Beyond Value Function Methods in Multi-Criteria Decision Analysis for Health care

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Abstract

In health care decision-making, the predominance of some value function multi-criteria decision analysis (MCDA) methods may obscure the existence and potential usefulness of alternative MCDA methods. The current chapter provides an introduction to alternative value function and non-value function methods. The alternative value function methods presented are approaches based on multi-attribute value theory (MAVT): measuring attractiveness by a categorical based evaluation technique (MACBETH), Variable Interdependent Parameters (VIP) Analysis, and Stochastic Multicriteria Acceptability Analysis (SMAA). Non-value function methods described include goal-programming models, the dominance-based rough set approach and outranking models. The chapter also reviews their use in health to date and ends with concluding remarks.

1. Introduction

MCDA, used as an umbrella term, is a decision-making framework that encompasses a large set of methods or approaches that simultaneously and explicitly take account of multiple and conflicting criteria [1]. These methods can roughly be classified into five main families: elementary methods [2], value function methods [3], goal and reference methods [3], outranking models [3] and dominance-based approaches [4-6]. MCDA consists of three steps [3]. The first step, referred to as problem identification and structuring, deals with identifying the decision-makers and setting their goals. At this step, the relevant competing options and their evaluation criteria are defined. The second step, called multi-criteria evaluation model development and use, requires the selection of the relevant aggregation model and the elicitation of the model's parameters, which defines the role played by each evaluation criterion when synthesizing the performance of the alternatives in multiple attributes. The last step, called the development of action plans, consists of making recommendations to decision makers. Additionally, the presentation of sensitivity analyses informs the decision-makers regarding their level of confidence about the plans.

Even though analysts and researchers have access to a wide range of evaluation models in MCDA to respond to multifaceted problems in health care, the use has been confined to the application of only a few value function methods. Adunlin et al. conducted a systematic review to identify applications of MCDA in health care [7]. The time horizon for the search spanned the years 1980-2013 and encompassed a wide range of bibliographic sources (electronic databases, grey literature). Of the 66 studies that met the inclusion criteria of the review, 91% used a value function method, a method that computes a single value to summarize the performance of an alternative on multiple criteria [7].

Value function methods are techniques that compute an overall value for each competing alternative representing the global performance of each alternative on their attributes. As a result, these methods are referred to as full aggregation or compensatory methods. Other MCDA methods that do not compute an overall value and/or are not compensatory are available, but have been applied less in healthcare.

The objective of this chapter is to highlight alternative MCDA methods that can be used to address health care decision-making problems. The chapter is structured as follows. Sections 2 and 3 describe alternative value function methods and non-value function methods respectively. Both sections review the use of these methods in health to date. The chapter ends with concluding remarks.

2 Alternative value function methods

Multi-attribute utility theory (MAUT) and multi-attribute value theory (MAVT) [8] are well-known approaches in MCDA to obtain an overall score for an alternative being evaluated on multiple criteria, The main difference between these approaches is that MAUT makes use of utility functions that account for decision-makers' attitudes towards risk, utilizing the concept of lotteries, as opposed to MAVT where a global value function is constructed for each alternative to represent the global performance of the alternatives on the decision criteria, using the concept of preference intensity. This section briefly reviews how MAVT can be used to obtain an overall valuation for an alternative and suggests related approaches that can constitute an alternative to the traditional way of applying MAVT.

The implementation of the MAVT traditionally involves two main steps. The first step deals with the construction of a partial value function for each criterion. A partial value function reflects how the value of an attribute varies along the measurement scale for the decision maker. It can be an increasing function for an attribute such as Quality of life, or a decreasing function for an attribute such as Cost. The second step aggregates the partial value functions to obtain a global value function. The most common aggregation model is the additive value function where the partial value of the alternative on each decision criterion is weighted by a scaling coefficient assigned to the respective value function, and these weighted values are then added yielding a global value. This requires the determination of scaling coefficients, which indicate the weight of each value function. Scaling coefficients can be elicited using a number of techniques including swing weighting [9]. The alternative with the highest global value is the preferred one. Construction of value functions needs to satisfy the transitivity of preference and indifference rule while the additive aggregation model used in MAVT needs to satisfy the additive independence condition (namely, that trade-offs between two criteria do not depend on the level of the remaining criteria) [3].

There are only a few published applications of MAVT in health care. To our knowledge, there is only one study that applied the MAVT to patient-bed assignment in hospital admission management [10] in addition to a tutorial that illustrated the way to use MAVT to support reimbursement decision-making in health care [9]. Nevertheless, a recent project of the European Medicines Agency suggests using MAVT as the framework to support regulatory decisions about medicinal products [11].

It is the authors' opinion that MAVT is an intuitive and easy to understand MCDA method, since it uses a way of aggregating scores that individuals are familiar with (e.g. computing GPA scores

in academia, building composite indices such as United Nation's Human Development Index, etc.). It thus reflects the way data are aggregated in the above and many other examples. Like MAUT, MAVT defines an axiomatically based process for the construction of commensurable value scales and the definition of scaling coefficients.

A potential obstacle to using MAVT is the potential difficulty of eliciting precise values for the scaling coefficients that reflect the decision-maker's trade-offs [12]. However, to cope with this concern it is possible to assess the robustness of conclusions through the use of software such as the Variable Interdependent Parameters (VIP) Analysis [12]. VIP Analysis suggests an alternative process to conduct a MAVT-based analysis consisting of eliciting only information that is easier to obtain, such as a ranking of the scaling coefficients, rather than precise numerical values. To the authors' best knowledge, there are no applications of VIP Analysis in the health domain.

Another alternative approach to conduct a MAVT-based analysis is Stochastic Multicriteria (or Multiobjective) Acceptability Analysis (SMAA) [13]. Similar to the VIP analysis, this method does not require decision-makers to specify a vector of scaling coefficients. The space of all admissible scaling coefficients is sampled using Monte-Carlo simulations in order to produce statistics about the ranking of each alternative. SMAA can also provide information about what scaling coefficients, if any, make each alternative a winner. The potential for SMAA has been advocated for health economic evaluation of medical interventions and was illustrated on a case of infertility treatment selection [14].

A third alternative process to conduct a MAVT-based analysis is MACBETH [15,16]. MACBETH is distinguished from other MCDA methods by the fact that only qualitative

judgments about the difference of attractiveness (desirability) between pairs of alternatives are needed. The decision maker can state the difference of attractiveness between two alternatives using an ordinal qualitative scale composed of 6 levels, from "very weak" to "extreme". A consistency check is conducted to ensure the responses obtained from such pairwise comparisons do not conflict. The MACBETH procedure allows for the computation of numerical scores on an interval scale (0-100) for the alternatives on each criterion by the means of linear programming. A similar process is used to weight the criteria. A global score is estimated for each alternative using an additive aggregation, taking into account the scores of the alternative on the multiple criteria and the respective criteria weights. The alternative with the highest global score is considered the most attractive. The implementation of this method is supported by a software called M-Macbeth.

In health care, MACBETH has been applied to diagnosis and treatment of Alzheimer's and Diabetes [17-20]. MACBETH shares similar features with the AHP. They both use pairwise comparisons to derive criteria and alternatives priorities, except that the MACBETH derives value functions based on linear programming whereas AHP derives priorities using the eigenvalue method [15, 21]. As a result, MACBETH may be of interest for decision-makers that would like to explore the use of other methods that convert verbal preferences into numerical scores. Recent works have demonstrated the feasibility of using MACBETH for group decision-making [22,23].

4. Non-value function methods for health care decision-making

Using value function methods entails accepting that a very poor performance on one criterion can always be compensated by a very good performance on some other criterion. Therefore these methods may not be the most appropriate when such compensatory effects are not considered to be adequate in the decision-making process. For instance, this type of compensability may be inadequate if criteria refer to impacts on different stakeholders (e.g, patients versus hospital managers or medical staff), or when criteria refer to rather different dimensions (economic, versus social or environmental risks, for instance) [24].

The following families of non-value function methods are presented in this section: 1) Goal and reference point methods, 2) Dominance-based approaches, and 3) outranking methods.

4.1 Goal and reference point methods

There are several MCDA methods that evaluate alternatives by comparing them to some reference(s). The references can be internal (i.e. defined exclusively based on the set of alternatives) or can be external to the set of alternatives. The evaluation of each alternative does not depend only on its characteristics as in value-based approaches, but also on the chosen references.

A popular MCDA method based on comparisons with internal references is TOPSIS [2]. In this case, there are two references defined with regard to the set of alternatives being evaluated. The first reference is the so-called ideal point, a fictitious alternative defined by selecting, for each criterion, the best observed performance in the set of the alternatives. The second reference is referred to as the anti-ideal point, a fictitious alternative defined by selecting, for each criterion,

the worst observed performance in the set of the alternatives. The idea is to select an alternative that is near the ideal point and far from the anti-ideal point.

In TOPSIS, the evaluation score for an alternative is the distance to the anti-ideal solution divided by the sum of the same distance and the distance to the ideal solution. This yields a score between 0 and 1, like value function methods do. However, this value is not an evaluation of the alternative on its own merits, but an evaluation of how the alternative compares to the chosen references. The chosen distance metric is the weighted Euclidean distance, which allows placing different importance on different criteria. In order to make the distances comparable, a normalization operation is needed to transform the criteria scales into a common scale. The most common normalization in TOPSIS, performed separately for each criterion, consists of dividing each performance of an alternative by the square root of the sum of the squares of the performances of all alternatives on that criterion. An important concern about this method is that depending on the normalization method, the resulting scores can be different [15]. Another major concern is that introducing a poor and possibly irrelevant alternative that changes the anti-ideal point can reverse the relative positions of the remaining alternatives.

Upon reviewing the literature, one example framework was found using TOPSIS for Health Technology Assessment (HTA) by Liang et al. (2014) [25]. This framework was built to appraise different medicines based on economic and health-related criteria. The method suggested by these authors was a variant of TOPSIS using judgment from different stakeholders, combined with the use of AHP to derive criteria weights. A similar combination of AHP, to derive weights, and TOPSIS, to rank alternatives, was used by Akdag et al. to evaluate the service quality of some hospitals in Turkey [26]. This study constitutes one of the several examples of TOPSIS applications to problems other than HTA in the health sector [27-29].

There are many other methods based on distances to references [30], which include goal programming [31]. Such methods are used to set the value of decision variables subject to constraints, but the same principles can be used to rank a finite list of alternatives in order of their distance to a given reference point. Distances may or may not be weighted, attaching importance weights to the criteria. The reference alternative is usually an external reference indicating goals or aspiration levels.

In the health sector, goal programming has been mainly used for scheduling beds, staff and/or patients [32]. No application of goal programming for HTA was identified in the literature, except for an illustration of how this approach could be used to support reimbursement decision-making in health care [9].

Methods based on references may potentially be interesting for health care decision makers as they are often able to verbalize their aspirations by setting goals to be attained on each criterion. Then, a logical consequence is to seek which of the alternatives is closer to satisfying such goals, according to some metric, and possibly assigning a different weight to each goal. For instance, if a manager has a set of targets that he or she would like to attain (possibly including targets set by external entities), then it may be helpful to evaluate different decision alternatives considering their contribution to these targets. If the set of targets is very large, and therefore they cannot all be met at the same time, then a reference-based approach will indicate which alternatives are most interesting with regards to those targets.

As a separate note, we might also mention Data Envelopment Analysis (DEA) [32,34] as a close relative of MCDA [15,35,36,37] that uses references. Indeed, DEA evaluates the performance of each alternative (decision making unit in DEA terminology) considering the entire set of

alternatives as potential references, rather than asking decision makers to indicate aspiration levels. DEA could potentially be used to support decisions about whether or not to approve a new health technology, based on how it compares with the set of technologies already in operation.

4.2 Dominance-based approaches

A different way to perform a comparison of alternatives based on MCDA is to compare them directly, rather than computing an overall value (value-based approach) or comparing them with a reference. The simplest way to compare alternatives is to perform a pairwise comparison, i.e. a comparison of two alternatives, to check whether one of them is clearly superior to the other. An alternative x is said to dominate another alternative y if it is better on some criteria and is not worse in any other criterion. The resulting dominance relation does not require any subjective parameters such as criteria weights. If the purpose of the analysis is to identify a single best alternative, dominated alternatives can be discarded. However, the dominance relation typically applies to a few pairs of alternatives and there are usually several non-dominated alternatives (especially if the number of criteria is large).

One of the most recent methods in MCDA, the Dominance-based Rough Set Approach (DRSA), is based on exploiting the idea of dominance using Rough Sets Theory (RST) [38]. This approach can be used in sorting problems (assigning alternatives to categories) or in problems where a ranking of the alternatives is sought. RST does not require setting any preference-related parameters (such as importance weights), but requires the decision makers to provide examples of comparisons, e.g., stating that alternative x is better than alternative y. The method is able to extract *if-then* rules from such examples of preferences by an induction process. As an

illustration, a rule might state "if alternative x is much better than alternative y on criterion 1 and it is not much worse on criterion 2 then x is better than y". Another approach that uses induction rules based on qualitative assessments is Verbal Decision Analysis (VDA) [39,40], which can also be used for sorting or ranking problems based on statements provided by a decision maker.

In the health field, DRSA has been mainly used as a tool to discover knowledge from data, e.g., to identify metabolites involved in disease pathogenesis [41] or to identify which factors predispose patients to return to intensive care units after cardiac surgery [42]. VDA has been mainly used as a diagnostic tool in the neuropsychology and neurologic disease domains (e.g., [43,44]).

Dominance-based approaches, particularly DRSA, are appealing for the modest information they require from decision makers and for conveying results in the form of rules that are easy to understand. The method is particularly interesting when the set of alternatives is very large, and when the decision maker wishes to have a set of rules in natural language (*if… then…*) to sort alternatives. However, the requirement of comparing a few alternatives as examples can be difficult unless they differ only in a couple of criteria, and the resulting set of rules may be insufficient to provide a crisp sorting or a complete ranking of the alternatives as an output.

4.3 Outranking approaches

As described in the previous section, the establishment of dominance relations does not require any subjective parameters such as criteria weights. That being said, the relation is usually poor, *i.e.*, it applies to a few pairs of alternatives, not allowing to distinguish between alternatives which are not dominated. Outranking methods use additional inputs to enrich this relation such

that even if an alternative *x* is not better than (or possibly equal to) an alternative *y* on every criterion, a decision maker can conclude that *x* outranks *y* if a majority of the criteria support this assertion contingent upon the fact that there is no criterion on which *x* is too much worse than *y* (in which case this criterion might "veto" the outranking assertion). This is the basic principle of ELECTRE (Elimination Et Choix Traduisant la Réalité, in French or ELimination and Choice Expressing REality, when translated into English) methods, the first methods of this kind [45,46].

In ELECTRE methods, each alternative is compared to every other alternative, one at a time (as in a round-robin tournament) to assert whether an alternative outranks (i.e. is as good as) another one. The outranking relations are established by taking into account the weights of the criteria in favor of the outranking relation (i.e. concordance) and also the possibility that an opposing criterion vetoes that outranking relation (i.e. discordance). These outranking relations obtained are then exploited using an appropriate method from the ELECTRE family. There are methods to select a winner (ELECTRE I and IS), to rank the alternatives (ELECTRE II, III and IV), or to sort them into predefined categories (ELECTRE TRI). The outranking relation is not transitive (if *x* outranks *y* and *y* outranks *z*, then it does not necessarily hold that *x* outranks *z*) and it is not complete (it may happen that *x* does not outrank *y* and *y* does not outrank *x*, in which case they are said to be incomparable). In other words, the ELECTRE methods do not always yield a single winner or a complete ranking. This can be seen as a shortcoming of these methods (the method may not distinguish between some alternatives) or it can be seen as a plus in the sense that the method highlights situations where alternatives are incomparable and does not force a conclusion that is not supported by sufficiently strong arguments.

Another popular outranking method is PROMETHEE [47,48]. Contrary to ELECTRE, PROMETHEE does not require a majority threshold and does include the possibility of one criterion vetoing an outranking assertion. PROMETHEE is able to provide a partial or a complete ranking of the alternatives by considering, on average, how much an alternative outranks or is outranked by its competitors. Other outranking methods that deserve consideration, but less known, are NAIADE [49] and methods that use qualitative information such as ORESTE, QUALIFLEX and REGIME [50].

There are numerous examples of application of outranking methods to support health care decision-making. ELECTRE IS has been used in France to select strategies for screening haemoglobinopathies taking into account cost, effectiveness and five other qualitative criteria [51]. More recently, Diaby and Goeree illustrated how ELECTRE IS could be used for a hypothetical HTA problem. ELECTRE TRI has been used in several applications [9]. Figueira et al. (2011) used this method to assign couples seeking assisted reproduction to embryo-transfer categories defining the number of embryos to be implanted [52]. The use of PROMETHEE for health care decision-making includes, but is not limited to, the ranking of alternative strategies to deal with an overcrowded emergency room in Brazil [53] and the ranking of regional hospitals assessing their degree of specialization [54]. Chen et al. used a variant of QUALIFLEX to select the best treatment to a patient with a diagnosis of acute inflammatory demyelinating disease, evaluating three therapies against eight health-related criteria and a cost criterion [55].

Outranking methods were devised to avoid one of the main characteristics of value function models, full compensation. As a result, it is the authors' opinion that outranking methods may be appealing to decision makers who wish to avoid making trade-offs, or those who deem that an

alternative's poor performances on some decision criteria should not be compensated by its high performances on other criteria.

5. Concluding remarks

MCDA was developed outside health care, but has been increasingly applied in this field. It provides a unique opportunity to align decision-makers' preferences with their choices and provide a systematic and transparent way of making health care decisions. Even though value functions are largely used in health care, MCDA users should be aware of the existence alternative families of MCDA methods. Within value function methods, which synthesize the merits of each alternative into a global value figure, there are methods that have been applied less in healthcare, such as MACBETH, which were presented in this chapter. However, value function methods have certain key characteristics. First, these methods allow compensation, i.e. an alternative can make up for its poor performance on some criteria by compensating with higher performance on other criteria. Second, the weights represent the trade-offs between criteria, which need to satisfy conditions such as the preferential independence of criteria. Third, there is a requirement to elicit precise numerical weights for all criteria and scores for each alternative on all criteria. These characteristics may be too restrictive for some decision problems, where alternative methods to function methods may be more appropriate.

This chapter reviewed these other methods besides value function methods. A different way of evaluating alternatives is to compare these with given references, which can be based on the best observations (e.g., TOPSIS) or be externally provided. This type of approach may best suit situations in which decision makers have a clear idea of the goals they wish to achieve. However,

if the reference is derived from the actual performances of the alternatives, adding or removing an alternative may alter the conclusions pertaining the remaining alternatives.

Dominance-based approaches may be particularly interesting if the decision makers prefer to reason in terms of examples rather than weights. DRSA, in particular, only require modest information from end-users (parsimonious models). This allows decision makers to avoid dealing with the parameters of a mathematical model, provided that they have a set of exemplary decisions (e.g., from past experience) that can be provided as an input to the method. Although decision makers may be quite unfamiliar with RST (hindering transparency), the results it produces are in the form of decision rules that can be easily understood.

Finally, outranking methods are particularly suited to decision makers that are not willing to define substitution trade-offs between criteria. Outranking methods may also be useful if the goal is to identify a small subset of alternatives that fulfill a minimum requirement from a large set of alternatives as developing a total value score for each alternative using value function methods might be impractical. However, outranking methods do not always provide a clear-cut result, i.e. these approaches might lead to incomparability between two alternatives; That being said, one could argue that this is appropriate as further deliberation might be needed to choose between them.

By offering this large set of methods, MCDA proves to be flexible enough to accommodate the needs of decision-makers. However, as presented in this chapter, there are a diverse set of MCDA techniques each with different features and advantages/disadvantages. There is a long way to go before the potential of MCDA is used to its fullest extent. To that end, we call for

further research with the decision makers to identify which of these alternative methods in health care are suitable in different decision contexts.

Acknowledgement

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