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Use of the equivalent attribute technique in multi-criteria planning of local energy systems

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ABSTRACT

This paper discusses how the equivalent attribute technique (EAT) can be used to improve the comprehensibility of a multi-attribute utility theory study. When using EAT, 'vague' expected total utility values are converted into equivalent values for one of the attributes being considered, often an economic attribute. Two models are considered: a simplified linear model, and a more advanced non-linear model that includes the DM's strength-of-preference and risk attitude. EAT is particularly useful in distinguishing between alternatives with similar utility values. When the difference between utility values is larger, the choice among the alternatives should be clear, and EAT therefore becomes less useful. The technique can still be used, although extra care is needed when choosing the equivalent attribute. A local energy-planning problem is used as a case study to illustrate and exemplify the EAT approach.

1. Introduction

One of the best-known multi-criteria decision analysis (MCDA) methods is the multi-attribute utility theory (MAUT). In MAUT, the expected total utility is determined for each of the alternatives under consideration. The expected total utility is calculated using a multi-attribute utility function, which is derived from interviews with the decision-maker (DM). For many DMs, the concept of expected utility values might be somewhat vague. To really understand the concept of utility values, it is necessary to fully understand the MAUT methodology. That can in some cases be difficult for DMs, as they often have limited time available for the decision process. An alternative – and possibly better – approach is to introduce the DMs to the concept of equivalent attributes, which is much easier to understand. The idea of the equivalent attribute technique (EAT) is to find a method to convert a change in the expected total utility into an equivalent quantity in one of the decision attributes. Most often, an economic attribute is used as the equivalent attribute. However, other attributes can be used if desired.

This paper is organized as follows. First, we provide a short presentation of MAUT, and discuss the EAT in more detail, including a comparison to the cost–benefit analysis. Then, to illustrate the use of the technique, we apply EAT to a local energy-planning problem that is characterized by multiple energy sources and carriers. We discuss the results from the case study and offer conclusions.

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2. The multi-attribute utility theory (MAUT)

MAUT was first described in detail by Keeney and Raiffa (1976). The method has often been used for energy-planning purposes, e.g. by Buehring et al. (1978), Pan et al. (2000) and Schulz and Stehfest (1984). MAUT is suitable for incorporating risk preferences and uncertainty into multi-criteria decision problems in a consistent manner. In MAUT, a multi-attribute utility function U describes the preferences of the DM. The multi-attribute utility function measures preferences along several dimensions. First, both the strength-of-preference (valuation of outcomes) and the attitude towards risk are represented for each individual criterion. Second, trade-offs between different criteria are also included in the function.

In this paper, the additive form of the multi-attribute utility function (Eq. (1)) has been used, so that the total utility of an alternative equals the weighted sum of the single attribute utilities.

$$U(a) = \sum_{i=1}^{m} k_i \cdot u_i(x_i(a)), \tag{1}$$

where $U(a)$ is the overall utility value of alternative a, $x_i(a)$ the alternative a's performance value for attribute i, $i = 1,2\ldots m$, $u_i(\cdot)$ is the partial utility value reflecting the performance for attribute i, and k_i is the weight of attribute i.

Additive models are easier to understand and construct than alternative models. However, the use of additive utility functions will only be valid if the criteria are preferentially independent (Keeney and Raiffa, 1976). Preferential independence means that the DM is "able to express meaningful preferences and trade-offs between levels of achievement on a subset of criteria, assuming that levels of achievement on the other criteria are fixed, *without* needing to be concerned with what these fixed levels of achievements are" (Belton and Stewart, 2002, p. 88). An 'ideal' alternative (all attributes at their best level) will per definition achieve a total utility value of 1.0, while an alternative where all attributes are at their worst level has zero total utility.

The DM's multi-attribute utility function is usually determined through a two-step interview process. The first step defines the partial utility functions for the various attributes, while the second step determines the weights of the various criteria, i.e. how important the DM finds one criterion as compared to another, given the ranges of the attributes (the relative worth of the swing between the minimum and maximum value of the attribute compared to the corresponding swings for the other attributes (Belton and Stewart, 2002)).

After the two-step process of quantifying the DM's preferences, the expected total utility for the different investment alternatives can be calculated. Uncertainty is included in the analysis by assigning probability distributions to the attributes. A common representation of uncertainties is in terms of scenarios with corresponding probabilities. The expected total utility for an alternative can then be expressed as:

$$E(U(a)) = \sum_{j=1}^{n} p_j \cdot U(a_j), \tag{2}$$

where $E(U(a))$ is the expected total utility for alternative a, $U(a_j)$ the total utility for alternative a scenario j (defined by Eq. (1)), and p_j is the subjective probability for scenario j.

3. The equivalent attribute technique (EAT)

3.1. Motivation

Utility values are constructed to convert performance values to preference values. This simplifies the analysis of complex decision problems. Although expected utilities are convenient for ranking and evaluation of alternatives, they are only "instrumental for the purpose of comparing alternatives" (Matos, 2007). Accordingly, they do not have direct physical meaning (Keeney, 1980), and are of no interest outside of the specific decision problem (Matos, 2007). Expected utility values may therefore seem complex and somewhat fuzzy as a concept for DMs who are not familiar with the approach.

MAUT and other MCDA methods themselves cannot substitute for a DM. The MCDA method's purpose is to aid DMs in making better decisions by providing good recommendations. However, some people might find it difficult to understand the actual difference between two alternatives, if expected total utility values are the only factors for consideration. In these situations, it might be difficult for DMs to actually trust the results from the multi-criteria analysis and make decisions on the basis of expected total utilities. This is particularly important when the differences between the alternatives' expected total utilities are small, as is often the case in actual MAUT analyses.

Moreover, in some decision problems, there are additional criteria that principally should have been included in the MAUT analysis, but which were skipped for various reasons, for example because it was not possible or too difficult to quantify each alternative's performance against these criteria. Typical examples on such additional criteria are aesthetics and stakeholder opposition. It is possible that an alternative's strong performance against any of the additional criteria can compensate for a small difference in expected total utility. However, since the utility concept may seem fuzzy, and because utilities cannot be traded off against attribute values (Matos, 2007), it is difficult for a DM to comprehend if the compensation sufficiently improves the alternative with the lower utility.

3.2. Description of EAT

A possible approach to improve the understanding of the differences between the alternatives is to apply the Equivalent Attribute Technique (EAT). Variants of EAT have been used by Keeney and co-workers for many years, for example in Keeney (1980), Merkhofer and Keeney (1987), Keeney et al. (1995), Keeney and von Winterfeldt (2007). In particular, Keeney and von Winterfeldt (2007) showed how the mathematical basis of equivalent costs can be used for assessing value functions, particularly if the single attribute value functions are linear. Except for this presentation, theoretical descriptions and the concrete mathematical background of EAT are generally lacking in the literature.

In this paper, we will show how EAT can be used to simplify the interpretation of results from a multi-criteria analysis where MAUT was used in the preference-elicitation interviews. However, EAT can also be used with other MCDA methods as long as a continuous function is used by the MCDA method for the evaluation of attributes. The paper presents two possible models for equivalent attribute calculations: a simplified, linear model, which has many similarities to the version used by Keeney and co-workers, and a more advanced, non-linear model, which is more strictly based on the equivalent attribute's utility function. Accordingly, the latter model takes into account the DM's risk attitude in the equivalent attribute conversions.

The main EAT principle is straightforward, and can be illustrated with a simple example. Assume that we have two alternatives (a and b) that have different performance values for a number of attributes, one of which is cost. An expected total utility has been determined for each alternative. In this case, $a \succ b$, i.e. $E(U(a)) > E(U(b))$. It might be of interest to calculate how much the cost of the least preferred alternative, b, must be reduced (ΔRed) (assuming more cost is worse than less cost) for b to reach the same expected utility as a, provided that all other attributes are held at a fixed level. ΔRed will in this case be the equivalent cost difference between the two alternatives. Another possibility is to calculate how much the cost of the best alternative, a, must be increased (ΔInc) for this alternative to reach the same expected total utility as b.

This simple example illustrates the main principles used by EAT to convert 'vague' expected total utilities to equivalent values for one of the considered attributes. In theory, any continuous attribute can be used as the equivalent attribute. However, according to Keeney (2006), it makes most sense to choose an attribute that the DM considers to be important when considering the ranges of the various attributes. Accordingly, an important attribute with a wide range of values is most suitable. The attribute selected should also be one that the DM is familiar with. Therefore, it is often appropriate to choose one of the cost attributes. Most DMs are familiar with cost attributes, and costs are among the more important criteria in most energy-planning studies. Because of this familiarity, the term 'cost-equivalent model' has been used to describe this approach, e.g. by Keeney et al. (1995). However, the DMs and the analyst should be aware that difficulties in using a cost attribute as the equivalent attribute might arise from the fact that some of the other attributes in the analysis may be associated with external costs not reflected at present in the market prices.

The main reason for converting utility differences to equivalent cost differences is that the conversion makes it much easier for the DM to differentiate between the desirability of the alternatives. An additional effect is that the use of equivalent costs makes it much easier to include additional non-quantifiable criteria in the analysis. While utilities cannot be traded off against additional attribute values, this is not a problem for equivalent cost differences. This can be illustrated by an example. An alternative *X* has some positive aesthetic properties compared to an alternative *Y*. These properties were not originally accounted for in the MAUT analysis, because the DM found it difficult to quantify aesthetics on a numerical scale. The DM may be told that according to the preferences elicited in the MAUT process, the utility for *X* is 0.80 and the utility for *Y* is 0.82, and that the equivalent cost difference between the two alternatives is 0.5 MNOK/yr. It is likely that many DMs will find the information provided about the equivalent cost difference much more useful than the information about expected total utility values, if the DMs need to determine if the positive aesthetic feature of alternative *X* is sufficient to compensate for the originally lower utility value.

3.3. Comparison between the equivalent attribute technique and cost–benefit analysis

In a cost–benefit analysis (CBA), all performance values are translated into monetary values using appropriate conversion factors. The most desirable alternative is generally the one with the highest net benefit (benefit – costs).

Clearly, there are important similarities between CBA and EAT, particularly if a cost attribute is used as the equivalent attribute. In both methods, an important aspect is the conversion from performance values for the various attributes, to preference values measured in terms of a cost attribute. This kind of conversion helps the DM in the decision process, because the various objectives are expressed in the same unit and thus can be more easily compared/synthesized. Additionally, if a constant trade-off between the attributes was used in the preference-elicitation process, this will lead to a linear value/function, which again is the basis for the EAT calculations. In this case, the EAT and CBA processes are mathematically analogous, and can be used for similar purposes. EAT can therefore be said to be a step from MCDA (for instance MAUT) in the direction of CBA. In other words, it can be argued that CBA works as a sort of EAT without the intermediate preference-elicitation phase that defines the DM's utility or value functions.

Despite their similarities, the EAT and CBA concepts are different in nature. CBA is supposed to be an objective model of the environment (Watson, 1981). All trade-offs between conflicting goals should be derived from the marketplace, and must be explicitly determined for each criterion (at least in the traditional CBA approach). CBA generally relies on constant, linear monetary conversion factors throughout the ranges of the attribute. The analysis is generally limited to aspects that can be priced in a non-controversial manner. No subjective preferences should be included, and the general idea is that different people performing a CBA are supposed to end up with the same result (at least in the traditional CBA approach).[1] Equivalent costs, on the other hand, are calculated on the basis of the results from the preference-elicitation process, for instance the MAUT interview. Comparing two alternatives given expected total utilities, the cost difference that is equivalent to the difference in terms of utility can be calculated. In other words, the DM's preferences against each criterion are imbedded in the equivalent cost difference. Since the equivalent cost difference is based on the DM's preferences, it is also possible to include uncertainties, in contrast to CBA, where uncertainty generally is disregarded (Watson, 1981).

[1] However, the original idea of everyone ending up with the same result has to some extent been replaced by a more flexible way of thinking, and the price used to represent the same criterion (for instance human life) in various CBA analyses varies considerably.

The difference between CBA and EAT becomes even clearer when externalities such as environmental issues are included as attributes in the decision process. Putting a cost on emissions, for example, allows this attribute to be monetized and included in a CBA. The only issue that could be debated is the price used in the analysis. However, this price should normally be based on published impact studies, the results of extensive opinion surveys etc. When emissions are included as attributes in MAUT and can be evaluated by a DM according to his preferences, explicit monetary valuations of the various criteria are not necessary. Of course, the DM's judgements in the MAUT analysis may reflect existing market prices. However, market prices are not always available for the criteria considered, such as when it comes to environmental externalities. Other trade-offs can be chosen if the DM finds that approach more relevant, and trade-offs involving attributes where there are no existing markets can be included without necessarily thinking in monetary terms. With this approach, externalities are taken into account by using the DM's subjective assessments of their importance. The DMs are free to include or exclude various aspects from the multi-criteria analysis, based on their own assumptions regarding what is important, instead of being limited by the comparatively strict rules of the CBA.

EAT allows trade-offs to be non-linear if desired. For instance, the DM may consider increased emissions of NO_x to be less important if existing emissions already are very high than if there are no emissions in the first place. If EAT is used in combination with MAUT, the partial utility functions are only linear if the DM is risk-neutral for the outcome of the attributes. We are not arguing that there necessarily should be non-linearities in any particular evaluation. However, we believe it is an advantage of the approach that non-linearities easily can be represented if they do indeed exist.

4. A local energy-planning problem and the use of MAUT

The EAT has been tested in a pilot case study based on Helseth (2003). In the case study, we used data from an existing planning problem in Norway to analyze the future energy-supply infrastructure for a suburb with approximately 2000 households and possible additional industrial demand. We carried out preference-elicitation interviews with six people with a background in energy research and industry. The participants were asked to imagine themselves as the manager of the energy company that is the main supplier of energy for residential and industrial customers in the region.[2] The participants were asked to decide on an expansion plan for the existing energy system in order to satisfy the future increase in local demand. Interviews were performed using MAUT for all the participants. More details about the case study, including information about uncertainties and the performance values of the alternatives in the various scenarios, is presented by Botterud et al. (2005) and Løken (2007, Chapter 6 and 7).

4.1. Criteria, alternatives and uncertainties in the case study

We limited the scope of the analysis to include the following five criteria; minimize (1) investment and (2) operating costs [MNOK/yr], (3) CO_2 and (4) NO_x emissions [tonnes/yr], and (5) heat dump from combined heat and power (CHP) plants to the environment [MWh/yr]. Investment and operating cost were kept as separate attributes to make it possible for the DMs to express their preferences regarding trade-offs between these criteria.

[2] None of the participants normally makes decisions of this nature. Consequently, they were probably not behaving the same way that a real DM would have. Among other factors, they did not have information about the economic conditions of their hypothetical company.

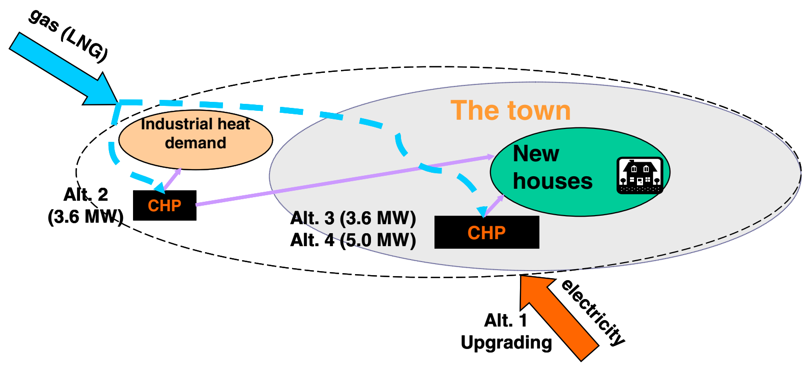

Fig. 1. Illustration of the four alternatives in the case study.

Four investment alternatives were analyzed, all of which would be able to supply the future increase in local demand for electricity and heating. Alt. 1 consists of reinforcing the electricity grid with a new power supply line. Accordingly, the entire local stationary energy demand will be met by electricity. Traditionally, this has been the most common solution in Norway, due to abundant access to cheap hydropower. Now the electricity production capacity in Norway is insufficient to meet the demand, and electricity must be imported from other countries, where much of the electricity is produced by thermal power plants. Accordingly, use of electricity in Norway might cause CO_2 emissions in other countries. Because CO_2 is a global problem, these emissions have been included in the analysis.

In the three other alternatives, a district-heating network is built to serve the heat demand, while the specific electric demand will be met by the already existing electric infrastructure. The bulk of the heat is produced in a CHP plant where natural gas (LNG) is combusted. A gas boiler is used to meet the peak demand. The CHP plant is built either near an industrial site (alt. 2), or nearby the residential area (alt. 3 and 4). In alt. 2, heat is delivered to the industrial site in addition to the residential area. The only difference between alt. 3 and 4 is the size of the CHP plant. The bigger CHP plant in alt. 4 facilitates generation of more electricity, which can be sold to the electricity market when profitable. The consequences of the greater electricity generation are excess heat from the CHP plant, which must be dumped to the local surroundings, and less CO_2 emissions, because the electricity import to Norway can be reduced. Fig. 1 summarizes the four alternatives. Other alternatives – for instance based on heat pumps or oil – could also have been included in the analysis. However, the local energy company considered use of natural gas as the most appropriate alternative to an all-electric solution in this area.

The alternatives are meant to be directly comparable, in the sense that they offer the same service, i.e. they meet the customers' electric and thermal energy demands. However, the technical characteristics of the alternatives are different, particularly between alt. 1 – where electricity is used to meet both the electric energy demand and the heating demand – and the three others – where the heating demand is met by district-heating. Accordingly, the customers might feel that the products they are offered are not equivalent. There might be differences concerning the reliability, technical quality and comfort of the service provided by the various solutions. Such effects could have been modelled as additional criteria in the analysis. However, in this case study, we assumed that these differences were negligible.

Three scenarios were introduced to be able to include uncertainties to the problem formulation. One main uncertainty in energy-planning problems is the price of electricity. Three scenarios were used for hourly prices of electricity (low, medium and high). In addition, it was assumed that more efficient electricity production technologies are used in the low price scenario, so that the marginal CO_2 emissions are lowest when the electricity price is low. 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 natural gas, and the price paid for heating at the industrial site, were assumed to be constant in the analysis.

4.2. Calculation of costs and other criteria

The operating costs and emissions for the various alternatives were calculated in the eTransport model (Bakken et al., 2006, 2007), which is being developed by SINTEF Energy Research. For each of the four alternatives, the eTransport model found the economically optimal[3] operation of the local energy system and calculated the values of the economic and environmental decision criteria.

In order to simplify the analysis, we considered the operation of the system for only one time stage (year) in the future. Hence, all future uncertainties were neglected, including long-term changes in demand and the timing of investment decisions. Total investment costs were converted to levelized annual costs and could therefore be compared to the annual operating costs. An interest rate of 7% was used to calculate levelized costs.

The cost of CO_2 emissions is not modeled as a direct cost in the system, as Norway is not a member of the European Emission Trading System (ETS). However, it can be assumed that the exchange price for electricity includes a CO_2 premium, since the electricity price is in reality determined in an international market, which includes countries participating in the ETS. Nevertheless, reduction of CO_2 emissions has also been included as a separate objective in the analysis. Accordingly, imported electricity to the region is assumed to have a marginal CO_2 emission rate associated with it. Strictly speaking, the CO_2 objective represents the supplementary effects of CO_2 emissions, i.e. to what extent the DMs care about CO_2 emissions in addition to an increased electricity price. Note that we do not try to calculate the total socio-economic costs of CO_2 emissions. This is a very complex task, which is beyond the scope of the analysis. Our objective was rather to estimate the DM's subjective assessment of the importance of the CO_2 emissions compared to other decision criteria.

4.3. Performance values and preference-elicitation

A standard MAUT interview procedure was used to elicit partial utility functions for the considered attributes and criteria weights. We assumed that the DM's risk attitude could be modelled using a normalized exponential form. The exponential form is frequently used in MAUT applications, and implies that the DM has constant

[3] Other criteria were not included in the operational analysis.

risk aversion over the attribute range considered (Keeney and Raiffa, 1993). The second step in the preference-elicitation procedure is to determine the weights k_i of the various criteria i, i.e. the relative worth of the swing between the minimum and maximum value of the attribute compared to the corresponding swings for the other attributes. The procedure that was used is explained in more detail by Løken (2007, Chapter 6). Thereafter, expected total utility values for the alternatives, considering the three scenarios described above for uncertainties in the price and CO_2 emissions, were calculated using Eq. (2).

In this article, we have chosen to focus on the results for two of the decision-makers with significant difference in their decision preferences (DM A and DM C). Table 1 shows the expected total utility values, order of preference, and criteria weights for the two participants. The expected total utilities listed in the table show that DM A preferred the three CHP alternatives (alt. 2–4), due to low weighting of the NO_x and heat dump criteria. DM C, on the other hand, weighted NO_x emissions and heat dump higher. Accordingly, DM C seems to prefer the all-electric alt. 1, while alt. 4, which causes large NO_x emissions and a considerable heat dump, has been given a very low expected total utility by this DM. Note that for DM A, the range of expected total utility values is very narrow (8% increase from the least preferred to the most preferred), while it is much broader for DM C (37%).

5. EAT applied to the case study

In this section, we show how EAT can be applied to the local energy-planning problem described above. As discussed in Section 3.2, cost attributes are suitable for use as the equivalent attribute, provided that the DMs consider cost to be among the most important attributes. Table 1 shows that DMs A and C both gave highest criteria weight to the annual operating cost (OC). Accordingly, it seems reasonable to use OC as the equivalent attribute in this case study. Below, we will present two EAT models that can be used in the process: one simplified, linear model, and one more advanced model that includes the DMs' strength-of-preference and risk attitude. All EAT calculations referred to in this paper were performed using values for all three scenarios. In other words, performance values and utility values were found for each of the scenarios, and the EAT calculations were performed using the scenario values. However, in order to simplify the presentation of results, only expected values are presented in this paper.

5.1. Simplified, linear EAT model

In the simplified EAT model, it is assumed that the DM is risk-neutral and has a constant marginal strength-of-preference for all criteria. In other words, linear calculations can be used to convert the expected total utilities of the alternatives to equivalent costs. Even though linear calculations are used in the EAT conversion, the method is not equivalent to a cost–benefit analysis, because linearities were not assumed in the calculations of the DM's utility values, which is used as the basis for the EAT calculations.

When assuming linearities, EAT is straightforward. To illustrate the procedure, we will give an example for DM A, based on the values shown in Table 1. From the table, it can be seen that DM A has assigned highest expected utility to alt. 3 ($E_A(U(\text{alt. }3)) = 0.679$), while alt. 1 has been assigned the lowest utility ($E_A(U(\text{alt. }1)) = 0.631$). We want to find the necessary reduction of the OC in alt. 1 for this alternative to be assigned the same expected total utility as alt. 3 (while all other attributes remain fixed). This means that we want to increase the expected total utility of alt. 1 by $\Delta U_{\text{alt}1} = 0.679 - 0.631 = 0.048$. The cost reduction is called $\Delta\text{Red}_{A1'}$ where the $'$ indicates that the simplified method has been used.

By definition, if an alternative's OC is reduced from its worst level to its best level (i.e., $\Delta OC_0 = 27.6 - 12.9 = 14.7$), the expected total utility of the alternative will be increased by the weight of the OC criterion ($k_{A1} = 0.60$). If the desired increase of the expected total utility is lower than k_{A1}, the necessary reduction in the OC will be proportionally lower, when using a linear EAT model.

Hence, $\Delta\text{Red}_{A1'}/\Delta OC_0$ will have to be equivalent to $\Delta U_{\text{alt}1}/k_{A1}$=>

$$\frac{\Delta\text{Red}_{A1'}}{\Delta OC_0} = \frac{\Delta U_{\text{alt. }1}}{k_{A1}} \iff \Delta\text{Red}_{A1'} = \Delta U_{\text{alt. }1} \cdot \frac{\Delta OC_0}{k_{A1}} = 0.048 \cdot \frac{14.7}{0.6} \approx 1.2\ [\text{MNOK/yr}].$$

The calculation above shows that the OC (expected value) of alt. 1 must be reduced from 21.2 to 20.0 MNOK/yr for alt. 1 to be assigned the same utility as the originally preferred alternative (alt. 3), assuming that all other performance values are fixed. This means

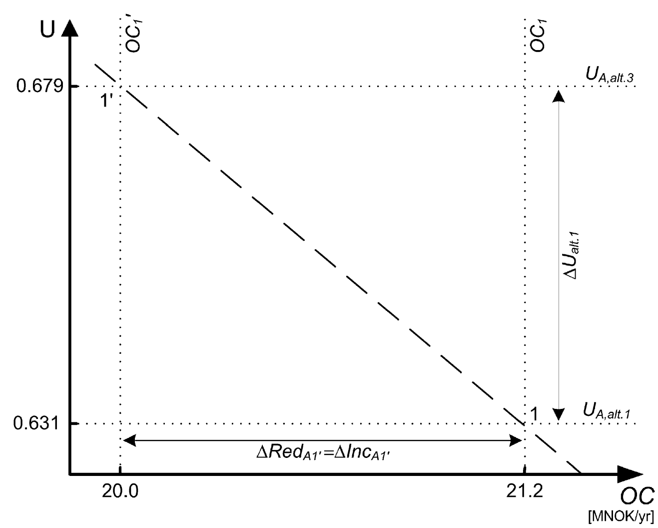

Fig. 2. Expected total utility for DM A as a function of alternative 1's OC (assuming that all other attribute values are held constant).

Table 1
Expected total utility values and weights for two DMs

Alt. *a*	Expected total utility DM A $E_A(U(a))$		Expected total utility DM C $E_C(U(a))$		Op. cost [MNOK/yr]	Invest. cost (annualized) [MNOK/yr]	CO_2 emissions [tonnes/yr]	NO_x emissions [tonnes/yr]	Heat dump [MWh/yr]
1	**0.631**	(**4**)	**0.743**	(**1**)	21.2	2.9	51,325	0.0	0
2	**0.675**	(**2**)	**0.676**	(**3**)	15.8	6.8	37,439	45.2	306
3	**0.679**	(**1**)	**0.716**	(**2**)	16.9	5.5	40,298	44.0	3544
4	**0.660**	(**3**)	**0.541**	(**4**)	16.3	6.3	38,745	56.7	9016
Worst					*27.6*	*6.8*	*61 590*	*62.7*	*12,604*
Best					*12.9*	*2.9*	*32 902*	*0.0*	*0*
	Weights k_i		DM A = >		***0.60***	***0.10***	***0.14***	***0.14***	***0.03***
	(Rounded)		DM C = >		***0.46***	***0.14***	***0.04***	***0.23***	***0.14***

Alternatives described by *expected* performance values and max/min for the various scenarios.

Table 2
Equivalent cost reduction; simplified, linear model (originally preferred alt. in italics) (numbers have been rounded for clarity)

Alternative n	Original expected utility $E(U(n))$		Original expected annual OC [MNOK/yr]	Decision-maker A				Decision-maker C			
				Equiv. red. $\Delta \text{Red}_{An'}$ and adjusted OC for alt. n to be preferred		Equiv. inc. $\Delta \text{Inc}_{An'}$ and adjusted OC for alt. 3 to get the same exp. utility as alt. n		Equiv. red. $\Delta \text{Red}_{Cn'}$ and adjusted OC for alt. n to be preferred		Equiv. inc. $\Delta \text{Inc}_{Cn'}$ and adjusted OC for alt. 1 to get the same exp. utility as alt. n	
	DM A	DM C									
1	0.631	0.743	21.2	1.2	20.0	1.2	18.1		*21.2*		*21.2*
2	0.675	0.676	15.8	0.1	15.7	0.1	17.0	2.2	13.6	2.2	23.4
3	0.679	0.716	16.9		*16.9*		*16.9*	0.9	16.0	0.9	22.1
4	0.660	0.541	16.3	0.5	15.8	0.5	17.4	6.5	9.8	6.5	27.7
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]

Table 3
Equivalent cost reduction, non-linear model (originally preferred alt. in italics) (numbers have been rounded for clarity)

Alternative n	Original expected utility $E(U(n))$		Original expected annual OC [MNOK/yr]	Decision-maker A				Decision-maker C			
				Equiv. red. ΔRed_{An} and adjusted OC for alt. n to be preferred		Equiv. inc. ΔInc_{An} and adjusted OC for alt. 3 to get the same exp. utility as alt. n		Equiv. red. ΔRed_{Cn} and adjusted OC for alt. n to be preferred		Equiv. inc. ΔInc_{Cn} and adjusted OC for alt. 1 to get the same exp. utility as alt. n	
	DM A	DM C									
1	0.631	0.743	21.2	1.1	20.1	1.5	18.4		*21.2*		*21.2*
2	0.675	0.676	15.8	0.2	15.6	0.1	17.0	3.4	12.4	1.9	23.1
3	0.679	0.716	16.9		*16.9*		*16.9*	1.2	15.7	0.8	22.0
4	0.660	0.541	16.3	0.7	15.6	0.6	17.5	13.3	3.0	5.1	26.3
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]

that the OC in all the three scenarios must be reduced by 1.2 MNOK/yr. The calculations are illustrated in Fig. 2.

Corresponding calculations have also been performed for the other alternatives for both DMs A and C. The results are listed in Table 2 as $\Delta \text{Red}_{in'}$, where i is the DM, n is the alternative and $'$ indicates that the simplified method has been used. An alternative way of thinking is to find the necessary increase of the originally most preferred alternative's OC, for this alternative to reduce its expected utility to the same level as the other alternatives. These increases are listed in Table 2 as $\Delta \text{Inc}_{in'}$. Note that when using the simplified model, $\Delta \text{Red}_{in'}$ is equal to $\Delta \text{Inc}_{in'}$ because of the linear calculations.

5.2. Advanced, non-linear EAT model

In the real world, few DMs will provide linear utility functions. Their strength-of-preferences are dependent on the attribute values, and few DMs are entirely risk-neutral. They are either risk prone, or more commonly – especially when it comes to cost attributes – risk averse.[4] Accordingly, the linear EAT model presented above may be too simplified. We will here apply a more advanced non-linear model for the two DMs presented above. Both DM A and DM C were risk averse with almost identical risk attitude for OC. In the calculations, we used the Microsoft Solver add-in in Microsoft Excel to find which ΔRed's and ΔInc's that would give the desired utility values. In the calculations, the same reductions/increases (absolute values) were implemented in all scenarios. Note that if the utility function for the equivalent attribute is linear, the simplified model will be identical to the advanced model. The same will happen if EAT is used together with another MCDA technique which are using linear evaluation of attribute values.

The appendix gives an example of how the calculations in the advanced model can be performed. The results, tabulated as expected costs – to simplify the presentation – are shown in Table 3, and illustrated in Figs. 3 and 4.

Note that when the advanced model is being used, ΔRed_{in} and ΔInc_{in} are not equal (column 5 vs. 7 and 9 vs. 11), as they were in the simplified model. If we compare the ΔRed_{in} values to the ΔInc_{in} values, we see that for DM A the differences are modest, while they are much more prominent for DM C (particularly for alt. 4). This is because DM A gave very similar utility values for all alternatives, while there was much more difference between DM C's utility values. Larger utility differences lead to a more pronounced curvature of the non-linear utility function. This is illustrated in Figs. 3 and 4, which show how the expected total utilities of alternatives are affected by changes in the alternative's OC, both using the linear and the non-linear model.

Table 3 shows that for DM A the ΔRed_{An} values and ΔInc_{An} values are quite similar. There are some differences – especially for alt. 1 – but they are not substantial. For DM C, on the other hand, the differences are much more prominent. As shown in column 3 in

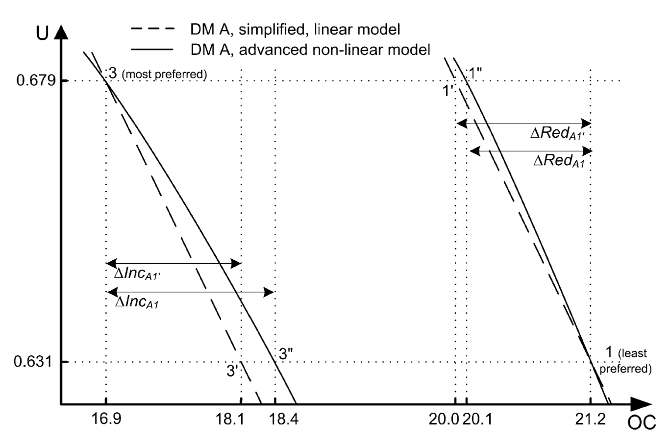

Fig. 3. Expected total utility for DM A as a function of the alternative's OC (assuming that all other attribute values are held at a fixed level).

[4] They might also exhibit both risk averse and risk prone attitudes within the range of a single attribute. However, we have chosen to disregard that possibility in this case study.

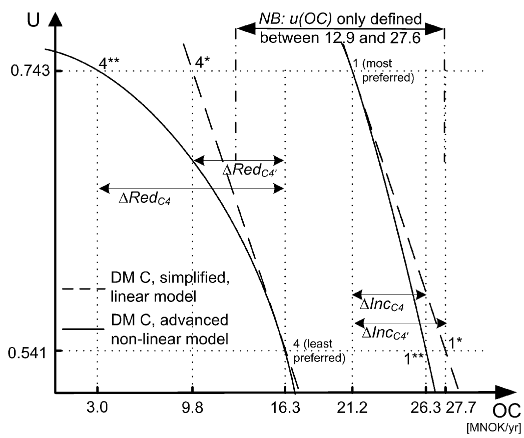

Fig. 4. Expected total utility for DM C as a function of the alternative's OC (assuming that all other attribute values are held at a fixed level).

Table 1, DM C has given alt. 4, as well as alt. 2, a considerably lower expected total utility value than his more preferred alternatives (alts. 1 and 3). The main reason for these differences is that alts. 2 and 4 have higher NO_x emissions and heat dump, which were considered very important by DM C. According to Table 3 and Fig. 4, it appears that a cost reduction (ΔRed_{C4}) of 13.3 MNOK/is necessary for alt. 4 to be as preferred as alt. 1. However, a considerably lower cost increase (ΔInc_{C4}) of 5.1 MNOK/yr is sufficient for alt. 1 to be assigned the same utility as alt. 4. The difference between ΔRed_{C4} and ΔInc_{C4} is caused by the curvature difference between the two alternatives. As can be seen from the left part of Fig. 4, the utility for alt. 4 as a function of the OC has a rather non-linear shape when the OC is low. For alt. 1, which has a much higher OC, we observe that the curvature of the non-linear curve is much less distinct. Large differences can also be found for DM C for alt. 2 (column 9 vs. 11 in Table 3). For DM A, there are no such large differences, mainly because the difference in the original utility values between this DM's most and least preferred alternatives is much less than for DM C.

However, the ΔRed values for DM C referred to in the last paragraph are not valid. Strictly speaking, the partial utility function is only defined between the min and max OC values listed in Table 1 (12.9–27.6 MNOK/yr), as is also indicated in Fig. 4. Use of partial utility functions outside the attribute ranges involves partial utility values below zero or above one, which is mathematically incorrect. Nevertheless, it seems reasonable to assume that small deviations below the min or above the max OC do not lead to any major changes in the shape of the utility functions. Consequently, it might be acceptable to use the utility function for OC values just outside the attribute ranges. Still, in the case described in Fig. 4, the adjusted OC values are so much lower than OC_{min} that the calculated change in equivalent costs cannot be assumed to be reasonable. In practice, this is not a major problem. When the differences in utility values are so considerable that problems like this arise, the choice between the alternatives is clear, and it is probably not necessary to apply EAT.

The use of adjusted OC values far outside the attribute ranges for the utility function, as described above, makes the use of EAT more or less meaningless. To be able to use EAT in such cases, new utility functions that are also valid for OCs outside the original attribute range must be defined. This means that parts of the MAUT procedure must be repeated. It will be necessary to elicit the reference attribute's utility function for the new range, and then re-scale the weights adequately based on the newly expanded range. The ΔRed values will in that case probably be closer to the ΔInc values, because the utility function will be mapped over the entire range, including the lower cost values needed when OC is to be used as the equivalent attribute. If it is known at the start of the analysis which criterion will serve as the reference, the utility function for this criterion can be elicited for an interval that is wider than the one defined by the minimum and maximum performance values of the alternatives. This will avoid having to deal with this issue *a posteriori*. In addition, such broadening of the attribute range makes it easier to include additional alternatives at a later stage of the MCDA process.

An alternative way to deal with this issue is to choose another attribute as the equivalent attribute. It might be possible to find an attribute that in addition to being continuous and important for the DM, is more suitable as the equivalent attribute when considering the performance values for the alternatives. An attribute where it is possible to increase the performance value of the most preferred alternative and reduce the performance value of the other alternatives to some extent without extending the attribute ranges of the attribute's partial utility function is most suitable.

6. Conclusions

This paper has discussed how EAT can be used to simplify the comparison of results from an MAUT analysis of a local energy-planning problem. The technique is useful in distinguishing between alternatives with similar utility values in order to check if the difference is significant. Instead of comparing utility values directly, DMs can compare more familiar cost data by using EAT. For example, it appears to be much easier for a DM to compare alternatives after being told that the difference between alts. 1 and 3 is equivalent to an increase in the OC of 1.2 MNOK/yr, compared to only knowing that the difference is 0.048 on a utility scale.

Two possible models for the equivalent attribute technique have been presented: a simplified, linear model, and a more advanced model, where the DMs' strength-of-preference and risk attitude are included in the calculations. Calculations using the linear model are definitely much easier to perform. For alternatives that are assigned similar utility values, the difference between using the linear and advanced model is often insignificant. Accordingly, the linear model is probably good enough in many cases, in particular in situations where the equivalent attribute's utility function is linear or close to linear. The advanced EAT model uses the utility functions derived from the MAUT elicitation interviews with the DMs and do not assume linearity. Accordingly, the advanced model takes into account the DM's risk attitude in the equivalent attribute conversions, and consequently, it is mathematically more correct than the linear model. When comparing alternatives where the differences between the expected total utility values are large, there are also large differences between the results from the two EAT models. We have shown that in these cases, one should carefully ensure that the performance values of the attributes will not go significantly outside the original attribute ranges of the utility function. We have proposed some procedures that can be used to avoid these problems. However, the main reason for using EAT is to better be able to distinguish between alternatives with similar utility values. In cases where there are large utility differences, the choice between the alternatives will be clear, and consequently, there is no particular need to use EAT.

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Table A1
Multi-attribute achievement matrix in pilot case study (all results are per year)

Alt.	Scenario	Probability	Total annual cost [MNOK]	Total inv. cost [MNOK]	Annual inv. cost [MNOK]	Annual op. cost [MNOK]	CO_2 emissions [tonnes]	NO_x emissions [tonnes]	Heat dump [MWh]
1	Low	0.25	17.7	35.6	2.87	14.9	41 060	0.0	0
	Medium	0.50	24.1	35.6	2.87	21.2	51 325	0.0	0
	High	0.25	30.5	35.6	2.87	27.6	61 590	0.0	0
2	Low	0.25	19.7	85.0	6.85	12.9	32 902	44.7	0
	Medium	0.50	22.6	85.0	6.85	15.8	37 440	45.4	377
	High	0.25	25.5	85.0	6.85	18.6	41 974	45.5	468
3	Low	0.25	19.3	67.7	5.46	13.8	36 188	36.8	0
	Medium	0.50	22.5	67.7	5.46	17.0	40 170	46.2	4547
	High	0.25	25.3	67.7	5.46	19.9	44 665	47.0	5082
4	Low	0.25	20.1	78.3	6.31	13.7	35 662	42.6	821
	Medium	0.50	22.8	78.3	6.31	16.5	38 701	60.8	11 319
	High	0.25	24.9	78.3	6.31	18.6	41 917	62.7	12 604

Table A2
Expected total utility and ranking of alternatives for DM A

Alt.	Exp. total utility DM A	
1	0.631	(4)
2	0.675	(2)
3	0.679	(1)
4	0.660	(3)

Ron Whitfield, also at Argonne, for his help in general, and specifically for providing the idea for Figs. 2–4.

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Appendix

The main part of the paper presented all calculations only as expected values, as a way of simplifying the presentation. However, when performing the calculations, performance values and utility values were found for each of the scenarios, and the EAT calculations were performed using the scenario values. In this Appendix, we provide an example of the actual calculations used in the non-linear EAT model. Table A1 shows the performance values for the five attributes for all alternatives and scenarios.

This example will consider the same problem as in the example with the linear model in Section 5.1. Expected total utilities ($E(U)$) are determined for the four alternatives for DM A (Table A2). We want to find how much we need to reduce the OC of alt. 1 for this alterative to be assigned the same $E(U)$ as alt. 3, which originally was the most preferred by this DM.

For alt. 1 to be assigned the same $E(U)$ as alt. 3, it is necessary to increase the $E(U)$ of alt. 1 by $\Delta E(U) = 0.679 - 0.631 = 0.048$. All attributes except the operational cost (OC) should be held at fixed levels. Table A3 shows how the weighted expected partial OC utility ($E(u_{OC})$) was calculated. Note that the DM A's derived weight for the OC criteria was $k_{OC} = 0.60$ (see Table 1).

The weighted $E(u_{OC})$ for alt. 1 is 0.309. Since all other attributes are fixed, all increases in $E(U)$ must be due to reductions of the OC, and accordingly increases in $E(u_{OC})$. Accordingly, $E(u_{OC})$ must be increased by $\Delta E(U) = 0.048$. We want to increase $E(u_{OC})$ by reducing the annual OC of all the scenarios by the same value. We have assumed that the risk attitude can be modelled by a normalized exponential form, as given by

$$u_i(x_{aj}) = \left\{1 - e^{-\beta_i(\bar{x}_i - x_{aj})/(\bar{x}_i - \underline{x}_i)}\right\}/(1 - e^{-\beta_i}) \quad (3)$$

where x_{aj} is the performance value for attribute i, for alternative a, scenario j, $u_i(x_{aj})$ the partial utility for attribute i for the performance value x_{aj}, β_i the risk parameter for attribute i ($\beta_{OC} = -1.117$ for DM A), and $\bar{x}_i, \underline{x}_i$ is the upper and lower limit (worst/best performance value) for attribute i.

The calculations for finding the necessary OC reduction were done numerically by using the Microsoft Solver add-in in Microsoft

Table A3
Calculation of weighted expected partial OC utility for the original OC values

Alt. a	Scenario j	Probability p_j	Annual OC original x_{aj} [MNOK]	Partial OC utility for each scenario $u_{oc}(x_{aj})$	Expected partial OC utility $E(u_{oc,a}) = \Sigma p_j \cdot u_{oc}(x_{aj})$	Weight k_{OC}	Weighted expected partial OC utility $k_{OC} \cdot E(u_{oc,a})$
1	1	0.25	14.9	0.922	0.515	0.60	**0.309**
	2	0.5	21.2	0.570			
	3	0.25	27.6	0.000			

Table A4
Calculation of weighted expected partial OC utility for the adjusted OC values (numbers have been rounded for clarity)

Alt. a	Scenario j	Probability p_j	Annual OC adjusted x_{aj} [MNOK]	Partial scenario OC utilities $u_{oc}(x_{aj})$	Expected partial OC utility $E(u_{oc,a}) = \Sigma p_j \cdot u_{oc}(x_{aj})$	Weight k_{OC}	Weighted expected partial OC utility $k_{OC} \cdot E(u_{oc,a})$
1	1	0.25	−**1.1** **13.8**	0.969	0.597	0.60	**0.357**
	2	0.5	−**1.1** **20.1**	0.647			
	3	0.25	−**1.1** **26.5**	0.124			

Excel. The adjusted OCs are shown in Table A4, including calculations of the new weighted expected partial OC utility.

Table A4 shows that it was necessary to reduce the annual OC of alt. 1 in all the scenarios by 1.1 MNOK, for alt. 1 to achieve the same expected total utility as alt. 3, i.e. to make alt. 1 as preferred as the originally most preferred alternative. The same changes in utility values could obviously be achieved by other combinations of OC reductions. For example, the entire reduction could have been made in the middle scenario, or we could search for a percentage reduction that would give the same increases of expected total utility. However, such calculations were not performed in this paper.

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