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ScienceDirect
Renewable and Sustainable Energy Reviews
11 (2007) 1584–1595

RENEWABLE
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ENERGY REVIEWS

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Use of multicriteria decision analysis methods for energy planning problems

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Received 28 October 2005; accepted 23 November 2005

Abstract

Most decision making requires the consideration of several conflicting objectives. The term multiple criteria decision analysis (MCDA) describes various methods developed for aiding decision makers in reaching better decisions. Energy planning problems are complex problems with multiple decision makers and multiple criteria. Therefore, these problems are quite suited to the use of MCDA. A multitude of MCDA methods exists. These methods can be divided in three main groups; value measurement models, goal, aspiration and reference level models, and outranking models. Methods from all of these groups have been applied to energy planning problems, particularly in the evaluation of alternative electricity supply strategies. Each of the methods has its advantages and drawbacks. However, we cannot conclude that one method generally is better suited than the others for energy planning problems. A good alternative might be to apply more than one method, either in combination to make use of the strengths of both methods, or in parallel to get a broader decision basis for the decision maker. Until now, studies of MCDA in energy planning have most often considered energy networks with only one energy carrier. More advanced energy systems with multiple energy carriers have been neglected, even though this field ought to be suitable for use of MCDA due to its high complexity, many decision makers and many conflicting criteria.

Keywords: Energy planning; Multiple criteria decision analysis (MCDA)

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1364-0321/$ - see front matter
doi:10.1016/j.rser.2005.11.005

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1. Introduction

When making decisions, decision makers (DMs) always try to choose the optimal solution. Unfortunately, a true optimal solution only exists if you are considering a single criterion. In most real decision situations, basing a decision solely on one criterion is insufficient. Probably several conflicting and often non-commensurable objectives should be considered. Because of this, it is impossible to find a genuine optimal solution, a solution that is optimal for all DMs under each of the criteria considered [1].

Multiple criteria decision making (MCDM) is a generic term for all methods that exist for helping people making decisions according to their preferences, in cases where there is more than one conflicting criterion [2]. Using MCDM can be said to be a way of dealing with complex problems by breaking the problems into smaller pieces. After weighing some considerations and making judgments about smaller components, the pieces are reassembled to present an overall picture to the DMs [3].

Another term which is often used is multiple criteria decision analysis (or aid) (MCDA). The reason for using 'decision analysis' or 'decision aid' instead of 'decision making' is to emphasize that the methods should aid DMs in making better decisions. The methods themselves cannot make the actual decisions. The aim of MCDA methods is to help DMs organize and synthesize the information they have collected, so that they feel comfortable with and confident in their decisions. By using MCDA methods, DMs should feel that all important criteria have been properly accounted for. This should help to reduce the post-decision regret [4]. Ideally, the MCDA methods will help the DMs to understand and identify the fundamental criteria in the decision problem, and avoid making important decisions out of habit.

Energy planning is a field that is quite suitable for MCDA methods because it is subject to many sources of uncertainty, long time frames and capital-intensive investments [5], along with featuring multiple DMs and many conflicting criteria. The complexity in the planning of local energy systems is discussed in more detail in Ref. [6]. Before the 1970s, little effort was made in the formal planning of energy systems. The oil crisis in the 1970s resulted in more emphasis being placed on identifying efficient supply options. However, most studies were based only on cost minimization [7]. In the 1980s, the public started to become more aware of environmental issues. Consequently, it was necessary to start incorporating environmental considerations in energy planning [8]. This led to a more comprehensive use of MCDA methods. Subsequently, it has become common to include other criteria in the studies, such as reliability, land use, aesthetics and human health concerns [9].

The purpose of this review article is to provide an overview of some of the most important MCDA methods that have been proposed over the years. I will present examples of how different methods have been applied for energy planning purposes. The examples have been chosen to give a broad overview of all the methods that have been used for energy planning. The main advantages of the different methods, as well as the difficulties that they may be subject to, will also be evaluated. In the end, I will argue that MCDA can be a very useful tool for the planning of local energy systems with multiple energy carriers and multiple energy resources, even though no MCDA studies have examined this type of problem until now.

2. Multicriteria decision analysis methods

Over the years, hundreds of MCDA methods have been proposed [10]. The methods differ in many areas—theoretical background, type of questions asked and type of results given [11]. Some methods have been created particularly for one specific problem, and are not useful for other problems. Other methods are more universal, and many of them have attained popularity in various areas. The main idea for all the methods is to create a more formalized and better-informed decision making process.

I will start this section by providing guidelines on the selection of the most appropriate method for a given problem. Thereafter, I will present some of the most well known MCDA methods.

2.1. Choosing an MCDA method

When choosing an MCDA method, there are many criteria to consider. The most important is to find a method that measures what it is supposed to measure (validity). Different methods are likely to give different results, so a method that reflects the user's 'true values' in the best possible way should be chosen. In addition, the method must provide the DMs with all the information they need, and the method must be compatible with the accessible data (appropriateness). The method must also be easy to use and easy to understand [10]. If the DMs do not understand what is happening inside the methodology, they perceive the methodology like a black box. The result may be that the DMs do not trust in the recommendations from the method. In that case, it is meaningless to spend time applying this method.

2.2. Classifying MCDA methods

There are many possible ways to classify the existing MCDA methods. In this review, I have chosen the same classification as Belton and Stewart used in their book [4]. According to Ref. [4], there are three broad categories (or schools of thought):

- Value measurement models.
- Goal, aspiration and reference level models.
- Outranking models (the French school).

In the next sections, I will describe the main characteristics of the three categories, and I will present some of the most important methods that belong to each group. For more detailed descriptions of the methods, I recommend Ref. [4], or specific literature for each method written by the developers of the various methods.

2.2.1. Value measurement models

When using value measurement methods, a numerical score (or value) V is assigned to each alternative. These scores produce a preference order for the alternatives such that a is preferred to $b\,(a \succ b)$ if and only if $V(a) > V(b)$. When using this approach, the various criteria are given weights w that represent their partial contribution to the overall score, based on how important this criterion is for the DM(s). Ideally, the weights should indicate how much the DM is willing to accept in the tradeoff between two criteria [4,12,13].

The most commonly used approach is an additive value function (multiattribute value theory (MAVT)):

$$V(a) = \sum_{i=1}^{m} w_i\, v_i(a), \tag{1}$$

where $v_i(a)$ is a partial value function reflecting alternative a's performance on criterion i. The partial value function must be normalized to some convenient scale (e.g. 0–100). Using Eq. (1), a total value score $V(a)$ is found for each alternative a. The alternative with the highest value score is preferred. MAVT is a pretty simple and user-friendly approach where the DM—in cooperation with the analyst—only needs to specify value functions and define weights for the criteria to get very useful help with his decision [4].

The multiattribute utility theory (MAUT) first proposed in detail by Keeney and Raiffa [14] can be said to be an extension of MAVT. MAUT is a more rigorous methodology for how to incorporate risk preferences and uncertainty into multicriteria decision support methods. When using this approach, multiattribute utility functions $U(a)$—where the risk preferences are directly reflected in the values—must be established instead of value functions [4,14].

The analytical hierarchy process (AHP) developed by Saaty [15] has many similarities to the multiattribute value function approach. Belton and Stewart [4] described AHP "as an alternative means of eliciting a value function". However, they pointed out that the two methods rest on different assumptions on value measurements, and that AHP is developed independently of other decision theories. Of these reasons, many of the proponents of AHP claim that AHP is not a value function method [4]. However, both MAUT and AHP present their results as cardinal rankings, which mean that each alternative is given a numerical desirability score. Consequently, the results from the two methods are directly comparable.

The major characteristic of the AHP method is the use of pair-wise comparisons, which are used both to compare the alternatives with respect to the various criteria and to

Table 1
Fundamental scale

1	Equally preferred
3	Weak preference
5	Strong preference
7	Very strong or demonstrated preference
9	Extreme importance
2, 4, 6, 8	Intermediate values

estimate criteria weights [4,13]. In the pair-wise comparisons, a special ratio scale (Table 1) constructed by Saaty [15,16] is used:

The results from all the comparisons are put into matrices. From these matrixes, an overall ranking of the alternatives can be aggregated. The alternative with the highest overall ranking is preferred to the others [13]. The mathematical procedure that is used to calculate the overall rankings is quite complex (more details can be found for instance in Ref. [15]), and the procedure is, therefore, normally performed with specially designed computer programs.

2.2.2. *Goal, aspiration and reference level models*

Alternatives to value measurement methods are goal programming (GP), the aspiration level and the reference level methods. Often GP is used as a common abbreviation for all these approaches, and this simplification is used also in this article. When using GP approaches, we try to determine the alternatives that in some sense are the closest to achieve a determined goal or aspiration level [4]. Often the GP approach is used as a first phase of a multicriteria process where there are many alternatives. In that case, GP is used to filter out the most unsuitable alternatives in an efficient way.

Mathematically, we can say that the idea in the GP methods is to solve the inequalities $z_i + \delta_i \geqslant g_i$, where z_i is the attribute values, δ_i is the non-negative deviational variables and g_i is the goals (a desirable level of performance) for each criterion i. The aim is to find a feasible solution that minimizes the vector of deviational variables. If it is possible to find a solution where $\delta_i = 0$ for all i, this will be the recommended solution. In most cases, this is not the case, and another solution must be found. The simplest method for this purpose is to minimize the weighted sum of deviations $\sum_{i=1}^{m} w_i \delta_i$ [4], where w_i is the importance weight and δ_i is the deviation of criterion i.

A more advanced possibility is to use the so-called Tchebycheff norm, where the aim is to minimize the maximum weighted deviation, i.e. to minimize $\max_i\{w_i \delta_i\}$. It means that the focus is always placed on the relatively worst performance area [4].

GP methods are well-suited for the use of interactivity. There are many possible methods. I will only give a brief explanation of some of them. A well-used interactive method is the method of displaced ideals, as proposed by Zeleny [17]. The concept in this method is to minimize

$$\left[\sum_{i=1}^{m} [w_i \delta_i]^p\right]^{\frac{1}{p}}, \tag{2}$$

for different values of p. p is a constant that decides the penalty for greater deviations compared to smaller deviations. After the DM has been presented for solutions for various values of p, he is supposed to eliminate clearly undesirable solutions. This is called displacement of ideals. After the displacement, the procedure will be repeated until the difference between the ideal solution[1] and compromise solution are acceptably small [4,11].

In the STEM approach (also called the step method) proposed by Benayoun [18], the ideal solution is used as a goal for each criterion, and deviations are found by the Tchebycheff norm explained above. The weights for the criteria are not specified by the DM, but are calculated by the relative range of values available on each criterion. Consequently, the weights are only giving a normalization of the objective function to some convenient scale, i.e. 0–100. When a possible solution is found, the DM is asked which of the calculated values he finds satisfactory and which he finds unsatisfactory. In the next loop, the unsatisfactory values will be improved, while the satisfactory values are "sacrificed". This is repeated until the DM is happy with the proposed solution [4].

The basic idea in the technique for order preference by similarity to ideal solutions (TOPSIS) method is to compare the alternative solutions with the ideal and anti-ideal solutions. The best solution is the solution with the highest so-called "relative closeness to the ideal solution," which is a proportion between the Euclidean distances to the ideal and anti-ideal solutions [8,19].

2.2.3. Outranking models

In outranking models, the alternatives are compared pair-wise to check which of them is preferred regarding each criterion. When aggregating the preference information for all the relevant criteria, the model determines to what extent one of the alternatives can be said to outrank another. We can say that an alternative a outranks an alternative b if there is enough evidence to conclude that a is at least as good as b when taking all criteria into account [4]. The methods based on this way of thinking are often called the French school. The two main families of methods in the French school are ELECTRE and PROMETHEE. Below, I will give a brief explanation of these methods.

The family of ELECTRE methods was developed as an alternative to the utility function and value function methods. Details of the ELECTRE methods can, e.g. be found in Ref. [20]. The most common ELECTRE method in energy planning problems is ELECTRE III, so I will concentrate on that one is this review. The main idea in ELECTRE III is to choose alternatives that are preferred for most of the criteria. However, alternatives which are very unfavorable for any of the criteria should not be chosen, even if this alternative is favorable for most of the other criteria. The method makes use of the so-called indifference thresholds and strict preference thresholds. These thresholds are used to calculate concordance and discordance indices. From these indices, we can calculate graphs for strong and weak relationships, and these graphs are used to rank the alternatives through an iterative process. The method is sometimes not able to find the best alternative. However, it is often useful to apply the ELECTRE III method in the beginning of the decision process to produce a shortlist of the best alternatives. These alternatives can then go through further analysis by using another, more detailed method [4,21].

[1] In the world of multicriteria, an ideal solution is a theoretical solution where all the criteria have been respectively maximized or minimized.

An alternative outranking approach is the PROMETHEE method, developed by Brans and his co-workers [22]. In this method, a pair-wise comparison of alternatives is performed to make up a preference function for each criterion. Based on the preference function, a preference index for *a* over *b* is determined. This index is a measure of support for the hypothesis that *a* is preferred to *b*. It is defined as a weighted average of preferences on the individual criteria. The preference index is used to make a valued outranking relation which determines a ranking of the alternatives [4,8].

3. MCDA in energy planning

As mentioned in the introduction, energy planning is a field very suitable for MCDA methods. Over the last years, many applications of MCDA methods for energy planning problems have been published. In this section, I will give some examples that describe use of various MCDA methods for energy planning problems.

3.1. Value measurement models

Value measurement models have been used in various application areas in energy planning problems, especially for choosing/ranking energy strategies or technologies. Some of the applications have been evaluating alternative electricity supply strategies, using either analytical hierarchical process (AHP) [17,19], an AHP-similar method [23] or MAUT [24,25]. MAUT has also been used for an energy supply optimization process [26]. Hobbs et al. have done some interesting studies where they have compared various methods for collecting weights in MAVT analyses for evaluating demand-side management (DSM)[2] programs [10], and in the choice of an energy resource portfolio [11]. In Ref. [11], the MAVT approaches were also compared to a GP approach.

Buehring et al. [24] emphasized that the MAUT process in itself has many benefits for the DMs. They claimed that the process of assessing utility functions will help the DMs to identify the most important issues, generate and evaluate alternatives, resolve judgment and preference conflicts among the DMs and identify improvements to the impact. Siskos and Hubert [27] were more concerned about the drawbacks of the MAUT approach in their description of various MCDA methods. They claimed that MAUT presents many complications in the decision process, especially concerning the assessment of probabilities and attaching utilities to the criteria. To establish utility functions is a difficult and cumbersome task, because most DMs do not have a good perception of their own risk preferences [28]. However, MAUT is one of few MCDA methods designed especially for handling risk and uncertainties.

Advantages and shortcomings of the AHP method were discussed by Ramanathan and Ganesh [29]. They claimed that the main reasons for the AHP method's popularity are its simplicity, flexibility, intuitive appeal and its ability to handle both quantitative and qualitative criteria in the same framework. However, the method also has some drawbacks. According to Ref. [29], the main disadvantage is that AHP is very time-consuming when the number of alternatives and/or criteria is large, as is often the case in

[2]DSM activities are designed to encourage the customers to reduce their energy consumption and/or change their energy usage pattern. Such activities can to some extent be introduced as an alternative to increase the energy production.

energy problems. Another, often criticized problem, for instance Refs. [30–34], with the AHP method is the conversion from verbal to numerical judgments given by the fundamental scale (Table 1). It seems like the conversion table tends to overestimate preference differences [33]. There is also a lot of other criticism raised against the AHP method which are covered in more detail, e.g. in Ref. [32].

3.2. Goal, aspiration and reference level models

Another approach that has been used for energy planning studies is goal programming. The most commonly used GP method in energy planning problems seems to be the method of displaced ideals. The method has, e.g. been used for energy supply optimization [35], comparing different electricity generations systems from an environmental point of view [36] and for choosing an energy resource portfolio [11]. In these last two studies, the method of displaced ideals was compared to a monetization method[3] [36] and to a number of value-based methods [11], respectively.

Other GP methods that have been used for energy planning are the STEP method, which was used for energy resource allocation [37], and the TOPIS method, which was used for evaluation of alternative electricity supply strategies [19]. Ramanathan and Ganesh [29] has used the weighted sum of deviations to solve an energy resource allocation problem.

A reason to use GP techniques is that GP is less subjective than value theory and utility theory. In addition, GP offers a very straightforward procedure that DMs find easy to understand [29]. A third advantage is that many of the GP methods are suitable for being implemented directly into LP solvers [35]. It means that MCDA can be included into already existing one-criterion optimization models in a simple way. However, there is also a lot of criticism raised of GP, especially regarding the assignment of weights, the determination of goals and the normalization of the variables [29]. Another main disadvantage with the GP approach is that each criterion needs to be associated with an attribute defined on a measurable scale, which means that the methods are generally not able to handle non-quantitative criteria [4,29]. Therefore, GP must be combined with other techniques if qualitative criteria are going to be included in a study.

Pokharel and Chandrashekar [8] presented some advantages of the STEP method. According to them, the STEP method is the only method that allows direct comparison among the alternate solutions. This is supposed to help DMs to be aware of "the impact of a preference for an objective function on the solution". In addition, they found the STEP method easy to understand and to implement. However, they also found some drawbacks of the method. The main drawback is that the method requires that the DMs are able, precisely, to define their goals at each iteration. Furthermore, the method will—as other GP methods—in some cases present dominated solutions as being optimal.

3.3. Outranking models

Outranking models seems to be popular for energy planning problems. Outranking was used in many studies for evaluation of alternative electricity supply strategies (demand side management was also included in some of them). The most popular outranking

[3]In a monetization method, all criteria are translated into monetary values so that they can easily be compared.

methods in these evaluations is PROMETHEE II [7,17] and ELECTRE III [27,38–40]. PROMETHEE II has also been used for evaluating alternative strategies concerning geothermal energy usage [41].

Some of the main advantages of the outranking methods are that they provide a deep insight in the problem structure, they model the DM's preferences in a realistic way by recognizing hesitations in the DM's mind, and they are able to treat uncertainties in various ways [7,41]. In addition, it is claimed that the representation of the results from the outranking methods is simpler and easier to understand than the results from other MCDA approaches, such as MAVT [40].

A main difference between PROMETHEE II and ELECTRE III is the calculation procedure that is used. PROMETHEE II has a transparent calculation procedure, which is easy for DMs to understand [7], while the DMs often find the calculations from ELECTRE III too complex. Consequently, the ELECTRE method ends up as a 'black box' which feels unsatisfactory for the DMs [40,41].

The outranking methods are normally not used for the actual selection of alternatives, but they are very suitable for the initial screening process (to categorize alternatives into acceptable or unacceptable) [13]. After the screening process, another method must be used to get a full ranking or actual recommendations among the alternatives.

3.4. Combination of methods

Some researchers have tried to combine use of different MCDA methods. The AHP method has been especially popular to combine with other methods. Tzeng et al. [17] combined the use of AHP and PROMETHEE II, while Yang and Chen [19] combined AHP and TOPSIS in their evaluations of energy strategies. Ramanthan and Ganesh [29] integrated AHP and the GP method called the weighted sum of deviations for an energy resource allocation problem in India.

A proper combination of two (or more) methods might be very favorable. Such integration will help to make use of the strengths of both the methods. Moreover, even though both methods have some limitations, their limitations might be complementary. Ramanathan and Ganesh [29] argue that GP and AHP are well-suited to combine for a resource allocation problem. It is likely that suitable combinations of MCDA methods can be found also for other types of problems.

4. Conclusions and suggestions for further work

This literature review has shown that energy planning is a field that is quite suitable for the use of MCDA. I have shown that there exists a multitude of MCDA methods, and that many of these methods have been applied to energy planning purposes. Choosing among all the MCDA methods that exist can be said to be a multicriteria problem. Each of the methods has its own advantages and drawbacks, and it is not possible to claim that any one of the methods is generally more suitable than the others are. Different DMs will always disagree about which methods are most appropriate and valid.

The choice of method mostly depends on the preferences of the DM and the analyst. It is important to consider the suitability, validity and user-friendliness of the methods. It is also important to realize that use of different methods will most probably give different recommendations. This should not lead to the conclusion that there is anything wrong with any of the methods. It just means that the different methods work in different ways.

Hobbs and Horn [10] emphasized that choice of method can significantly affect judgment decisions. They claimed that change of method often makes more difference than change of the person that is applying the method. Hobbs and Horn [10] and Hobbs and Meier [11], therefore, concluded that ideally more than one multicriteria method should be used in a decision making process. This will give the DMs a broader decision basis. Additionally, DMs should be allowed to reflect upon and change their values after they get the first results from the methods. Accordingly, Hobbs and his colleagues proposed an interview process and a discussion among the DMs after the first collection of weights. During the interview and discussion, inconsistencies among the methods should be discovered. According to Buehring et al. [24], individuals will be more likely to discuss their judgments after they have been through a formalized decision making process. The extra effort required by the use of more than one method and the implementation of an interview process is not large compared to the potential benefits, which include enhanced confidence in the decision and a more reliable process [11].

In this review article, I have given many examples of how different MCDA methods have been utilized for energy planning. All the studies I have presented consider different aspects of energy networks with only one energy carrier (which was electricity in most of the studies). The majority of the studies are at a high planning level, such as a regional or even national level.

What seem to be missing in the research until now, are multicriteria studies on local energy systems with multiple energy carriers. Such combined energy systems with infrastructure such as networks for electricity, district heating and natural gas are common all over the world. In the past, these infrastructures were normally planned and commissioned by independent companies. It is believed that synergetic effects might be lost when such infrastructures are planned independently. Consequently, planning tools that can evaluate and analyze alternative energy carriers in mutual combination will give some benefits.

There is no doubt that if properly applied, MCDA can be a valuable tool also for planning of combined energy systems. Such systems may include several energy resources (hydro, oil, gas, garbage, etc.) and several energy carriers (electricity, district heating, natural gas, hydrogen, etc.) combined in a complex network with various conversion, storage and transportation technologies [6]. Often, there is more than one DM in such systems, and each of them will probably have many conflicting objectives which they would want to include in the study. In sum, these aspects make for a very complex problem. Because of this complexity, it is difficult for the DMs to get the full overview of their problem without using some decision-aid systems. Due to the conflicting objectives, some kind of MCDA should be well-suited. The problem, however, will be to choose which of the multitude of MCDA methods are most suitable for this type of problem.

Acknowledgements

I would like to acknowledge Nancy Bazilchuk for all her help and constructive feedback during the work with this review article. I would also like to acknowledge my main supervisor Professor Arne T. Holen.

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