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 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 the 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….X_m when analysing the available alternatives, A_1, A_2,…A_n for the 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, i.e. the total utility equals the weighted sum of the single attribute utilities:

$$u(\boldsymbol{x}) = \sum_{i=1}^{m} k_i \cdot u_i(x_i) \tag{1}$$

where

$u(\boldsymbol{x})$	total utility for attribute set $\boldsymbol{x} = x_1, x_2, ..., x_n$
$u_i(x_i)$	utility for single attribute, i = 1,2, ..., m
k_i	scaling constant, attribute i

There are two main steps in determining such a multi-attribute 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. In our preference model we chose the following exponential function, based on the description in [9]:

$$u_i(x_i) = 1/(1 - e^{-\beta_i}) \cdot \left\{1 - e^{-\beta_i (\bar{x}_i - x_i)/(\bar{x}_i - \underline{x}_i)}\right\} \tag{2}$$

where

$u_i(x_i)$	utility for single attribute, i = 1,2, ..., 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 quantifying the 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 then be expressed as:

$$E\left(u_j(\boldsymbol{x}_j)\right) = \sum_{k=1}^{n} p_k \cdot u_{j,k}(\boldsymbol{x}_{j,k}) \tag{3}$$

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 1. First, input data for the analysis will have to be specified. It is important that the decision makers are involved already at this stage, especially when it comes to deciding on which attributes and uncertainties to consider. 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. operating 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).

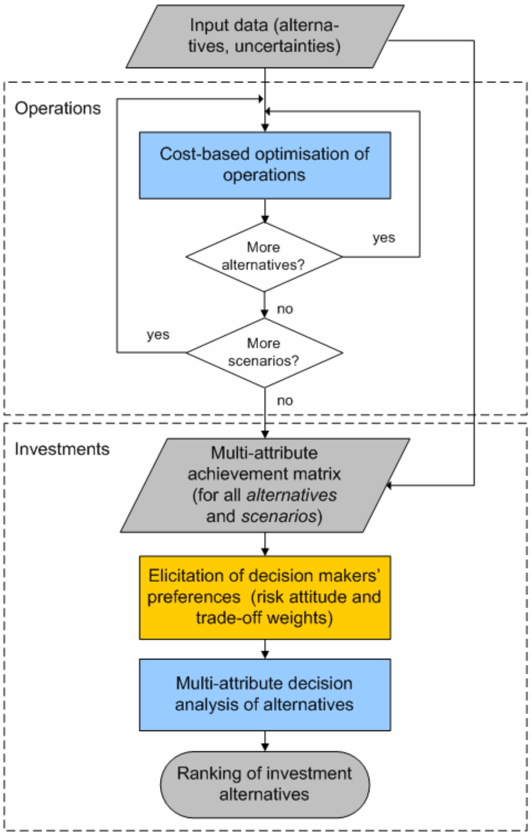


Figure 1: Flowchart of integrated planning model.

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 matrix to calculate total expected utilities for the investment alternatives, using equations (1)-(3). Afterwards, it is straightforward to rank the alternatives based on expected utility. Note that the MA achievement matrix that is calculated in the first part of Figure 1 can also be used as input for alternative paradigms for decision making under uncertainty, such as minimax and minimax regret. However, in this paper we focus on the decision paradigm based on MAUT.

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 considered the operations of the system for one time stage (year) in the future. Hence, in this analysis we did not consider the long-term changes in demand, and the timing of investment decisions. Total investment costs were 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 was 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 were used for hourly electricity prices (Figure 2). For simplicity we used the same price data for all the 8 load days.

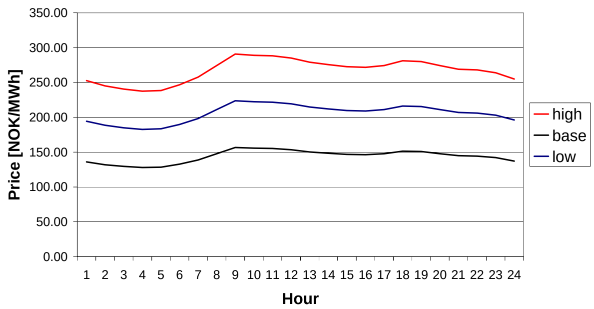


Figure 2: Price scenarios. Currency rate: € 1 ≈ NOK 8.

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 from a diesel boiler. In alternatives 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.

Alternative	*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 three scenarios are shown in the MA matrix in the appendix (Table 6). We can see from the table that alternative 1 has higher operating cost and CO2 emissions than the other three 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. 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 in order to formally incorporate the main preferences of the decision makers involved in the analysis. As mentioned in section 2.2, 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 makers pay great attention and if they are willing to think hard about the problem being analysed. Consequently, the decision makers had to think if the results presented to them were relevant for the analysis: if they would like to consider more criteria or eliminate the ones with little relevance. The first type of questions was 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 between these two options (Figure 3). The procedure was repeated for all 5 attributes in the analysis.

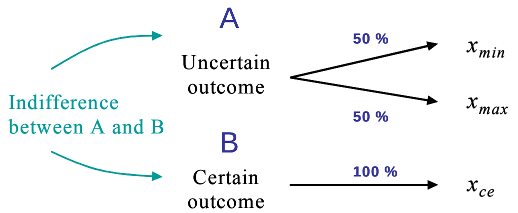


Figure 3: Example of lottery question for single attribute risk preference elicitation.

The ranges of attribute values discussed in the lottery questions were obtained using the impact model. The answers to the questions were collected by the analyst and used to estimate individual utility functions. An exponential form for the single utility function was used, as explained in section 2.2. Table 3 shows the decision makers single utility risk parameters for all attributes. A positive β implies a risk averse attitude, whereas a negative 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 prone, E is risk neutral, whereas C is risk averse (Figure 4).

	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.

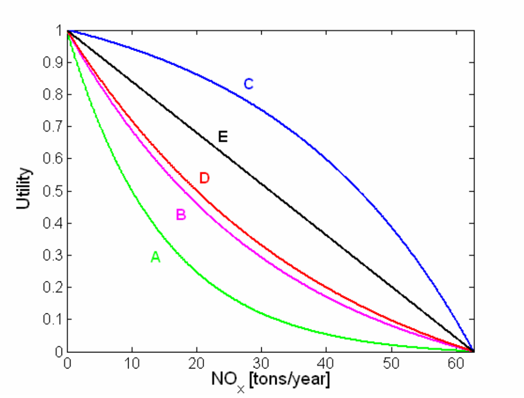


Figure 4: Individual utility functions for attribute 4, i.e. NO_x-emissions, for all respondents (A, B, C, D, and E).

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 Figure 5. 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.

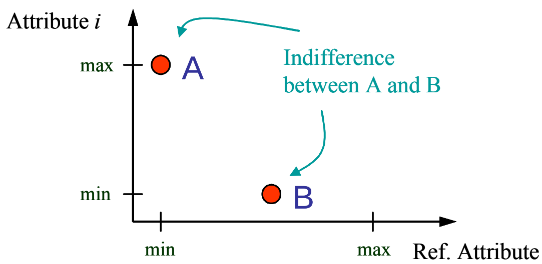


Figure 5: Example of question for trade-off preference elicitation.

	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.

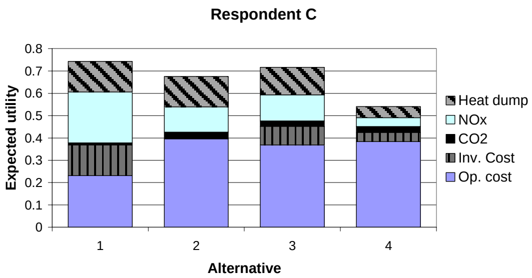
3.5 Ranking of alternatives

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 the 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, B, 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. 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 6 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.



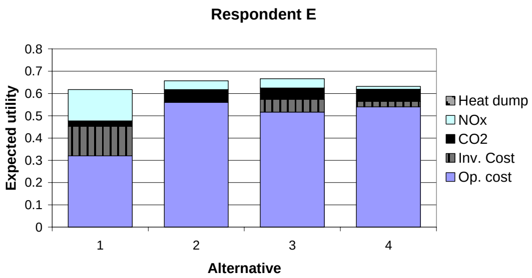


Figure 6: Expected utility for respondents C and E.

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 built instead of reinforcing the electricity grid. Separate planning of the electricity and district heating networks could easily result in suboptimal solutions.

4 DISCUSSION

We believe that the major advantages of using multicriteria 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 utility 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]	1 Annual operating cost [MNOK]	2 Annual inv. cost [MNOK]	3 Annual CO2 emissions [tons]	4 Annual NOx emissions [tons]	5 Annual Heat dump [MWh]
1	1	0.25	17.7	35.6	14.9	2.87	41060	0.0	0
	2	0.50	24.1	35.6	21.2	2.87	51325	0.0	0
	3	0.25	30.5	35.6	27.6	2.87	61590	0.0	0
2	1	0.25	19.7	85.0	12.9	6.85	32902	44.7	0
	2	0.50	22.6	85.0	15.8	6.85	37440	45.4	377
	3	0.25	25.5	85.0	18.6	6.85	41974	45.5	468
3	1	0.25	19.3	67.7	13.8	5.46	36188	36.8	0
	2	0.50	22.5	67.7	17.0	5.46	40170	46.2	4547
	3	0.25	25.3	67.7	19.9	5.46	44665	47.0	5082
4	1	0.25	20.1	78.3	13.7	6.31	35662	42.6	821
	2	0.50	22.8	78.3	16.5	6.31	38701	60.8	11319
	3	0.25	24.9	78.3	18.6	6.31	41917	62.7	12604

Table 6: Multi-attribute achievement matrix in pilot case study.