A hypothetical method for evaluating energy policy options using the evidential reasoning approach

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Abstract

Decision-making in environmental issues and social sciences is already known to be as complex and difficult as it concerns public, government and other organisations. In addition, the decisions made are not only important but can also be controversial, because there can be many attributes to consider and also many objectives to achieve with multiple decision-makers involved. The main aim of this paper is to introduce the evidential reasoning (ER) approach to energy policy planners as an alternative multiple criteria decision-making (MCDM) method in order to evaluate and select the best energy policy option. In this paper, we examine solving the UK energy options selection problem by using the ER approach. The decision criteria may be available in quantitative nature and all relate to future predictions. Therefore, the data used to solve this problem may be uncertain, imprecise and incomplete. In such a situation, the ER approach can be useful to grapple with patchy data. The ER approach is supported by a computer software programme called IDS (an Intelligent Decision System via evidential reasoning). The use of IDS as a decision support tool is explained and its potential future application is also described in the latter part of the paper.

Key Words: *Energy policy selection, Decision making, Evidential reasoning*

Introduction

It is always a difficult task to arrive at clear resolution of a decision regarding social and environmental issues for governments, as it concerns public and future generations. There are several reasons why decision making is considered to be difficult (Hipel, Radford, and Fang, 1993). Firstly, there are multiple criteria usually conflicting with each other. Secondly, multiple decision-makers are involved in the decision making process, which increases the complexity of the problem since a rational consensus among them is necessary. Finally, as

the decision criteria outcomes are all related to the future and are therefore based on predictions, the data and the assessments may be uncertain, imprecise and incomplete. Several multiple criteria decision making (MCDM) methods are proposed in the literature. This then leads to the question, which amongst these is the most appropriate in a given context; i.e. choosing a right and a suitable MCDM method for a particular decision problem is in itself a key issue (Ozernoy, 1992; Sen and Yang, p. 214-216, 1998). From amongst the many the evidential reasoning (ER) approach based on decision theory and the Dempster-Shaffer theory of evidence is already known to be capable of handling uncertain, imprecise and incomplete data (Yang and Sen, 1994). That is why the ER approach which is considered to be a MCDM method has been chosen in this paper to solve a hypothetical UK energy policy selection problem. The decision criteria for this problem are obtained from the article written by Jones *et al.* (Jones, Hope and Hughes, 1990).

Decision analysis has long been used in environmental and social issues. Many decision analysis applications in these issues can be found in the literature. For example, Corner and Kirkwood listed decision analysis applications between 1970-1989 in Operations Research literature. They grouped these applications into five categories as shown in Figure 1 (Corner and Kirkwood, 1991):

Decision Analysis Application Areas:

1. ENERGY
   1.1 Bidding
   1.2 Product and project selection
   1.3 Regulation
   1.4 Site selection
   1.5 Technology choice
2. MANUFACTURING and SERVICES
   2.1 Budget Allocation
   2.2 Product Planning
   2.3 Strategy
   2.4 Miscellaneous
3. MEDICAL
4. PUBLIC POLICY
   4.1 Standard Setting
   4.2 Miscellaneous
5. GENERAL

Figure 1: Decision Analysis Application Areas

To the best of our knowledge, the ER approach has never been used to tackle decision-making problems in the energy industry. One reason for this may be that the ER approach has been mainly used in 'Artificial Intelligence' and 'Expert Systems' as a technique for modelling reasoning under uncertainty (Beynon et al., 2000). To fill this gap and to make practitioners aware of the availability of this method, the ER approach is used to select the best UK energy policy. There are several reasons for choosing this approach. First of all, it copes well with uncertain, imprecise and incomplete data and assessments. Second, it is well supported by computer software so that the decision-maker (DM) or decision-makers (DM's) are only required to input their assessments with supporting evidence. Third, even though the assessments are incomplete or DM's are unable to make judgements due to the lack of information or because may lack expertise, the ER approach can still help guide the users to reach a decision by using all available data. The main purpose of the present paper is to demonstrate the application of the ER approach for selecting the optimum UK energy policy.

The paper, apart from the obvious contribution, explores the new ideas behind the modelling work that may be unique in energy policy analysis.

The paper is structured as follows. Following a brief introduction, some of the past decision analysis applications in energy are summarised. In the third section, the ER approach is explored and then the hypothetical UK energy policy selection problem is described. Then, the results will be shown. The discussion of these results follows next. Implications arising from the research are captured in the presentation of conclusions.

Past Decision Analysis Applications

In this section, we summarise some of the decision analysis applications in the area of energy. As mentioned earlier, applications related to energy can be found in (Corner and Kirkwood, 1991). Golabi, Kirkwood and Sicherman (1981) used multiattribute utility theory (MAUT) to select a portfolio of a solar energy project for the US Department of Energy. The reasons for choosing MAUT in their analysis were that the MAUT provides logical procedures for 1) handling multiple criteria, 2) explicitly uses the experience and knowledge of the R&D manager, and 3) handles non-monetary aspects. In addition, a number of successful applications in a variety of fields indicate that multiattribute utility models are generally not considered difficult to understand by managers (Golabi, Kirkwood, and Sicherman, 1981). Lathrop and Watson (1982) used decision analysis first to evaluate risk and then to construct risk evaluation indices for the regulation of nuclear waste management. They interviewed 58 people, a mixture of concerned parties: 13 national advisers, 33 concerned citizens, 7 nuclear power opponents and 5 nuclear power advocates. Lathrop and Watson explain their approach briefly as follows. “Our approach consists of developing a multidimensional utility function over the health-effect consequences of a nuclear waste

management system, separately assessing a probability distribution over those consequences for each alternative system, and then calculating the risk index for each system as its expected utility." Detlof von Winterfeldt (1982) described a test application of a decision analytical model, which is used to solve the problem of setting standards for offshore oil discharges. There were three main decision makers; The Petroleum Production Division of the UK Department of Energy, the multinational firms (operating the North Sea platforms and having responsibility for cleanup operations), and the fishermen (who are concerned with the environmental and economic impact of oil pollution). Each decision-maker has a different set of alternatives and has considered different multiple conflicting objectives when evaluating the alternatives. Uncertainty was another difficulty for this problem. Winterfeldt used formal decision analysis to deal with the complexity and difficulty of the problem. Peerenboom, Buehring, and Joseph (1989) explain a decision analysis procedure used in the US Department of Energy to develop a portfolio of environmental and health research programs for a commercial scale synthetic fuels facility. Rietveld and Ouwersloot (1992) propose a random sampling approach to generate quantitative values, which are consistent with the underlying ordinal information. They use stochastic dominance concepts to rank the best nuclear power plants sites/location in the Netherlands. They describe the features of their approach as follows. (i) It can deal with ordinal information on criterion scores, weights and the combination of both. (ii) The method can also be used in the case of mixed (ordinal/cardinal) data. (iii) The method can be applied in the case of ordinal data with degrees of difference, and (iv) it can deal with various types of ties.

Ramanathan and Ganesh (1995) used an integrated approach to solve India's energy resource allocation problem. Their integrated model consisted of Goal Programming (GP) and the Analytic Hierarchy Process (AHP) developed by Saaty (1986). Energy resource allocation

problem is described as a MCDM with both quantitative and qualitative attributes. Ramanathan and Ganesh wanted to draw benefit from both of these approaches in the following manner. (a) Employing the quantitative criteria directly in the GP model, (b) deriving AHP priorities for the qualitative criteria after eliciting the expert judgements, (c) employing AHP priorities as coefficients of the decision variables in the corresponding objective functions of the GP model. By doing so, they aimed to extend the applicability of GP to problems involving qualitative criteria, and at the same time, to reduce the burden on decision-makers when eliciting AHP judgements. Furthermore, they used AHP to find the weights to be given to the objectives in the GP model. Mills, Vlacic, and Lowe (1996) developed a computer-based decision support system to help electricity supply planners to meet future power demands. Their approach is based on a planning methodology known as integrated resource planning (IRP) developed to allow supply technologies to be compared with various demand-side management options. They displayed the decision criteria in hierarchical order and then they used a so-called order-consisted achievement function to scalarize achievements on each of the multiple objectives. This allows decision-makers to assess options against two reference points; a level of achievement, which is desired, and a minimum level for acceptability. Hobbs and Horn (1997) used a multimethod MCDM to build public confidence in energy planning. Their main reason for using different MCDM methods is that decision-makers feel manipulated by a single MCDM method. In order to eliminate this effect, they suggested that each person should be allowed to use different MCDM methods to build understanding. The result was that no single method was best for each person. Hokkanen and Salminen (1997) used the ELECTRE III decision-aid method to choose a waste management system in the Oulu region of Finland. They selected ELECTRE III as the decision aid mainly because available environmental data tend to be imprecise in cases like theirs.

Jones, Hope, and Hughes (1990) develop a multiattribute utility value model to study the UK energy options. Their model was adopted from the SMART technique for multiattribute utility measurement. It consists of ten steps: identification of stakeholders; identification of options for action; identification of empirical indicators; ranking of attributes; rating of attributes in importance-preserving ratios; scaling of ratings, scoring options on each attribute; calculation of utilities; and finally, decision. In their study, authors used numbers 0 and 10 as scores for worst and best outcomes of relevant decision criteria, respectively. They suggested that the intermediate values would either be linear or non-linear according to the preferences of decision-makers. However, it is our opinion that it may not be easy for individuals to explain the scores that they assign to each attribute. For example, when scoring, one is supposed to differentiate the score 6 and 7, and also be able to explain or present evidence why he or she assigned that particular number. Another disadvantage of using this scoring system is as to why one has to evaluate alternatives using numbers 1 to 10, when the decision criteria outcomes can be available in quantitative form. Thus, we applied the evidential reasoning approach to the UK energy policy selection problem. The uncertainty and imprecision in this problem are represented through the concept of the degree of belief (see Figure 4 and Figure 5).

The Evidential Reasoning Approach

There are several MCDM methods proposed in the literature. A categorisation of the methods can be seen in (Hwang and Yoon, 1981). Multiattribute Utility Theory (Keeney and Raiffa, 1993), Analytic Hierarchy Process (AHP) (Saaty, 1986), PROMETHEE (Brans and Vincke, 1985), ELECTRE methods (Vincke, 1986), TOPSIS (Hwang and Yoon, 1981), Fuzzy Sets and Systems (Roubens, 1997) are a few commonly used methods to mention. The evidential

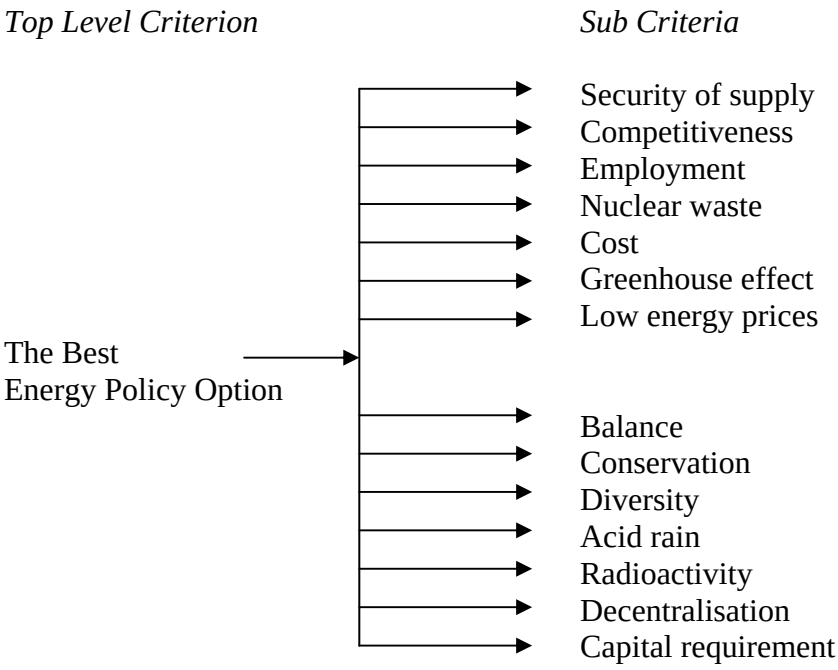
reasoning (ER) approach can also be added to the above list, as it has been increasingly used in such diverse areas as engineering, management, and safety (Yang and Sen, 1994; Yang and Singh, 1994; Yang and Sen, 1997; Yang, and Xu, 1998). In this section, we will illustrate the ER framework by using the UK energy policy selection problem.

Decision problems are usually structured as a hierarchical order. In the first level, the goal of the problem is stated. In the second level, there are several criteria each of which has a different contribution to the overall objective. Then, some of these criteria are broken into further criteria called sub-criteria. This process -i.e. breaking the main criteria into sub criteria, and sub criteria into sub sub-criteria- continues until the point where decision-makers are able to make assessments. Once the division of criteria is completed, decision-makers are asked to evaluate each alternative based on the lowest level criteria. In order to find how well an alternative has performed across all the criteria, the lowest level criteria assessments need to be transformed to the upper level criteria and then to the top level. This requires a multiple criteria decision making (MCDM) method, which is capable of combining and transforming the lowest level criteria assessments to the upper level criteria.

The Evidential Reasoning (ER) approach is such a MCDM method that not only combines both qualitative and quantitative assessments but can also handle uncertain and imprecise information or data. The state of an attribute (a criterion) may be determined by factors (sub criteria) at a lower level. For example, in our hypothetical energy policy selection problem, the best energy policy option (top level criterion) may be evaluated based on a number of sub criteria as can be seen in Figure 2. The best energy policy option may be assessed by using the following grades: best, good, average, poor, and worst. The best policy option can be associated with all, some or just one of these grades. If, for example, all the sub criteria are

judged to be good, then the policy option is said to be good, too. However, in real world decision-making problems, judgements are rarely precise and certain. On the contrary inconsistent evaluations may occur.

Figure 2: Hierarchical Display of the UK Energy Policy Selection Problem Criteria



(**Source:** Jones, M.; Hope, C. and Hughes, R. (1990))

The ER approach uses the concept of the degree of belief to elicit the decision-maker's preferences. In other words individuals are asked to evaluate decision criteria by using their degree of belief, which indicates their expectation that an alternative will yield a certain outcome. An individual's degree of belief can be described as their knowledge of the subject and their life experience. The use of the degree of belief can be justified by the fact that human decision making involves ambiguity, uncertainty and imprecision. In the existing ER framework, the objective or goal of the problem is assessed by a set of grades. For example, in our case study the potential alternatives are classified and assessed by five grades as far as the objective is concerned. Then, the ER algorithm carries out the transformation of several criteria assessments to the top level (i.e. the objective). In other words this approach collapses

several criteria into one so that individuals can be able to rank all the alternatives in order of preference.

The UK Energy Policy Selection Problem

This section describes the UK energy policy selection problem. The problem is elaborated at length in Jones *et al.* (Jones, Hope and Hughes, 1990). It has all the characteristics of a MCDM problem namely multiple attributes, multiple objectives and multiple decision-makers. The decision criteria outcomes are usually related to future and prone to uncertainty and risk. Also, sometimes the data for some of the criteria may not be available. In this case, the ER approach is an appropriate MCDM method to solve this problem. Our main aim is to show how the ER approach is applied to this problem and display that even though the data are uncertain, imprecise, incomplete, and some of them are not available, a decision can still be made.

Since a background and a description of this problem are well explained in Jones *et al.* (Jones, Hope and Hughes, 1990), we do not intend to repeat it here. However, we will use the same criteria and relative importance of the criteria, which can be seen from Figure 3. In Jones *et al.*'s paper, the direct rating weighting method was used as it is easy to understand and easy to apply. DM's are required to list the decision criteria from the most important to the least important and then asked to assign weights 100 and 0 to the most important and the least important ones, respectively. The intermediate weights are assigned to the criteria between the most important and the least according to their relative importance. However, as mentioned earlier, other weighting methods could have also been used such as pair-wise comparisons technique, which is used in AHP (Saaty, 1986). In Figure 3, DM's or experts established the best and worst outcomes for all attributes so that only the options whose

outcomes between the best and the worst will be considered for selection. Say, for example, an option whose security of supply disruption is more than 50 hours will not be included in the selection process. Another advantage of defining the best and worst values is that it allows DM's to classify options by using the range between the best and worst values. For example, an option with a 25-hour supply disruption may be considered as an average alternative.

Figure 3: The UK Energy Policy Selection Problem Criteria: best and worst outcomes

Attribute	Indicator	Best	Worst	Rating
Security of supply	Hrs of supply disruption/person/yr	0	50	100
Competitiveness	Ratio UK: world fuel prices in 2010	0.33	3	90
Employment	'000 jobs created by 2010 due to policy	500	-1500	70
Nuclear waste	% change in activity not disposed by 2010	-20	20	60
Cost	£bn total cost of supply/yr	25	100	60
Greenhouse effect	% change in CO_2 emitted by 2010	-20	20	50
Low energy prices	% change in energy prices by 2010	-50	50	50
Balance	% supplied from largest fuel in 2010	20	90	40
Conservation	% change in demand by 2010	-75	50	40
Diversity	Number of fuels supplying >10% in 2010	5	1	40
Acid rain	% change in SO_2 emitted by 2010	-70	20	40
Radioactivity	% change in dose per person by 2010	-20	10	40
Decentralisation	Number of energy suppliers in 2010	50	4	30
Capital Requirement	Max. energy investment (% of total inv.)	8	20	30

Source: Jones, M.; Hope, C. and Hughes, R. (1990)

In our case study, the criteria are of a quantitative nature. Hence, the assessments are either certain or random numbers. However, the alternatives may be classified by using a set of grades at the top level as mentioned earlier. Therefore, the quantitative assessments need to be transformed to the top criterion without loss of original data. The reason for this is that an overall aggregated result is necessary so that all alternative options can be ranked. For example, the best and worst values for the criterion "Security of Supply" are already defined as 0 and 50 hours of supply disruption/person/year, respectively. Without doubt, these values can be directly assigned to the best and the worst grades. In other words, if an option has no

supply disruption, it is considered to be a best alternative as far as the criterion "Security of Supply" is concerned. On the other hand, if an option has 50 hours of supply disruption per year, it is thought to be a worst alternative. Suppose that experts or DM's stated that 35, 25, and 10 hours of supply disruption are considered to be bad, average, and good. Of course, these numbers are defined based on the past records and the knowledge and experience that DM's or experts have. Suppose an alternative option has 15 hours of supply disruption. The ER approach transforms this value as 50% average and 50% good since this value is half way between two grades (25 and 10 respectively). These transformation procedures need to be carried out for each criterion so that an overall assessment result can be obtained. As can be seen from Table 1, the DM's are required to define the rules for converting several criteria assessments to the top level.

Table 1: Transforming Decision Criteria Assessments to the Top Level

Assessment Transformation	Assessment Grades at the Top Level				
Decision Criteria	Best	Good	Average	Bad	Worst
Security of supply	0	10	25	35	50
Competitiveness	0.33	0.8	1.3	2	3
Employment	500	0	-500	-1000	-1500
Nuclear waste	-20	-10	0	10	20
Cost	25	40	60	80	100
Greenhouse effect	-20	-10	0	10	20
Low energy prices	-50	-25	0	25	50
Balance	20	40	60	75	90
Conservation	-75	-50	-10	25	50
Diversity	5	4	3	2	1
Acid Rain	-70	-50	-10	10	20
Radioactivity	-20	-10	-5	5	10
Decentralisation	50	36	20	12	4
Capital requirement	8	12	16	18	20

In the hypothetical UK energy selection problem, we have assumed that for each option we have been provided with uncertain, imprecise, and missing data. In order to examine the effects of such patchy data, we assumed to have two different sets of evaluations. The first

one has a complete series of assessments while the other one has a mixture of certain, uncertain, imprecise and incomplete assessments due to the missing information. The reason for using two sets of assessments is to compare the results and find out the value of missing information and also to prove that a decision can still be made in the absence of some assessments. The data for the first case and for the second one can be seen in Figure 4 and in Figure 5, respectively. In Figure 4, we assumed that the assessments given by the DM's are complete and precise but not certain. For example, Option 2's supply disruption was expected to be between 8 and 22 hours. DM's stated their expectations and degrees of belief as follows: supply disruption may be most likely between 8 and 17 hours (50 and 40 per cent, respectively). However, DM's also think that there is a small expectation that it may be 22 hours (10%). This assessment is both complete and precise as the degree of belief adds to 1 or 100%. Nevertheless, it is an uncertain assessment as DM's are unable to state a single value for the supply disruption. On the other hand, the assessments in Figure 5 are mixed. For example, Option 2 has not been assessed on the criterion "Competitiveness" due to missing information. Option 3 was to create 400 thousand jobs by 2010, which is a complete and certain assessment. Option 2 promises lower energy prices by 2010 but the assessment is neither complete nor certain. Decrease in energy prices is expected to be 32, 24, and 16 per cent to some extents. Different decision criteria outcomes may have several possible values due to uncertainty and predictions since energy policy selection problem is related to the future. Take criterion "Security of Supply" for example, the distribution of assessments for each option displays different patterns as shown in graphs in Figure 6. These graphs show the variety of assessments and different expectations and the degrees of belief that the options may yield the anticipated outcomes.

Figure 4: Energy Policy Selection Problem (case 1): criteria and assessments

Alternatives / Attributes	Option 1	Option 2	Option 3	Option 4	Option 5
Security of Supply	15(0.1), 20(0.3), 30(0.6)	8(0.5), 17(0.4), 22(0.1)	6(0.6), 15(0.3), 20(0.1)	28(0.25), 30(0.5), 39(0.25)	40(0.05), 43(0.15), 47(0.8)
Competitiveness	1.0(0.3), 1.2(0.7)	0.7(0.2), 0.8(0.8)	0.7(0.1), 0.8(0.9)	1.1(0.1), 1.3(0.9)	2.3(0.6), 2.7(0.4)
Employment	0(0.5), -500(0.5)	0(0.3), 500(0.7)	0(0.3), 500(0.7)	-1000(0.65), -1500(0.35)	-1000(0.6), -1500(0.4)
Nuclear Waste	-2(0.3), 0(0.4), 2(0.3)	11(0.3), 12(0.4), 13(0.3)	9(0.3), 10(0.4), 11(0.3)	-10(0.3), -12(0.4), -14(0.3)	-18(0.2), -19(0.3), -20(0.5)
Cost	50(0.2), 58(0.3), 62(0.3), 65(0.2)	36(0.15), 38(0.3), 40(0.3), 42(0.25)	34(0.25), 37(0.3), 40(0.3), 43(0.15)	50(0.2), 58(0.3), 62(0.25), 65(0.25)	78(0.1), 80(0.4), 82(0.25), 84(0.25)
Greenhouse Effect	-10(0.5), 0(0.5)	-20(0.3), -10(0.7)	-11(0.5), -9(0.5)	-20(0.85), -10(0.15)	-20(0.9), -19(0.1)
Low Energy Prices	-15(0.2), -13(0.5), -10(0.3)	-32(0.3), -24(0.6), -16(0.1)	-32(0.3), -24(0.6), -16(0.1)	-5(0.25), 0(0.5), 5(0.25)	34(0.4), 45(0.5), 50(0.1)
Balance	50(0.1), 55(0.2), 60(0.4), 65(0.2), 70(0.1)	44(0.1), 48(0.2), 52(0.4), 56 (0.2), 60(0.1)	44(0.1), 48(0.3), 52(0.4), 56(0.1), 60(0.1)	50(0.1), 55(0.2), 60(0.4), 65 (0.2), 70(0.1)	44(0.1), 48(0.2), 52(0.4), 56(0.2), 60(0.1)
Conservation	-15(0.5), -5(0.5)	-15(0.5), -5(0.5)	-40(0.5), -20(0.5)	-60(0.7), -48(0.3)	-60(0.7), -48(0.3)
Diversity	1(0.5), 3(0.5)	2(0.5), 4(0.5)	2(0.5), 3(0.5)	1(0.5), 2(0.5)	1(0.5), 3(0.5)
Acid Rain	5(0.2), 10(0.7), 15(0.1)	-20(0.2), -10(0.7), 10(0.1)	-10(0.3), -5(0.6), 5(0.1)	-10(0.3), -5(0.6), 5(0.1)	-10(0.3), -5(0.6), 5(0.1)
Radioactivity	-10(0.4), -5(0.4), 5(0.2)	-5(0.2), 5(0.4), 10(0.4)	-5(0.3), 0(0.4), 5(0.3)	-18(0.3), -14(0.5), -10(0.2)	-18(0.1), -19(0.4), -20(0.5)
Decentralization	12(0.65), 36(0.35)	12(0.5), 20(0.5)	12(0.8), 20(0.2)	36(0.7), 50(0.3)	36(0.1), 50(0.9)
Capital Requirement	14(0.5), 18(0.5)	18(0.7), 19(0.3)	17(0.3), 18(0.7)	10(0.75), 12(0.25)	17(0.4), 18(0.6)

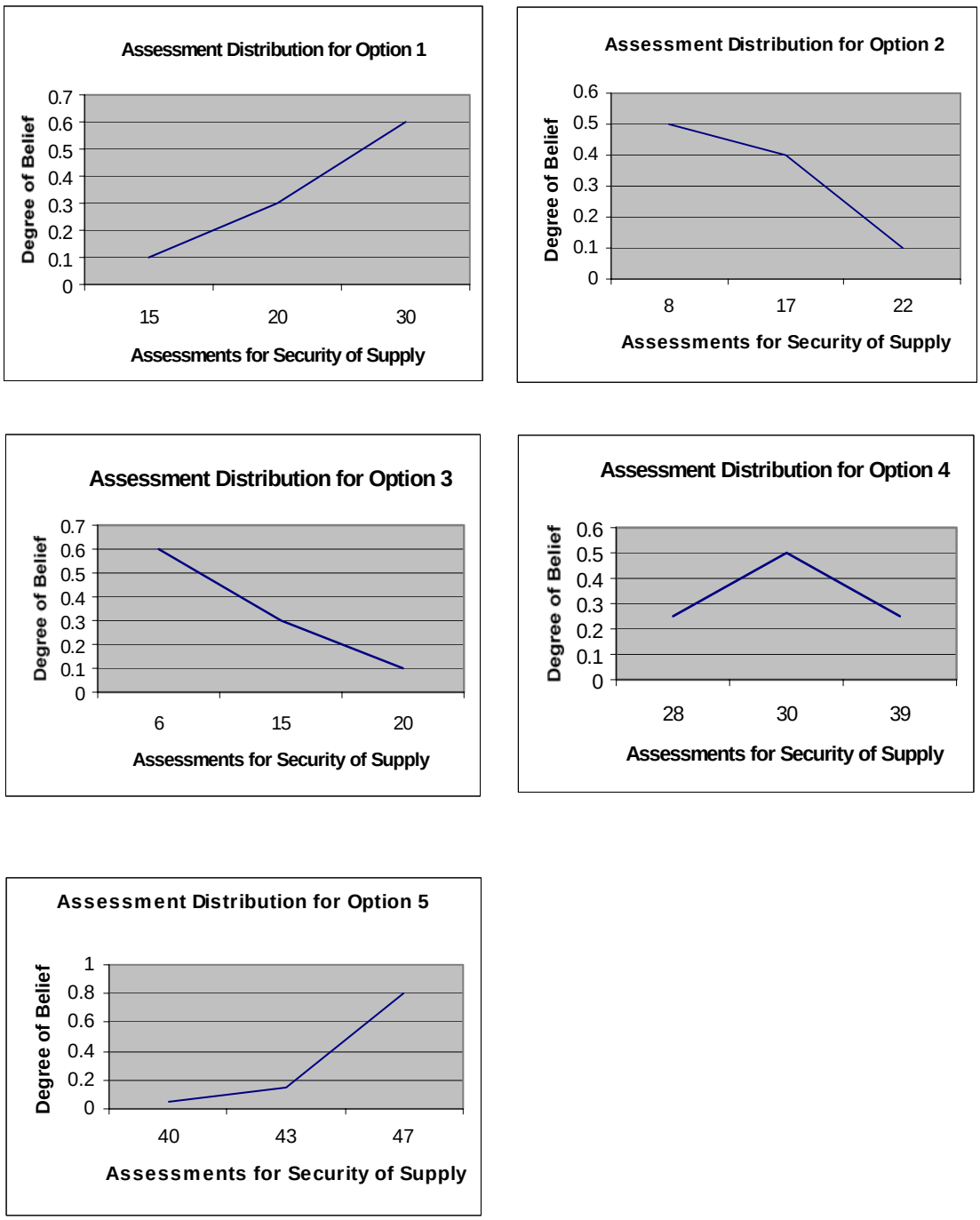
Note that the numbers in brackets show the degree of belief (total degree of belief must be less than or equal to 1).

Figure 5: Energy Policy Selection Problem (case 2): criteria and assessments

Alternatives / Attributes	Option 1	Option 2	Option 3	Option 4	Option 5
Security of Supply	15(0.1), 20(0.3), 30(0.6)	8(0.35), 17(0.4), 22(0.1)	6(0.6), 15(0.3), 20(0.1)	28(0.2), 30(0.4), 39(0.25)	40(0.05), 43(0.15), 47(0.8)
Competitiveness	1.0(0.25), 1.2(0.6)	No Information	0.7(0.1), 0.8(0.7)	1.1(0.1), 1.3(0.9)	2.3(0.6), 2.7(0.4)
Employment	0(0.5), -500(0.5)	0(0.3), 500(0.7)	400(1.0)	No Information	-1000(0.5), -1500(0.4)
Nuclear Waste	No Information	11(0.3), 12(0.4), 13(0.3)	9(0.2), 10(0.3), 11(0.1)	-10(0.3), -12(0.4), -14(0.3)	-20(1.0)
Cost	50(0.2), 58(0.3), 62(0.3), 65(0.2)	36(0.1), 38(0.25), 40(0.3), 42(0.2)	34(0.25), 37(0.3), 40(0.3), 43(0.15)	50(0.2), 58(0.3), 62(0.25), 65(0.25)	78(0.1), 80(0.4), 82(0.25), 84(0.25)
Greenhouse Effect	-10(0.5), 0(0.5)	No Information	-11(0.5), -9(0.35)	-20(0.75), -10(0.15)	-20(1.0)
Low Energy Prices	-15(0.2), -13(0.35), -10(0.25)	-32(0.3), -24(0.3), -16(0.1)	No Information	0(1.0)	34(0.3), 45(0.45), 50(0.1)
Balance	60(1.0)	44(0.1), 48(0.15), 52(0.35), 56 (0.15), 60(0.1)	44(0.1), 48(0.2), 52(0.3), 56(0.1), 60(0.1)	50(0.1), 55(0.2), 60(0.4), 65 (0.2), 70(0.1)	44(0.1), 48(0.2), 52(0.4), 56(0.2), 60(0.1)
Conservation	-15(0.3), -5(0.5)	-10(1.0)	-40(0.5), -20(0.5)	-60(0.55), -48(0.3)	No Information
Diversity	2(1.0)	3(1.0)	2(0.5), 3(0.5)	1(0.4), 2(0.5)	1(0.5), 3(0.5)
Acid Rain	5(0.2), 10(0.6), 15(0.1)	-20(0.2), -10(0.7), 10(0.1)	-10(0.3), -5(0.45), 5(0.1)	No Information	-10(0.3), -5(0.5), 5(0.1)
Radioactivity	-10(0.4), -5(0.4), 5(0.2)	-5(0.2), 5(0.4), 10(0.3)	-5(0.3), 0(0.4), 5(0.3)	-15(1.0)	-20(1.0)
Decentralization	20(1.0)	12(0.5), 20(0.4)	No Information	36(0.6), 50(0.3)	50(1.0)
Capital Requirement	14(0.3), 18(0.5)	18(0.55), 19(0.3)	17(0.3), 18(0.7)	10(0.7), 12(0.2)	17(0.4), 18(0.6)

Note that the numbers in brackets show the degree of belief (total degree of belief must be less than or equal to 1).

Figure 6: Assessment Distribution of the Criterion "Security of Supply" on All Options



Results and Discussion

In this section, we will present the results of the two sets of assessments given earlier and implement them. The results are provided and stored in a notepad editor by the

IDS. The results for the first set of assessments (shown in Figure 4) can be seen in Table 2 while results for the second set of assessments can be seen in Table 3.

Table 2: Results for the Complete Set of Assessments Made in Figure 4

Grades	Worst	Bad	Average	Good	Best
Option 1	0.0615	0.1113	0.5486	0.2786	0.0000
Option 2	0.0685	0.1775	0.1494	0.4336	0.1710
Option 3	0.0248	0.2199	0.1394	0.4407	0.1752
Option 4	0.0604	0.2187	0.3092	0.2865	0.1252
Option 5	0.2428	0.3897	0.0753	0.0506	0.2416

Table 3: Results for the Imprecise Set of Assessments Made in Figure 5

Grades	Worst	Bad	Average	Good	Best
Option 1	0.0022	0.1614	0.5093	0.1899	0.0000
Option 2	0.0461	0.1244	0.2555	0.2253	0.0832
Option 3	0.0074	0.1262	0.1685	0.3819	0.1221
Option 4	0.0276	0.0959	0.3705	0.1854	0.1232
Option 5	0.2739	0.2952	0.0964	0.0189	0.2366

The ER approach propagates the degrees of belief assigned to each criterion under the grades defined at the top level. Initially a distributed assessment of each alternative is obtained (as in Table 2 and Table 3). Then, in order to be able to rank the alternatives, the grades need to be quantified. There are a number of ways of doing this. One is to use the multiple attribute utility theory as suggested in (Hwang and Yoon, 1981). Another is to use goal programming as recommended by (Yang and Sen, 1996). For simplicity we assumed that the following utilities were assigned to each grade:

U(Best) = 1, U(Good) = 0.85, U(Average) = 0.7, U(Bad) = 0.4 and U(Worst) = 0

Based on the given utility values of each grade, we can calculate each option's expected utility in Table 2. Since the assessments made by the DMs are complete, the total degree of belief assigned to each grade in Table 2 adds to one. For example, the

total degree of belief for Option 1 is distributed to each grade as follows: 0.0615 (worst), 0.1113 (bad), 0.5486 (average), 0.2786 (good) and 0 (best) (0.0615 + 0.1113 + 0.5486 + 0.2786 + 0 = 1). Thus, the expected utility of the Option 1 is:

U (Option 1) = [(0.0615 x 0) + (0.1113 x 0.4) + (0.5486 x 0.7) + (0.2786 x 0.85) + (0 x 1)] = 0.5306. The other options' expected utilities have been found in the same way and as follows: U (Option 2) = 0.6459, U (Option 3) = 0.6634, U (Option 4) = 0.5746 and U (Option 5) = 0.4366. The ranking of alternative options in order of preference is therefore Option 3 > Option 2 > Option 4 > Option 1 > Option 5.

In Table 3 the total degree of belief is less than one due to the imprecise and missing assessments. For example, the degree of belief assigned to each grade for Option 1 is as follows: 0.0022 (worst), 0.1614 (bad), 0.5093 (average), 0.1899 (good), 0 (best) and adds to 0.8628 (i.e. 0.0022 + 0.1614 + 0.5093 + 0.1899 + 0 = 0.8628). Therefore, the unassigned degree of belief is 1 – 0.8628 = 0.1372. The following are the unassigned degrees of belief for other options: Option 2 = 0.2655, Option 3: 0.1939, Option 4: 0.1974 and Option 5: 0.079. In reality these unassigned degrees of belief may fall into any of the grades. However, the ER framework considers two extreme cases where the unassigned degrees of belief are assigned to the least and the most preferred grades (worst and best in our case). Hence, the ER algorithm yields two utilities for each option: minimum and maximum. It is a minimum when the unassigned degree of belief goes to the least preferred grade and a maximum when the unassigned degree of belief goes to the most preferred grade. The minimum expected utility of the Option 1 can be calculated as follows:

Min U (Option 1) = [(0.0022 x 0) + (0.1614 x 0.4) + (0.5093 x 0.7) + (0.1899 x 0.85) + (0 x 1) + (0.1372 x 0)] = 0.4550

Max U (Option 1) = [(0.0022 x 0) + (0.1614 x 0.4) + (0.5093 x 0.7) + (0.1899 x 0.85) + (0 x 1) + (0.1372 x 1)] = 0.5922. The other options have the following minimum and maximum expected utilities.

Alternatives	Minimum Utility	Maximum Utility
Option 1	0.4550	0.5922
Option 2	0.4285	0.6940
Option 3	0.5497	0.7436
Option 4	0.4855	0.6829
Option 5	0.3885	0.4675

Table 4: Minimum and Maximum Expected Utilities of the Options

Each option has an expected utility range, which makes the ranking of the options difficult. Theoretically, in order to say one option dominates the other, the first option's minimum utility should at least equal or greater than the second option's maximum utility. For example, from the above results, one can deduce that both Option 3 and Option 4 dominate the Option 5 because their minimum utilities are greater than the Option 5's maximum utility (0.5497 > 0.4675 and 0.4855 > 0.4675 respectively). However, we cannot tell whether Option 3 dominates the Options 1, 2 and 4. There are several ways to solve this. First, the DM may be asked to revise the previous judgements and required to give more precise assessments if possible. Another solution is to assume that the missing assessments for Option 3 are assessed to be at the least preferred grade, while for the other options are at the most preferred grade. Since assessments are changed from an imprecise state to a precise state, a single utility value for each option can be obtained and the options can be ranked directly. However, one would argue that the missing assessments for each option could be in different attributes. As a result of this, it may be hard to tell whether an

option really dominates the other one. A final suggestion would be to obtain more information or seek expert's advice to change imprecise assessments to precise ones. We assume that the DMs decided to use the average utility ((Minimum Utility + Maximum Utility) / 2) to rank the options in order of preference. Then, the ranking is as follows: Option 3 > Option 4 > Option 2 > Option 1 > Option 5.

Conclusion and Future Work

In this paper, we tried to select the best UK energy policy by using the evidential reasoning approach. It has been shown that the ER approach is capable of dealing with multidisciplinary data. Even though the evaluation assessments are uncertain, incomplete and imprecise, a decision still can be made based on the available information. Another advantage of using the ER approach is that the decision making process does not require much time and effort from the DM. Since the ER approach is well supported by computer software, the DM is only asked to input his preferences and judgements.

In our hypothetical case study, decision criteria outcomes are of a quantitative nature. However, in real world decision-making problems this may not be the case. The decision criteria can be a mixture of both quantitative and qualitative criteria. The existing ER framework is designed to tackle the multiple criteria decision-making problems with both quantitative and qualitative criteria under uncertainty. Although decision criteria in our example can be expressed in quantitative terms, some of the criteria may be prone to subjectivity and may be evaluated better by linguistic terms. In the future, our research will focus on developing a model to establish a unique

evaluation process for MCDM problems with both qualitative and quantitative criteria.

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