alternative, eTRANSPORT has been used. The operational module has been set up to calculate four operational attributes: operating cost, CO2 emissions, NOx emissions and heat dump from CHP plants to the environment.

The main uncertainty considered in the analysis was the price of electricity. Low, medium and high price scenarios have been simulated. Variations in electricity prices may affect the total CO_2 emissions in different alternatives: it has been assumed that low price electricity imports have been generated by more efficient and clean technologies while imports with high prices came from more expensive coal based generation (in Poland or Germany). Subjective probabilities were assigned to the scenarios, using 0.25 for the high and low scenarios and 0.5 for the medium price scenario. Other prices, such as the price for gas supply to CHP plants and gas boilers, and the price paid for heating at the industrial site were assumed constant in the analysis

The investment cost for each alternative has been considered in analysis, as the fifth attribute, in addition to the operation-related attributes. Then the following table was presented to the decision-makers:

Alt.	Scen.	Prob.	Total annual cost [MNOK]	Total inv. cost [MNOK]	Annual inv. cost [MNOK]	Annual operating cost [MNOK]	CO2 emissions [tons]	NOx emissions [tons]	Heat dump [MWh]
1	1	0.25	17.7	35.6	2.87	14.9	41060	0.0	0
	2	0.50	24.1	35.6	2.87	21.2	51325	0.0	0
	3	0.25	30.5	35.6	2.87	27.6	61590	0.0	0
2	1	0.25	19.7	85.0	6.85	12.9	32902	44.7	0
	2	0.50	22.6	85.0	6.85	15.8	37440	45.4	377
	3	0.25	25.5	85.0	6.85	18.6	41974	45.5	468
3	1	0.25	19.3	67.7	5.46	13.8	36188	36.8	0
	2	0.50	22.5	67.7	5.46	17.0	40170	46.2	4547
	3	0.25	25.3	67.7	5.46	19.9	44665	47.0	5082
4	1	0.25	20.1	78.3	6.31	13.7	35662	42.6	821
	2	0.50	22.8	78.3	6.31	16.5	38701	60.8	11319
	3	0.25	24.9	78.3	6.31	18.6	41917	62.7	12604

Table 5.2 Multi-attribute achievement matrix for the pilot case study

At this step each decision-maker was asked if he could make a decision right away based on the data presented. Although the case-study analysed was small, most of the respondents declared that they would need some time to compare the data and perhaps write down some figures and make some calculations in order to be able to make a choice. In general however, it has been observed that the larger the problem, the less reliable holistic judgements may be [3].

Instead of providing holistic judgements, decision-makers have been asked to participate in a more extensive decision-support procedure which would help them further with the analysis. Each participant was informed that the aim of this additional procedure was to explicitly take into account his preferences (way of thinking) regarding all aspects that mattered in the given decision-situation.

Slides 1-9 in *Appendix D* have been used for this initial step of problem setting.
Then each application continued with a presentation of the method used for preference elicitation and followed by the specific preference elicitation questionnaires.

5.2.2.2 The MAUT application

MAUT (Multi-attribute Utility Theory) was chosen in the first place because it allows for preference modelling in presence of multiple criteria and uncertainty. First, the steps of the preference elicitation procedure have been briefly explained to the decision-makers (slides 10, 11 and 20 in *Appendix D*). Figures 5.4 and 5.5 illustrate the two sets of *single-utility* and *trade-off* elicitation questionnaires.

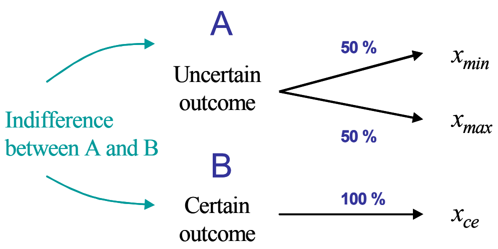

Figure 5.4 Example of lottery question for single attribute risk preference elicitation

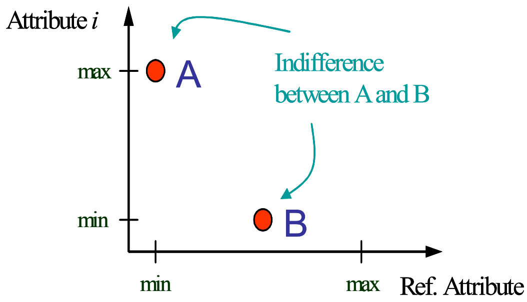

Figure 5.5 Example of question for trade-off preference elicitation

Then the actual preference elicitation procedure took place. First decision-makers have been asked to think in terms of each individual criterion and to answer to a series of lottery questions (slides 12-18 in *Appendix D*). To obtain single attribute utility functions each person has been offered a choice between receiving a certain outcome and a hypothetical lottery which would result in either the best outcome (with 50% chance) or the worst (also with 50% chance). Then the certain value has been varied until the decision-maker was indifferent between the certain or uncertain outcomes.

The second type of questions was the trade-off questions. The decision-maker was first asked which of the attributes (criteria) analysed was the most important. This was used as reference attribute for the trade-off comparisons. The trade-off questions consisted in asking the decision-maker to compare two hypothetical alternatives A and B, measured along the reference attribute and one of the other attributes, as illustrated in Figure 5.4. The indifference point was found by changing the *reference attribute* level of alternative B, keeping the level of *attribute i* at its best (minimum), until the respondent was indifferent between the two alternatives. This type of questions has been repeated for all criteria except the reference one. The trade-off questions have not been represented in the slides, being carried out simply by drawing Figure 5.5 on a blackboard for each pairwise comparison.

5.2.2.3 The AHP application

The AHP application is described in details in [1]. In this experiment, decision-makers could 'see' the values for each attribute and in all three scenarios. Hence, they could to take somehow directly into account the uncertainty in attributes when comparing alternatives. Decision-makers' answers in the AHP application have been studied with both the fundamental scale and the balanced scale. The software Super Decisions 1.4.1 has been used for processing data from the AHP experiment.

5.2.2.4 Results

The results from these two experiments can be found in Paper 3 (*Appendix C*) and [1]. In [1] a comparison of results is also made. Base on this paper, table 5.3 that sums up the calculated rankings with the two methods is reproduced here. This data will be used to support the discussion at the end of this paragraph.

To make the results from the MAUT and AHP methods comparable, all scores have been normalized, so that the highest ranked alternative in each method for each decision-maker is given a score of 1.00. Results are calculated in the AHP method for both the fundamental and the balanced scale.

		Decision maker **A**	*Decision maker* **B**	*Decision maker* **C**	*Decision maker* **D**	*Decision maker* **E**	Decision maker **F**
MAUT	Alt. 1	0.93 (4)	0.83 (4)	1.00 (**1**)	0.94 (4)	0.93 (4)	0.91 (3)
	Alt. 2	0.99 (2)	1.00 (2)	0.91 (3)	0.96 (2)	0.99 (2)	1.00 (**1**)
	Alt. 3	1.00 (**1**)	1.00 (**1**)	0.96 (2)	1.00 (**1**)	1.00 (**1**)	0.94 (2)
	Alt. 4	0.97 (3)	0.99 (3)	0.73 (4)	0.96 (3)	0.95 (3)	0.89 (4)
AHP Fundamental scale	Alt. 1	0.74 (3)	0.64 (3)	1.00 (**1**)	1.00 (**1**)	0.54 (2)	1.00 (**1**)
	Alt. 2	1.00 (**1**)	1.00 (**1**)	0.63 (2)	0.67 (2)	1.00 (**1**)	0.93 (2)
	Alt. 3	0.55 (4)	0.50 (4)	0.41 (3)	0.37 (3)	0.27 (4)	0.52 (4)
	Alt. 4	0.76 (2)	0.66 (2)	0.33 (4)	0.37 (4)	0.38 (3)	0.57 (3)
AHP Balanced scale	Alt. 1	0.98 (2)	0.94 (2)	1.00 (**1**)	1.00 (**1**)	0.49 (2)	1.00 (**1**)
	Alt. 2	1.00 (**1**)	1.00 (**1**)	0.75 (2)	0.57 (2)	1.00 (**1**)	0.76 (2)
	Alt. 3	0.84 (4)	0.78 (4)	0.65 (3)	0.39 (3)	0.28 (4)	0.58 (3)
	Alt. 4	0.90 (3)	0.85 (3)	0.52 (4)	0.38 (4)	0.40 (3)	0.55 (4)

Table 5.3 Ranking alternatives using MAUT and AHP

For a better illustration, the results for two of the participants in these applications (decision-makers A and C) are showed in Figures 5.6 and 5.7. In both MAUT and AHP, the total values are built up as additive functions. Consequently, the total score for each alternative can be split into sub-components for each of the five criteria, as in the two following figures.

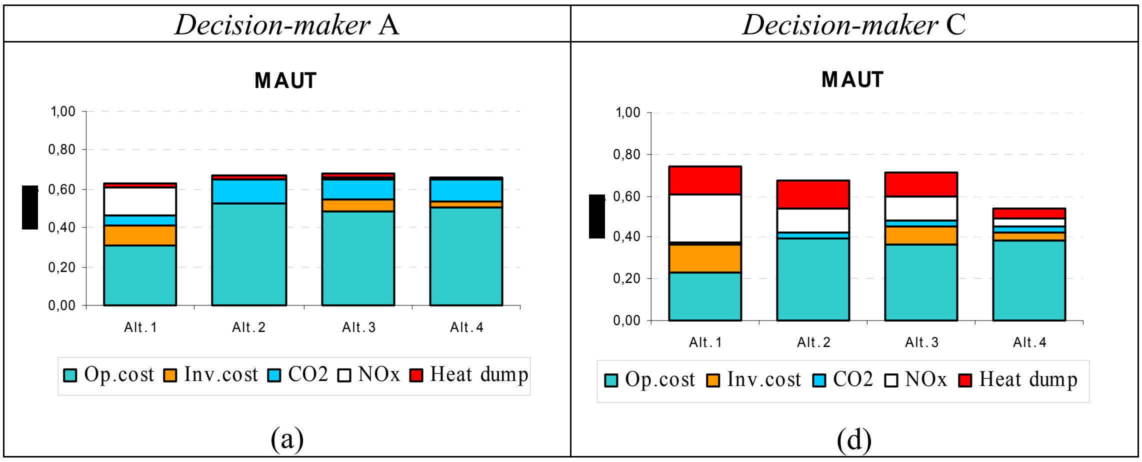

Figure 5.6 Detailed results for decision-makers A and C in the *MAUT* application [1]

The results from the MAUT experiment represent the total expected utilities for each of the four alternatives. The expected utilities have been calculated based on decision-makers' answers and based on the assumptions regarding the probabilities of occurrence of each scenario.

In the charts representing the results from AHP application, the numeric scores (*y axis*) do not have any special meaning. They are only instrumental and allow a simple comparison between alternatives. This is because of the normalization process that is used in the AHP method [1].

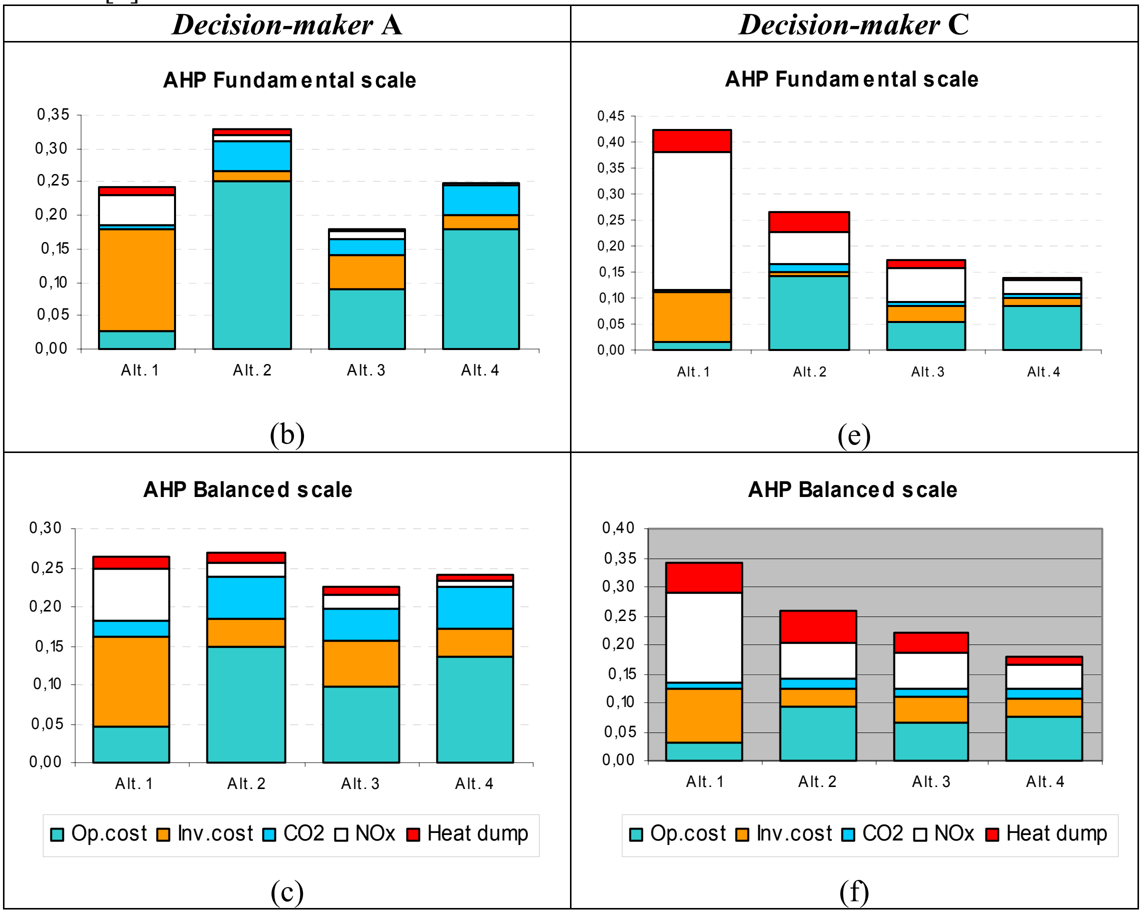

Figure 5.7 Detailed results for decision-makers A and C in the *AHP* application

5.2.3 Discussion

Applications like the ones described above have shown that the eTRANSPORT model can be used in complex decision settings where decisions must be based on more than cost-based analyses. Relevant insights into the integration of the model with advanced decision support MCDA procedures have been obtained with these applications.

The following discussion will focus on how the results from the decision-support part (the recommendations) may depend on the method used, the information presented to the decision-maker for analysis or on the actual setting in which the preference elicitation is performed. These issues can be further taken into consideration when combining energy modelling and preference modelling into one integrated tool.

The method used for preference elicitation and modelling

The process of preference elicitation and modelling may have a major influence on the decision. Although only two multi-criteria methods have been applied to a relatively small problem, it has been observed that it is possible to end up with different recommendations when applying different elicitation methods to the same decision problem, and involving the same decision-maker (see table 5.3, Figures 5.6. and 5.7 and [1]).

The field of MCDA does not offer any clear guidelines for comparing the results obtained through different methods. Factors that can influence these differences are for instance: the way decision-makers understand and accept the procedure for preference elicitation and the underlying assumptions when modelling preferences with each method, but other factors may also have an effect.

The calculations in these experiments showed that the main differences in results come from differences in scores (inter-criteria evaluations) and values (intra-criterion evaluations) obtained with the two methods. The elicitation of values in MAUT is based on the decision-maker's evaluations of attributes described within intervals – thus no specific reference was given about where in the interval each alternative lies. Alternatively, in the application with AHP, decision-makers had a clear view of how the different options are positioned in relation to the others in each criterion. Each method thus offers different conditions (circumstances) in which decision-makers must express their preferences. This observation is important when comparing the results obtained with the two methods, because even though both methods are designed for the same purpose, they may not measure the same thing.

This also applies when comparing the way that uncertainties have been taken into consideration with the two methods. MAUT captures the general features of the decision-maker's attitudes toward risk: in the preference elicitation procedure, decision-makers have been asked to compare certain outcomes with lotteries of obtaining the most extreme values in a criterion. Again, no specification about where each alternative lies in the interval between extreme values was given. After all, the utility model based on each decision-maker's answers could have been applied to any set of alternatives contained in that interval. Some authors have argued that because the lotteries are only imaginary, the decision-maker's judgements about the relative attractiveness of the lotteries might not actually reflect what he would really do [3].

AHP has been applied after MAUT on the same set of data, but in this case uncertainties have been presented in terms of probabilistic scenarios. When asked to compare between alternatives, decision-makers could evaluate both expected values and all other probable attributes. Thus in this last experiment, decision-makers had the ability to 'see' directly how uncertainty affects the outcomes in each alternatives. From a practical standpoint, they validated these alternatives in terms of all possible outcomes. Of course, this validation took place in their mind, independently of any other risk elicitation procedure.

As an observation it is important to add that differences in recommendations may also appear even when applying the same method to the same problem but in different circumstances. The MAUT application does not allow such affirmation because each participant has been involved only in one interview with each method. However, this observation is in general important and it has been reported in many studies before – for instance in [4-7] – and has been intensely debated by theoreticians and practitioners in the MCDA field. Preference judgements have a labile nature, which has been studied and demonstrated in behavioural research. *Small changes in the problem structure, question* *format, response mode, individual perspective or other aspects in the assessment process can sometimes dramatically change the preferences of an individual decision maker.*

Theoretically, a MCDA procedure can be applied in a decision situation if certain requirements are fulfilled. In many decision making situations, the methods at hand may require or dictate assumptions that are difficult to validate. For example, it has been documented that decision-makers may have problems in deriving utility functions (in the Von Newman and Morgenstern sense) consistent with underlying axioms [8]. Thus people in decision making situations might not be good in making the judgements that the expected utility model requires of them.

From this point of view, the application using MAUT might have overlooked some characteristics of the decision environment. For instance, for simplicity, we used an additive model for the representation of utilities. Such an assumption is made in many applications [9, 10]. However, an additive preference model can be applied when criteria are preferentially independent, i.e. the decision-maker is able (willing) to analyse the alternatives in terms of one criterion, without considering how they perform in any other criteria. In planning decisions, this assumption might not be valid because of the way energy planners still think today. This remark doesn't apply to all energy experts, of course, but it is important to consider this possibility for future applications. For instance, when asked to analyse the environmental impact of the system in terms of annual quantities of NO_x or CO_2 emitted, decision-makers would have liked to know if there was a tax to pay or any other economic sanction imposed on these pollutants. Obviously the preference independence condition is not met in this situation, although during the preference elicitation process, decision-makers can be asked to not think in terms of monetary values but only in terms of environmental impacts.

These situations impose additional assessments of the validity of the assumptions used and, if necessary, modifications of the theoretical procedures to adapt to the type of information available. This is one way to eliminate potential sources of biases in utility assessment [10, 11]. Another alternative would be to provide better representations of attributes that might encourage decision-makers to think in real terms when evaluating environmental impacts. This issue will be discussed in the next section.

In general, thorough applications with MAUT require much more time than it has been used – each interview lasted approximately 100 minutes. However in real situations the time available for a decision-support procedure might not be longer than what we allocated. Real decision-makers might not be willing to go through a long and cumbersome decision processes.

To summarise this discussion, it is possible that different handling of assumptions in assessing utilities could lead to different results. With AHP, this aspect is more evident. Here, differences in results appeared when using different scales for translating the decision-makers verbal answers into numerical values – information that is detailed in table 5.3, Figure 5.7 and [1].

Some studies [12] have also described how the decision analyst might unavoidable shape the assessment process, because he is in general the one who formulates the decision problem (identifying alternatives, choosing the measurement scales for criteria etc), controls the preference elicitation procedure, and even calculates the final value structure which may be based on restrictive assumptions. This aspect has also been observed in our exercises.

Many sources of bias in different methods can be found and all reside in the simple fact that the human decision process is very hard to capture in mathematical models. A general recommendation from behavioural studies is to use more than one method (or assessment procedure). From a theoretical point of view this advice makes sense. However, following it and applying different methods in the real word, with real problems and real decision makers may not be possible. And even in cases when it is possible, one might find that it is difficult to compare results.

The type of information used

Previously it has been briefly mentioned that the way criteria are represented can influence the results in a decision support procedure.

eTRANSPORT can be used for quantitative simulations of how alternatives perform under different criteria. Measurement scales such as tonnes of CO2 or NOx emerged directly from the set of equations describing the operation of the energy system. Quantities of CO2 or NOx can definitely give a clear indication about the impact different alternatives may have on the environment. However, from the decision making point of view, these quantities are only proxy measurements for what is generically called environmental impact (air quality, health impact, etc.). When asked about their preferences regarding quantities of pollutants emitted, decision-makers felt the need to ask back for more information about what exactly these quantities mean (both in terms of money or other impacts). Although all respondents agreed that environmental impacts must be taken into consideration, they found it difficult to express their opinions and preferences for alternative attributes measured in terms of quantities emitted. Thus, additional representations (more relevant measurement scales) should be provided for some of these criteria. The more relevant the decision maker finds an attribute and the more accustomed he is to thinking in terms of an attribute, the more easily he will be able to express preferences. Thus it will be more likely that he will understand the relationship between the attribute, the alternatives and the basic criteria [10].

Better measurements for some criteria are difficult to assess [13]. Decision-makers should preferably be directly involved in the process of problem identification and structuring. However, in energy planning which is still a kind of routine activity, people are used to think in certain ways without giving much consideration to new issues, although the planning context is changing. In many cases (real) decision-makers have not yet started to think seriously in terms of the environmental consequences of their business. And, perhaps one of the reasons for this is precisely this lack of direct and relevant measurement of consequences. Thus*, when choosing and applying different preference quantification methods it is very important to reflect about how much the reality of the situation- the way decisions are taken nowadays –' matches' the research assumptions!*

It might be easier and perhaps more relevant to consider qualitative (verbal) descriptions for some of the attributes, such as: '*most of the NO_x emissions in this alternative (e.g. x…tonnes/year) are due to the new power plant which will be built near the neighbourhood **Y** which is situated in the vicinity of the highway*'. NO_x has a local impact and thus, more specifications can be given, for example: the estimated area affected, or the number of persons living in that area, etc. In this way, the decision-maker will be able to be aware and compare, intuitively, the impact of different alternatives. However, in order to deal with qualitative attributes, other elicitation procedures have to be used instead of MAUT.

The validity of results in laboratory settings.

Experiments run under laboratory conditions are needed in order to gain useful practical knowledge regarding how to apply the theory in designing and conducting such decision aid procedures. When applying the theory, one might not be aware of a multitude of factors that can affect the results, despite the fact that many types of experiments and elicitation procedures have been reported in literature [10, 14, 15]. Each decision problem is unique and therefore the method used to solve it must be carefully chosen. Repeated exercises with different methods would be of great help for researchers and practitioners in preparing for real-life applications.

One should note, however, that laboratory experiments are not the same as real applications. People think differently when they are in a real decision situation and they have to make real choices that may affect directly themselves or others greatly, as opposed to when they are asked to play this role. In these experiments the respondents had no real commitment towards the final results, although they were asked at the beginning to imagine themselves in a real decision situation. Future experiments may be more relevant if the decision-makers were to be involved in the earlier stages of (real) problem identification and structuring, or in using eTRANSPORT for simulations and optimization.

As an overall conclusion, an important result with these applications has been that: *the respondents involved in the applications considered the multi-criteria approach to problem solving both interesting and relevant.* This is probably because the participants in our experiments were familiar with the type of problems proposed, i.e. they were aware and concerned, regarding the fact that energy decisions should be judged against several criteria. Furthermore all participants had sufficient knowledge about the methods used for preference elicitation - in special utility theory, although none of them had ever been involved in practical applications of these methods.

After both the AHP and MAUT interviews were performed, some of the participants were asked their opinion about the two methods. [1] presents a discussion on this issues, which is summarised in short here. Participants were asked general questions such as: which of the two methods is easier to understand, which is easier to apply or which method they think it captures better their way of thinking.

Most of the participants in these experiments gave the impression that they preferred the AHP method because they found the questions in this method easier to relate to. For instance, one of the participants declared that he felt it is easier to answers the AHP questions. In the MAUT interviews, he felt that his numerical answers were more or less random, and he would have found it more difficult to give his MAUT answers than his AHP answers. In addition, some of the participants mentioned that they think it is easier to avoid inconsistencies in the AHP questions because they very easily can adjust their already given answers to make them consistent to the others. However, some participants considered this as a drawback of the AHP method because they felt that after such adjustments, the answers were not the decision-maker’s real preferences anymore.

Some of the decision-makers found the weighting process of the AHP method difficult to understand. When asked to weight the average score on the criteria, some of the participants in the experiment had problems understanding this concept. How can one compare the importance of one cost number (MNOK/yr) to one emission number (tonnes/yr)? This is in accordance with the opinion [9] that it is more difficult to conceptualize this way of thinking than the more common weighting of swings from minimum to maximum values, as used in MAUT and many other MCDA methods.

From a practical standpoint it is no doubt that the interview process is easier in the AHP method. The AHP preferences can basically be captured from a questionnaire with little participation by the analyst. In contrast, the MAUT procedure requires that the decision-makers are interviewed by the analyst, procedure which also requires much more preparations.

5.3 INTEGRATING MCDA IN eTRANSPORT

The integration of '*impact'* and '*preference*' modelling should result in one stand-alone decision support tool. The idea here is that the eTRANSPORT model which has been studied so far as impact model, should be extended with an additional module that will facilitate multi-criteria and uncertainty analysis of energy planning problems. Thus, in this setting, the existing *operational* and *investment* modules will be parts of the *impact model*, while the *advanced DA* (advanced decision analysis) module will facilitate *preference modelling*.

5.3.1 The role of the *advanced DA* module

The *advanced DA* module will replace, in principle, the facilitated dialog necessary in the previous applications. Thus the model will undertake most of the tasks the analyst had in the applications just described: it will directly display the information relevant for analysis, provide the dialog for preference elicitation, carry through the value calculations and display recommendations.

The *advanced DA* module should be seen as an additional decision-support option *if* the alternatives in a given problem context have to be judged in terms of several criteria. This additional module should not restrict or influence the use of the other modules. In other words, if the user does not consider it necessary to go through a more advanced analysis of his problem, then he should not be forced to do so. Flexibility is a characteristic that may contribute greatly to the success of a decision-support tool.

Because of these considerations, the person who will use the *advanced DA* module should be the person in charge of the final decision. As shown in Chapter 2 the other (*impact*) modules require very detailed information about the energy system analysed. Although the same decision-maker can setup and use these modules, it is probably more realistic to assume that this task will be performed by somebody else, who will be called 'the analyst' in this context as well. It will be further assumed that this analyst has a broad overview of the possibilities for analysis offered by the model and that he can offer support to the decision-maker in using the *advanced DA* module.

From a theoretical point of view, the *advanced DA* module transforms the *impact information* into *value information*. Recall that multi-criteria decision support procedures seek to extract and model information about the values (preferences, etc.) or the way a decision-maker thinks in a decision situation. Then, this *value information* is used to derive recommendations, if possible.

5.3.2 An evaluation of possibilities for constructing the advanced DA module

The assumption regarding who will be the user of the *advanced DA* module has important implications when designing the extension of the eTRANSPORT model. The new tool will facilitate relevant multi-criteria analysis if the user is allowed to:

- learn and explore facets of the problem that might not be easy to observe in an incipient analysis
- interactively use the tool, both in terms of analysing different impacts (uncertainty) and changing preferences
- freely answer the preference elicitation questions which should encourage (and not discourage) him to use it, and
- easily analyse the final recommendations – which must be displayed in an comprehensive way.

The experience gained with previous applications can also contribute to the design of the new module. It has been observed that:

- the representation of the problem, i.e. the range of impacts that can be integrated in the multi-criteria evaluation procedure is limited by modelling possibilities
- the process of choosing the criteria for analysis should be flexible; decision-makers should be involved in the selection and definition of criteria, since their problems may range from simple cost-based analyses to complex multi-criteria (quantitative or qualitative) analyses, and
- complete preference statements, as in MAUT or AHP may be difficult to obtain, thus more freedom in expressing judgements may increase the relevance (and usability) of multi-criteria analysis.

In the view of the above considerations, the search for a design scheme for the *advanced DA* module has been guided by the following criteria:

- the procedure should allow the user to define his decision criteria no matter if these criteria result from the impact calculations with eTRANSPORT or not, and
- the method should allow for incomplete preference elicitation procedures.

The structure, the assumed use of the existing model and the need for decision-support as identified above, limited the search for methods in the MCDA field to methods for multi-attribute decision-making which allow for incomplete preference information and interactive use.

Analysing the classifications in Part B of this thesis, *preference programming* is the first candidate procedure and probably the easiest to implement. This approach solves part of the internal uncertainty related to the imprecision inherent in judgements. The external uncertainty - explicitly modelled in the previous experiments – can be as well accounted for with the new tool. From a theoretical/modelling point of view, there is no problem with generating alternative scenarios and displaying the attribute table (something similar to Table 5.1) within the eTRANSPORT model. Then a strategy similar to *Model 1,* for example, (as proposed in paragraph 4.2.2.1, Figure 4.5), can be applied to aggregate the uncertain outcomes before the actual multi-criteria evaluation is conducted.

When extending the eTRANSPORT model it is relevant to observe how other decision support software is built. Many tools have been specifically developed to support multiple criteria decision making by assisting decision-makers at various stages of structuring and solving decision problems [16]. The majority of available software (developed by academics or as commercial packages) is applicable in any decision situation, i.e. with any impact data. A step further is to use the principle upon which decision support software is built in the extension of the eTRANSPORT model.

A proposal for extending the eTRANSPORT model will be discussed in the next chapter. This proposal has been inspired by the set of decision support tools provided by the *Decisionarium* site [17]. The site provides an open source of testing tools for multi-criteria decision-making that are also well documented. The software relevant for this research is *Web-HIPRE*, *RICH Decisions*, *WINPRE* and *PRIME* Decisions.

Web-HIPRE [18] is designed to support different phases of a multi-attribute decision analysis process: modelling the problem, weighting attributes, evaluating alternatives and analysing results. The graphical user interface facilitates relevant visual representations of all these phases. Five methods are incorporated into this tool: *SMART*, *SWING*, *SMARTER* and *AHP,* and *classical value functions*. The software is very valuable for practitioners since it allows testing and the comparison of results from different methods.

RICH Decisions (Rank Inclusion in Criteria Hierarchies) [19] allows decision makers to supply incomplete, ordinal preference information about the relative importance of attributes (value trees).

WINPRE (Workbench for Interactive Preference Programming) [20] and *PRIME Decisions* (Preference Ratios in Multiattribute Evaluation) [21, 22] also support multi-criteria analysis with incomplete information. Both software packages allow for interval evaluations with different methods. *WINPRE* supports the AHP with interval judgements as well as PAIRS and interval SMART/SWING methods. *PRIME Decisions* [23] is an implementation of the PRIME method which allows for preference elicitation and analysis based on: a) the conversion of possibly imprecise ration judgements into an imprecisely specified preference model, b) the use of dominance structures and decision rules in deriving decision recommendations and c) the sequencing of the elicitation process into a series of elicitation tasks.

The proposal in Chapter 6 consists of guidelines for designing the new *advanced DA* module of eTRANSPORT and the mathematical background supporting this proposal.

5.4 CONCLUDING REMARKS

This chapter has presented an investigation of strategies for combining energy modelling and MCDA techniques. In particular it has examined ways to extend the use of the eTRANSPORT model in supporting complex decision analyses involving multiple criteria and uncertainties. The discussion can be summarized with the following issues:

1. The eTRANSPORT model can provide *impact* information useful in analyses at different decision levels: in operational as well as in tactical or strategic planning. However, the issues of concern at different decision levels are not the same, thus the requirements for problem representation and modelling also differ.

2. From the perspective of extending the use of the eTRANSPORT model in multi-criteria settings, an important observation is that *the operation and the investment analyses have to be treated separately* because the issues of concern at these two planning levels are not the same, nor are the possibilities for modelling. For example, the *operational problem* can be extended to become a *multi-objective optimization problem* (MODM) while the investment problem can be seen as a *multi-attribute* problem. A careful analysis is required when extending the model, because MCDA decision support frameworks differ with the way preferences can be articulated, i.e. the moment in the process the intervention of the decision-maker is accounted for, as has been shown in Chapter 3.

3. Two strategies for combining impact and preference modelling have been studied. The first idea was to use the two models separately to test the applicability of some MCDM methods on the type of data the eTRANSPORT can provide. The second idea was to find a good way for integrating the two models, by adding to eTRANSPORT a new module to allow for preference elicitation, and advanced decision aid.

4. The target problems in this discussion have been system planning problems, in which the main concern is to choose between alternative system configurations for supplying a given energy load. These problems involve a limited number of discrete alternatives for which MADM techniques are adequate.

5. Multi-Attribute Utility Theory (MAUT) and the Analytical Hierarchy Process (AHP) have been applied to a pilot case study, where the impact information has been provided by the eTRANSPORT model. Relevant insights into the integration of the model with advanced decision-support MCDA procedures have been obtained with these applications. It has been found that the results of such decision support procedures may depend on the method used, the information presented for analysis to the decision-maker, or on the actual setting in which the preference elicitation is performed.

6. The experience gained with these applications contributed to the evaluation of the possibilities of integrating '*impact*' and '*preference*' modelling in one stand-alone decision support tool. The search for a design scheme for the *advanced DA* module in the eTRANSPORT model has followed two main criteria: *flexibility* in defining the decision problem (i.e. decision criteria) and *the ability to assess incomplete preference elicitation*. Preference programming has been identified as the method to be implemented.

7. The set of decision support tools provided by the *Decisionarium* site have been proposed as models for extending the eTRANSPORT model.

The next chapter consists of a proposal for designing a new, *advanced DA* module to be part of the eTRANSPORT model. Guidelines for designing the preference elicitation procedure and the mathematical background supporting this proposal will be presented.

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Chapter 6 EXTENDING eTRANSPORT

An approach to designing the *advanced DA* module

6.1 ASSUMPTIONS

This chapter continues the discussion about integrating MCDA into eTRANSPORT. The focus here is to present a proposal for extending this model with a new module for *advanced DA* (decision analysis).

This proposal has not yet been implemented into the eTRANSPORT model, thus no conclusive results will be offered.

6.1.1 Problems addressed

The reason for extending eTRANSPORT is to create a tool that can be used to support complex analyses for energy planning. It has been previously established that the new tool will be used for decision aid in planning at both a tactical and strategic level. Thus, the *advanced DA* module, which will be proposed in this chapter, will address the multi-attribute type of decision problems, which are characterized by few relevant alternatives but a fairly complex set of criteria. Recall that an alternative refers to a specific energy system configuration; it may integrate several supply networks for different energy carriers, relevant in satisfying a given demand for different end-use energies (electricity, heat, gas, etc).

In terms of the criteria, it has been shown that these may vary depending upon the complexity of the decision situation; in other words the planning level (operational, tactical or strategic) at which a decision-maker acts. Basic information about each alternative (costs, emission levels, etc.) can be provided by the first two modules (the *operational* and the *investment* modules) of eTRANSPORT. Depending on the needs for decision support, the user may need to study additional criteria that can not be modelled with eTRANSPORT such as aesthetical impact, noise or other similar criteria, all of which may be difficult to measure or express, but which can be extremely relevant in some decision situations.

Uncertainty regarding the different impacts that alternatives may have is also a very important issue that must be taken into consideration when planning.

6.1.2 Possibilities for decision support

The new *advanced DA* module should be designed to allow an analysis that accommodates both relevant multi-criteria and uncertainty. Chapter 5 has been dedicated to an evaluation of possible strategies for extending the use of the eTRANSPORT model to allow more complex analyses than the cost-based optimization it allows at the moment.

A two-stage approach has first been adopted: the MAUT and the AHP methods have been applied to a pilot case-study where eTRANSPORT has been used to generate the impact data for analysis. During these applications - *facilitated by researchers* - important insights have been gained. First, we gained knowledge about possible ways to obtain and model preference information in the context of energy system planning, as emphasised in this thesis. Second, the participants in these experiments - *potential users of the new, integrated tool* – were supportive of this type of analysis and found it meaningful in the context of energy planning. These applications showed that eTRANSPORT can be used in complex decision settings when planners must take into consideration multiple criteria and uncertainties.

Chapter 5 also ends with a proposal on how MCDA can be integrated into the eTRANSPORT model. As examples of how to built the new *advanced DA* module, the software belonging to the *Decisionarium* site [1] has been proposed.

6.1.3 Features the integrated tool should have

Before discussing the new *advanced DA* module, it is relevant to recall what eTRANSPORT currently looks like. Figure 6.1 shows a snapshot from an application session with this model. As one can see, the tool allows the user to choose from two types of analyses: operational and investments analysis. The proposal in this chapter refers to a new type of analysis, the *advanced DA*[4].

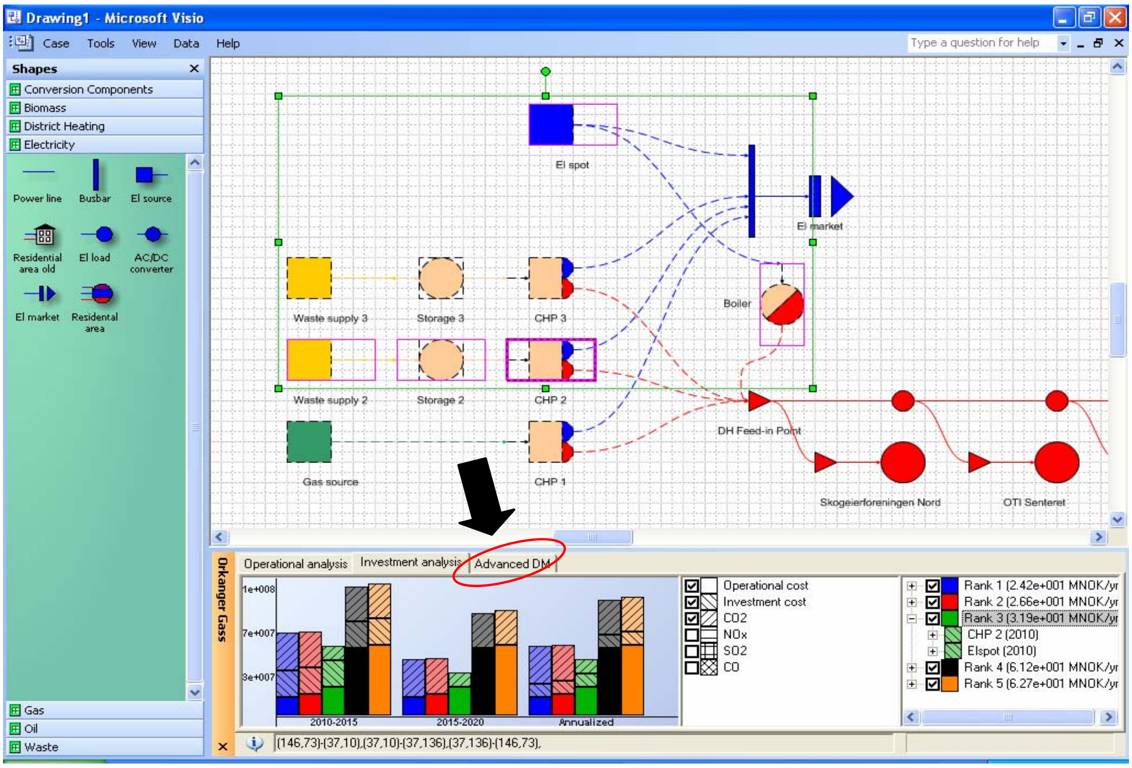

Figure 6.1 Main screen with drawing area, component libraries and result window

The *advanced DA* module will be useful only when the problem is sufficiently complex, i.e. when the decision-maker considers it necessary to take into consideration several criteria

[4] *Advanced DM* as it appears in this version of the model, depicted in figure 6.1.

when making a decision. Because not all problems that can be studied with eTRANSPORT are necessarily complex, the multi-criteria analysis (advanced decision analysis) should not be integrated into the two existing modules, thus allowing thus the user to choose between cost-based *operational/investment* analyses or *advanced DA*. Such a feature would probably increase the acceptability of the eTRANSPORT tool, encouraging users to carry out different types of analyses and interactively discover new facets of the problem, without entering into complicated multi-criteria analyses to early.

Theoretically, the *advanced DA* module replaces most of the dialog between the analyst and the decision-maker that is needed in the two-stage approach. In this proposal it will be thus assumed that the integrated tool, or at least the *advanced DA* module, would be used by the persons in charge with taking decisions. Nevertheless decision-makers would probably need guidance from an expert analyst in setting up the model (defining the relevant system alternatives), identifying and organizing criteria relevant in a decision situation, or in assessing the recommendations obtained with the model.

The *advanced DA* module cannot be used without relevant impact information. The existing *operational* and *investment* modules can provide part of this impact information (costs, emission levels, losses) while others (the aesthetical impact for example) may imply the use of other sources or impact models.

As a component of eTRANSPORT, the *advanced DA* module should be similar, in terms of use[5], to the rest of the tool, i.e. the *operational* and the *investment* modules. This observation combined with the experience gained with the facilitated decision-support procedures (MAUT and AHP) led to the identification of several relevant characteristics the integrated tool should ideally have. These are:

1) Facilitating problem structuring in terms of alternatives, multiple criteria and several scenarios
2) Facilitating interactive procedures, and
3) Providing means for incomplete preference elicitation.

It is important to emphasise that with such features, the new decision support tool will address several sources of uncertainty. For example, part of the external uncertainty (uncertainty in impacts) will be modelled through scenario simulations, while part of the internal uncertainty (uncertainty inherent in human judgements) will be addressed through incomplete preference elicitation.

6.2 THE *ADVANCED DA* MODULE

The following proposal for extending the eTRANSPORT model takes into consideration the assumptions reviewed previously. The general guidelines for designing the structure of this new module and the preference elicitation procedure will be first proposed. The mathematical model that can sustain such decision-support tool will be also discussed.

[5] Recall that when using **eTRANSPORT**, the decision-maker can draw and define system configurations by dragging-dropping system components from an available library of components

This proposal is based on the PRIME (Preference Ratios In Multiattribute Evaluation) technique developed by Ahti A. Salo and Raimo P. Hämäläinen at the Helsinki University of Technology [2]. This technique can handle imprecise preference statements such as: holistic comparisons between alternatives, ordinal preference judgements or ratio comparisons about preference differences. From a practical point of view, the method can be used for decision support in planning or in negotiations, because such situations are usually characterized by novel and difficult-to-express concerns. Thus PRIME can be relevant when building an *advanced DA* module to support tactical or strategic planning of energy systems. Moreover, PRIME has a strong mathematical foundation, as it has already been successfully implemented in the decision-support software called PRIME Decisions, by Tommi Gustafsson [3].

6.2.1 Structure

The *advanced DA* module will have the role of: 1) facilitating problem structuring and display the information relevant in a decision situation, 2) facilitating preference elicitation and 3) facilitating the analysis of results (recommendations). Correspondingly, there will be three procedural steps the decision-maker should undertake: defining the decision problem by choosing and structuring criteria, answering preference elicitation questions and analysing the recommendations. Figure 6.2 shows the details of this procedure.

Step1: *Problem structuring*

Decision-maker's tasks:

Identifying criteria

The first step in using the *advanced DA* module consists of *identifying the criteria relevant in a decision situation*. Similarly to defining the energy system, in the eTRANSPORT, this task also implies the use of a library of criteria components. This library may include *three types of criteria*:

- **Criteria of type 1**: criteria (attributes) that can be calculated using the eTRANSPORT model: operation cost, emissions (CO_2, NO_x, etc.) and losses

- **Criteria of type 2**: criteria that may be of interest to the decision-makers in some situations but that cannot be calculated with the eTRANSPORT model. A list of this type of criteria can be *suggested* by the model, for example: noise, aesthetical impact, the company's image, or other criteria that may generally concern energy planners (model developers can conduct a survey among different energy planners for finding good candidates for this criteria list). The model should also suggest measurement scales for these criteria, although decision-makers should be allowed to change these scales if they do not entirely reflect their concerns.

- **Criteria of type 3**: additional criteria that a decision-maker may want to consider in an analysis. These criteria are not defined in the tool itself, and thus they must be defined by the user, who should be able to provide relevant measurements scales and descriptions of the impact each alternative may have.

Note that the more complex a decision problem is (tactical or strategic level) the more need to consider and define new criteria (criteria of type 2 and 3) exist.

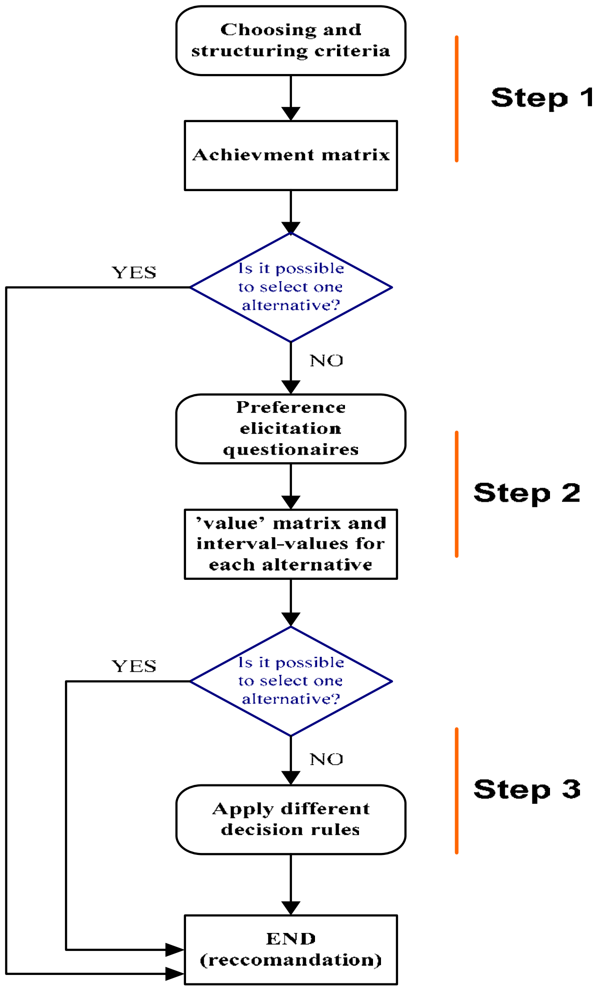

Figure 6.2 Steps in using the '*advanced DA*' sub-module

Identifying and structuring criteria is an essential step in the success of the *advanced DA* process, as it provides the decision-makers with more opportunities to identify and understanding decision options, and may even lead to the discovery of new alternatives. Within this first step *of problem structuring*, the user should also be allowed to organize and structure criteria in a hierarchy[6], if necessary. This is however not an easy task; it may require the assistance of an analyst or preliminary training on the part of the decision-maker in the field of MCDA.

When defining criteria, it is important to distinguish between:

- *Quantitative criteria*, measurable on quantitative scales such as: costs (measured in monetary values - $, NOK), or emissions (measured in tonnes of CO_2, NO_x), etc.
- *Qualitative criteria*, for which verbal, subjective descriptions are more relevant, such as: aesthetic impact (description of a new power producing facility), noise , etc.

[6] However, the procedure proposed in this chapter considers only criteria at the lowest level of the hierarchy, as a basis for preference elicitation (and for building the underlying mathematical model).

Previous experience has shown that it might be difficult for a decision-maker to compare alternatives in terms of some quantitatively measured criteria, such as emissions (CO_2 or NO_x). The reason for this is that it is difficult to understand the impact and to put values on differences (which may sometimes not be too large) in emissions levels. This inconvenience can be solved either by changing the measurement scales for these criteria (proposing for example to count the number of people who get sick because of emissions) or, perhaps by treating them as a '*qualitative'* criterion and describing it verbally.

Other criteria for which quantitative measurements might not be relevant are *noise* or the *aesthetic impact* criterion. Noise can be measured numerically (db) but qualitative definitions may be more appropriate in some analyses since various sources of noise may exist in a region and not all are due to the energy system under consideration. For the *aesthetic impact* one can also find numerical scales as for instance the number of persons affected in a negative way by the aesthetical aspect of a part of the energy system. The *aesthetical impact* of a solution might depend on its the degree of novelty and acceptability. However relevant measurements in this respect might be difficult to obtain.

It is important to emphasise that if the user is interested in considering different criteria in a decision process, then he must be able to supply measurements and descriptions (that he finds relevant) of how alternatives perform in these criteria.

Taking uncertainty into account

Apart from defining and structuring criteria, another task a decision-maker can undertake at this step is to identify the external factors that induce uncertainty in impacts different alternatives can have. As discussed previously, uncertainty in electricity prices or in energy demands can be easily taken into consideration with eTRANSPORT through scenario simulations. In the two-stage applications described in Chapter 5 probabilities have been assigned to each scenario considered, and the methods used allowed us to take into account uncertainty in this way.

The PRIME method proposed here for the construction of the *preference model* is basically a multi-attribute value method. Value theory cannot be used for decision support when attributes are uncertain (defined in terms of scenarios). Thus, comparing with the pervious applications the approach proposed in this chapter brings conceptual limitations in modelling the external uncertainty through quantitative scenarios.

From a mathematical point of view there are however no limitations to continue to model uncertainty though scenario simulations in this proposal. A possibility is to use the approach of *Model 1* described in Chapter 4 (paragraph 4.2.2.1). This approach prescribes the aggregation of attributes over different scenarios to which probabilities are assigned. This aggregation should take place probably in an additional *module* inside eTRANSPORT since so far this model does not integrate scenario analysis. This new module should collect all quantitative data from the simulations with the *operational* or *investment* modules of eTRANSPORT and should allow the aggregation of attributes over scenarios based on a *decision paradigm* the user would specify (*Expected Values*, *Minimax Regret*, *Maximax*, *Maximin*, etc.). Then once the attributes are aggregated the approach based on PRIME method can be used.

Conceptually however, this approach has an important disadvantage. This is because the value model (based on PRIME) will be constructed over attributes that have been already ‘evaluated’ and that already incorporate some sort of risk attitude (induced by the decision paradigm the user should choose). Thus, during the multi-criteria evaluations, these attributes will be considered again, but now in a different ‘context’ (as it will be described further). An idea to overcome this double evaluation is to ‘automatically’ transfer to the multi-criteria procedure the *expected values* of the attributes (only informing the user about what these values represent and not asking him to do no anything at that point).

An advantage of scenario aggregation is that, in general, potential users (engineers) of the extended eTRANSPORT are quite used to this type of analysis. However it is important that the tool will allow the definition of scenarios and the procedure to aggregate them as *an option* (similar to the option of performing the multi-criteria analysis). Being flexible in this respect, the tool would also allow the analysis of *one scenario at the time*. Furthermore, this can facilitate the analysis of complex scenarios (defined through combinations of factors that can influence attributes at both operational and investment level). As discussed in the previous chapter, the uncertainty in investment-related attributes (qualitative) is in general difficult to model but nevertheless there may be situations when decision-makers would like to consider it, at which time the model should allow them to do so. Otherwise there is a risk that some expansion planning alternatives may be excluded from evaluations, no matter how well they may perform in terms of operation. However, it is important to observe here that the final analysis of scenarios will be carried out separately (not ‘inside’ eTRANSPORT). An approach suggested in [7] would be to consider each scenario as such, without allocating probabilities.

However, there is no single or easy way to deal with uncertainty. To summarise this discussion, it is important to recall that the PRIME method deals with incomplete preference information. This means that the uncertainty which is related to problem analysis (how well decision-makers can compare and evaluate different attributes) is taken into account with this method. This type of analysis can be sufficient when planning. In cases when the external uncertainty is and important issue, then this can be modelled through scenarios.

The proposal in this chapter is to create a flexible tool that can allow the user to choose to model the external uncertainty through scenarios (in a separate ‘uncertainty module), and analyse these scenarios if this would be an issue in a given problem context. If for instance, the scenarios would not induce great differences in attributes, then the user can choose to go further to the step of multi-criteria analysis with one set of impact data. If on the other hand, there will be a significant difference in the impacts alternatives would have in different scenarios, then the user can either choose to analyse and aggregate attributes (and then go further to the multi-criteria analysis) or to analyse each scenario at a time.

Information display:

Assuming that all relevant criteria have been chosen, the tool should display a matrix table that will collect all information about the impacts of potential alternatives in different criteria: the rows of the matrix will correspond to the available (relevant) alternatives, while the columns will correspond to the criteria/attributes chosen. Thus, if it is possible to characterize the decision problem through a set of criteria, denoted by $C = \{C_1, C_2, \dots C_n\}$

and a set of alternatives, A = {A_1, A_2, …A_m}, then the achievement matrix can be constructed in the following way:

Criteria

$$
\text{Alternatives}\quad
\begin{array}{c|cccc|}
 & \mathbf{C_1} & \mathbf{C_2} & & \mathbf{C_m} \\
\mathbf{A_1} & a_{11} & a_{12} & \cdots & a_{1n} \\
\mathbf{A_2} & a_{21} & a_{22} & \cdots & a_{2n} \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
\mathbf{A_m} & a_{m1} & a_{m2} & \cdots & a_{mn}
\end{array}
$$

where a_{ik} is the level of achievement (possibly an aggregated attribute) of alternative ***i*** in criteria ***k***.

If, at this point the DM is able to select one alternative, the decision aid process should be terminated. If not, then the next step will be to help him in analysing the matrix and expressing his values, through a *preference elicitation* procedure (which replaces the questionnaires from the previous, facilitated applications). It is important to observe here that the multi-criteria achievement matrix, in the *advanced DA* mode is practically an extended version of the *investment matrix* which makes the connection between the *operational* and the *investment* sub-modules (see also Figure 2.1 in Chapter 2).

Step 2: *Preference elicitation*

Once all information available is structured as described previously, the decision-maker has to analyse it and choose an alternative that best suits his purposes. *Preference elicitation* consists of a series of evaluation questions that seek to reveal the decision-makers values in a specific decision situation.

In PRIME, a user is allowed to specify incomplete preference information such as: ordinal preference judgements, value intervals or holistic comparison. A decision-maker can start with those comparisons that are easier to make and move towards more difficult judgements. After each new statement, the judgements are synthesized into a value model that determines the dominance relationships among alternatives by solving a series of linear programming problems [2, 4].

As explained in Chapter 3, value function models can be built based on scores (evaluations of alternatives in each of the criteria considered) and weights (comparisons between criteria). The elicitation of the relative magnitudes of scores can be based on ratio comparisons of differences in consequences (attributes). Trade-off information about the relative importance of attributes can be elicited through ratio judgements where the achievement levels of the consequences differ on at least two attributes. Because a large number of comparisons can be performed, the elicitation process must be carefully structured. This proposal emphasises the necessity of addressing both quantitative and qualitative criteria at the lower level in a value tree (twig-level). Thus, the following types of questions can be adopted:

- *Single criterion evaluations (scoring)* in both quantitative and qualitative criteria*:*

    - Ordinal ranking of attributes, and
    - Comparisons of differences between pairs of attributes, such as:
        - asking the decision-maker to compare value differences defined by adjacent achievement levels, proceeding from the least preferred to the more preferred ones, or
        - defining all value differences in reference to the least preferred attributes and asking the decision-maker to compare them.

- *Comparisons between criteria (weighting):*

    - Order criteria in terms of their importance
    - Express the relative importance of criteria – ratio estimates regarding weights. The elicitation process must be structured in terms of 1) the attributes with regard to which the comparisons are made and (choose an reference attribute) 2) the alternatives that are included in the comparisons. In [2] several possibilities for the design of questions are proposed:
        - formulate ratios in terms of value differences between the most and the least preferred alternatives (interval SMARTS), or
        - select any two alternatives and formulate ratios in terms of value differences between these.

The design of questionnaires - the user interface – that may be relevant for the *advanced DA* module has not been studied in this thesis. However, an illustrative example of how the evaluation procedure looks like in PRIME Decisions will be offered at the end of this chapter.

Step 3: *Issuing a recommendation*

Preference elicitation will practically translate the problem of choosing the alternative with the 'best' impact into a problem of choosing the alternative with the highest *overall value*. These *overall values* are calculated based on the answers a decision-maker provides to the preference elicitation questionnaires. The result of *advanced DA* will be a *recommendation* about which alternative to choose.

The mathematical model that can sustain such an advanced multi-criteria analysis will subsequently be described, but for the moment it is relevant to emphasise that these *overall values* for each of the alternatives considered, *are obtained in terms of intervals*. These intervals result from the imprecision in preference statements (inputs are given in terms of intervals), thus they represent the uncertainty in human judgements: the larger the intervals, the more ambiguous were the answers that led to it. To illustrate the type of results one can obtain in a simple example, suppose that in a decision problem with six relevant decision alternatives, the decision-maker's answers lead to the calculation of overall values for each alternative, as in the Figure 6.3.

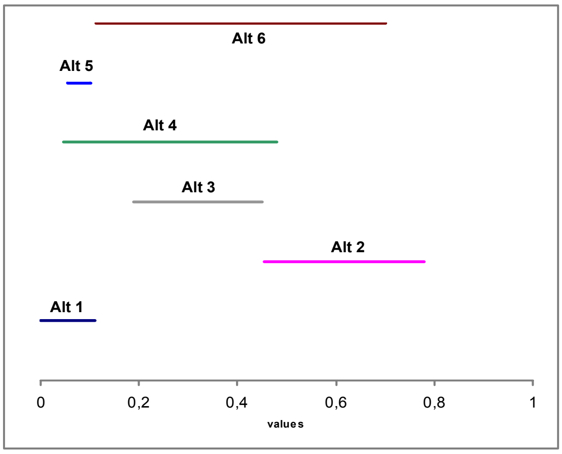

Figure 6.3 Displaying the overall values of alternatives

One can observe that these kinds of results may not lead to a clear recommendation, because the intervals of variation do not offer enough information to clearly show which alternative is best (non-dominated): for instance it is easy to eliminate alternative 1 (having the lowest values) but it is difficult to choose between alternatives 2 and 6 since their values are comparable towards their maximum.
In a problem, the set of dominated alternatives can be determined based on dominance structure. In PRIME, two dominance structures are used: *absolute dominance* and the *pairwise dominance*.

If there are several non-dominated alternatives, it is not possible to conclude which alternative is the best without having additional information from the decision-maker. This additional information can be obtained either when the decision-maker goes through the preference elicitation process again, or when he is able to specify a *decision rule* that may further distinguish between alternatives. Some of the decision rules proposed in [2] are:

- the *Maximax* rule: choose the alternative for which the largest possible value is greatest
- the *Maximin* rule: choose the alternative for which the smallest possible value is the largest
- the *Minimax Regret* rule: choose the alternative for which the largest possible loss of value (in the case of the selection of any other alternative) is smallest, or
- the C*entral values* rule: choose the alternative for which the midpoint of the value interval is the greatest.

Based on a thorough evaluation of decision rules with PRIME, it has been observed that the *Minimax Regret* and the *Central Values* rules outperform the other decision rules in terms *of loss of value* (associated with the possibility that a rule leads to the choice of a nonoptimal alternative).

Thus, in practice, an analysis can be terminated by dominance structures or by decision rules. The clearer the decision-makers are in expressing preferences, the more chances exist that the model will converge directly to a recommendation. The more imprecise and incomplete the preferences are, the more likely it becomes that decision rules will be needed.

6.2.2 The mathematical model

The first part of this chapter presented a proposal for how the *advanced DA* module in eTRANSPORT should be designed. This proposal suggested the succession of the procedural steps for this module, i.e. problem structuring, preference elicitation and issuing the final recommendation. This paragraph presents the mathematical model that can sustain such a decision support procedure.

6.2.2.1 The basics of the preference model

The *preference model* is the mathematical representation that sustains the *advanced DA* module. Structurally, this model will be independent of the existing mathematical algorithm that supports the *operational* and *investment analyses* in eTRANSPORT. This separation is necessary because conceptually these two mathematical models represent different things.
The existing eTRANSPORT models the physical characteristics of an energy system (conversion, transport, storage components and energy, costs and other quantitative flows within a system) and is used to estimate the impact that different system alternatives may have in different circumstances (in operation or expansion planning).

The *preference model*, on the other hand, models the decision-maker's values or preferences when confronted with the problem of choosing among different relevant system alternatives. The scope of *a preference model* is to provide supplementary information that can help planners in making a decision, i.e. in selecting an alternative. A *preference model* can be also used to provide data for comparing the alternatives but this time in terms of *decision-maker's values* and not in terms of *impacts*. The main assumption when constructing such model is that the decision-maker is able express these preferences or values.

The *preference model* is based on the *preference elicitation* step described previously. Thus preferences can be modelled after the problem is structured, i.e. after the decision-maker identifies the relevant set of alternatives, A = $\{A_1, A_2, \ldots A_m\}$ and the set of criteria, C = $\{C_1, C_2, \ldots C_n\}$ upon which these alternatives should be judged. As has already been shown, this proposal addresses multi-attribute problems, which can simply be described through a multi-attribute matrix:

$$\begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} \tag{6.1}$$

Each element in this matrix, i.e. each attribute $\boldsymbol{a_{ik}}$ describes the level of achievement of an alternative $\boldsymbol{i}$, ($i \in [1,..m]$) in a criterion, $\boldsymbol{k}$ ($k \in [1,..n]$). Depending upon how criteria are chosen, some of the $\boldsymbol{a_{ik}}$ are calculated directly with the eTRANSPORT model (costs, emission levels or losses) while others must be specified in addition, as described in the previous paragraph.

The decision-maker has to analyse this multi-attribute matrix and choose an alternative that best suits his purposes. It is assumed further that the user has some preferences (values) in mind when analysing the different options. These *values* are considered here as being *implicit* in the sense that the decision-maker might not be able to explicitly specify them (as required, for example with MAUT or AHP). The main idea with preference modelling is to try to approximate, as best as is possible, these implicit values and then compare alternatives accordingly.

Another assumption when building the preference model is that an additive value function can be used for finding the overall value for each alternative A_i, i.e.

$$V(A_i) = \sum_{i=1}^{n} v_k(a_{ik}) \tag{6.2}$$

where $v_k(a_{ik})$ is the implicit preference (value) a decision-maker has for an attribute $\boldsymbol{a_{ik}}$ ($i \in [1,..m]$, $k \in [1,..n]$). Illustratively, the *multi-attribute matrix describing impacts* (6.1) can be translated into a *value matrix* in the preference model:

$$\begin{pmatrix} V(A_1) \\ \vdots \\ V(A_m) \end{pmatrix} = \begin{pmatrix} v_1(a_{11}) & \cdots & v_n(a_{1n}) \\ \vdots & \ddots & \vdots \\ v_1(a_{m1}) & \cdots & v_n(a_{mn}) \end{pmatrix} \tag{6.3}$$

The variables in the preference model are the implicit values $v_k(a_{ik})$, *the objective(s)* is to find the overall value $V(A_i)$ while the *constraints* can be modelled based on the answers to a series of preference elicitation questions.

Because preference elicitation questions would allow decision-makers to specify answers in terms of intervals the actual mathematical problem underlying the *preference model* will be composed of a series of smaller linear optimization problems. In principle, two optimization problems can be defined for each alternative A_i: one to *maximize* the alternative's overall value $V(A_i)$ and the other to *minimize* this value. In the end, alternatives will be compared in terms of their overall values, obtained within intervals:

$$[\mathrm{Max}\, V(A_i) = \sum_{k=1}^{n} v_k(a_{ik}),\ \mathrm{Min}\, V(A_i) = \sum_{k=1}^{n} v_k(a_{ik})] \tag{6.4}$$

One can observe at this point that *preference elicitation* is in fact the key in building preference models. The *preference elicitation procedure* can be designed in different ways in order to encourage the user to think and compare attribute levels.

As explained previously in Chapter 3, the main ingredients when building multi-attribute value functions are the *scores* (comparisons within each criterion) and the *weights* (comparisons between criteria). The overall values in formula 6.4 can be thus further written such as:

$$V(A_i) = \sum_{k=1}^{n} v_k(a_{ik}) = \sum_{k=1}^{n} \left[v_k(a_k^*) - v_k(a_k^0) \right] \frac{v_k(a_{ik})}{\left[v_k(a_k^*) - v_k(a_k^0) \right]} = \sum_{k=1}^{n} w_k v_k^N(a_{ik}) \tag{6.5}$$

where $v_k^N(a_{ik}) = \left[v_k(a_{ik})\right] / \left[v_k(a_k^*) - v_k(a_k^0)\right] \in [0,1]$ is the *normalized score* for attribute ***k*** in view of alternative ***i,*** and the difference $w_k = v_k(a_k^*) - v_k(a_k^0)$ can be interpreted as the *weight* of the ***k***-th attribute. In order to derive such equivalence, it is assumed that:

1) the least preferred (a_k^0) and the most preferred (a_k^*) achievement levels for each criterion ***k***, can be identified and $v_k(a_k^0) = 0$
2) by convention, an *ideal* alternative can be defined as the alternative that would reach the most preferred achievement levels (a_1^*, a_2^*, … a_n^*). To this alternative, an overall value of 1 is assigned, such that $V(A^*) = \sum_{k=1}^{n} v_k(a_k^*) = 1$

It is important to observe that the value function model will have as its main variables the partial values $v_k(a_{ik})$, which will be constrained by the answers about scores and weights that a decision-maker would supply. Thus the scores and the weights will not be included in the model as such, because they would introduce non-linearity (the objective functions $V(A_i)$ would be non-linear if expressed as in the last part of equation 6.5).

6.2.2.2 Modelling incomplete preference information

This paragraph will present examples of how the answers to the preference elicitation questions can be modelled mathematically.

The preference model described in paragraph 6.2.1 implies that the user can specify different types of preference information either ordinal or cardinal in terms of intervals. All preference statements can be modelled as linear constraints and as new statements are introduced, more constraints will restrict the feasible space for each $v_k(a_{ik})$. Different mathematical formulations can model different answers, as will be emphasised further:

1) The least and the most preferred achievement levels and ordinal ranking

Information about the *leas*t and the *most preferred achievement levels* and ordinal ranking can be modelled as following:

If for each criterion ***k***, the least preferred (a_k^0) and the most preferred (a_k^*) achievement levels can be identified, then:

$$v_k(a_k^0) = 0 \text{ and } v_k(a_k^0) \le v_k(a_k^*) \le 1 \tag{6.6}$$

Sometimes, when judging in terms of *quantitatively* measured criteria, the least preferred achievement level (available for analysis, thus corresponding to an alternative analysed) might not the be 'worst' on the list. For instance, when comparing alternatives in terms of costs, the least preferred achievement level might not always be the higher cost (corresponding to the 'worst' alternative) but a cost level well under the maximum level, a limit up to which the decision-maker would agree to pay. Thus, if for any criterion ***k,*** there is and alternative $\boldsymbol{A_i}$ so that its corresponding attribute level is under the least preferred one, $a_{ik} \le a_k^0$ then

$$v_k(a_{ik}) = v_k(a_k^0) = 0 \tag{6.7}$$

Once the least and the most preferred levels are identified for *quantitative* criteria it is assumed that all other achievement levels (corresponding to the remainder of the alternatives) can be automatically ordered. This assumption is also sustained by the additive value model adopted.

Ordinal preference information should be specified, if possible for the *qualitative criteria* as well. However, the task of comparing alternatives in terms of qualitatively measured criteria (such as the aesthetic impact) may be quite difficult and sometimes may be impossible. PRIME for example permits the decision-maker to leave an assessment undefined, if he cannot assess it.

Then, if attributes can be ordered, for any criterion $\boldsymbol{k}$ such as: $a_k^0 \prec a_{ik} \prec a_{jk} \leq a_k^*$ (where $a_{ik} \prec a_{jk}$ means that a_{jk} is preferred to a_{ik}) then the following set of inequality constraints would result on values:

$$0 \leq v_k(a_{ik}) \leq v_k(a_{jk}) \leq v_k(a_k^*) \tag{6.8}$$

2) Cardinal ranking

Cardinal ranking supplies additional information regarding the strength of preferences, which were left undefined by ordinal ranking. A cardinal preference can be specified as a ratio with an upper and lower bounds. The PRIME method offers several possibilities for expressing cardinal information in terms of scores and weights, as defined as in equation 6.5.

The general format of ratio comparisons that reflects the relative magnitudes of ***scores*** is:

$$\frac{v_k(a_{ik}) - v_k(a_{i^*k})}{v_k(a_{jk}) - v_k(a_{j^*k})} \tag{6.9}$$

where a_i and a_{i^*}, a_j and a_{j^*} are pairs of alternative achievement levels corresponding to the $\boldsymbol{k}$-th criteria. If the decision-maker can specify bounds on these ratio estimates [L_k, U_k], then additional linear constraints can be added to the model:

$$v_k(a_{ik}) - v_k(a_{i^*k}) \geq L_k[v_k(a_{jk}) - v_k(a_{j^*k})] \text{ and}$$

$$v_k(a_{ik}) - v_k(a_{i^*k}) \leq U_k[v_k(a_{jk}) - v_k(a_{j^*k})] \tag{6.10}$$

The challenge, however, is to formulate the questions that will lead to the assessment of such bounds. One way would be to ask the decision-maker to provide estimates for all differences with reference to the least preferred achievement level (a_k^0) such as:

$$\frac{v_k(a_{ik}) - v_k(a_k^0)}{v_k(a_{jk}) - v_k(a_k^0)} \tag{6.11}$$

which preferably starts from the most preferred achievement level (at the top of the fraction) and continues with less preferred levels.

The way to design the questions is dependent on whether the attribute is an *increasing* or *decreasing* one (the attribute expresses 'costs' or 'gains'). For instance, if the decision maker has specified that $a_k^0 = a_{1k} \prec a_{2k} \prec a_{3k} \prec a_{4k} = a_k^*$ then he is requested to provide estimated for ratios

$$\frac{v_k(a_{4k}) - v_k(a_{1k})}{v_k(a_{2k}) - v_k(a_{1k})} \text{ and } \frac{v_k(a_{4k}) - v_k(a_{1k})}{v_k(a_{3k}) - v_k(a_{1k})} \tag{6.12}$$

The formulation of such questions is: '*which difference* (loss or grain) *has a greater importance* (and how much larger is the importance – in terms of intervals) *to you*: *moving from the best alternative to the worst or from the second best to the worst*…etc'

The assessment of preference information regarding the relative importance of criteria (*the weights*) will add more constraints to the optimization problem. According to the representation (6.5), the weights can reflect the range of the attribute being weighted, as well as its importance.

A large number of preference elicitation questions are required in order to restrict the values of the weights. Several guidelines for structuring such a long elicitation process are given in [2]. In PRIME, the weight of an attribute is defined as the gain in overall value obtained by a change from that attribute's worst consequence to its best one. PRIME Decisions uses SWING with intervals as its weighting method, which means that the most important criterion is assigned 100 points and the weights of the other criteria are compared to this value and are given in intervals [L,U] with bounds ranging from 0 to 100. Then, for each attribute, this leads to a new set of inequalities:

$$\frac{L}{100} \le \frac{w_k}{w_{ref}} \le \frac{U}{100} \Leftrightarrow \frac{L}{100} \le \frac{v_k(a_k^*) - v_k(a_k^0)}{v_{ref}(a^*_{ref}) - v_{ref}(a_{ref}^0)} \le \frac{U}{100} \tag{6.13}$$

6.2.2.3 Preference synthesis

After preferences have been expressed, the value model has been built and the overall values for each alternative have been obtained, preferences must be derived. In order to reach a recommendation, it is important at this step to further select non-dominated alternatives from the list. Dominance structures and decision rules may help the decision-maker to further compare the alternatives.

For instance, in an *absolute dominance* sense, an alternative A_1 is preferred to A_2 if the least possible value of A_1 is greater than the largest possible value of A_2 (i.e., the value intervals of the two alternatives do not overlap). Mathematically this means the following:

$$A_1 \succ A_2 \Leftrightarrow \underline{V}(A_1) = \min \sum_{k=1}^{n} v_k(a_{1k}) \succ \max \sum_{k=1}^{n} v_k(a_{2k}) = \bar{V}(A_2) \tag{6.14}$$

The set of alternatives can be also be determined using the *pairwise dominance criterion*. According to this criterion and alternative A_1 is preferred to A_2 if and only if the value of A_1 exceeds the value of A_2 for all feasible scores, i.e.:

$$A_1 \succ A_2 \Leftrightarrow \underline{v}(a_1) = \min[V(A_1) - V(A_2)] = \min \sum_{k=1}^{n} [v_k(a_{1k}) - v_k(a_{2k})] \succ 0 \tag{6.15}$$

In situations where dominance relations are not sufficient to drawing a conclusion, and the possibilities of obtaining further preference information (i.e. going back to preference elicitation) are limited, decision rules can be applied. Such decision rules are in fact ways of organising the final results. The following mathematical formulas can be used for expressing the results according to different rules [2]:

1) *Maximax*: determine the alternative with the largest possible value):

   i.e. an alternative A such that $\overline{V}(A\ ) \geq \overline{V}(A')$, for any *A'* in the set of alternatives.
2) *Maximin*: determine the alternative for which the least possible value is greatest):

   i.e. an alternative A such that $\underline{V}(A\ ) \geq \underline{V}(A')$, for any *A'* in the set of alternatives.

3) *Minimax Regret*: determine the alternative for which the greatest possible loss of value, measured as the largest difference between $V(A\ )$ and the value of all other alternatives, is smallest

   i.e. $\max_{A''\neq \grave{A}}[V(A'') - \underline{V}(A)] \leq \max_{A''\neq \grave{A}'}[V(A'') - \underline{V}(A')]$, for any *A'* in the set of alternatives.

4) *Central Values*: determine the alternative for which the midpoint of the value interval is greatest:

   i.e. an alternative A such that $[\overline{V}(A) + \underline{V}(A)] \geq [\overline{V}(A) + \underline{V}(A')]$, for any *A'* in the set of alternatives.

6.3 AN ILLUSTRATIVE EXAMPLE

The proposal discussed in this chapter is about how to extend the energy model eTRANSPORT such that it will allow for analysis of options in terms of multiple criteria and uncertainty. The structure and the mathematical model behind a new module of eTRANSPORT (the *advanced DA* module) have been emphasised. This new module will be practically an addition to the existing model, and it will give the user a possibility to perform a more advanced analysis of a problem, in addition to the cost-based analysis (which is already implemented).

This proposal has not been implemented at the time this thesis was written. However, in order to show how such a module will work and look like, the software PRIME Decisions (built on the same method proposed for the *advanced DA* module) is used. The same case study used to test MAUT and AHP will be resolved now with this software. The difference between this application and the previous ones is that a computer tool is used now to find decision-maker's preferences, as the *advanced DA* module would do. However, because the integrated tool is not developed yet, this example is again a two-stage procedure: eTRANSPORT is used to generate impact data and PRIME Decisions is used for preference elicitation and displaying the (results) recommendations.

Recall that the problem was to analyse and make a decision regarding four possible alternatives for expanding a local energy system. In order to compare among alternatives, five criteria have been taken into consideration: operation and investment costs, CO_2 and NO_x emissions and heat dump.

Step1. *Problem structuring*
PRIME Decisions allows for problem structuring in terms of criteria and alternatives. First, criteria have to be defined. The problem studied (named *Expansion* in this example) involved the five twin-level criteria. The data used in this example is the same as in the applications presented in Chapter 5.

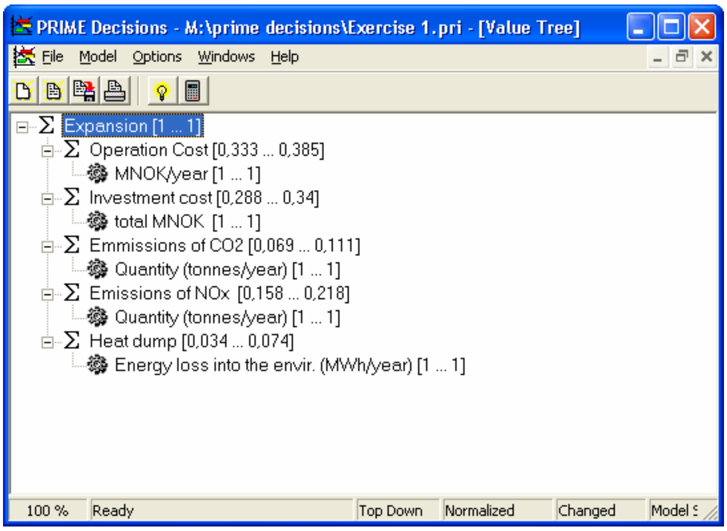

Figure 6.4 Structuring criteria with PRIME Decisions

PRIME Decisions can also be used in more complex problems where criteria must be structured in value trees, for example. After the value tree has been created (or the criteria have been defined), the alternatives should next be identified.

The *Alternatives* window of PRIME Decisions is designed for this task. The problem analysed concerned four alternatives: 1) *The base case,* 2) *Build a 3,6MW capacity CHP near the industrial site,* 3) *Build a 3,6MW capacity CHP near the town* and 4) *Build a 3,6MW capacity CHP near an industrial site*. For all these alternatives, attributes have been specified, as in Figure 6.5.

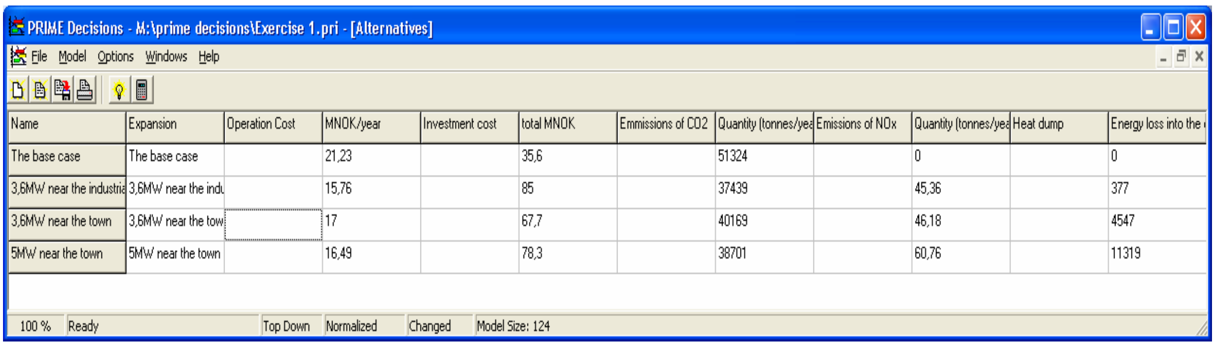

Figure 6.5 Structuring alternatives with PRIME Decisions

In the initial problem, uncertainties have been considered in terms of three scenarios (see Table 5.1). Because PRIME does not provide means for uncertainty analysis, in this example only the middle scenario has been considered.

Step 2: *Preference elicitation*
The second step proposed is the preference elicitation step. In PRIME decisions three types of preference information items are available: score assessments, holistic comparisons and weight assessments. An *Elicitation Tour* can be chosen from the Model menu, to guide the user through all elicitation steps. Alternatively the questionnaires can be selected manually. Figure 6.6 shows all types of preference information a user can specify.

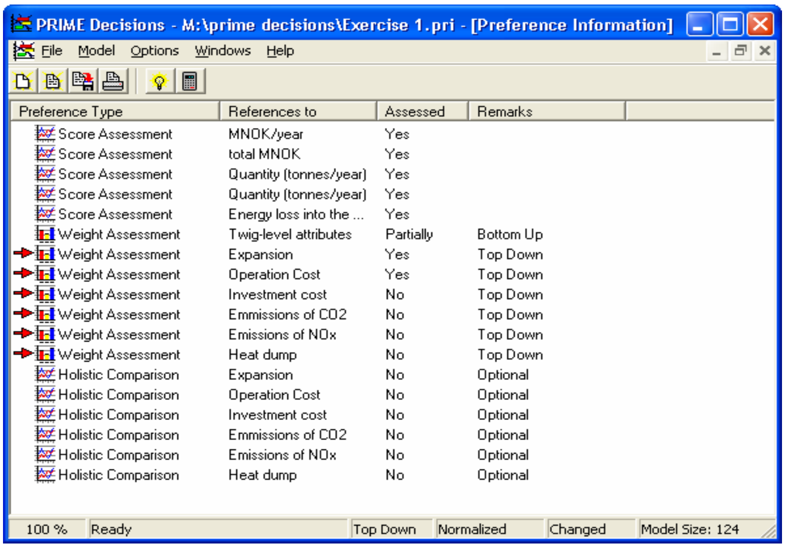

Figure 6.6 Preference information window in PRIME Decisions

<u>Score assessment</u> consists of ordinal ranking (defining the preference order of consequences) and cardinal ranking. Figure 6.7 shows an example on how the ordinal ranking (in this case in terms of operational cost) of alternatives can be done.

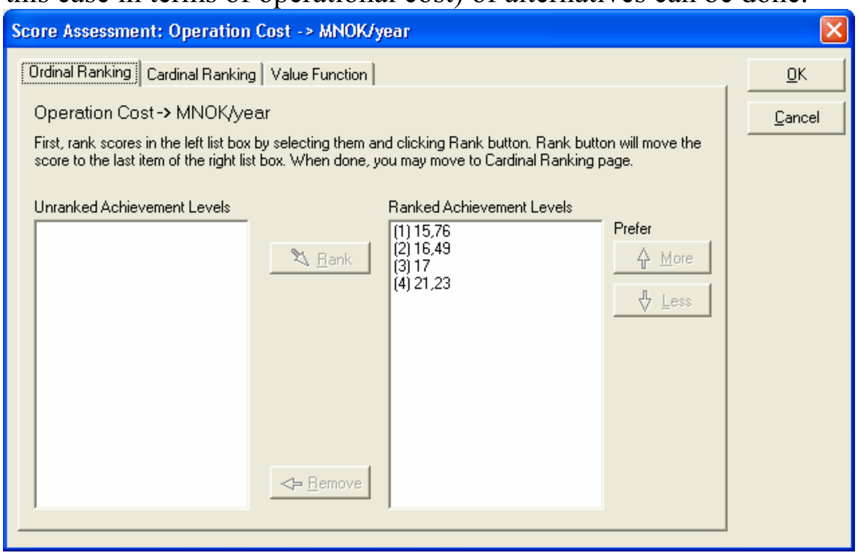

Figure 6.7 Ordinal ranking of attributes in PRIME Decisions

Cardinal ranking supplies information about the strength of decision-maker's preferences, which was left aside in ordinal ranking. A cardinal preference can be specified as a ratio with an upper and lower bound. A bound can be a nonnegative number, or it may be left undefined. PRIME Decisions provides different types of elicitation styles: *Comparison of Successive Differences*, *Comparison of Two Differences from Lowest Level*, *Comparison of Difference from Lowest and to Highest Level*, and *Direct Rating in [0, 1]-scale*. A cardinal ranking window for this example is shown in Figure 6.9.

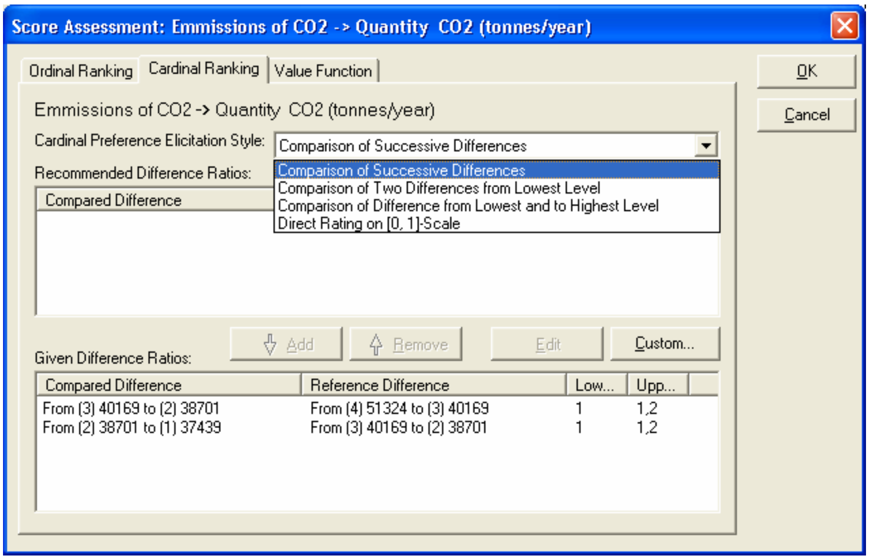

Figure 6.8 Cardinal ranking of attributes in PRIME Decisions

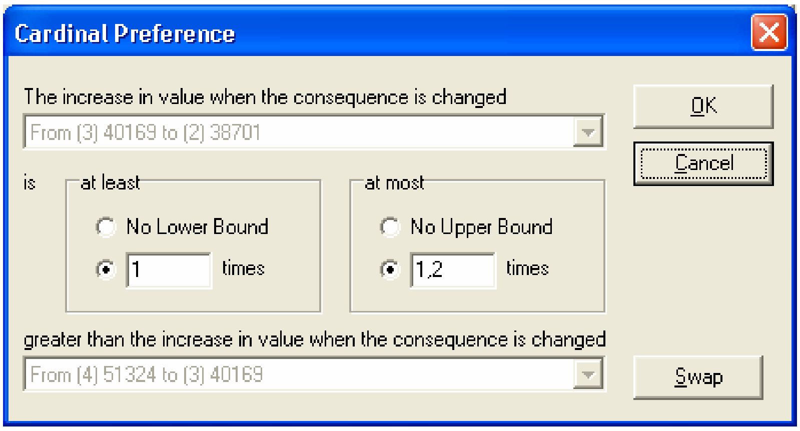

Figure 6.9 Example of questions for cardinal ranking of attributes (CO_2) in PRIME Decisions

For instance, for the CO_2 emissions criterion, one can choose to compare successive differences. Thus, an increase between 1 and 1,2 times in values is specified here, when moving from alternative (3) to alternative (2) than when moving from alternative (4) to (5). That means that a decrease in emissions at higher levels is slightly more important than a decrease in emissions at lower levels.

The second phase in preference elicitation is the ***assessment of weights***. PRIME defines the weight of an attribute as the gain in overall value obtained by a change from that attribute's worst consequence to its best one. PRIME Decisions uses SWING with intervals as its weighting method, which means that the greatest value is represented as an interval of [100, 100]. The weights of the other attributes are compared to this value and are given an interval with bounds ranging from 0 to 100.

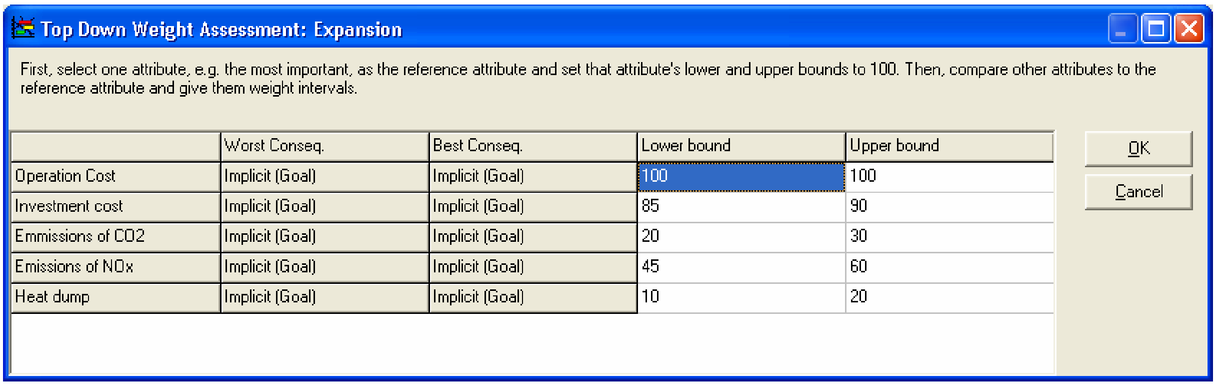

Figure 6.10 Top-down weight assessment in PRIME Decisions

PRIME Decisions has two styles for making weight assessments: bottom-up and top-down. In bottom-up weight assessment the decision maker needs to weight the attributes with respect to each other. In top-down weight assessment, the decision maker compares the weights of different criteria with respect with a reference criterion. In this example (see Figure 6.10) a top-down assessment has been chosen, with the reference criterion chosen as the *Operation Cost* – with all other criteria being compared to it.

Step 3: *Issuing a recommendation*
In PRIME Decisions results can be displayed in different windows: value intervals, weights intervals, decision rules or dominance results, as shown in Figure 6.11.

The Value Intervals window shows the calculated value intervals. The graph shows that both alternatives that implied the construction of the power plant near the town i.e. alternative 3 (3.6MW near town) and alternative 4 (5MW near town) are absolutely dominated. Moreover, the values for alternatives 1 and 2 do not offer enough information to choose one of them.

The dominance results show the same thing. PRIME offers additional information about weights. A weight is the value of an attribute's (or a goal's) best consequence. It represents the importance of an attribute with respect to other attributes. In this example, the decision-maker cares more about costs (operation and investment costs) then about local emissions (NOx) and less about global emissions (CO2) and heat dump.

To reach a final conclusion, decision rules must be applied. PRIME Decisions provides four decision rules that can be applied simultaneously: *Maximax*, *Maximin*, *Central Values*, and *Minimax Regret*.

In the example presented here, three of the four decision-rules recommend *alternative 1* as the one complying most with the decision-maker's values. A more optimistic decision rule (the *Maximax* rule) indicates however *alternative 2*. So far the problem is not 'solved' because the decision-maker still needs to make a choice of which decision-rule's recommendation to follow.

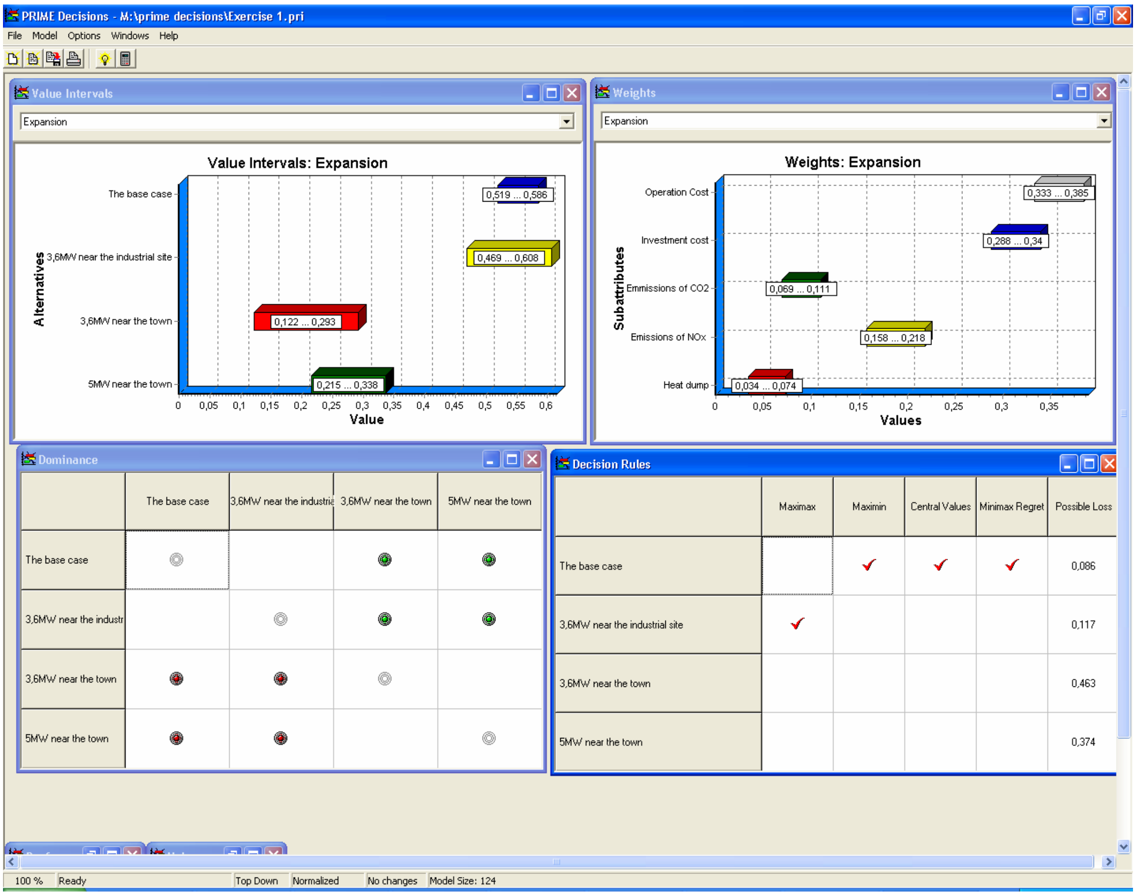

Figure 6.11 Displaying results in PRIME Decisions

6.5 Discussion

This chapter presented a proposal for designing a new module for the eTRANSPORT model. While the basic mathematical formulations that can support the new module have been illustrated, substantial work remains to be done to implement this approach. This work can be briefly summarized, and comprised two main areas:

1) Designing the user interface and in particular, the dialog with the decision maker, i.e. the types of preference elicitation questions. This should be based on additional surveys about how users may perceive such model, understand its rationale and accepts the solutions. PRIME Decisions can be used in a first phase to test if different energy planners would be interested in carrying out their analyses. For a relevant testing, real decision problems and real decision makers should be involved. As a recommendation, future developers of the model can benefit from earlier experiences with developing decision support software reported for example in [5-7].

2) The proposal in this chapter has been mainly focused on describing a multi-criteria procedure that can be integrated into eTRANSPORT. This procedure takes into consideration the uncertainty residing in decision-makers' way to specify his judgments (deals with incomplete preferences). The proposal include a discussion on how the

uncertainty in impact attributes (external uncertainty) can be considered with this new integrated tool, however no mathematical formulation of this part of the model have been given. Practically, the multi-criteria procedure (based on the PRIME method) would not depend on how the scenarios will be taken into consideration (one by one, or using some form of aggregation of attributes). In fact the scenario analysis (or aggregation) should take place *after* attributes are calculated (within the *operational* and *investment* modules) and *before* the multi-criteria analysis starts (within the *advanced DA* module). Further research is necessary if scenario aggregation is to be included in the model.

3) Once the dialog (i.e. the preference elicitation questions) is decided, the value model needs to be built. A series of biases may appear with preference modeling. For instance, cardinal rankings may create biases, because numeric bounds may be difficult to establish. One bias type described in [8] appears when in comparison of differences not all differences are of about the same size, or at least in the same order of magnitude. For instance, if a difference in the comparison is remarkably greater (or smaller) than the reference difference, one cannot reliably determine the order of magnitude of the bounds. *Research is still going on in this direction, and new methods are developed for dealing with incomplete preference information [4].*

6.4 CONCLUDING REMARKS

This chapter has presented a proposal for extending the eTRANSPORT model with a new module, i.e, *the advanced DA* module. Several issues have been discussed:

8. The proposal is based on the PRIME (Preference Ratios In Multiattribute Evaluation) technique developed by Ahti A. Salo and Raimo P. Hämäläinen at the Helsinki University of Technology. This method can be used for decision support in planning or in negotiations because such situations are usually characterised by novel and difficult – to-express concerns. Since such situations can occur in tactical or strategic planning of energy systems, the method can be adopted when building the *advanced DA* module. Moreover, PRIME has a strong mathematical foundation and has already been successfully implemented in the decision-support software, PRIME Decisions.

9. The *advanced DA* should include three procedural steps: *problem structuring*, *preference elicitation* and *issuing a recommendation*.

10. The idea behind the design of the new module for eTRANSPORT was that is should be similar, in terms of use, with the rest of the tool. Accordingly, this module should allow the decision-maker to define decision problems in terms of several criteria, as the energy system has been previously defined in terms of its components.

11. Although important impact information such as costs or emission levels can be provided in eTRANSPORT, in some situations decision-makers might need to add additional issues of concern to the analysis. Thus the tool should be flexible in terms of allowing the user to define additional criteria.

12. An important concept when building value models is that the preference elicitation procedures translate the problem of choosing the alternative with the 'best' *impact* into a problem of choosing the alternative with the highest *value*. When building such models it is assumed that decision-makers have some implicit preferences (values) for any achievement level of any alternative and any criterion. *These values* are revealed through the preference elicitation procedure.

13. The basic mathematical background for modelling preference information, calculating values and deriving recommendations has been presented. The approach is similar to the one used by the PRIME method. If this approach is going to be implemented, more work needs to be done with the most important direction for research being the establishment of the final structure for the preference model, and based on this the development of the user interface and the dialog with the decision maker.

14. PRIME Decisions have been used to solve the same problem addressed previously in the *two-stage approach*. The example illustrates how a procedure such as the one proposed in this chapter for extending the use of the eTRANSPORT model, could work.

15. Uncertainty is also taken into consideration in this approach. The method proposed as a basis for the preference model (PRIME) takes into consideration the *internal* uncertainty that stems from the incomplete preference information. This method is based on a value function model and cannot deal, as such, with the uncertainty in impacts (external uncertainty). However, if this type of uncertainty is to be considered in terms of scenarios (as in the two-stage approach), some sort of aggregation of attributes has to be carried out before the *advanced DA* module is used. Although no technical limitation exists in this respect, from a conceptual point of view this approach practically implies a repeated evaluation of attributes. The proposal in this chapter is to create a flexible tool that can allow the user to choose to model the external uncertainty through scenarios (probably in a separate 'uncertainty' module), and analyse these scenarios if this would be an issue in a given problem context. If for instance, the scenarios would not induce great differences in attributes, then the user can choose to go further to the step of multi-criteria analysis with one set of impact data. If on the other hand, there will be a significant difference in the impacts alternatives would have in different scenarios, then the user can either choose to analyse and aggregate attributes (and then go further to the multi-criteria analysis) or to analyse the problem in each scenario at a time.

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CONCLUSIONS

I. Planning of local energy systems: Challenges

The research in this thesis has addressed important issues regarding the activity of planning energy systems. Decentralization, the interconnection of different energy and emission markets and a trend toward sustainability are changing the priorities of energy planners and policy makers. Therefore the process of local energy system's planning nowadays is or should be based on new values and that new decision support tools are needed to address this change.

Within the local planning context, the need for decision support varies with the decision level and the number of participants in the decision process. Operative planning decisions can be supported by optimization and simulation models. Planning at tactical or strategic levels is more difficult to address with traditional energy models because several conflicting and complex issues have to be taken into consideration when making decisions.

Within this framework, the use of energy models and multi-criteria decision analysis (MCDA) in decision support has been discussed.

II. Impact and preference modelling

Due to the large amount of information that must be studied and processed, an energy system model should always be the basis for planning decisions. Such a model can be used to estimate the *impact* different decision alternatives may have on the economy and the environment in a region. The research in this thesis has been developed in parallel with a new *impact model*, eTRANSPORT. This model has been applied, at different stages in its development, to several case studies, contributing gradually to better understanding of the needs for decision support in energy planning.

eTRANSPORT can be used to calculate basic impact information about how relevant system alternatives may differ in terms of costs (operational and investment costs) quantities of pollutants emitted (NO_x, CO_2 or other pollutants) or energy losses. At the local planning level, many other criteria may be important when making a decision about the energy sources, energy carries and energy technologies to be used in supplying an increasing energy demand. These criteria can include the local impact on the environment (not only in terms of pollution but in terms of noise or aesthetic impact), the social impact or the need to comply with political and regulatory norms.

eTRANSPORT has allowed for a cost-based analysis of the operational and investment alternatives. Although monetization of all these criteria has been (and still is) useful, in the new planning environment an approach based on an explicit analysis in terms of multiple criteria might in fact be more relevant for planners since it is difficult to find monetary values for a number of important factors in planning, such as emissions or for other criteria given such rapid changes in climate, social situations and economics. Therefore new techniques for analysis are needed in order to allow planners to evaluate their options in terms of their real impacts.

The field of MCDA (Multi-Criteria Decision Analysis) provides methods for helping decision makers in dealing with complicated problems in which many issues of concern must be revealed and taken into consideration for decision. These methods can help in identifying and structuring both the reality independent of the decision-maker and his way of thinking (preferences) as well.

Methods for multi-criteria analysis can help planners to make 'justifiable' decisions, in the sense that they will better understand the problem and their own contribution to the decision and thus they would be able to justify their choices. The application of multi-criteria techniques depends very much on the ability to model the impacts in a specific circumstance or problem. The use -in a relevant way- of such methods can increase the chances that real decision makers will adopt the solutions provided by energy models.

This thesis has provided different classification schemes that can contribute to the understanding of how MCDA methods can be applied in practice.

III. Dealing with uncertainty

The issue of dealing with uncertainties in decision-making has also been discussed. The notion of uncertainty in decision-making is broader than defined by practical engineering approaches. Uncertainty results from both the fact that it is difficult to forecast the future (external uncertainty) and also from the ambiguity inherent in human judgements (internal uncertainty). *Recognizing* the uncertainty in a decision context, *accepting* it, making an effort to *structure*, *understand and model* it, are the main steps in dealing with uncertainty and in making it part of the decision process.

IV. Combining energy modelling and MCDA

The last part of this thesis proposes different approaches for decision support in local energy planning. An investigation of strategies for combining energy modelling and MCDA techniques is first presented. In particular this thesis examines how to extend the use of the eTRANSPORT model in supporting complex decision analyses involving multiple criteria and uncertainties.

Two strategies for combining impact and preference modelling have been studied. The first idea was to use the two models separately; to test the applicability of some MCDM methods using the type of data the eTRANSPORT can provide. The second idea was to find a good way for integrating the two models, by adding a new module to the eTRANSPORT model, to allow for preference elicitation and advanced decision aid.

A two-stage approach

The target problems in this discussion have been system planning problems, in which the main concern is to choose between alternative system configurations for supplying a given energy load. These problems involve a limited number of discrete alternatives for which MADM techniques are adequate. eTRANSPORT can be easily used to simulate the impacts different future evolutions of important system parameters (energy prices, end-used demands) may have on the performances of different alternatives, thus allowing uncertainties to be studied in terms of scenarios.

Multi-Attribute Utility Theory (MAUT) and the Analytical Hierarchy Process (AHP) have been applied to a pilot case study, where the impact information has been provided by the eTRANSPORT model. Relevant insights into the integration of the model with advanced decision support MCDA procedures have been obtained with these applications. It has been observed that the results of such decision support procedures may depend on the method used, the information presented for analysis to the decision-maker, or on the actual setting in which the preference elicitation is performed. An important result obtained was that the participants in these applications found these methods relevant to the types of problems studied.

Integration of energy modelling and decision aid

The experience obtained with the first application eased the way towards proposing a scheme for integrating multi-criteria analysis in the eTRANSPORT model. Chapter 6 of this thesis proposes an approach to designing a new module for eTRANSPORT, *the advanced DA module.* This approach assumes that the model can be used in *problem structuring*, *preference elicitation* and *issuing a recommendation*.

The proposal is based on the PRIME (Preference Ratios In Multiattribute Evaluation) technique developed by Ahti A. Salo and Raimo P. Hämäläinen at the Helsinki University of Technology . This technique has been chosen because it can be used for decision support in planning or in negotiations, when novel and difficult to express concerns must be considered. PRIME allows its users to specify *imprecise preference statements* such as: holistic comparisons between alternatives, ordinal preference judgements or ratio comparisons about preference differences. Moreover, PRIME has a strong mathematical foundation, and has already been successfully implemented in the decision-support software, PRIME Decisions.

Guidelines for building the preference elicitation procedure in the *advanced DA* module have been given. Practically, the elicitation of preferences helps in translating the problem of choosing the alternative with the 'best' *impact* into a problem of choosing the alternative with the highest *value*.

The results in *the advanced DA* module are in fact recommendations. In practice, an analysis can be terminated by *dominance structures* or by *decision rules*. The clearer the decision-makers are in expressing preferences, the more chances exist that the model will converge directly to a recommendation. The more imprecise and incomplete the preferences are, the more likely it becomes that decision rules will be needed.

To illustrate how such a procedure as the one proposed for building the *advanced DA* module may work, PRIME Decisions has been used to solve the same problem addressed previously in the *two-stage approach*.

Dealing with uncertainties

The approaches proposed for extending the use of the eTRANSPORT model, account for uncertainty in different ways. In the applications with MAUT and AHP, the *uncertainty in the impact* (external uncertainty) that different alternatives may have, has been modelled in terms of scenarios with probabilities. The preference elicitation procedure in MAUT seeks to explicitly take into account the decision-makers risk attitudes regarding uncertain impacts that alternatives may have. The preference model is based on *complete statements* decision-makers would need to make when asked various lottery and trade-offs questions.

The approach proposed for building the new *advanced DA module* in eTRANSPORT can also model uncertainty. The method proposed will primarily address the uncertainty that stems from the *incomplete preference information* (internal uncertainty). The proposal is based on a value function model and cannot deal, as such, with the uncertainty in impacts (external uncertainty). Nevertheless, if uncertainty in impacts is to be considered in terms of scenarios, some sort of aggregation of attributes has to be carried out before the *advanced DA* module is used. Although no technical limitation exists in this respect (scenario aggregation can be easily modelled), from a conceptual point of view this approach practically implies a double evaluation of attributes.

The proposal in this thesis is to create a flexible tool that can allow the user to choose to model the external uncertainty through scenarios (probably in a separate 'uncertainty' module), and analyse these scenarios if this would be an issue in a given problem context. If for instance, the scenarios would not induce great differences in attributes, then the user can choose to go further to the step of multi-criteria analysis with one set of impact data. If on the other hand, there will be a significant difference in the impacts alternatives would have in different scenarios, then the user can either choose to analyse and aggregate attributes (and then go further to the multi-criteria analysis) or to analyse the problem in each scenario at a time.

V. Suggestions for future research

This thesis can be a basis for future research in several areas.

The first is to go further into the details of understanding the planning process and explaining the planning needs. This can only be done by involvement in real-life applications, with real problems and real decision-makers.

Further research can be also dedicated to the testing of the applicability of other MCDA methods in real life planning. A comparison of how different methods can be used for decision-support should preferably be based on the feedback real-life decision-makers provide when using these methods in real situations.

So far, eTRANSPORT has been used for investment (expansion) planning. Further research would be useful in addressing the operation-planning problems, and the implications that a multi-criteria evaluation performed at this stage might have on decisions made at higher levels.

Uncertainty is a very important issue in planning. Further research can be directed towards problem structuring (for example, identifying the factors that induce uncertainty in the impacts at operational, tactical and strategic levels) or towards the integration of MCDA and scenario planning.

Moreover, important work remains in extending eTRANSPORT based on the approach proposed in Chapter 6. The implementation of this approach requires additional effort in:

4) Designing the user interface and the dialog with the decision maker, i.e. the types of preference elicitation questions. This should be based on additional surveys about how users may perceive such a model, understand its rationale and accept the solutions. PRIME Decisions can be used in a first phase to test if different energy planners would be interested in carrying out such analyses. For relevant testing, real-life decision problems and real-life decision makers should be involved.

5) Programming (modeling) the additional value model, once the dialog (i.e. the preference elicitation questions) is decided.

APPENDIX A

PAPER 1

'Modelling local energy systems from a multicriteria perspective'

This paper appears in the Proceedings of the 17th International Conference on Efficiency, Costs, Optimization, Simulation and Environmental Impact of Energy and Process Systems, (ECOS 2004), Guanajuato, Mexico, July 2004

Modelling local energy systems from a multicriteria perspective

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Abstract

The planning of local energy systems must deal with a wide range of options and conflicting objectives. It is also subject to a large degree of uncertainty due, for example, to demand growth for different types of energy, price (or price elasticity) for different energy carriers, behaviour of different players in the energy or financial markets, cost and availability of fuels and technologies, economic growth, environmental regulation, inflation and interest rates and public opinion. The modelling approach presented in this paper is used in the construction of a planning tool that will allow different types of decision-makers, with different interests to use it in an equally efficient manner.

Keywords: Local energy systems, Planning, Multicriteria and risk analysis

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1. Introduction

The development of energy systems planning models all over the world was more or less related to the first oil crisis in 1973 [1]. Many of these models involved one energy carrier -electrical systems [2, 3, 4, 5]- and specific energy conversion and transport technologies [2,6]. The optimisation performed was mainly related to quantifiable objectives like minimising costs (or maximising profit) and minimising environmental emissions [6] while less attention was given to non-quantitative aspects or uncertainty and risks associated with the planning problem. Significant research worldwide was carried out in the field of energy planning [1, 6, 8, 9, 13] and some methods and models will be mentioned further, but a review of it is outside the scope of this paper.

However, the complexity of this field and the multitude of ways to handle related problems allow us to propose a different modelling approach. The focus will be set on understanding the steps in the energy system planning process and the challenges modelling. The basic assumptions related with multicriteria and uncertainty modelling are the keys to social-economic profitable and sustainable energy solutions. At this point, the focus is set less on the mathematical details of the problem, but based on an optimisation model under development the general modelling framework will be outlined. The discussion will consider the problem, the system model that basically specifies the components of the energy system, a network flow operation model that convert the previous one into the computer code,

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and finally an optimisation model that includes multicriteria and uncertainties. Thus, the first part of this paper will focus on the general settings regarding the problem of energy systems planning and then the modelling approach is presented. The last part concludes the present work and outlines further research.

2. Energy Systems Planning: Problem Formulation

Generally, the planning problem for an energy system can be formulated as follows: Decide the best operation plan and the new investments (in different conversion technologies, transport networks, etc) in order to meet the future energy service demands, at minimum possible cost while taking into consideration all types of technical and resource constraints, the environmental and social requirements and an uncertain planning environment.

In this problem the system definition, including its boundaries, can be very complex. It might involve several energy resources (hydro, oil, gas, coal, sun, biomass, wind, wave, etc) and energy carriers (electricity, gas, hydrogen, oil, etc) together with different conversion, storage and transport technologies. It also involves a changing energy consumption pattern and new technologies to improve end user flexibility in choosing the type(s) of energy to be supplied with (electricity, gas, heat, hot water, etc). Thus, some of the resources (hydro, wind, wave) must be converted to other forms of energy while others can also be energy carriers (gas, coal, biomass). Consequently, a key element in the planning is to decide where in the system the necessary conversions should take place and which are the system boundaries.

Another key element in the planning process is the decision-maker(s) involved. The problem will be different if the decision-maker is representing the local administration, an industrial customer, a utility company or association of residential users. Each of these potential decision-makers might have different interests and different points of view regarding the criteria of analysis. Moreover the uncertainty related to the planning will be characterised and included in the problem in a different way by different decision-makers.

3. Modelling local energy systems

3.1 Description of the current model

As an illustration of the above discussion, a municipal energy system model with alternative solutions for distributed energy (electricity and heat) from biomass and waste can be represented as in Figure1. Available energy resources are shown on the left in the figure: Waste from municipal and business offices, institutions and companies, gas from old land fill and biomass and waste from forestry and farming [11]. These energy resources have to be transported, processed and stored in different locations and forms before converted to end user energy like electricity and heat. Often a choice has to be made between large centralised CHP units feeding local electricity and district heating networks, or remote mini-CHP installations in single buildings like offices, schools, health care centres etc.). The actual electricity and district heating networks are omitted from the figure for simplicity.

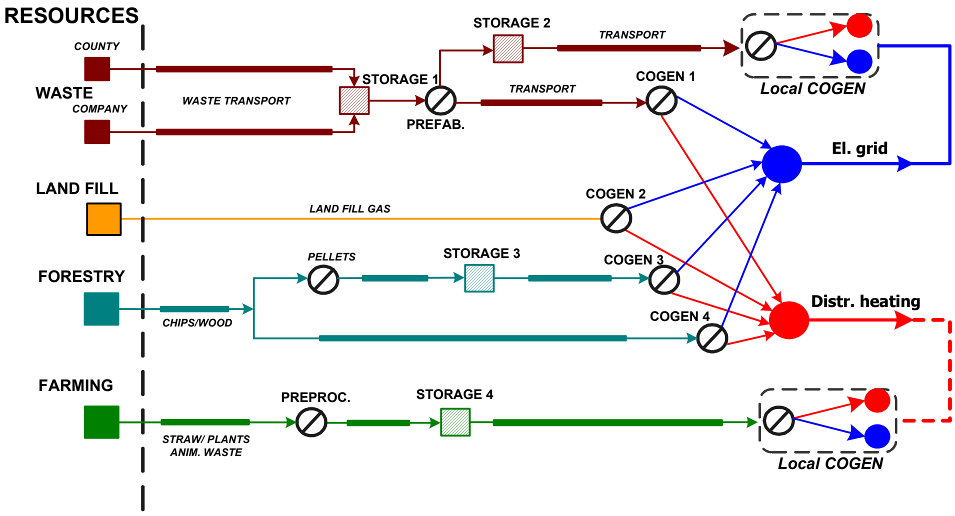

Fig.1. System model with alternative solutions for distributed energy from biomass and waste [11]

From mathematical point of view the planning problem is a non-linear integer programming problem that, with certain simplifications, can be solved by linear programming, non-linear programming, dynamic programming or integer programming techniques or various emerging techniques such as expert systems, fuzzy logic, neural networks, analytic hierarchy process and genetic algorithms. However, because the planning problem must deal with a great number of variables, objectives and parameters, we use a linear optimisation model. The advantages of linear programming applied to energy systems are considerable in terms of sensitivity analysis and the possibility to include it in a system dynamics or a fuzzy logic approach [9, 10]. Many existing models are using it as well [1, 9].

Starting from the system model in Figure 1, its components are modelled with sufficient detail in order to 'translate' the three types of technologies in the system:

- conversion technologies: convert one energy carrier into another at a specific geographic location;
- transport technologies: transport a given energy carrier over a defined geographic distance;
- storage technologies: storing one energy carrier at a given time.

The result is a graphical network flow model that can be represented as in Figure 2. The components are linearly modelled which allows flexibility when including multiple criteria and uncertainties into the optimisation. The optimisation deals with a generic flow of energy that will 'carry' trough the model information related to the attributes associated to different criteria like costs, environmental impact (emissions) etc.

At present, the structure of the linear model, represented in computer code, includes an operation sub-model and an investment sub-model that run in parallel.

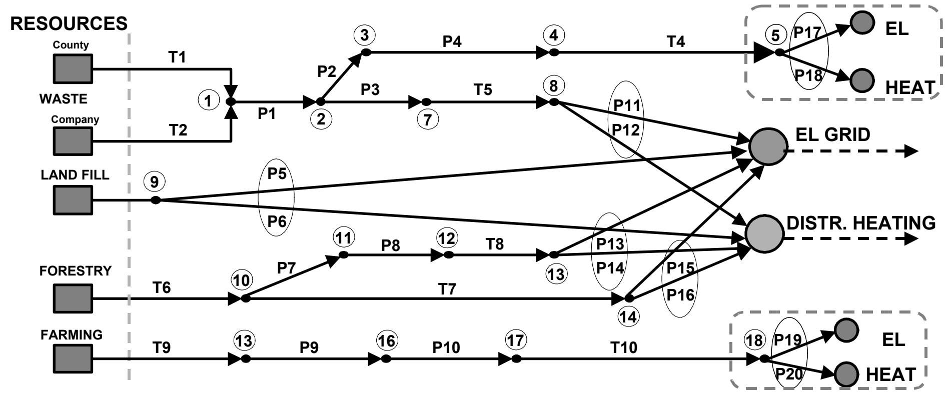

Fig.2 Network model for distributed energy from biomass and waste [11]

The operation model includes separate modules (files) describing available energy sources (electricity, gas, waste, etc), load points (for heat, electricity, hot water, etc.) and transport networks for different energy carriers (district heating network, electrical network, thermal power plant, discrete transport of gas and storage points). Each of these modules includes objective functions that are added up when the whole model is run. The model contains fixed technical parameters, which are not dependent on the problem analysed, and parameters that differ with each application. The constraints are either specific technical restrictions or related to load requirements, transport capacities and availability of primary resources used.

3.2 Including multicriteria and uncertainties

The linear model described above is able to handle multiple energy carriers in a geographically distributed network with energy transmission, conversion and storage technologies. Additionally, the planning of local energy systems must deal with a wide range of options, conflicting objectives and uncertainty.
This modelling approach allows a robust analysis of the system planning process, regardless of the decision-maker and specified uncertain decision situations. The planning tool gives the possibility to the user to 'build' his energy system model by using a library of available components. For each decision-maker it is very probable that the system will look different, at least regarding its boundaries, the selection of criteria and characterisation of uncertainty.

3.2.1 Multicriteria analysis

Models considering multiple criteria are of increasing importance in decision support. Understanding and identifying fundamental criteria and the essential reasoning that matter in any given decision context is a very important part of the decision process. Often decisions are based on an insufficient problem analysis because inadequate consideration is given to the fundamental decision criteria in the first place, or because certain initial assumptions are easy to make or are made out of habit, or the experts making it are not actually the ones that will make the decision. In complex decision situations there may be several objectives that must be considered and there may be others that can be used in evaluating potential consequences of the decision.

In order to measure the accomplishment of the fundamental objectives, attribute scales can be used. Some attribute scales are easy to define (cost) while for others there are no obvious ways of measure (environmental impact, aesthetics, etc.). Thus, as a classification, the criteria can be related to:

- cost: Minimise operation and/or investment costs;
- direct economic and technical benefits: Maximise (profit, utility finances), Maximise (reliability, stability, flexibility);
- environmental and health risks: Minimise (air and water pollution, flora and fauna influences, history, culture and aesthetics), Minimise (no. of accidents, diseases caused by pollution);
- socio-economic impact: Maximise employment, Maximise business growth;
- political impact: Minimise residents' concerns, Maximise the acceptability of different technologies.

On the other hand, the decision-maker must be aware of the fact that when looking at more that three or four criteria in the same time, he might lose track of his assumptions and the efficiency of the final result might be debatable.

3.2.2 Uncertainty issues

In planning complex systems usually uncertainty and risks are either neglected all together or they are dealt with by making rigid distribution assumptions. In the first case, risk factors are introduced by the decision maker through the definition of criteria that are somehow intended to control the risk inherent in the decision problem [12]. This is the case for example when the decision is made from a political point of view. In the second case it is simply assumed that a probability distribution is available which is then used as input for the multicriteria decision analysis.

The whole source of uncertainty in planning resides in the necessity to establish energy system boundaries. In theory, all systems should be seen as open since they are all influencing the 'environment' and in the same time they are influenced by it [9], but a practical and useful decision cannot be made outside a very well defined system problem. Thus, in establishing system boundaries, the decision-maker must be aware about a series of feedback loops that connect the markets for different energy sources and carriers, regulatory and political changes related to environmental issues, developments of new energy technologies etc.

The decomposition of uncertainty is often the subject of research in decision theory, and related to our purpose, the following structure can be useful [12]:

- *uncertainty about the data used to build the model*: future demand levels, forecasted value for the prices of future energy carriers, the cost of developing new equipment, etc;

- *uncertainty about the 'external' factors*: the behaviour of other decision makers, regulators, etc.;

- *uncertainty about the model*: the human decision making process can hardly be captured in mathematical models. For example, from a human point of view it does not make sense that a solution changes from being entirely feasible to infeasible within very small variations of parameters;

- *uncertainty about the outcome of a decision*.

This decomposition is very general but it is necessary to have it in mind when trying to capture uncertainty, as much as possible, in modelling details. Many modelling approaches presented in the field of energy systems planning are not considering the whole uncertainty. The reason is probably that in the 'traditional' planning, decisions were not always taken after a thorough analysis of the optimisation results, but from socio-political reasons. Moreover, only recently the decision problems became obviously extremely complex because of the development of different markets for energy. On the other hand, in the conventional representation of decision making under uncertainty, the decision-maker is assumed to have sufficient information to be able to specify the complete probability distributions over the outcomes of each alternative. This is often not a realistic assumption.

3.3 Modelling multiple criteria and uncertainties

The approach we propose here is to create a tool that will allow different types of decision-makers, with different interests to use it in an equally efficient manner. At the moment only a cost optimisation is implemented, but future developments of the linear model will allow addition of multiple criteria and uncertainties, as shown in Figure 3. The optimisation process will be interactive and, depending on the size of the problem, will probably necessitate the presence of an analyst to supervise it.

First the decision-maker will 'build' his own system model by selecting, from an available library, the components of the energy system that he wants to analyse. A drawing as in Figure 1 will result. Then he will have to specify which types of uncertain situations to include into the analysis, from several available types provided by the planning tool. The optimisation model will need also as input, the specification of a decision paradigm that will capture the attitude of the decision-maker towards risk. This decision paradigm can be related to expected value, regret, etc. The next step is selection of criteria. Depending on the number of it and on the size of the problem, the intervention of an analyst might be needed to assist the decision process. Within an interactive dialog the analyst will capture the preferences of the decision-maker regarding different criteria. These steps until now belong to the pre-optimisation phase when the decision-maker contributes in problem formulation.

There are several decision-aid methodologies in order to assess the preferences of the decision-maker regarding different criteria. The most common one is to ask directly the decision-maker to specify weights regarding criteria as an input to the optimisation routine. It is well known that this might complicate the decision process simply because the decision-maker might not be able, or might not want to specify these weights especially when many criteria are considered.

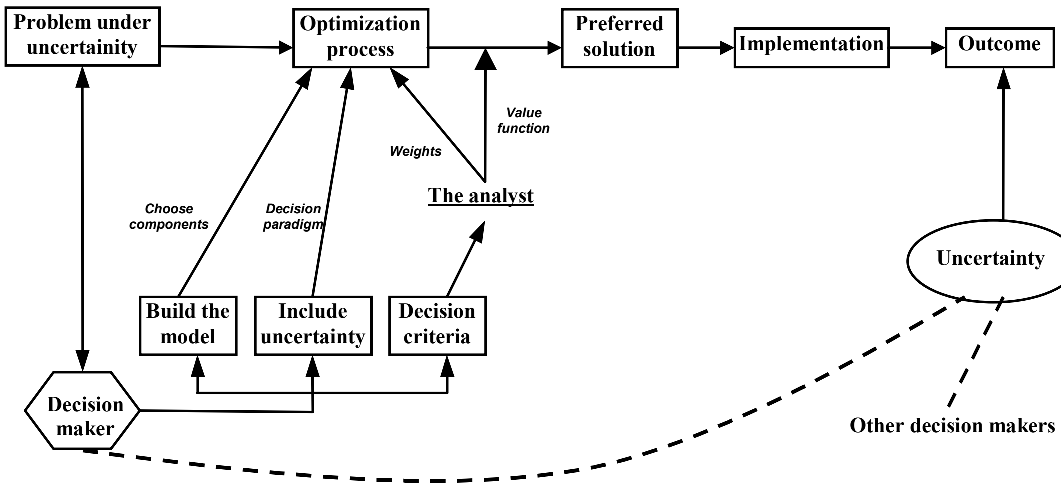

Figure 3. Optimisation including multicriteria and risk

A better option is to involve the analyst in building a value function of the decision-makers preferences. An interactive dialog will take place after the optimisation routine generates a list of possible solutions, in order to find out the indifference limits of the decision-maker regarding pairs of criteria. This will also allow the decision-maker to better understand the decision process and the consequences related to his choices.

Once the decision-maker ends his contribution to the optimisation process, a preferred solution will be obtained and implemented. As discussed earlier there are different types of uncertainties associated to this decision process. Even the uncertainty regarding the model and input data can be carefully included and analysed, in the end the results will still contain the uncertainty associated with the decision maker involved, or other actors in the planning scenery.

4. Conclusion and future work

We have discussed a modelling framework for energy planning. The basic issues were related with the premises and expectations of introducing multicriteria and uncertainty analysis into a robust and reliable decision process. A planning tool, based on a linear optimisation model under development was described. This tool will allow different types of decision-makers, with different interests to use it in an equally efficient manner.

Further research will focus on defining and modelling a coherent family of criteria, relevant uncertainty situations and investigating possible ways to include these into the planning tool.

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APPENDIX B

PAPER 2

'Constructing a multicriteria framework for local energy systems planning'

This is a reviewed version of the paper that appears in the Proceedings of the 17th International Conference on MultipleCriteria Decision Analysis (MCDM 2004), Whistler, Canada, August 2004.

This paper has been sent for review and publication to the *Journal of Multicriteria Decision Analysis*

CONSTRUCTING A MULTICRITERIA FRAMEWORK FOR LOCAL ENERGY SYSTEM PLANNING

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Keywords: local energy systems planning, MCDM, decision support tool

Summary: This paper recalls the problem of planning local energy systems as an interesting and challenging application for MCDA methods and methodologies. The main contribution in this paper consists of defining, structuring and understanding the complex decision process and of proposing a consistent framework for introducing multiple criteria and uncertainties into the problem formulation. The main ideas presented in the paper will serve as a basis for the development of a new planning tool for local energy systems. This decision support tool is the scope of an ongoing research project that aims at offering to the local energy planners a consistent methodology for analysing expansion problems.

1. Introduction

A large number of energy planning models and methods have been developed all over the world, since the first oil crisis in the seventies, with various applications at regional, national and even international scale. The scope of these models varies from engineering models focused on specific energy conversion technologies and single fuels or energy carriers, to more complex models describing the energy system as an integrated part of the overall economy [Rath-Nagel and Voss 81, Hobbs and Meier, 94, Borges and Antunes, 03]. There are also several multicriteria models and applications for the energy system's planning problem, many of them considering multiple actors as well [Psarras et. all, 90, Becalli et. all, 98, 03]. Overviews, discussions and comparisons of these methods can often be found in the literature [Psarras and Capros, 90, Hobbs and Horn, 97, Greening and Bernow, 04]. In this paper we will restate the decision making process and the main challenges in modelling the energy system. We propose a framework for dealing with the complex decision problem, by stating the basic ideas for a new planning tool for local or regional energy systems. By including multiple criteria and uncertainties into the decision making process, this tool should enable different types of decision-makers, with different priorities, to use it in an equally efficient manner. For example public decision-makers will be able to run scenario studies of the energy systems with respect to environmental impacts and consequences of different regulatory regimes. Public or corporate decision makers will also be able to analyse the mutual interdependence between different energy carriers and infrastructures.

The paper is organized as follows. We first introduce a general definition of the local energy system and the main aspects that have to be considered in the planning process. Then the focus will be set on the decision makers and stakeholders that are typically involved in the planning of such systems, how their objectives can be classified and measured, the number of possible and available alternatives and which are the main sources of uncertainty. At the end, we propose a consistent framework for how multiple criteria and uncertainties should be incorporated within a computer-based decision support tool that can be used by different decision makers in the planning of local energy systems.

2. Local energy systems planning

A local energy system can be very complex from several points of view: technical, economic and organisational. Such a system can include several energy resources, several energy carriers (electricity, district heating, gas, and in the future possibly also hydrogen) and a diversified energy demand (Figure 1). The supply side of the system can consist of both local and imported energy resources. Some of the energy resources, such as gas or firewood, can be utilized directly at the end-user location. The development of new technologies for distributed generation has transformed some of the traditional end-users in the system (mainly industrial customers) into suppliers of electricity or heat. At the demand side of the system, the energy meets a number of important services in society, such as heating, lighting, mechanical work etc., both in the industrial and residential sectors.

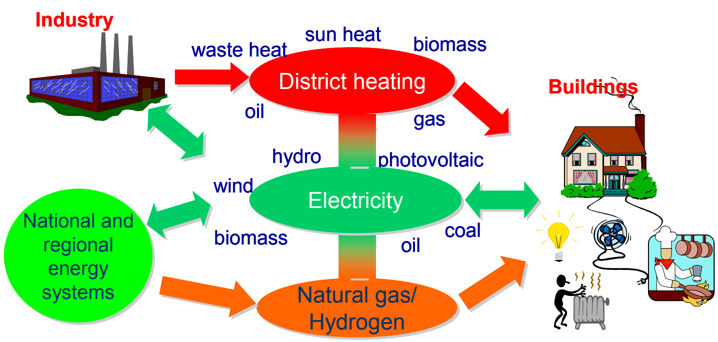

Figure 1: A local energy distribution system.

The local planners, in many countries, are currently confronted with new challenges. In the short term, the biggest challenge is to understand the complexity that the restructuring of the energy sector and the development of different energy markets, are adding to the decision making process. In addition, the widely discussed environmental problems and the continuous depletion of primary resources are giving new dimensions to the planning problem in the medium and long run. Consequently, there is a need for new planning methodologies and tools, in order to propose solutions both for the short and long run.

The next sections will give some guidelines for the process of understanding and structuring the energy system planning problem. The focus will be set on four key elements: 1) decision makers and other stakeholders involved in the local planning; 2) the multitude of criteria and conflicting objectives; 3) the main uncertainties associated to the planning problem and 4) possible alternatives.

1.1. Decision makers and stakeholders in the local energy system

The number of decision makers involved in the planning of local energy distribution networks will depend on the actual situation at the specific location. However, in general we identify three important groups of decision makers: energy distribution companies, regulatory bodies and authorities. The most visible group in the system is formed by the *distribution companies* for different energy carriers, as these companies make the investment decisions. Since energy distribution through networks is a natural monopoly, the distribution companies do not need to worry about competition from other investors. However, if different distribution companies are in charge of the different energy networks, there will be competition between the energy carriers about meeting the energy needs of the end-users. Co-ordinated planning is therefore difficult in this situation, as each company is only concerned with optimising operation and investments in its own distribution network. Investments in other distribution networks will be an uncertain variable not a decision variable, for each decentralized decision maker. In some situations the distribution company will make a combined analysis of investments in both production and distribution facilities. For electricity, the ongoing industry restructuring tend to separate production and distribution, while for district heating vertically integration is typically still the case.

Since distribution of energy is a natural monopoly, the system *regulators* will play a crucial role in deciding a regulatory framework, through which the distribution companies are given the correct incentives to invest in new infrastructure. So-called incentive-based regulation is frequently used to achieve cost efficient distribution systems for energy. Other objectives can also be achieved through incentive mechanisms. However, more direct regulations, for instance in terms of specification of requirements for system reliability or limitations of harmful emissions, are sometimes also needed. When several energy carriers are involved, there is a challenge for the regulators to design a consistent set of rules, which takes into account the interplay between the energy carriers. A common regulatory body for all energy carriers would be an advantage in such situations, in order to achieve well-coordinated regulations for operation and expansion of local energy systems.

At an even higher level of aggregation in the system, the *authorities* will have an important role as a decision maker in the local energy system. In many countries it is common that local or regional authorities own the energy distribution companies (at least partly). Hence, these authorities can also exert direct control on the investment decisions.

There are many stakeholders involved in local energy system planning. Some of them can also be decision makers, while others are mainly affected by the final outcome without directly taking part in the decision process. For instance, from the last group, the independent power generation companies will obviously be affected by the distribution system planning, since the infrastructure investments will have an effect on the demand for electricity. Similarly, independent suppliers of oil, gas and district heating to the distribution networks will also be affected. The end-users are crucial stakeholders in the system, since they are the consumers of the services that the energy networks deliver. Different end-user groups will not necessarily have the same interests or the same power to influence major decisions. For instance, it is likely that residential customers have different objectives than industrial consumers. In fact, *large-scale consumers* can sometimes also be considered as decision makers, since they in certain situations can decide which energy distribution networks to connect to and make the necessary infrastructure investments themselves accordingly.

1.2. Criteria in energy systems planning

The process of decision making and planning of local energy systems is subject to a multitude of conflicting objectives. One of the most important steps in defining and solving the planning problem consists of identifying, structuring and providing guidelines for measuring the achievements in different planning criteria. This section will include a general discussion about different objectives that can be included in energy planning, but it is by no means a list of all possible ones. Specific measurement issues will be highlighted as well.

Energy 'products and services' play a very important role in the society. Consequently, the overall scope of any planning process should be to maximize the 'well-being of the society'. This approach is also adopted in other energy-specific multicriteria problems [Keeney, 80]. However it might be argued that this is the case when the decision maker is representing the state or different authorities but not when the decision maker is a profit-focused company that provides different energy services to its clients. We consider that this aspect will be captured in the next level of the hierarchy of criteria. At this level the decision maker is more or less free to choose which criteria to include and then what preferences to give to each of them. The overall objective can be broken down, naturally, in four main major objectives, as shown in Figure 2.

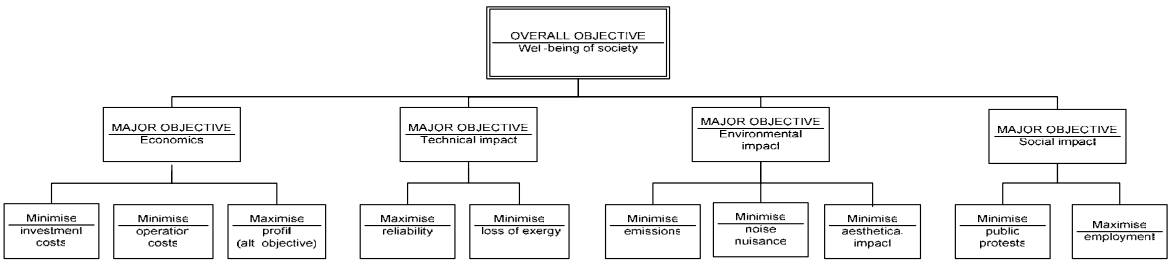

Figure 2: Objective hierarchy [based on Keeney, 80]

2.2.1 Economics

The '*economics'* criterion is and will probably be the most important one for the majority of decision makers. To assess this criterion, there are several objectives that can be considered separately, depending on whom the decision maker is and how competitive is his decision environment. For example, if the decision maker is representing a distribution company, the main interest will be maximizing the company's profit. An alternative is to minimize the total cost, especially for electricity distribution business where special regulations concerning the maximum income must be followed. The cost objective is also the most critical one when the decision maker is a large customer.

In general, when looking at the cost objective, it is also necessary to make a distinction between operation costs and investment costs for the different, expansion alternatives. This distinction is relevant when assigning decision maker's preferences or when exemplifying and including uncertainties in the analysis.

1.2.2. Technical impact

The *technical* criteria can be further detailed in at least two specific objectives concerning reliability of the system and energy quality.

In technological contexts, *reliability* is often defined as a component's or a system's ability to perform a required function, under specified environmental and operational conditions for a specified period of time [Høyland and Rausand, 94]. In energy systems, reliability will be the system's ability to meet the diversified energy demand. To assess *reliability* an objective may be to minimize the Expected Energy Not Supplied (EENS). EENS is the amount of energy (in kWh) not delivered because of a failure. The scale includes information about the Loss Of Load Probability (LOLP), the failure length, and the size of the failure, i.e. how many and how big are the customers influenced by it. Another possible objective is to minimize the socio-economic costs caused by the failure. A failure is much more serious for an industrial customer or a hospital than for a household or a farm. Consequently, it is useful to split between different end-user groups when looking into reliability. Socio-economic costs caused by the failure are given by: $\sum_{G} VOLL_G \cdot EENS_G$ where *VOLL* is Value Of Lost Load (monetary value, usually specified), and *G* is different end-user groups.

Energy quality is the relative usefulness per kWh of different energy carriers. Electricity is a very applicable type of energy that can be used for many purposes where alternative energy carriers are useless, like lighting or computers. This means that electricity has very high energy quality. Consequently, to use electricity for heating (and cooling) purposes can be regarded as abuse of high-quality energy. For heating purposes, it will be more suitable (from an energy quality point-of-view) to produce hot water directly from different energy sources (oil/biomass/natural gas/sun etc.), either at the customers location or in a common district heating central. Energy quality can be measured in kWh of exergy (availability). A possible objective can be to minimize the destruction and losses of exergy.

1.2.3. Environmental impact

Another major objective is to minimize the *environmental* impact associated with different system alternatives. Different kinds of energy projects have different impact on the environment. Ideally, all impacts on nature, i.e. the whole life-cycle impact (construction, operation and disposal) of the various alternatives, should be included in the analysis. This includes for example emissions, noise aesthetic impact, etc.

The decision maker must decide which *emissions* to take into consideration, according to the information about possible technical alternatives. Generally it is theoretically possible to estimate the levels of different types of emissions: CO_2, NO_X, SO_X, particles, etc. When looking at emissions, the geographical position of different technological solutions and the boundary of the system analysed are especially important. For some decision makers it might be important to distinguish between the local emissions, directly related to the local energy system, and the global emissions indirectly caused by the energy consumed locally but produced somewhere else (for example in the case of electricity imports). It can also be useful to distinguish between emissions in the construction phase, the normal operation phase and the ones caused by accidents.

As mentioned above, in some cases it will be necessary to minimize other environmental impacts like noise and aesthetics. *Noise* is theoretically measurable, and there are standards available for assessing the equivalent noise level ($L_{A,den}$). [Solberg, 01]. In addition, for measuring noise nuisance, the information about noise levels must be combined with information about who is affected by the noise sources. It must also be taken into account that it is very difficult to assess if people are annoyed by noise from the energy system or from other sources.

While for most of the criteria discussed above we can assume quantifiable measures, it is hard to measure the aesthetic impact associated with an energy project in an objective way. A possibility is to use a qualitative objective for this impact and let a representative group of affected people make priorities about which of the alternative solutions are more or less aesthetic. This will give an ordinal ranking of the aesthetic impact of the different alternatives.

2.2.4. Social impact

The main reason for building energy facilities and infrastructure is to serve the society with energy services. Therefore, it is useful to understand the social impact of different changes in the energy system's infrastructure by taking into consideration social values and public attitudes in the planning process. This will imply an open dialog that will give the opportunity to the public and concerned groups to express their opinions regarding specific energy projects. Such an involvement may result in "improved psychological well-being" in the local population. In turn, this might improve their understanding of and their trust in the involved companies [Keeney, 80]. However it is not easy to measure public attitudes. The public is not a homogenous group, and different persons will probably have different opinions about what is a good solution. Moreover it is difficult to decide what kind of attributes to use when measuring public attitudes. The main approaches are to use either a binary attribute (yes/no) or ordinal/cardinal rankings [Keeney, 80]. In addition quantifiable objectives can be included to capture the social aspect, e.g. in terms of maximizing the local employment caused by a specific project.

2.3. Possible alternatives

When thinking about energy system planning one probably has in mind a finite number of possible, expansion alternatives. This is logical considering the limitation in the number of local energy resources, and also the limited number of available technical solutions for conversion, storage and transportation of these energy resources. However, when looking at these discrete investment alternatives, a decision maker will want to know how the system will operate and how well the energy demand will be covered on a daily basis. From this point of view the set of 'alternatives' is often an infinite one since in reality various operational dimensions of energy infrastructure can be imagined [Capros, P et.al, 88].

Consequently we propose to separate the expansion problem into an operation problem and an investment problem. The operational problem can be seen as a multiobjective problem which can be formulated and solved trough a various number of optimization techniques. The investment problem is a multi attribute problem that can be solved for instance using interactive techniques. The main challenge then is to design a realistic and sound process to assess decision makers' preferences regarding the criteria corresponding to these two different parts of the problem.

1.3. The main uncertainties

While the main aspects of the planning problem are already discussed (decision makers and their possible objectives), it is also necessary to take into account the large degree of uncertainty inherent to the planning environment. The decomposition of uncertainty is often a subject of research in decision theory [Hallerbach and Spronk, 98]. A detailed discussion about risk and uncertainty associated with the decision making process in energy planning is not the scope of this paper. However we would like to briefly mention the main sources of uncertainty. These are: 1) uncertainty about the data available in the decision process; 2) uncertainty about the external factors and 3) uncertainty about the methodology or the model one chooses to represent the decision making problem. In the first category we have uncertainty due to: demand growth for different types of energy end-use, costs and availability of primary resources and technologies, market prices for different energy carriers, etc. When including uncertainty in the input data, it is again relevant to think about possible alternatives on short (daily operation), medium or long term. For example the uncertainty related to the spot price and the short-term demand forecast in the electricity market can strongly influence the electricity generation in a new local combined heat and power plant and probably the local heat production. This will cause disturbances in the short term local energy supply and probably a non-optimal operation of the entire local energy system. The second category includes uncertainty due to the behaviour of different decision makers within the energy or financial markets, economic growth, environmental regulation, inflation and interest rates or public opinion. The third source of uncertainty is mainly concerning the design of the model, the methods used and how well the decision maker understands the solutions obtained from an optimization model.

3. A framework for including MCDM and uncertainty in the decision making process

3.1. The basics of a new decision support tool

In the second chapter we listed the main aspects related to the process of decision making in the local energy systems planning. In Figure 3 [based on Matos and Pinho de Sousa, 03] we schematically represent a proposal on how to incorporate multiple criteria and uncertainties within traditional optimization procedures in order to solve the planning problem.

In the pre-optimization phase, the decision-maker will contribute in problem formulation and uncertainty characterization. This can be done in several steps:

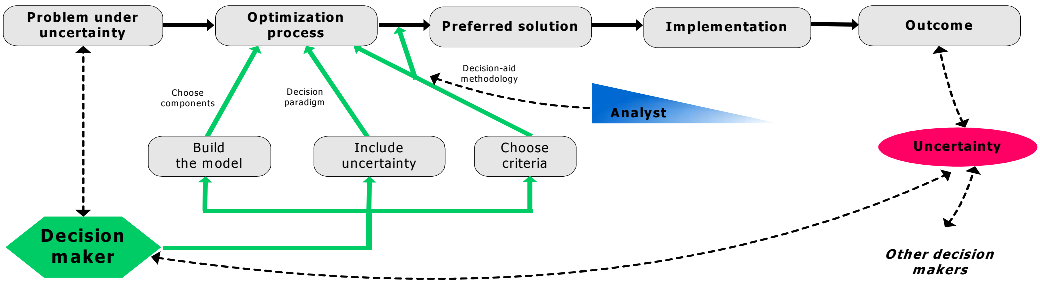

Figure 3: Framework for including multiple criteria and risk into the decision process

1) At the beginning, the decision maker should be able to specify the system he wants to analyse and several potential investment alternatives. The easiest way to do that is by simply 'drawing' the system as a network with all energy sources and demand points included. The graphical user-interface of the decision support tool will provide the user with an entire library of components to choose from. The network representation of the energy system is very often used in energy planning problems [Rath-Nagel and Voss, 81]. To exemplify this, a municipal energy system model with alternative solutions to meet a diversified energy demand can be represented as in Figure 4. Several available energy resources (that can be gas, biomass, waste, etc.) are drawn on the left in the figure.

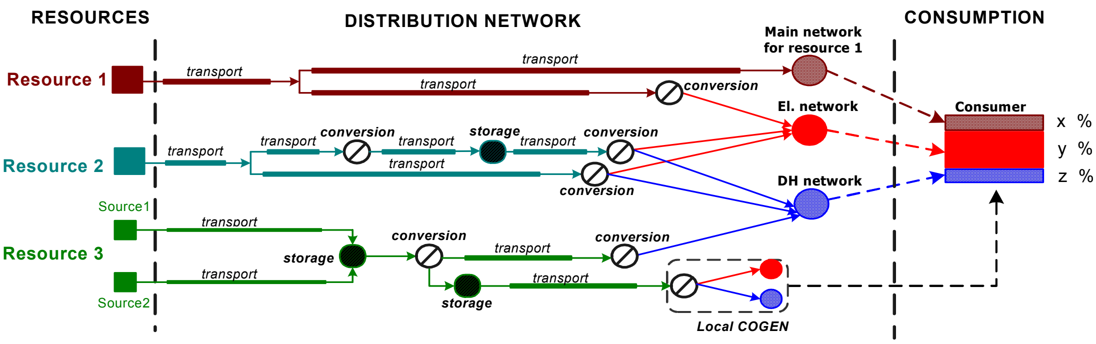

Figure 4: Example of a simplified local energy system model.

All these resources have to be transported, processed and sometimes also stored in different locations and forms before converted to end user energy like electricity and heat. Consequently we consider three different types of system components:

- *Conversion*: for conversion of one energy carrier into another at a specific geographic location;
- *Transport*: for transportation of a given energy carrier over a defined geographic distance;
- *Storage*: for storage of one energy carrier at a given time.

On the left side of the drawing, the consumers are represented by their total demand for different types of end-use energy: for instance from the total energy need, x % can be for gas, y % is for electricity, z % is for heat and hot water. Hence, the decision maker should also be able to have access to reliable data regarding the structure of the total energy demand which will be taken into consideration when planning the system.

2) In the second step, the decision maker should be able to specify which kind of uncertainties he wants to include into the analysis. Most decision makers would probably like to consider different price forecasts for different energy resources and carriers in different markets (spot prices for electricity, market price for gas and oil, etc). In addition, in most analyses it will also be relevant to consider the uncertainty in energy demand. Different decision paradigms (expected value, minimax, etc.) can be also provided inside the decision support tool, so that each user will be able to express his attitude towards risk.

3) The last step, according to Figure 3, is the selection of criteria. We assume that our decision making tool will be used by different decision makers, with different preferences regarding the criteria. Since the decision problem will be different for different decision makers, we aim at providing a consistent set of criteria that the decision maker can choose from when using the tool. A good decision making process should help the decision maker to understand his criteria and sometimes to add or eliminate some of them during the analysis [Henig and Buchanan, 96]. The decision maker should also be the one that specifies the necessary data and consequently influence the calculation of the attributes corresponding to different criteria.

Depending on the number of criteria selected by the decision maker and on the size of the expansion planning problem, the intervention of an analyst will probably be needed to assist the decision making process. At the end, once the decision-maker ends his contribution, the rest will mainly be optimization routine. A preferred solution will finally be obtained and recommended for implementation.

The decision support tool should be easy to use. Hence, the decision maker should be able to understand and trust the solutions obtained and also to perform different sensitivity analyses that will lead to a better understanding of his decision-making process. As discussed in one of the first chapters, we aim at developing a tool that will be used by one decision maker at a time. Consequently, the final outcome of the decision will incorporate the uncertainty associated with the decision maker's input, the uncertainty inherent to the mathematical methods chosen and modelling simplifications, and in addition, the actions of other decision makers. At the same time, the decision taken will also influence other actors' future decisions, as represented in the Figure 3.

3.2 The status of research

Based on the framework described above, we have started building an optimization algorithm using a linear description for the energy system. In the network representation of the energy system (Figure.4.) we suppose that all these system components can be linearly modeled with sufficient detail [Bakken et all, 99, Bakken and Holen, 04]. Hence the optimization will deal with a generic flow of energy. This energy flow is 'carrying' through the model information related to the attributes associated to different criteria like costs, environmental impact (emissions quantities) etc. At present, the structure of the linear model includes an operation sub-model and an investment sub-model that run in parallel, as discussed previously in section 2.4. The operation model includes separate modules (files) describing available energy sources (electricity, gas, waste, etc), load points (for heat, electricity, hot water, etc.) and distribution networks for different energy carriers (district heating network, electrical network, discrete transport of gas and storage points). Each of these modules includes objective functions that are added up to an aggregate objective. The model contains a large number of technical parameters, describing for example a list of standard technologies, which are not dependent on the problem analysed, and parameters that differ with each application (demands, prices, etc.). The constraints are either specific technical restrictions or related to load requirements, transport capacities and availability of primary resources. Until now, only a cost optimization is implemented, where different criteria are 'monetized'. Several case studies have been performed in order to verify the applicability of this incipient version of the optimization model. Future developments of the model will allow addition of multiple criteria and uncertainties. The future work concerns a thorough assessment of different ways to include multiple criteria analysis and consequently decision-maker's preferences.

Since we will deal with a large optimization model the simplest way to include data uncertainties will be trough scenarios (with probabilities or fuzzy scenarios). Then different decision paradigms (expected value, regret, etc) will be made available within the model so that the decision maker will be able to express and analyse his attitude towards risk.

4. Conclusion and future work

The scope of this paper was to restate the problem of complex energy systems planning. First the characteristics of the planning problem were discussed: the decision-makers involved their specific objectives and alternatives, and the main sources of uncertainty. We also proposed a framework for including multiple criteria and uncertainty in the decision making process characteristic for energy systems planning.

These ideas are the basis for the development of a new decision support tool that is the scope of an on-going research at NTNU and SINTEF Energy Research. This tool will have important practical applications in the context of decision making and planning of local or regional energy systems which are at the intersection of different energy markets and regulatory regimes.

In the next step of the research the focus will be set on the evaluation of different decision-aid methodologies for dealing with multiple criteria, uncertainties and risk preferences.

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APPENDIX C

PAPER 3

'Integrated energy distribution system planning: A multi-criteria approach '

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Integrated energy distribution system planning: A multi-criteria approach

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Abstract – This paper presents a decision support framework for expansion of local energy distribution systems. We focus on a complex decision environment, where the planners of the local electricity distribution system take into consideration the competition between different energy carriers in covering the total energy demand. At the same time, a number of criteria must be taken into account in the assessment of investment alternatives. By combining a linear optimisation model for the operation of the energy system with a preference model based on multi-attribute utility theory, we develop an integrated planning framework. In a pilot case study we test the framework on a problem with realistic data from a suburb in Norway. We interview five persons with background from energy research and industry. Their preferences are used to rank the potential expansion alternatives. The results and experiences from the case study are duly discussed.

Keywords: expansion planning, integrated energy distribution networks, multi-attribute utility theory, uncertainty.

1. Introduction

Electricity distribution companies are operating nowadays in an increasingly complex environment. With the ongoing industry restructuring the traditional vertically integrated utility companies are forced to unbundle their activities. However, at the same time there is often more horizontal integration at the distribution level. The distribution companies are not only distributing electricity, but also supplying, or competing with, alternative energy carriers, such as district heating and gas. Integrated analysis of the interaction between multiple energy carriers therefore represents an important challenge for the distribution companies.

We also see an increasing concern about the environmental impact of energy use, both at the local and global arena. A multitude of decision makers and stakeholders are usually involved in the planning process, and very often they have conflicting opinions and objectives. The planning process is further complicated by uncertainties about future development of load, fuel prices etc. At the same time, investment costs are high and expansion decisions irreversible. The complexity in the planning of local energy systems is discussed in more detail in [1].

In this paper we investigate how decision analysis and multi-attribute utility theory can be used to provide decision aid in this complex planning environment. We develop a planning framework, which can contribute to structure the problem, quantify the decision makers' preferences, and assess potential investment alternatives. An important advantage of using such an approach is that the decision process can be formalised and documented.

The paper is organised as follows. First, we give a presentation of the integrated planning framework. Then, we apply it on a pilot case study, which illustrates potential use of the methodology. The results from the study are discussed along with suggestions for future work, before concluding in the end.

2. An integrated planning framework

2.1. The impact model

In order to meet energy planners' need for quantitative simulation a linear optimisation model has been developed during the last 6 years, see e.g. [2]. A brief description of the model is included here. It minimises the socio-economic costs of meeting different types of energy demand in a defined area over a given planning horizon. The major advantages of the model are:

- Several energy carriers can be included (electricity, gas, district heating etc.)
- It includes energy sources, transmission, conversion, storage, demand as well as energy markets
- The components in the model have a physical description
- The geographical location of demand and infrastructure is taken into account

The model minimises the cost of meeting the stationary energy demand within an area, taking all the existing energy sources and transportation networks into consideration. In addition, energy can be sold in defined markets at given prices and quantities. The model provides a general set of system components, from which the analyst can design an energy system with the desired level of detail.

An hourly profile can be specified for each load type (e.g. electricity and heat) at several defined load points. The time resolution and planning horizon is typically 1 and 24 hours respectively in the operational analysis. Annual results can then be obtained by aggregating the results from several 24 hour periods with different demand levels. In an investment analysis the operational results are calculated for all relevant designs of the energy system, given a set of possible investment components. An investment algorithm is already implemented for cost-based expansion planning, as explained in [2]. In this paper we use the model to calculate not only costs, but also other impacts from the operations of the energy systems. Hence, it serves as an impact model, whose results are used as input to the preference model, as outlined below.

2.2 The preference model

Decision making for energy planners is a very complex process, highly exposed to uncertainties. In order to assist this process, we need, besides the impact model that gives an approximation of the system's performances regarding different criteria, a model that captures the preferences of the decision maker. This can be formally called the *preference model*. One way to build it is to use the multi-attribute utility theory (MAUT).

A decision maker has, practically, a set of relevant objectives in mind X_1, $X_2 \dots X_m$ when analysing the available alternatives, A_1, $A_2, \dots A_n$ for his energy system's planning problem. Each of these alternatives can be characterised by a set of achievement levels (attributes) of the objectives considered. Moreover, uncertainty can be included in the analysis by assigning probability distributions to these achievement levels. The MAUT theory offers the possibility of quantifying decision makers' preferences regarding the set of objectives (**X**) when the values of the attributes (***x***) are uncertain. If an appropriate utility is assigned to each possible consequence and the expected utility of each alternative is calculated, then the best course of action is the alternative with the highest expected utility. The theoretical background regarding MAUT is thoroughly described in several books [3] [4], and the theory has relevant applications in energy system problems [5] [6] [7] [8]. However, building utility functions is not an easy task and in order to obtain a better approximation of the reality, the theory offers us several frameworks. We use the additive form for the total utility function so that the total utility equals the weighted sum of the single utilities:

$$u(\boldsymbol{x}) = \sum_{i=1}^{m} k_i \cdot u_i(x_i) \qquad (1)$$

where

$u(\boldsymbol{x})$ total utility for attribute set $\boldsymbol{x} = x_1, x_2, \dots, x_n$

$u_i(x_i)$ utility for single attribute, $i = 1,2, \dots, m$

k_i scaling constant, attribute i

There are two main steps in determining such a multi-attribute total utility function. First, individual utility functions, $u_i(x_i)$, must be determined, for each of the objectives considered. This can be done by asking the decision-maker a set of lottery questions with respect to different achievement levels. The analyst can estimate, based on these answers, a set of qualitative and quantitative parameters that characterise the decision-maker's risk attitude. These estimations will be used to approximate the shape of the individual utility function related to each of the objectives considered. There are several functional forms that can be adopted, and for this preference model we chose the following exponential function, based on the description in [9]:

$$u_i(x_i) = 1/\left(1-e^{\beta_i}\right)\cdot\left[1-e^{\beta_i(\bar{x}_i - x_i)/(\bar{x}_i - \underline{x}_i)}\right] \qquad (2)$$

Where

$u_i(x_i)$ utility for single attribute, $i = 1,2, \dots, m$

β_i risk parameter, attribute i

$\bar{x}_i$ upper limit (worst outcome), attribute i

$\underline{x}_i$ lower limit (best outcome), attribute i

At this point a consistency check is necessary, to assure that the chosen form for the single utility functions is representing the true preferences of the decision maker involved. This implies additional sessions of questions that the analyst must design. The second step is to determine the scaling constants, k_i, using questionnaires of the trade-off type. In both types of questionnaires we use attribute values calculated within the impact model, prior to the preference elicitation process.

After this two-step process of quantification of decision-maker's preferences, the expected utility for the different investment alternatives can be calculated. Uncertainties are described in terms of scenarios with probabilities, and the expected utility for an alternative j can be expressed as:

$$E\left(u_j(\boldsymbol{x}_j)\right) = \sum_{k=1}^{n} p_k \cdot u_{j,k}(\boldsymbol{x}_{j,k}) \qquad (3)$$

where:

$E(u_j(\boldsymbol{x}_j))$ total expected utility, investment alternative j

$u_{j,k}(x_{j,k})$ total utility, alternative j, scenario k

p_k probability for scenario k

The ranking of the alternatives can now be done based on the calculated expected utility.

2.3 The integrated framework

A flowchart of the proposed integrated expansion planning framework is shown in Figure 5. First, input data for the analysis will have to be specified. It is important that th e decision makers are involved already at this stage, especially when it comes to deciding on which attributes and uncertainties to consider.

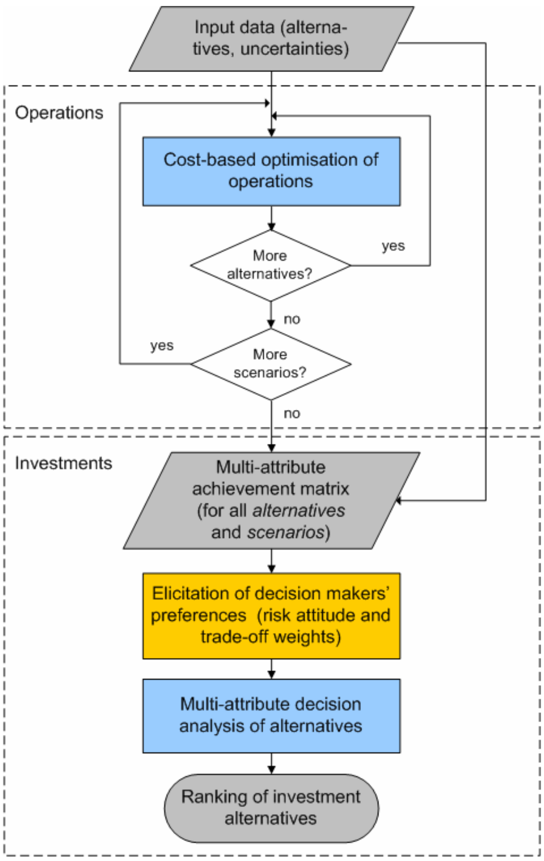


Figure 5: Flowchart of integrated planning model

A number of technical specifications, such as investment and operating costs, capacities, and emission and loss factors, also have to be determined for the components in the energy system.

Most of the input data are fed into the operations part of the analysis, where the impact model is used to calculate operational attributes (e.g. operational cost, local and global emissions). An algorithm is developed, which does this for all alternatives over all scenarios. The results from the operational analysis are collected in a multi-attribute (MA) achievement matrix together with attributes which are independent of the operation of the system (e.g. investment cost and visual impact)

The MA achievement matrix has to be calculated *before* the elicitation of decision maker preferences can be carried out. This is because the risk parameters and scaling constants are linked to the upper and lower limits of the attributes. These limits are a direct result of the operational analysis (impact model). The preference parameters are only valid for the calculated set of attribute limits.

After interviewing the decision makers, the derived preference parameters can be combined with the MA achievement table to calculate expected total utilities for the investment alternatives, using equations (1)-(3). Afterwards, it is straightforward to rank the alternatives based on expected utility. Note that although the expected value criterion is used in the MAUT approach, the MA table that we calculate can also be used as input for alternative paradigms for decision making under uncertainty, such as minimax and minimax regret.

3. Pilot case study

In order to test and improve the proposed decision support framework we developed a pilot case study. We used realistic data from an existing planning problem in Norway to analyse the future energy supply infrastructure for a suburb with ca. 2000 households and possible additional industrial demand. Based on results from the impact model we carried out preference elicitation interviews with five persons with background from energy research and industry. All persons participating in the test were asked to imagine themselves in the position of the top manager of an energy company that is the main supplier of energy for the residential and industrial customers in the region. The same problem was proposed to all of them, i.e. to decide on an expansion plan for the existing energy system in order to satisfy the future increase in local demand.

3.1 Assumptions for the operational analysis

In order to simplify the analysis we only consider the operations of the system for one time stage (year) in the future. Hence, in this analysis we do not consider the long-term changes in demand, and the timing of investment decisions. Total investment costs were therefore converted to annualised costs and could therefore be compared to the operating costs. An interest rate of 7 % was used for investment costs.

Hourly data for electricity and heat demand were specified for 8 different days in the year. The load days represented four seasons and two days within the week (weekday and weekend day). A 122 bus network was used for the electricity grid, with hourly electricity load specified in 55 of them. DC load flow equations were used to calculate the load flow and corresponding losses in the impact model. Potential district heating networks were represented with either 14 or 16 heat demand points, all of them with hourly demand data for the 8 load days. Note that while the electricity load can only be met by electricity, any connected energy carrier can meet the heat load. In this case that is electricity or district heating. The impact model finds the minimum cost solution for meeting both electricity and heat load for each of the days considered.

The main uncertainty considered in the analysis is the price of electricity. The electricity price is very important for the total cost of meeting the load, since there can be substantial exchange of electricity from the area, both imports and exports. Three scenarios are used for hourly prices of electricity, as shown in Figure 6. For simplicity we used the same price data for all the 8 load days.

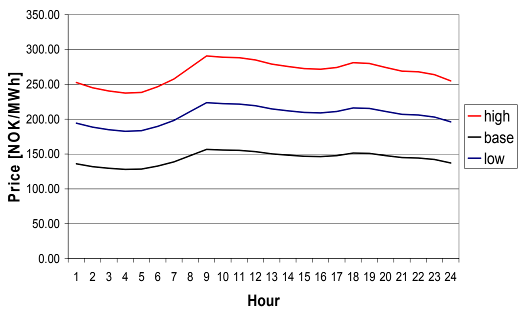


Figure 6: Price scenarios.
Currency rate: € 1 ≈ NOK 8.

In addition to the price uncertainty, we also assumed that the marginal change in global CO_2 emissions from exchange of electricity was uncertain. This factor affects the total CO_2 emissions from different investment alternatives. The marginal CO_2 factors for electricity exchange were set to 400, 500 and 600 g/kWh respectively, for the low, medium and high price scenarios, assuming that more efficient technologies are used in the low price scenario. Subjective probabilities were assigned to the scenarios, using 0.25 for the high and low scenarios and 0.5 for the medium price scenario. These probabilities were used when calculating the expected utilities, as expressed in equation (3).

Other prices, such as the price for gas supply to CHP plants and gas boilers, and the price paid for heating at the industrial site were assumed constant in the analysis.

3.2 Objectives

The impact model was set up to calculate four operational attributes: operating cost, CO2 emissions, NOx emissions and heat dump from CHP plants to the environment. In addition, investment cost is also an important attribute, which is not dependent on the system operation. Other criteria could of course also be considered in the analysis, either by extending the current impact model or by using additional models to estimate other impacts from the investment decisions. However, in this case study we limit the scope to the five attributes summarised in Table 1.

No.	*Attribute*	*Unit*
1	Operating cost	[MNOK/year]
2	Investment cost	[MNOK/year]
3	CO_2 emissions	[tons/year]
4	NO_x emissions	[tons/year]
5	Heat dump	[MWh/year]

Table 1: Summary of attributes considered in the pilot case study. MNOK is million NOK.

3.3 Investment alternatives

Four investment alternatives were analysed with the impact model prior to the interviews with the decision makers. The first alternative consists of reinforcing the electricity grid with a new supply line to the area, so that one can continue to rely on electricity to supply the local stationary energy demand. This is the alternative with the lowest investment cost. A district heating network and a CHP plant is built in the other three alternatives, to serve the heat demand for the customers in the residential area. In addition, a gas boiler is built to meet the peak demand for district heating. In the second alternative, the district heating network also covers an industrial site outside the residential area. The CHP plant is placed at the industrial site, and can also meet the heat demand there, which is currently supplied with a diesel boiler. In scenarios 3 and 4 the CHP plant is placed nearby the residential area. The only difference between these alternatives is the size of the CHP plant. The bigger CHP plant in alternative 4 facilitates generation of more electricity, which can be sold to the electricity market when it is profitable. A consequence of higher electricity generation might be excess heat from the CHP plant, which must be dumped to the local surroundings. Table 2 summarises the four alternatives.

Alt.	*New el line*	*DH network*	*CHP plant*	*Gas boiler*
1	yes	no	no	no
2	no	large	3.6 MW	5.0 MW
3	no	small	3.6 MW	5.0 MW
4	no	small	5.0 MW	5.0 MW

Table 2: Description of alternatives.

The impact model's results for the four alternatives over all scenarios are shown in the MA table in the appendix (Table 6). We can see from the table that alternative 1 has higher operating cost and CO2 emissions than the three other alternatives. On the other hand, the investment cost and the local emissions of NOx and heat are lower in scenario 1. The differences between the last three scenarios are smaller, but still significant, especially for NOx emissions and heat dump. There are also differences in the level of uncertainty for the attributes in the four alternatives, as can be seen when studying the results from the three price scenarios in Table 6.

The decision makers could of course base their decision on direct assessment of the information in Table 6, or on the corresponding expected values in Table 7. However, even with the simple example presented here it becomes difficult to judge the trade-offs and risks involved directly from the table. The advantages of using a formal approach based on decision analysis and MAUT are illustrated below.

3.4 Preference elicitation

The preference model was used further in order to formally incorporate the main values of the decision makers involved in the analysis. As mentioned in section 0, two types of questionnaires were designed. It is important to add here that the results following this type of dialogue are relevant only if the decision maker pays great attention and if he is willing to think hard about the consequences in the problem analysed. Consequently, the decision maker had to think if the results presented to him were relevant for his analysis: if he would like to consider more criteria or eliminate the ones with little relevance. The first type of questions where lottery questions for each of the objectives considered: the decision-maker was asked whether he would prefer an alternative with an uncertain outcome (A) or one with a certain outcome (B). The value of the certain outcome in B was repeatedly modified until the decision-maker became indifferent to these two options (Figure 7).

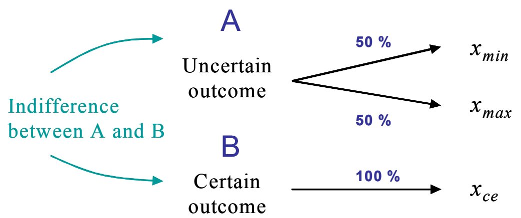


Figure 3: Example of lottery question for single attribute risk preference elicitation

Note that the range of attribute values discussed was obtained using the impact model. The answers to these questions were collected by the analyst and used to estimate individual utility functions. An exponential form for the single utilities was used, as explained in section 0. Table 3 shows the decision makers single utility risk parameters for all attributes. A negative β implies a risk averse attitude, whereas a positive β expresses risk proneness. It turns out that all decision makers are risk averse when it comes to investment and operating costs. In contrast, the decision maker's risk attitude varies more widely for the environmental attributes 3-5. For instance, when it comes to NO_x-emissions respondents A, B and D are risk averse, E is risk neutral, whereas C is risk prone (fig.3).

	A	B	C	D	E
β_1	-1.12	-0.70	-0.99	-0.99	-0.70
β_2	-1.65	-0.70	-2.24	-1.65	-0.70
β_3	-0.79	1.26	1.61	NA	0.00
β_4	4.24	1.95	-2.02	1.59	0.00
β_5	-0.45	NA	-2.48	NA	NA

Table 3: Single utility risk parameters (β_i) for all attributes and respondents (A, B, C, D, E). NA means that the decision maker considers the objective irrelevant.

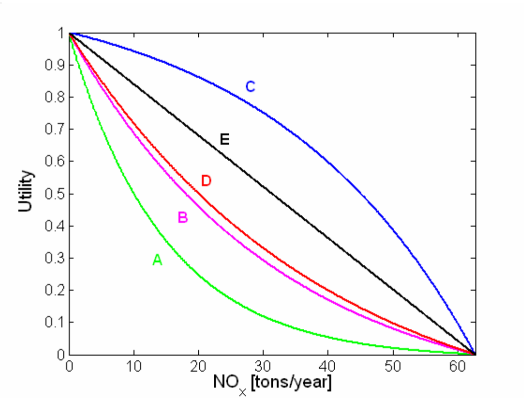


Figure 7: Individual utility functions for attribute 4, i.e. NO_x-emissions, for all respondents (A, B, C, D, and E).

The second type of questions was the trade-off questions. The decision maker was first asked which of the criteria analysed was the most important. This criterion was used as reference attribute for the trade-off comparisons. The decision maker was then asked to compare two hypothetical alternatives A and B, measured along the reference attribute and one of the other attributes, as illustrated in Table 4. The indifference point was found by changing the reference attribute level of alternative B, keeping the level of attribute *i* at its best (minimum), until the respondent was indifferent between the two alternatives. This was repeated for all criteria except from the reference one.

The resulting trade-off parameters, k_i, are shown in Table 4. Note that these parameters can not be directly compared for the five decision makers, since they have different individual utility functions. However, from the preference parameters in Table 3 and Table 4 it appears as if the decision makers *tend to be more risk prone about criteria they care less about*. In general, we had the impression that decision makers had problems expressing their risk preferences for attributes they were less concerned about.

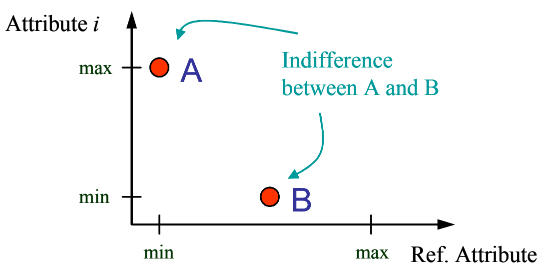


Figure 8: Example of question for trade-off preference elicitation.

	A	B	C	D	E
k_1	0.60	0.71	0.46	0.73	0.66
k_2	0.10	0.14	0.14	0.13	0.13
k_3	0.14	0.09	0.04	0.00	0.07
k_4	0.14	0.05	0.23	0.14	0.14
k_5	0.03	0.00	0.14	0.00	0.00

Table 4: Trade-off parameters (k_i) for attributes 1-5. A, B, C, D, E are the five respondents.

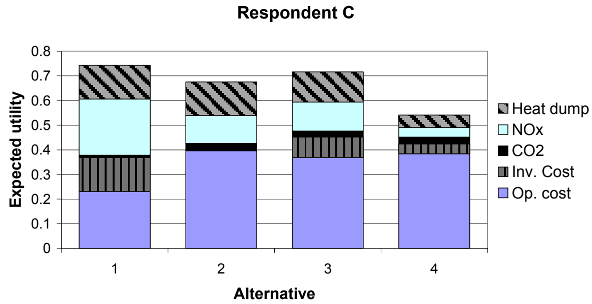
3.5 Ranking of alternatives

Having derived the decision makers' preference parameters we can now calculate total expected utilities based on equations (1), (2) and (3). We have only calculated expected utility for four alternatives. However, other alternatives could also be evaluated with the same preference parameters, given that their attributes for all uncertainty scenarios are within the attribute limits in Table 6. The results for the five respondents are shown in Table 5. Decision makers A, C, D and E end up with the same ranking of the four alternatives. Alternative 3, which is ranked first for these decision makers, is also the alternative with the least expected cost, as can be seen from Table 7. Respondent C puts more weight on the local pollution (NO_x and heat dump), and therefore ranks alternative 1 first.

Alt.	A	B	C	D	E
1	0.631 (4)	0.565 (4)	0.743 (1)	0.639 (4)	0.617 (4)
2	0.675 (2)	0.682 (2)	0.676 (3)	0.655 (2)	0.657 (2)
3	0.679 (1)	0.685 (1)	0.716 (2)	0.683 (1)	0.666 (1)
4	0.660 (3)	0.676 (3)	0.541 (4)	0.654 (3)	0.632 (3)

Table 5: Expected utility and ranking of the four alternatives for the five respondents.

In Figure 9 we show more detailed results for respondents C and E. The bars represent the total expected utilities for each of the four alternatives analysed. Since we use an additive utility function, the expected total utility can be split into sub-components for each of the five attributes. We clearly see that decision maker C's concern about the local pollution makes alternative 1 the one with the highest expected utility. We also see that respondent E is mainly concerned with the cost figures, and do not consider heat dump at all. The graphs give a good visualisation of how two decision makers in the same position analysing a problem, can have different preferences resulting in different decisions. It might also be that the resulting ranking of alternatives based on the total expected utilities is the same, even if the respondents' preferences are different. This is the case for respondents A, B, D, and E in our study.



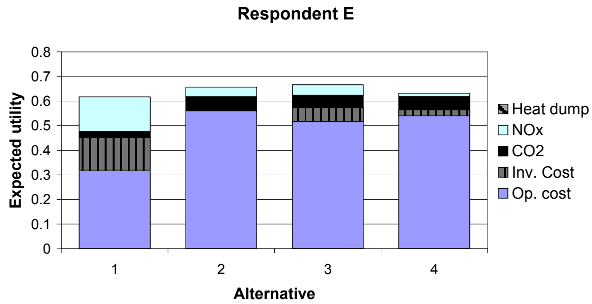


Figure 9: Expected utility for respondents C and E.

In the end, the pilot case study also demonstrates the importance of integrating the planning of the electricity distribution system with the planning of other energy distribution networks. In this example the preferences of four of the decision makers indicate that a district heating network should be build instead of reinforcing the electricity grid. Separate planning of the electricity and district heating networks could easily result in sub-optimal solutions.

4. Discussion

We believe that the major advantages of using multi-criteria decision methods lie in the structuring of information and preferences. Through the formalisation of the decision process, it also becomes easier to document the reasoning behind decisions. Another important strength of the MAUT applied in our integrated planning framework lies in its ability to cope with uncertainty and risk preferences in a consistent manner.

In our case study we looked at the planning problem from the viewpoint of the local energy distribution company only. However, the decision aiding methodology described here can also be useful when different interest groups are involved in the decision making process (end-users, regulators, NGOs etc.). It might be easier to reach consensus and agree on a solution when preferences are formalised and visualised. Extensions of the framework could also be implemented to further facilitate group decision making.

In the case study we only made one interview with each of the respondents. Important assumptions concerning input data, uncertainties, and choice of criteria were made in advance by the analysts. In a real planning process it is important that the decision makers are involved also in this part of the analysis. Earlier involvement of the decision maker will also reduce the analyst's impact on the results. Furthermore, more time should be devoted to perform consistency checks in the preference elicitation process, in order to obtain more reliable preference parameters. Each of our interviews lasted approximately 1 ½ hours, which was not sufficient for thorough consistency analysis.

A number of other extensions could also be done to the integrated planning framework, such as:

- Include additional impact models, which can calculate environmental consequences in units that are more relevant and easier to relate to for the decision makers.
- Incorporate the decision makers' preferences in the operations of the system, by using multi-objective optimisation in the operational analysis in the impact model.
- Introduce several time periods, in order to analyse optimal timing of investments.
- Implement alternative descriptions of uncertainty, and the possibility of applying other decision paradigms than the expected value for decisions under uncertainty.

5. Conclusion

New planning tools are needed to address the increasing complexity involved in the planning of local energy distribution systems. In this paper we have developed an integrated planning framework where a detailed impact model of the local energy system is combined with a preference model built on multi-attribute utility theory. In the pilot case study we show that the methodology can be used to quantify decision makers' preferences, both in terms of risk and trade-offs between conflicting planning criteria. The derived preferences were used to evaluate and rank a set of investment alternatives. Differences in the five respondents' preferences were clearly reflected in the results.

We believe that the most important advantage of using the proposed decision aiding framework is that the decision process can be structured, formalised and documented. This can clearly contribute to better informed decision making. However, for successful implementation it is important that decision makers are sufficiently involved and devoted, also in setting out the assumption in the early stages of the analysis.

ACKNOWLEDGEMENTS

The authors would like to acknowledge W. A. Buehring, R.G. Whitfield and T.D. Veselka at Argonne National Laboratory (Argonne, IL USA) for discussions and advice on the use of MAUT for energy system planning. We are also grateful to Arild Helseth at the Norwegian University of Science and Technology for providing us with realistic data for the pilot case study.

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APPENDIX

Alt.	Scen.	Prob.	Total annual cost [MNOK]	Total inv. cost [MNOK]	Annual inv. cost [MNOK]	Annual operating cost [MNOK]	CO2 emissions [tons]	NOx emissions [tons]	Heat dump [MWh]
1	1	0.25	17.7	35.6	2.87	14.9	41060	0.0	0
	2	0.50	24.1	35.6	2.87	21.2	51325	0.0	0
	3	0.25	30.5	35.6	2.87	27.6	61590	0.0	0
2	1	0.25	19.7	85.0	6.85	12.9	32902	44.7	0
	2	0.50	22.6	85.0	6.85	15.8	37440	45.4	377
	3	0.25	25.5	85.0	6.85	18.6	41974	45.5	468
3	1	0.25	19.3	67.7	5.46	13.8	36188	36.8	0
	2	0.50	22.5	67.7	5.46	17.0	40170	46.2	4547
	3	0.25	25.3	67.7	5.46	19.9	44665	47.0	5082
4	1	0.25	20.1	78.3	6.31	13.7	35662	42.6	821
	2	0.50	22.8	78.3	6.31	16.5	38701	60.8	11319
	3	0.25	24.9	78.3	6.31	18.6	41917	62.7	12604

Table 6: Multi-attribute achievement matrix in pilot case study. All results are per year.

Alt.	Total annual cost [MNOK]	Total inv. cost [MNOK]	Annual inv. cost [MNOK]	Annual operating cost [MNOK]	CO2 emissions [tons]	NOx emissions [tons]	Heat dump [MWh]
1	24,1	35,6	2,9	21,2	51325	0,0	0
2	22,6	85,0	6,8	15,8	37439	45,2	306
3	22,4	67,7	5,5	16,9	40298	44,0	3544
4	22,6	78,3	6,3	16,3	38745	56,7	9016

Table 7: Expected values of multiple attributes in pilot case study. All results are per year.

APPENDIX D

Material used in the application of MAUT

1

Integrated energy system planning

Preference assessment for pilot case study

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2

Background

- Multi-criteria decision analysis (MCDA) within SEDS and E-transport projects at NTNU/SINTEF
- Development of test case for local energy planning, using the E-transport optimization model
- The main purpose of this exercise is to test how relevant is to apply MCDA for energy planning
- We would like to have your sincere opinion and beliefs regarding this application!

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3


Your role:
You are the top manager of the integrated energy company that is the main supplier for the residential and industrial customers within the region X.
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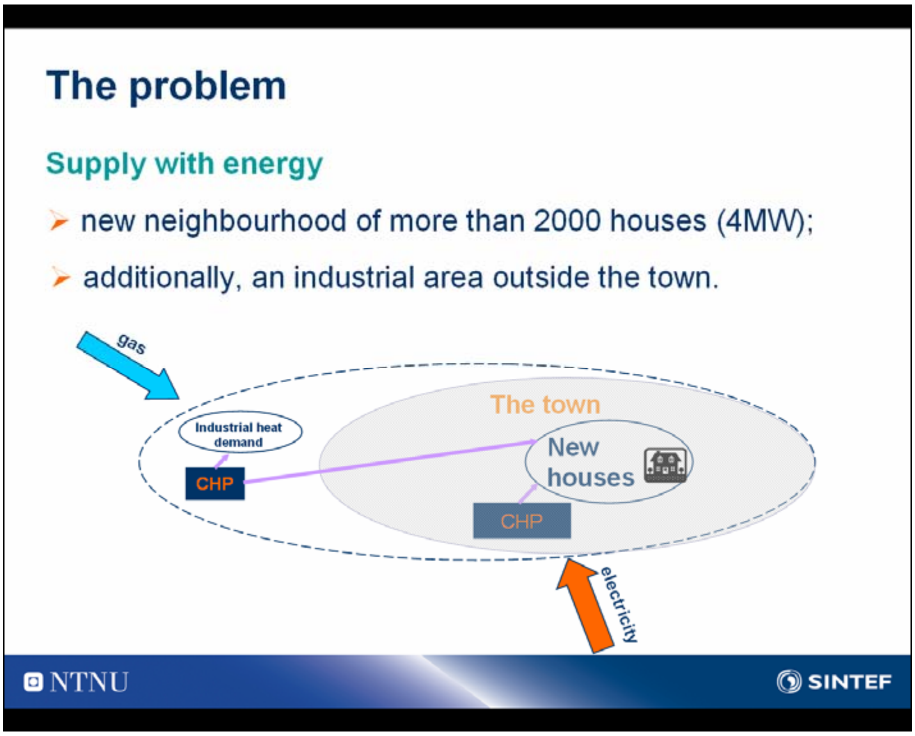
4


The problem
Supply with energy
new neighbourhood of more than 2000 houses (4MW);
additionally, an industrial area outside the town.
gas
Industrial heat demand
CHP
The town
New houses
CHP
electricity
NTNU
SINTEF

5

The problem

Assumptions:

- alternatives differ mainly with the location and the size of the new production capacity and the electrical and district heating networks;
- uncertainty is included in form of el-price and emissions scenarios, with probabilities;
- the results for this case-study where obtained using a cost-min. optimization (E-transport);
- the demand levels are equivalent, for the alternatives analyzed:
  - the main focus is to supply the new residential area <u>but</u>
  - it might be relevant to build the new capacity near the industrial site and sell additional heat there;
- the alternatives that consider a CHP have the advantage of selling electricity to the electricity market when it is profitable.

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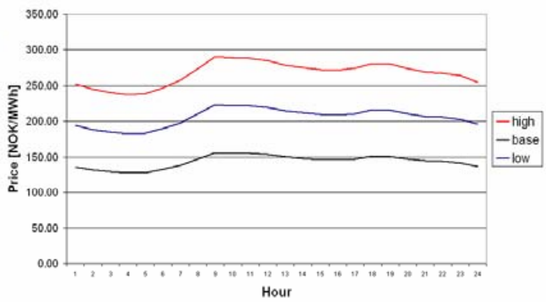
6

Assumptions regarding prices used in the analysis:

- **Electricity prices:**
  - 3 scenarios
    - high price (25 % probability)
    - medium price (50 % probability)
    - low price (25 % probability)
  - constant price profile for all load periods within the year
  - corresponding CO_2 emissions
    - 400 g/kWh (low price)
    - 500 g/kWh (med price)
    - 600 g/kWh (high price)



- **Constant gas price for combined plant and boiler: NOK 1/Sm3**
- **Constant price for heat sold at industrial demand: 150 NOK/MWh (heat)**
- **No CO_2 tax included**

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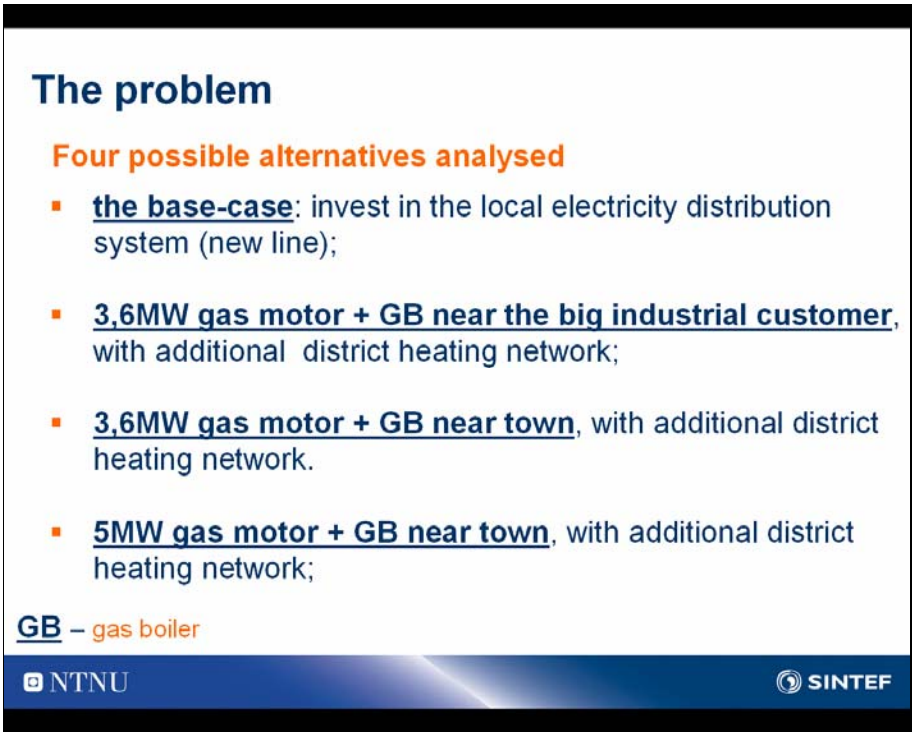
The problem
Four possible alternatives analysed
the base-case: invest in the local electricity distribution system (new line);
3,6MW gas motor + GB near the big industrial customer, with additional district heating network;
3,6MW gas motor + GB near town, with additional district heating network.
5MW gas motor + GB near town, with additional district heating network;
GB – gas boiler
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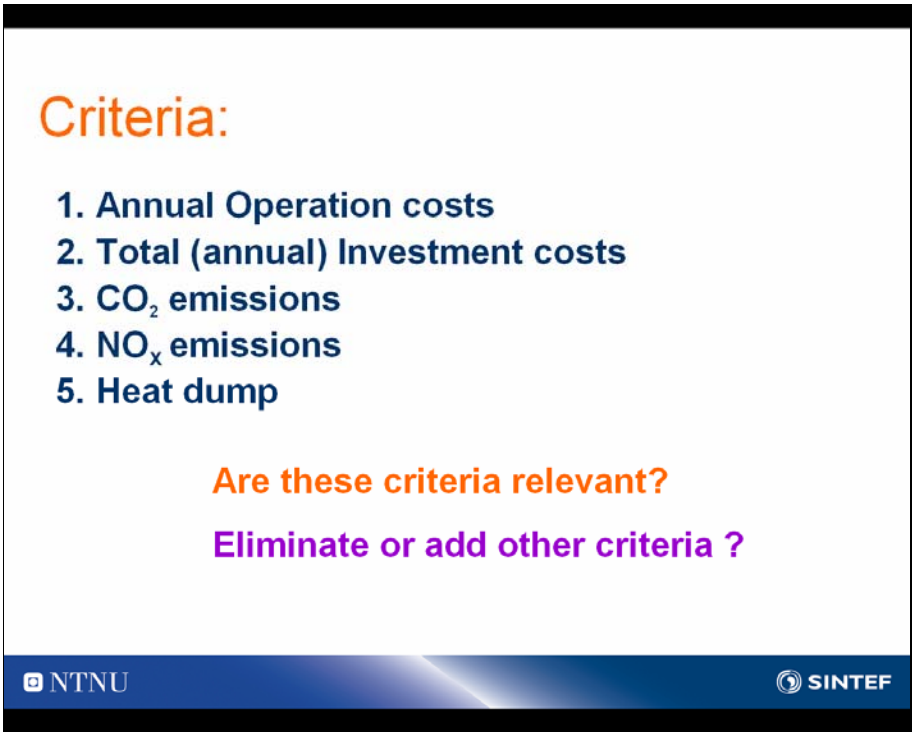
Criteria:
1. Annual Operation costs
2. Total (annual) Investment costs
3. CO2 emissions
4. NOx emissions
5. Heat dump
Are these criteria relevant?
Eliminate or add other criteria ?
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9

The main results:

Alt. \ Criteria	Investment Costs (MNOK)	Operation costs (MNOK/year)	CO_2 Emissions (tons/year)	NOx Emissions (tons/year)	Heat dump (MWh/year)
1.	35,6	14,86	41 059	0	0
		21,23	51 324	0	0
		27,6	61 589	0	0
2.	85	12,89	32 902	44,7	0
		15,76	37 439	45,36	377
		18,6	41 973	45,49	468
3.	67,7	13,84	36 188	36,8	0
		17	40 169	46,18	4 547
		19,8	44 664	46,97	5 082
4.	78,3	13,74	35 662	42,6	821
		16,49	38 701	60,76	11 319
		18,6	41 917	62,65	12 604

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10

Theoretical background:
Elicitation of preferences by building utility functions

Utility functions

– A formal way to include risk in the evaluation of alternatives

Requires:

- Definition of scenarios, with probabilities
- Construction of the utility function
- (multicriteria) Indifference judgments

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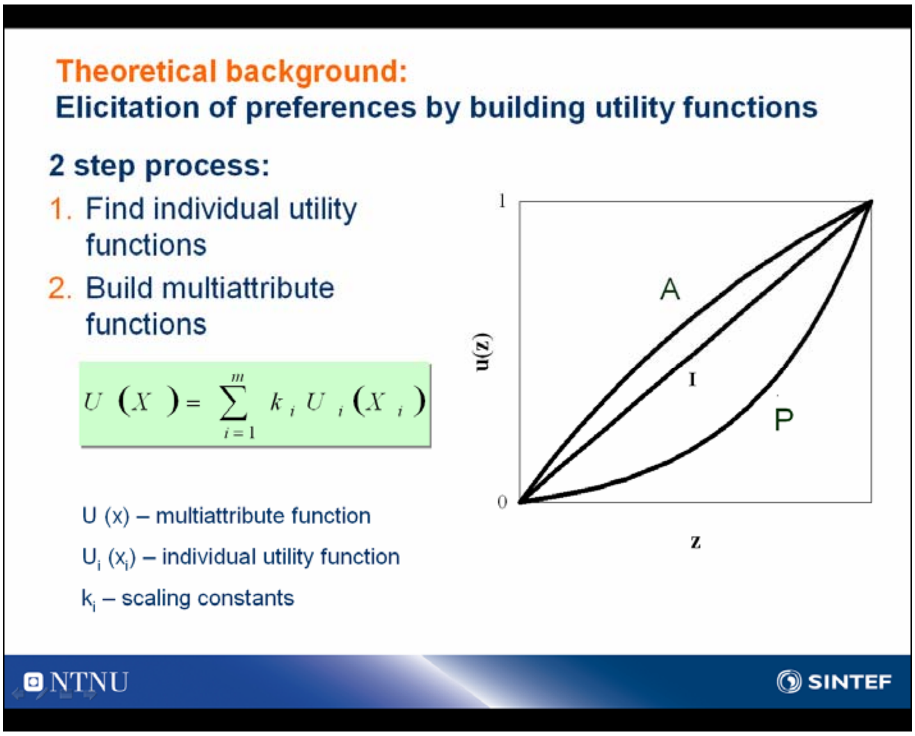
Theoretical background:
Elicitation of preferences by building utility functions
2 step process:
1. Find individual utility functions
2. Build multiattribute functions
$U(X) = \sum_{i=1}^{m} k_i U_i(X_i)$
U (x) – multiattribute function
U_i (x_i) – individual utility function
k_i – scaling constants
1
0
u(z)
z
A
I
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NTNU
SINTEF

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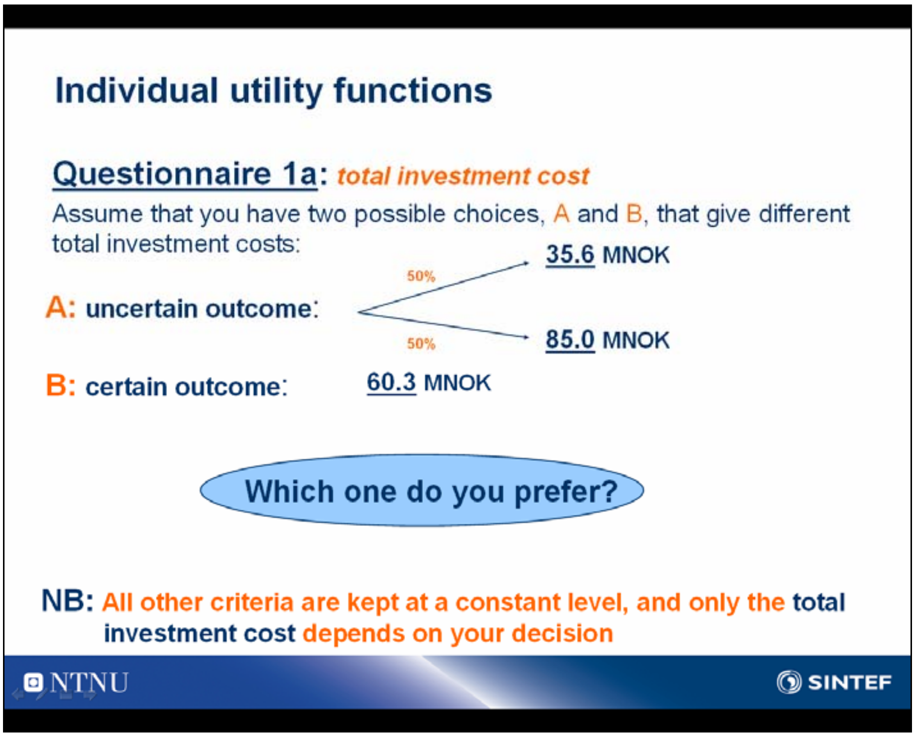
Individual utility functions
Questionnaire 1a: total investment cost
Assume that you have two possible choices, A and B, that give different total investment costs:
A: uncertain outcome:
50%
35.6 MNOK
50%
85.0 MNOK
B: certain outcome:
60.3 MNOK
Which one do you prefer?
NB: All other criteria are kept at a constant level, and only the total investment cost depends on your decision
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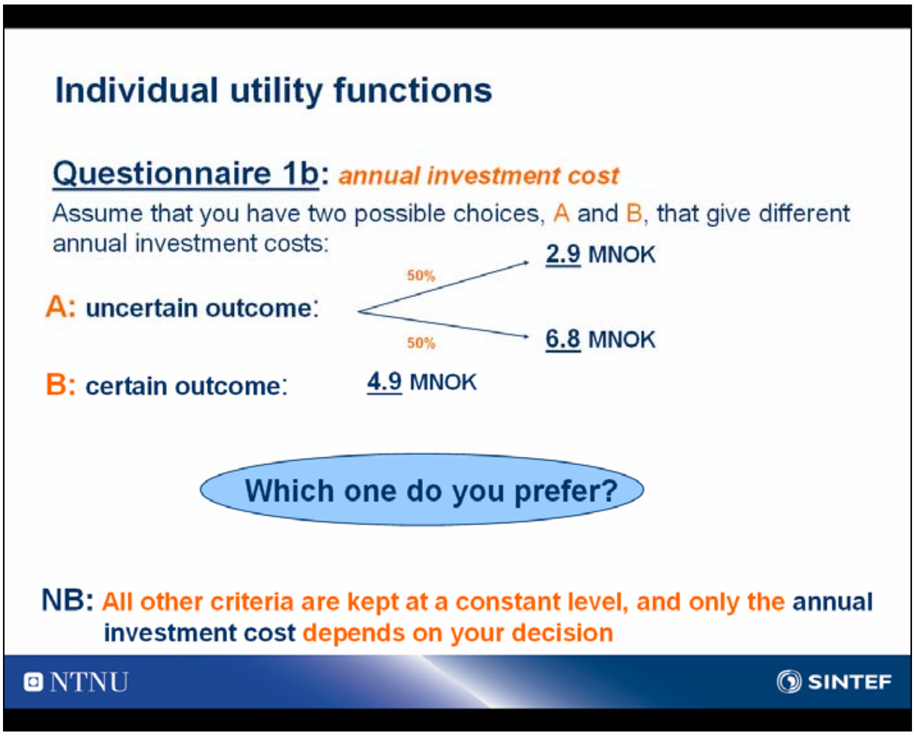
13


Individual utility functions
Questionnaire 1b: annual investment cost
Assume that you have two possible choices, A and B, that give different annual investment costs:
A: uncertain outcome:
50%
2.9 MNOK
50%
6.8 MNOK
B: certain outcome:
4.9 MNOK
Which one do you prefer?
NB: All other criteria are kept at a constant level, and only the annual investment cost depends on your decision
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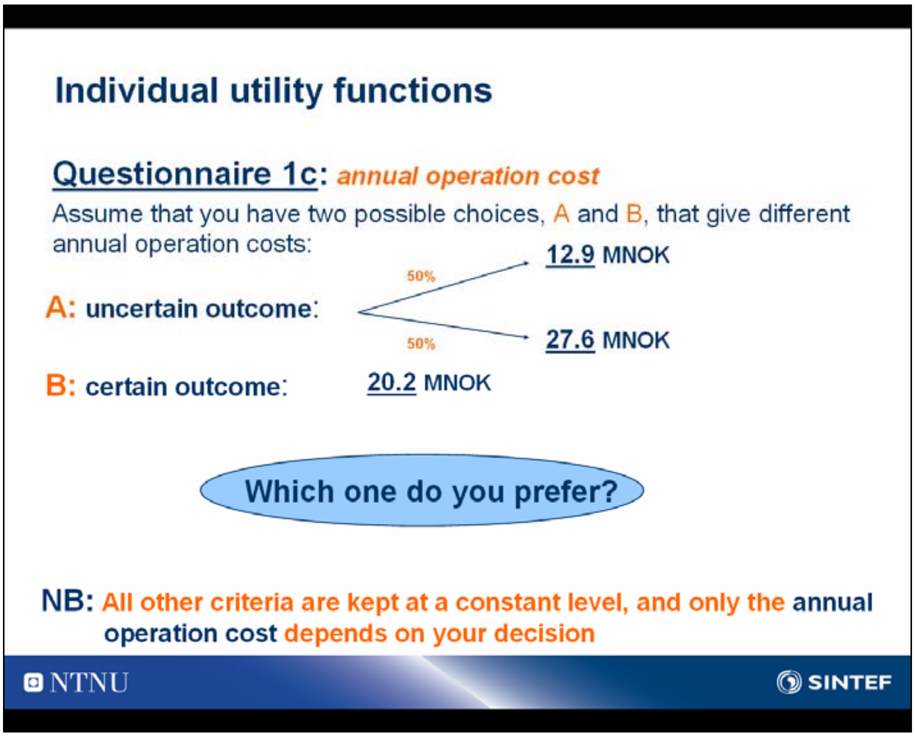
Individual utility functions
Questionnaire 1c: annual operation cost
Assume that you have two possible choices, A and B, that give different annual operation costs:
A: uncertain outcome:
50%
12.9 MNOK
50%
27.6 MNOK
B: certain outcome:
20.2 MNOK
Which one do you prefer?
NB: All other criteria are kept at a constant level, and only the annual operation cost depends on your decision
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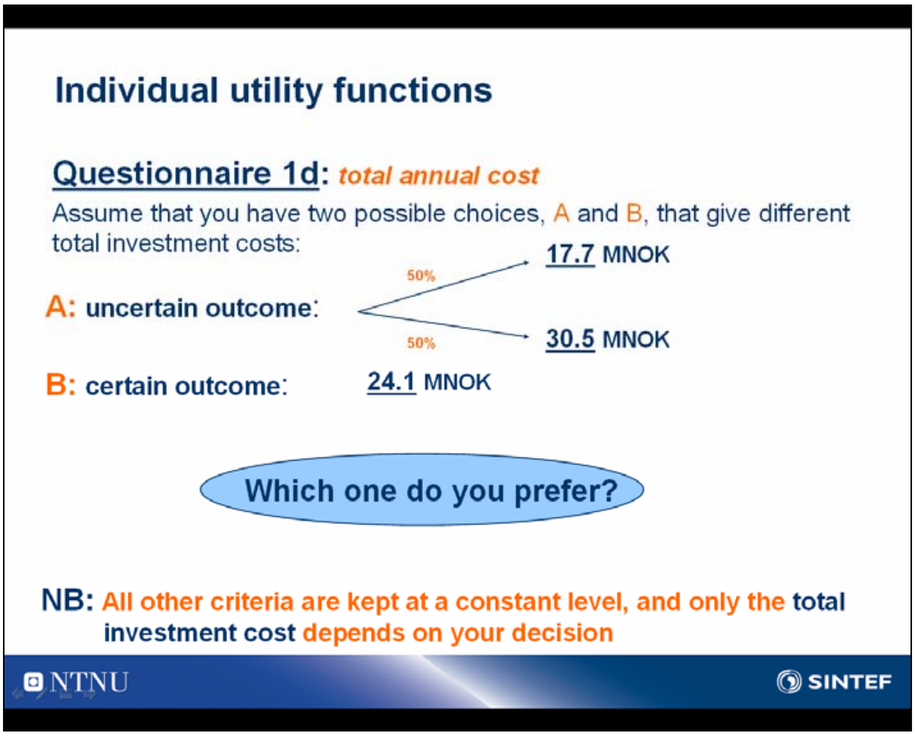
15


Individual utility functions
Questionnaire 1d: total annual cost
Assume that you have two possible choices, A and B, that give different total investment costs:
A: uncertain outcome:
50%
17.7 MNOK
50%
30.5 MNOK
B: certain outcome:
24.1 MNOK
Which one do you prefer?
NB: All other criteria are kept at a constant level, and only the total investment cost depends on your decision
NTNU
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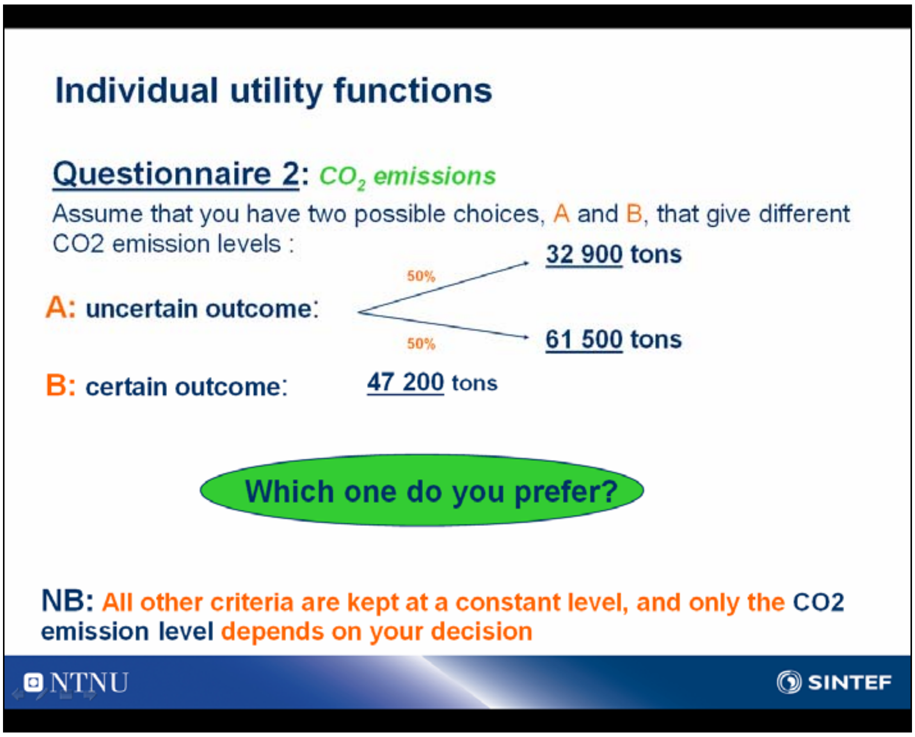
16


Individual utility functions
Questionnaire 2: CO_2 emissions
Assume that you have two possible choices, A and B, that give different CO2 emission levels :
A: uncertain outcome:
50%
32 900 tons
50%
61 500 tons
B: certain outcome:
47 200 tons
Which one do you prefer?
NB: All other criteria are kept at a constant level, and only the CO2 emission level depends on your decision
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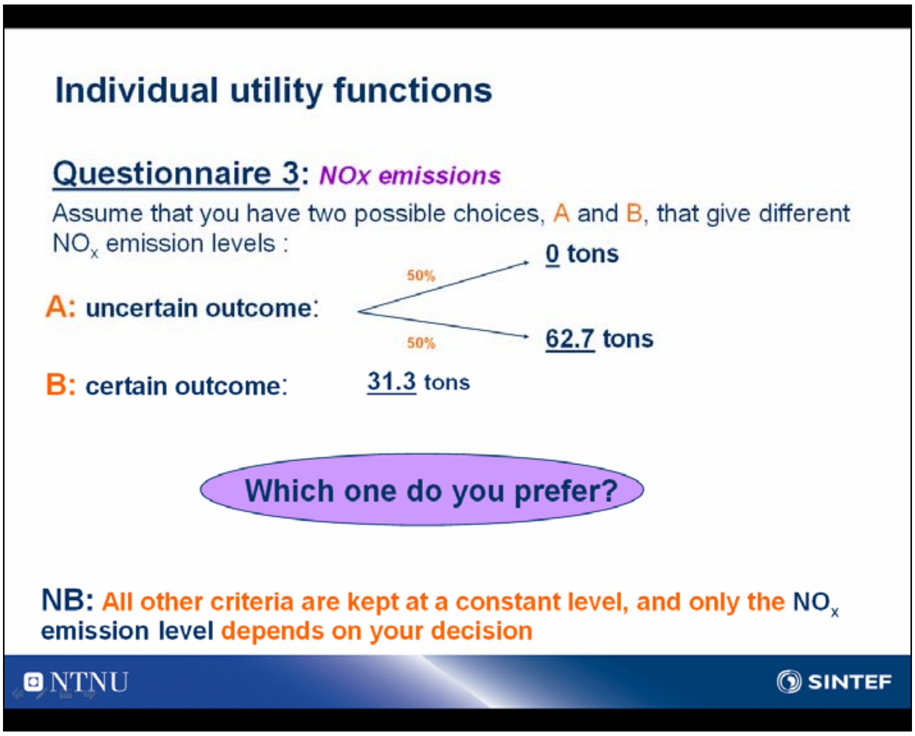
17


Individual utility functions
Questionnaire 3: NOx emissions
Assume that you have two possible choices, A and B, that give different NOx emission levels :
A: uncertain outcome:
50%
0 tons
50%
62.7 tons
B: certain outcome:
31.3 tons
Which one do you prefer?
NB: All other criteria are kept at a constant level, and only the NOx emission level depends on your decision
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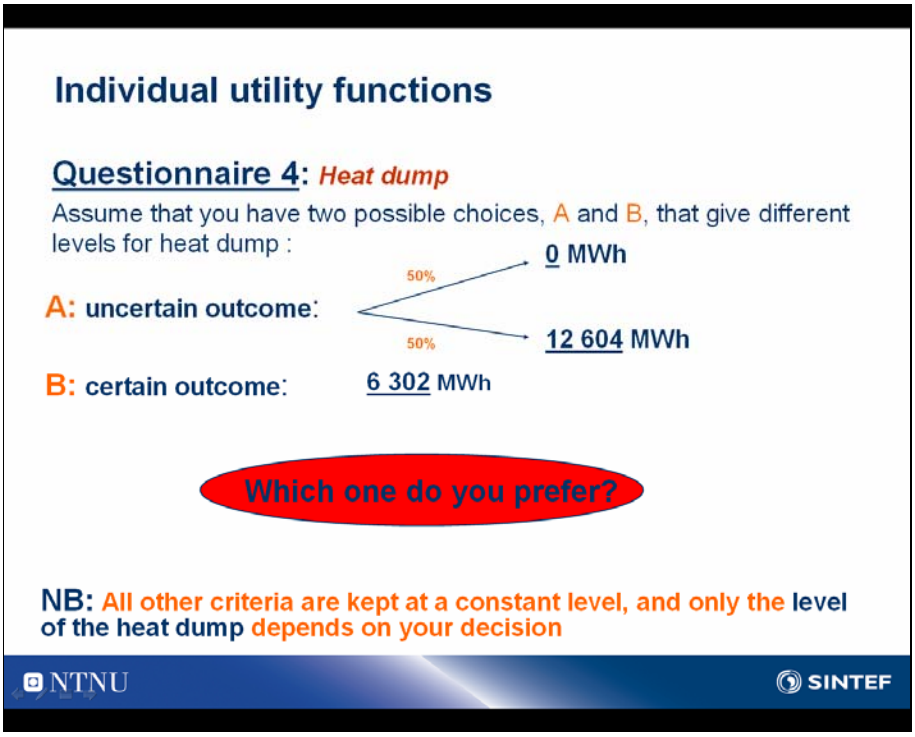
18


Individual utility functions
Questionnaire 4: Heat dump
Assume that you have two possible choices, A and B, that give different levels for heat dump :
A: uncertain outcome:
50%
0 MWh
50%
12 604 MWh
B: certain outcome:
6 302 MWh
Which one do you prefer?
NB: All other criteria are kept at a constant level, and only the level of the heat dump depends on your decision
NTNU
SINTEF

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Multiattribute utility functions

Question:

In your opinion, which of the criteria analyzed is the most relevant?

1. Operation costs	12.9	27.6	MNOK/year
2. Annual investment costs	2.9	6.8	MNOK/year
3. CO2 emissions	32900	61590	tons/year
4. NOx emissions	0	62.7	tons/year
5. Heat dump	0	12604	MWh/year

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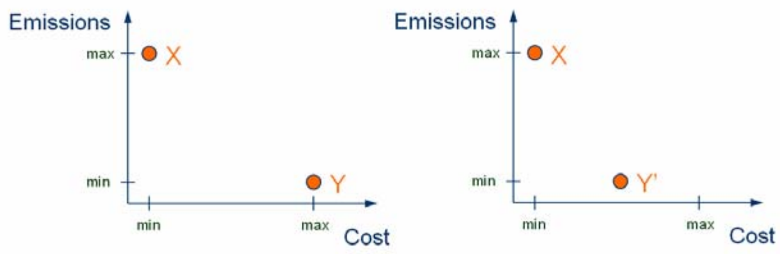
Multiattribute utility functions

Further, you will be asked to answer certain trade-off questions of the following type:

Two alternatives, X and Y will result in identical consequences for all attributes except two: investment cost and CO2 emissions (for example).

Alternative X gives you max CO2 emissions for min cost, while alternative Y gives you min CO2 emissions for the max cost. Which do you prefer?



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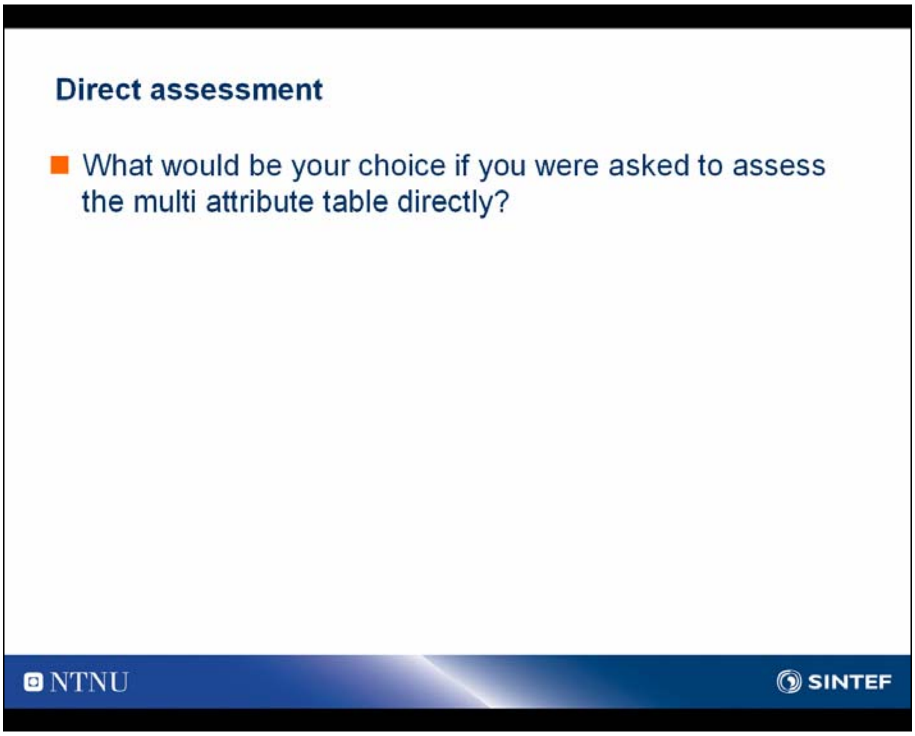
Direct assessment
What would be your choice if you were asked to assess the multi attribute table directly?
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