Multiple Criteria Decision Making

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Preference Disaggregation in Multiple Criteria Decision Analysis

Essays in Honor of Yannis Siskos

Springer

Multiple Criteria Decision Making

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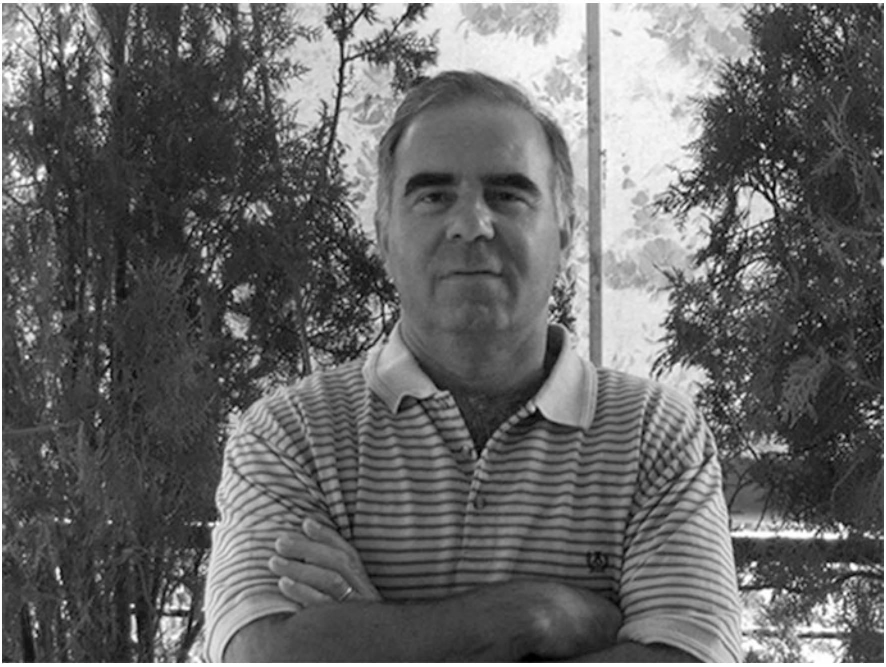
Preface



This volume is a Festschrift in honor of **Yannis Siskos** on the occasion of his retirement.

Yannis Siskos studied mathematics at the University of Athens, Greece. He then went to France for PhD studies with a scholarship of UNESCO and received his PhD degree in computer science and operations research from the University of Pierre and Marie Curie (PARIS VI, 1979). From 1981 to 1984, he taught at the University of Paris-Dauphine, at the rank of Maître de Conférence, where he fulfilled the State PhD (Doctorat d'Etat) in management sciences. He was Professor in the field of "Science of Decision Making" at the School of Production Engineering and Management of the Technical University of Crete, Greece (1984–2001), and at the Department of Informatics, University of Piraeus, Greece (2001–2015), from where he retired. He has also taught in the Technical Schools of Turin, Ecoles des Mines of Nancy, and Arts et Métiers of Paris and at the Universities of Laval and Montreal of Canada, Aix-Marseille II, Rouen, Brussels, and Cyprus as well as in the PhD programs of the National Technical University of Athens and the Athens University of Economics and Business. Yannis Siskos received Honorary Doctorate from the Department of Business and Administration, Piraeus University of Applied Sciences, and he has been elected as Emeritus Professor at the School of Production Engineering and Management, Technical University of Crete.

For several years, he has been chairman at the School of Production Engineering and Management, Technical University of Crete, where he founded the first laboratory of Decision Support Systems in Greece. From 1993 to 1997, he served as Vice-Rector of the Technical University of Crete. He has also served as President of the Hellenic Operational Research Society (HELORS) and as Vice-President of the International Federation of Operational Research Societies (IFORS), and he was the founder, and coordinator for over 20 years, of the Hellenic Working Group of HELORS in "Multiple Criteria Decision Making."

Yannis Siskos received in 2005 the National Award and Gold Medal of the HELORS for his contribution to the progress of operational research. He has been honored with the highest distinction in the field of multicriteria decision making in 2015, the Gold Medal of the International Society on Multiple Criteria Decision Making. Since its establishment, Yannis Siskos is the first Greek scientist who has received this medal for his contribution to the evolution of multicriteria decision making through his long-term research and in particular his contribution to the development of new theories, models, methodologies, and scientific applications of decisions in modern management. In 2016, he also received the Distinguished Service Medal (EDSM Award) from the Association of European Operational Research Societies (EURO) in the area of operational research. Yannis Siskos is the first Greek scholar who received the EDSM Award, which is the highest recognition in Europe of distinguished service to the European operational research community.

The main contributions of Yannis Siskos focus on two interrelated areas in the field of multiple criteria decision aid:

- Development of aggregation–disaggregation approaches
- Real-world applications of multicriteria decision aid tools in the marketing problems

In the first area, Yannis Siskos, with the collaboration of other colleagues in this field, developed the UTA family of methods, as the most famous and characteristic example of aggregation–disaggregation approaches. The UTA methods originated an entire family of preference disaggregation models in customer satisfaction evaluation (e.g., MUSA method), business excellence (e.g., MUSABE method), ordinal regression (e.g., ROR), and many others. At the occasion of the 30th anniversary of EURO, the *European Journal of Operational Research* (EJOR) selected the original publication of the UTA method by Yannis Siskos and Eric

Jacquet-Lagrèze as one of the most "influential" articles published in EJOR since its beginning.

In the second area, the passion of Yannis Siskos for real-world applications motivated him to develop novel approaches in several marketing problems, including consumer behavior analysis and simulation, customer satisfaction evaluation, etc. His contribution in this field is extremely important and, given the novelty of modeling real-world situations, shows how multicriteria decision aid tools may be applied in fields like marketing, which attracted relatively lower attention before by operational researchers.

Yannis Siskos is one of the pioneers of multiple criteria decision making worldwide. His work on the field of preference disaggregation continues to motivate scholars across the world to develop new methods and approaches and use operational research tools in real-world applications. At the same time, his influence in the Greek operational research society has been extremely strong, not only through the positions he held in HELORS during his active career but also through the supervisions of numerous doctoral, postgraduate, and undergraduate students and the collaborations with other Greek scholars. Yannis Siskos has supervised and/or collaborated with most authors of this edited volume during their PhD studies, while many of his doctoral students currently hold academic positions in several distinguished academic and research institutions. Thus, his work and ideas will continue to influence new researchers in the field of preference disaggregation modeling and analysis.

The main theme of this edited volume is preference disaggregation, the main contribution of Yannis Siskos in the operational research field. The previous very brief biographical sketch is not able to reflect the real influence of Yannis Siskos, and therefore this volume, including some indicative works in the field of preference disaggregation, tries to present several alternative methods and applications of the aggregation–disaggregation paradigm.

In addition to this short Preface, followed by a list of selected publications of Yannis Siskos, this volume consists of ten chapters. The first chapter by Alberto Colorni and Alexis Tsoukiàs presents a general framework for the design of alternatives in decision-making problems. This is one of the fundamental problems in preference disaggregation, where the clarification of the decision makers' global preference necessitates the use of a set of reference actions. The chapter also aims at providing archetypes for the design of algorithms supporting the generation of alternatives in a general context.

The second chapter by Nikos Tsotsolas and Spiros Alexopoulos discusses how facilitated forms of multicriteria decision aid could tackle different aspects associated with strategic decision making and provide effective support in dealing with the robustness of strategic decisions in designing complex strategies with long-term consequences. The authors address the seeming paradox, i.e., how can we evaluate the rationality of our decisions today, if the most important fact that we know about future conditions is that they are unknowable, and suggest robustness analysis as a way of supporting strategic decision making when dealing with uncertainties and ignorance. They also present case studies where multicriteria decision aiding has been used to tackle strategic decision problems.

The next chapter is devoted to collaborative decision making. Athanasios Spyridakos and Denis Yannacopoulos proposed the exploitation of UTA methods and voting collective functions of social choice theory in order to support the decision aid process in a multi-agent decision environment. They illustrate the applicability of the proposed approach through the use of the RACES system, which has been developed to support small group decision aid process, along with the MINORA and the MIIDAS decision support systems.

The fourth chapter by Michalis Doumpos and Constantin Zopounidis presents an overview of the preference disaggregation techniques in multicriteria classification. Classification problems refer to the assignment of a given set of alternatives into predefined categories/classes. In this context, preference disaggregation provides a valuable basis for facilitating the construction of appropriate models using a data-driven process. The presented overview covers the different types of decision models and discusses the alternative approaches used for model inference, as well as robustness issues.

The fifth chapter presents an overview of multiple criteria approaches in the customer satisfaction evaluation problem. Evangelos Grigoroudis and Yannis Politis emphasize that customer satisfaction can be perceived as a multicriteria evaluation problem, where the overall satisfaction with the provided service/product depends on a set of satisfaction criteria. The chapter presents an overview of recent developments in the context of the MUSA method, which is a collective preference disaggregation model following the principles of ordinal regression analysis approach. The authors also discuss alternative formulations of the customer satisfaction evaluation problem and present other multicriteria decision aid methods used, like outranking approaches.

The next chapter by Isaak Vryzidis, Athanasios Spyridakos, and Nikos Tsotsolas presents a methodological framework for project portfolio selection, combining the UTASTAR algorithm with a 0-1 multiobjective linear programming. The authors emphasize the complexity of this portfolio selection problem, given that the effectiveness of the resulting portfolio of projects is directly linked with the availability of resources, the social/economic environment, the efficiency of the project implementation teams, the overall strategic planning of the organization, etc. The chapter also discusses how stochastic criteria may be considered in order to evaluate alternative projects under uncertainty and presents a case study for a project portfolio selection problem in a contraction firm.

The seventh chapter by Stelios Antoniades, Nikolaos Christodoulakis, Pavlos Delias, and Nikolaos Matsatsinis presents an application of the aggregation–disaggregation paradigm in crude oil pipeline risk management. They emphasize that pipeline risk management is a primary concern for oil and gas companies, given the severe consequences on people's properties, human health, and the environment. The authors applied the stochastic UTA method in order to assess the risk of every part of a crude oil pipeline. The proposed approach considers the multiple dimensions of the examined problem, while it is able to deal with the uncertainties in the criteria measurements and aggregate the preferences of multiple experts.

The next paper aims to explore how the preference disaggregation–aggregation paradigm can support decision making in energy policy design and implementation. Alexandros Nikas, Haris Doukas, Eleftherios Siskos, and John Psarras present a detailed literature review of multicriteria analysis applications in this domain and emphasize the research gap regarding the application of preference disaggregation approaches in energy policy. The authors propose the application of the UTASTAR method in order to examine the potential development of clean electricity projects through the cooperation between European Union member states and 22 neighboring countries, with which the Union has already established ties toward economic and energy market integration.

The ninth chapter by Pavlos Delias, Evangelos Grigoroudis, and Nikolaos Matsatsinis presents an application of the MUSA method for developing regional tourism strategies. The authors discuss the results of a large-scale tourist satisfaction survey in order to provide regional policy makers with a strategic plan for a touristic destination strategy. The results of the MUSA method have been combined with loyalty data and demographic statistics in order to examine the heterogeneity of tourists and develop a SWOT analysis. The suggested plan focuses on potential improvements to the offered regional tourism product that may increase tourists' satisfaction and loyalty.

The last chapter of this edited volume presents a framework for analyzing perceived quality of healthcare services by combining the MUSA method and the theory of attractive quality. In this context, Evangelia Krassadaki and Evangelos Grigoroudis present a real-world study analyzing the satisfaction of citizens from a public hospital in terms of the perceived quality of its characteristics. The presented results focus mainly on the classification of the examined quality characteristics into the main categories of the Kano's theory of attractive quality (i.e., attractive, expected, and desired quality).

We would like to sincerely thank all the contributing authors who submitted papers. Their contribution has been essential in developing this volume, and we were impressed by their willingness to participate in this project. This willingness highlights and reflects the great impact of Yannis Siskos' works and ideas on the multicriteria decision aid community. We also wish to acknowledge the valuable help of Dr. Christina Diakaki for editing several parts of this volume. Finally, we would like to extend our sincere thanks to Springer Executive Editor, Christian Rauscher, for his patience and encouragement during the preparation of this book.

Chania, Greece
December 2017

Nikolaos Matsatsinis
Evangelos Grigoroudis

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What Is a Decision Problem? Designing Alternatives

Alberto Colorni and Alexis Tsoukiàs

Abstract This paper presents a general framework for the design of alternatives in decision problems. The paper addresses both the issue of how to design alternatives within "known decision spaces" and on how to perform the same action within "partially known or unknown decision spaces". The paper aims at providing archetypes for the design of algorithms supporting the generation of alternatives.

1 Introduction

Most scholar articles in decision analysis and operational research, when introducing the problem formulation they talk about, start with a claim of the type "given a set A of alternatives". Both researchers and practitioners know that in reality the set A is never "given" … It is actually constructed during the decision aiding process and most of the times defined several times during that same process.

Surprisingly enough this topic is almost ignored in the specialised literature. With the notable exception of Keeney (1992) who stated the principle that decision making should start considering "values" (in the sense of attributes) and not "alternatives" the latters derived from the formers, (see also Keeney 1994 and Leon 1999) very few contributions are available: some early attempts include Norese and Ostanello (1989) and Ozernoy (1985), while other contributions were mainly focussed on how to structure the decision problem suggesting alternatives generation algorithms (see Baetz et al. 1990, Chakhar and Mousseau 2006, Farquhar and Pratkanis 1993 and Pereira et al. 1994). To a certain extend work done in the area of preference disaggregation (Jacquet-Lagrèze and Siskos 1982, 2001) and

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preference learning (Fürnkranz and Hüllermeier 2010; Mousseau and Pirlot 2015) can also be seen as a tentative to work first of all upon values (preferences), which establish a potential decision space, and then to assess alternatives (or to compute an optimal solution). Finally, to our knowledge the topic has been partially considered in behavioural and cognitive science studies analysing how real decision makers handle alternatives construction (see Newstead et al. 2002).

This is remarkably strange. Practically the mainstream decision analysis literature focus on how to "choose" an alternative without considering where these alternatives come from and how they can be established. On the other hand it should be obvious: if all the alternatives in the considered set are "bad" we are going to choose a bad option even if it is the best one ... On the other hand who and how decides which are "good" options to include in the set of alternatives?

This paper is far from being a survey. We want to construct a general framework allowing handling this topic in a formal way. The topic results as part of the research in conducting decision aiding processes (see Tsoukiàs 2007). We recall that within that framework we will always make the hypothesis that the information used within such a process is the result of the interaction of at least two agents: the client and the analyst. This attempt follows our recent work on defining what a decision problem is (see Colorni and Tsoukiàs 2013) and should include both known procedures which are actually used in order to generate alternatives as well as to give the basis for defining new procedures of more general validity. Our objective is two-fold:

- show that constructing a set of alternatives is a decision problem itself;
- show which are the conceptual and algorithmic challenges in developing a general theory about alternatives construction, a key topic in conducting decision aiding processes (see Tsoukiàs 2007).

The paper is organised as follows. In Sect. 2 we present the general framework (what is a decision problem) within which we consider the problem of generating alternatives. In Sect. 3 we show that this problem is a decision problem itself. Section 4 discusses how existing methods handle the issue of generating "known" alternatives. In Sect. 5 we show instead how to handle the issue of generating "unknown" alternatives when the set of available ones is unsatisfactory. Section 6 discusses related literature.

2 Concepts and Notation

This work follows our previous contribution about "What is a Decision Problem" (Colorni and Tsoukiàs 2013) where we introduced a general framework aiming to characterise decision problems on the basis of the information the client in a decision situation can provide. Indeed our framework is independent of any method characterisation: it should instead help defining a decision problem (and thus choosing or constructing any new method) from some minimal information which we call the primitives. Within such a framework a decision problem is *"the* *partitioning of a set A satisfying some properties and preferential information"*. The primitives then are:

- the set A described along a set of attributes satisfying separability, in other terms these attributes are the minimal descriptors necessary to make a decision and each one considered alone is sufficient to make a decision;
- the problem statement Π establishing the type of partitioning to perform;
- the preference statements $\mathcal{H}$ provided by the client, to be modelled through appropriate structures and languages.

Let's present these topics with more details.

1. The set A of alternatives can be essentially of three types:
   - a subset of a vector space, where alternatives are described as points (vectors) of an n-dimensional "feasible" decision space (often each dimension being associated to a "decision variable"), $A \subseteq \mathbb{R}^n$;
   - a subset of a combinatorial structure, where alternatives are described as combinations of decision variables having a finite and discrete number of possible values (possibly binary), $A \subseteq \prod_j X_j$ where $\forall j X_j = \{x_{1j}, \cdots x_{nj}\}$, X_j being ordered;
   - an explicit enumeration of objects, possibly described by one or more features or attributes.
2. The problem statement Π can be:
   - a ranking: construct a partition of ordered equivalence classes which are not defined a-priori;
   - a rating: construct a partition of ordered equivalence classes which are defined a-priori;
   - a clustering: construct a partition of unordered equivalence classes which are not defined a-priori;
   - an assignment: construct a partition of unordered equivalence classes which are defined a-priori.
3. The preference statements $\mathcal{H}$ (the reader should note that we use the term of preference in a very general way: any ordering relation can be considered as a preference relation, see Öztürk et al. (2005) and Roubens and Vincke (1985), including similarity and equivalence relations) can be of different types:
   - single or multi-attribute ones;
   - relative (comparing elements of A among them) or absolute (comparing elements of A to some external norm);
   - simple (comparing single elements of A) or extended (comparing whole subsets of A);
   - ordinal or more than ordinal (expressing some notion of difference of preference);
   - positive or negative (negative preference statements should not be considered as the complement of positive ones);
   - first order or higher (preferences about preferences).

4. Let's recall finally that in order to choose or to construct a "resolution" method what we strictly need is the set A (minimally described), a problem statement Π and enough preference statements where we need to check (wrt to $\mathcal{H}$):
   - how differences of preferences are considered on each single dimension/attribute;
   - how differences of preferences are considered among the different dimensions or attributes;
   - whether preferences are conditional/dependent from other preferences;
   - whether negative preferences should be considered explicitly or not.

   It is important to note that the concept of "preference" applies to all three principal reasons for which decisions are variable: values, opinions and scenarios.

3 Constructing A as a Recursion

Proposition 1 *Constructing the set A is itself a decision problem.*

Proof Suppose a decision situation where any option is possible. In other terms a situation where we do not really have a well established set, but only hypotheses of what this should be. We can represent this situation representing this ill defined set $\mathcal{A}$ as follows:

$\mathcal{A} \subseteq \mathbb{R}^n \vee \prod_j X_j$ admitting that n is unknown and that equally exist unknown X_j. That is, the set $\mathcal{A}$ is only partially known (possibly totally unknown).

On the other hand let's recall that in order to establish a decision problem we need at least a set A, a problem statement Π and some preference statements $\mathcal{H}$ (at least of the type $x \succeq y$ or $x \succeq k$ where x and y are members of A and k an external norm not necessarily member of A). Finally the description of set A needs to satisfy separability. With these elements in mind we can establish a fix point:

A decision problem exists iff

- $\exists X_j$ such that X_j is known and
- $\forall X_j$ such that X_j is unknown these are not separable.

In other terms applying our minimality requirements either there is no decision problem or if there is one then there is at least one known descriptive dimension of the set $\mathcal{A}$, any other potential, but unknown dimension, being not separable and thus irrelevant. Let's call this the set $\hat{A}$.

We can now establish a recursion constructing the set A:

- $A_1 = \hat{A}$
- $A_n = \bigcup_i [A_{n-1}]_i$ where $[A_{n-1}]$ are some of the equivalence classes constructed for a decision problem defined at step $n-1$ and thus upon the set A_{n-1}. □

Let's explain better our proposition. Despite the fact that the set A is not given, there is always a starting point for constructing it. It can be large and ill defined, but there always exist a set to start with (otherwise there is no problem ... to work with). The construction of the set A is a recursion where at each step we construct a set as a result of the partition of the set defined at the previous step. The ending condition of this process is subjective. It is the client of the decision aiding process that declares that the present version of set A satisfies his/her requirements. In the following we provide three small examples in order to show the generality of our model.

Example 1 Consider the problem of constructing the feasible set of some linear programming problem. We can start establishing $\hat{A} = \mathbb{R}^n$, n being the known decision variables (at least one should be known). Then:

- $A_1 = \hat{A}$
- $A_2 = [A_1 : x_1 \geq 0]$
- $\cdots$
- $A_m = [A_{m-1} : x_m \geq 0]$
- establishing thus a first feasible set this being the non negative reals; then:
- $A_{m+1} = [A_m : f(x_1, \cdots x_m) \geq 0]$, introducing a first linear constraint
- and then introducing all known constraints.

The reader should note that each time we solve a rating decision problem with two possible equivalence classes (the feasible and the unfeasible solutions) defined by an external norm (the rhs of each constraint). It should also note our implicit preference statements (feasible solutions are better than the unfeasible ones) and that the preferences upon each variable and then upon bundles of variables (the constraints) are independent (thus allowing to establish a linear, additive, model).

Example 2 Consider the case of a company aiming to offer promotional tickets to the population for some advertising purpose. Then if Ω is the target population, $\hat{A}$ will be the subset of Ω for which some information is known (sex, age, education, income etc.).

A clustering decision problem would generate n equivalence classes (unknown at the beginning) $[A_1], \cdots [A_n]$ each being an homogeneous advertising target (i.e. young, female, not-single, no-children, low income). Each of such equivalence classes could then become the set A_1 for some ranking decision problems identifying the recipients of the promotional tickets.

Example 3 Consider the case of a national park administrator who needs to apply preservation policies for the park's animals. The starting point will be to consider the whole animal population Ω of the park. Then through an assignment decision problem she will identify the species within the park (let's say mammals, birds and reptiles, $A_1 = [A_1]_m \cup [A_1]_b \cup [A_1]_r$). Then a rating decision problem may distinguish between endangered and not endangered animals (A_2). A clustering decision problem will identify "geographical communities" of animals within the park (A_3). Further on an assignment procedure may distinguish between local and imported animals (A_4). Finally a ranking procedure may order the animals on the basis of their attractiveness for the visitors (A_5). Why these sets may be generated?

The client (the park administrator) first realises that different species need different policies (she thus introduces the attributes characterising species), then she realises that endangered animals may be a priority (using new attributes describing animals' threats), then she decides to consider the differences which might be necessary for the different locations in the park (using now spatial attributes), she decides to separate local from imported animals since this is imposed by bio-diversity considerations and finally considering cost (and revenue) issues she decides to rank animals by attractiveness. Different intersections (and unions of intersections) of the above partitionings will produce now the input for further decision problems. For instance, given a group of animals being described by their relevant attributes: "local endangered mammals breading around X", cluster preservation actions into policies. In this case the starting set will be a universe of potential preservation actions (known in the literature), but the separable attributes are the ones relevant for that specific group of animals, resulting to an initial set of relevant preservation actions for that group.

4 Generating Known Alternatives

All existing methods in operational research, decision analysis and artificial intelligence implicitly follow the general procedure shown in the previous section, generating sets of alternatives as part of the resolution algorithm they implement. Alternatives are implicitly known and only explicitly shown when they happen to be a solution for the algorithm within the method (most of the times an optimisation one).

The reason for this is that alternatives are almost never explicitly enumerated (most of the times the whole set could be impossible to describe explicitly or even be infinite). They are described as combination of variables. Humans also, in order to handle their limited computing capability, tend to use the same approach: either reduce the number of variables (thus reducing the number of alternatives) or just focus to a limited set of "interesting alternatives" (most of the times resulting from some screening process).

Let's start with some simple human heuristics. These are always based on two simple ideas: screening and choosing (see also Tversky 1972) and/or fixing the value of one or more variables and exploring the reduced set of combinations (possibly applying the method recursively). However let's consider the following simple example (borrowed from Rivett 1994):

Example 4 Consider the transportation problem shown in Table 1, implying three production units (p1, p2 and p3) and three warehouses (w1, w2 and w3; the figures in the cells representing the costs).

Most experienced managers, when trying to solve intuitively the problem, try to maximise the amount of shipping corresponding to variable x_1 (from p_1 to w_1, cost 0, the lowest), keeping at 0 the shipping corresponding to variable x_8 (p_3 to w_2, cost

Table 1 A simple 3 × 3 transportation problem

	w1	w2	w3	prd. capacity
p1	0	4	1	300
p2	1	6	3	600
p3	3	7	6	500
wrh capacity	600	300	500	

7, the highest). This gives a relatively reasonable solution, but far from the optimal one which is $\langle x_1 = 0, x_2 = 0, x_3 = 300, x_4 = 400, x_5 = 0, x_6 = 200, x_7 = 200, x_8 = 300, x_9 = 0\rangle$. The reason for failing to see intuitively the optimal solution is due to the fact that without a model and an algorithm is difficult to consider a counterintuitive choice (ship nothing from p_1 to w_1). For a more general and interesting discussion about these topics the reader can see Gilovich et al. (2002).

The use of a formal model and some exploring algorithm certainly improves the situation. However, we know that due to algorithmic complexity most exact resolution algorithms are of little practical interest since in the worst case they require inconceivable amount of computing resources or time. Most of the times we end using heuristics (see Ball 2011 and Pearl 1984).

The use of heuristics does not really change the problem. Consider the well known "knapsack" problem and the use of the equally well known simple heuristic consisting in choosing the variables (the objects to put in the knapsack) following the magnitude of the ratio between the value (the coefficient of the objective function) and the weight (the coefficient of the constraint). This procedure produces rapidly good results, but can easily miss the best solution since this may not necessarily respect this reasonable order. Heuristics generate sets of alternatives biased by the specific resolution procedure they use and in doing so they tend to eliminate alternatives which could be "interesting".

Finally let us consider the case where efficient exact algorithms are available for the problem at hand. In this case we are sure to be able to explore the whole set of potential alternatives although not explicitly enumerating them. The problem here is that despite this algorithm will provide a solution (most of the times denoted optimal), this might not be satisfactory for the client. The reason most of the times is that we are using the "wrong" set of alternatives. We should bear in mind that clients have a limited knowledge of the technical details of algorithms and more generally of problem solving methods. An initial description of a decision problem using a set of separable attributes (variables) might not be immediately perceived as partial. Usually it is when we present the results to the client that they realise that this first description of their problem does not really fit what they have in mind: all suggested solutions are perceived as unsatisfactory.

Let us summarise: generating alternatives only through resolution oriented procedures does not allow to conduct neither efficiently nor creatively a decision aiding process. We need to be able to generate further "unknown" alternatives and we need specific procedures to do so.

5 Generating Unknown Alternatives

Let's start with three examples where the known alternatives might be unsatisfactory for the decision maker.

Example 5 Ahmed, is a young man going to an appointment with his recent new girlfriend. Crossing a flowers' shop he suspects it might be her birthday. To buy or not to buy the flowers? That's the dilemma … However these two options appear to be equally unsatisfactory. If he buys the flowers and is not the birthday (actually the most likely scenario) there will be interminable discussions on why he did that. If he does not buy the flowers and it happens to be the birthday then it is just a tragedy. Ahmed needs more options before deciding.

Example 6 Aisha is a young French PhD student having the opportunity to visit Sydney for a conference (if her paper is accepted and conditional to the finances of the lab). Aisha's boyfriend is considering joining her. Tickets for Sydney sell presently as low as 1000 €, but they are expected to rise very soon. The problem is that Aisha will know if she will make the travel only 1 month before the conference, while today we are 4 months before the conference. Once again the available options are unsatisfactory: either low price tickets combined to high risk of losing the money in case Aisha does not make the travel, or being sure about the travel combined to a high risk of not being able to pay for the ticket. Aisha and her boyfriend would like to have more alternatives before deciding.

Example 7 Aisha and Ahmed are celebrating 10 years of living together and they look for a 1 week holiday package. The problem is that what they get are either expensive resorts in attractive locations or cheap resorts located in unattractive locations … Aisha and Ahmed need to expand the set of alternatives they are looking for.

The three examples are inspired from the decision analysis literature (see French 1988, Keeney 1992 and Smit and Trigeorgis 2004). Indeed there already exist suggestions on how to handle such decision situations expanding appropriately the set of alternatives. These include "decision trees", "real options theory" and "valued focussed thinking".

1. A well known strategy in decision under uncertainty consists in asking for more information (an action called an "oracle" given the limited trust to the information provided). Under such a perspective the two options b (buy) and $\neg b$ (not buy) can be expanded to ib (get information and then buy), $i\neg b$ (get information and then not buy), $\neg ib$ and $\neg i\neg b$ (same as before, deciding to buy or not without any further information). The reader will note that until information is not a separable characteristic of the decision to take, this variable simply does not exist (consistently with our hypothesis that not separable variables are not relevant). The new expanded set results thanks to information becoming a separable dimension (influencing our decision).

2. In real options theory the idea is to add "'time" as a separable explicit dimension among the attributes. The unsatisfactory nature of the alternatives is due to the fact that we need to decide today for something expected to occur after a certain time. Introducing time as a further dimension we could introduce alternatives which realisation has a shortest time horizon but not preclude realising the original options. For instance airlines offer today the possibility to pay a non refundable fee fixing the price of a ticket at today's price for a certain amount of time. Instead having the two options b_0 (buy today) and $\neg b_0$ (not buy today) we get the expanded set ob_1 (pay the fee and then buy 1 month later), $o\neg b_1$ (pay the fee, but then not buy), $\neg ob_0$ and $\neg o\neg b_0$ (same as before, deciding to buy today or not without paying any fee). This set can be further expanded if we introduce options with different time horizons. Once again we note that is the explicit separation of time as a relevant decision dimension that allows to expand the set of alternatives.
3. In valued focussed thinking Keeney suggests to consider principally the values behind any decision questioning instead fixing the set of alternatives. In the vacation example we can relax the "1 week" constraint allowing getting more interesting offers (for instance 2 weeks packages could be more valuable than the 1 week ones, although relatively more expensive). However, we can do more than that. After all, why celebrating 10 years of common life should be done through a holiday? What about buying ten concert tickets or booking ten famous restaurants or ten tickets for recent Broadway productions? Keeney's suggestion to distinguish between core objectives (celebrating) and mean objectives (buy a holiday) allows identifying dimensions with which we can compose more alternatives from the ones initially considered. An approach more likely to generate satisfying alternatives to assess.

Let's make a first summary of what we knew about the generating algorithms problem.

Claim 1 From a decision aiding process perspective (implying some time extension), generating further sets of alternatives is related to some non satisfactory assessment of the present set of alternatives.

Claim 2 Generating unknown alternatives is always related to some expansion (or more generally revision) of the separable attributes describing the existing set.

Let's focus on Claim 2 and see what happens in a combinatorial optimisation case.

Example 8 Consider a client formulating a problem where a city (organised in n districts) should be covered by shops belonging to the client's brand, under the hypothesis that a shop opened in a certain district "covers" also the adjacent ones. The client asks to do the minimum necessary.

This is a well known location problem formulated as follows:

$$\min \sum_j x_j$$
$$\text{st}$$
$$\mathcal{D}\mathbf{x} \geq \mathbf{1}$$
$$x_j \in \{0, 1\}$$

where $j = 1 \cdots n$ are the districts;

x_j are binary variables representing the opening in a certain district;
$\mathcal{D}$ is the adjacency matrix;
the meaning of the set of constraints being to satisfy covering the whole city.

Once the problem solved, the client realises that the minimum openings necessary to cover the whole city cannot be inferior of k (the minimum value of $\sum_j x_j$). At this point he realises that this goes beyond his budget capacity. How the problem formulation should evolve? A new version of the problem will be the following one:

$$\max \sum_j w_j y_j$$
$$\text{st}$$
$$\mathcal{D}\mathbf{x} \geq \mathbf{y}$$
$$\sum_j c_j x_j \leq C$$
$$x_j, y_j \in \{0, 1\}$$

where $j = 1 \cdots n$ are the districts;

x_j are binary variables representing the opening in a certain district;
y_j are binary variables representing the covering of a certain district;
$\mathcal{D}$ is the adjacency matrix;
w_j representing the importance of each district;
and c_j representing the cost of each opening, C being the available budget;
the meaning of the set of constraints being to satisfy the logical relations between opening and covering as well as the budget availability provided by the client.

The reader should note that the problem could also be formulated as a bi-objective optimisation one:

$$\max \sum_j w_j y_j$$

$$\min \sum_j c_j x_j$$

$$\text{st}$$

$$\mathcal{D}\mathbf{x} \geq \mathbf{y}$$

$$x_j, y_j \in \{0, 1\}$$

Discussion Initially, the problem being formulated under the constraint of covering the whole city, the covering dimension characterising potential alternatives is not separable (since all covering variables are implicitly equal to 1). The set A is established considering only combinations of the variables x_j. The unsatisfactory result obliges us to expand this set using the covering variables (since now we allow some of these to be 0: some districts might not be covered). To put it on a formal basis, using our general decision problem framework the decision aiding process will be described as follows:

1. The starting set A_1 is defined by all combinations of the variables x_j (openings).
2. The constraints $\mathcal{A}\mathbf{x} \geq \mathbf{1}$ defines a rating decision problem resulting to a new set A_2 to be used in the next step.
3. The objective function $\min \sum_j x_j$ defines a ranking decision problem resulting to a minimum of k openings. This information qualifies the whole set A_2 as unsatisfactory since k openings are practically impossible (but we only discover it at this stage of the process).
4. A_2 being unsatisfactory we backtrack to the initial set A_1 and we create a new starting set, let's call it B_1 as combinations of all opening and covering variables. This is possible relaxing the constraint obliging to cover the whole city, resulting in making the covering variables separable (relevant for the client's decisions).
5. The constraints $\mathcal{A}\mathbf{x} \geq \mathbf{y}$ and $\sum_j c_j x_j \leq C$ establish a new rating decision problem resulting to a new feasible set B_2.
6. The objective function $\max \sum_j w_j y_j$ establishes a new ranking problem which hopefully will provide a satisfactory solution to the client.

Can we generalise what we described until now? Yes! Let's go back to the procedure used in order to prove Proposition 1. Introducing at each step a generalised rating decision problem (is the resulting set A_i satisfying?) we are able to control the process of generating subsequent As. Further on we need to add two more possible actions (remember that A is always described by separable attributes):

– backtrack at any point of the recursion and open a new branch;

– revise the set of separable variables describing the set A in order to generate alternatives not considered until this moment (unknown alternatives).

What do we get?

Claim 3 Generating unknown alternatives is possible allowing within the recursion constructing A two actions: backtracking and revising the set of separable variables.

6 Discussion

What we are presenting here are not necessarily completely new ideas, although we are sure that they have never been discussed as in this paper and combined under our perspective.

Expanding the set of variables describing a set of objects is borrowed from C-K theory (Hatchuel 2001; Hatchuel and Weil 2009). This is the only formal theory of design we are aware of and is very powerful although essentially simple. The theory addresses the problem of designing new "objects" (products or services) identifying two spaces:

– the knowledge one, where objects are completely described on finite set of known attributes (a house, a car…);
– the concept one, where objects are only partially known, the list of attributes describing them being only partially defined;

The design process is then described as a sequence of variables transformation between the two spaces allowing the exchange of attributes between knowledge and concepts such that "new objects" can appear: a house which is also a car; a camping car.

We are firmly convinced that there are many more important links between C-K theory and our suggestion about the process of constructing alternatives. These links are yet to be explored.

Preference disaggregation (Doumpos and Zopounidis 2011) offers a first example of reorganising a set of alternatives due to a preference learning process. Robust regression preference learning methods (see Greco et al. 2008, 2012, 2014) are a good example of methods exploiting a progressive learning of value functions allowing also to identify solutions which initially might not be considered by the decision maker.

Algorithms controlling the execution of algorithms and allowing intelligent backtracking are as old as TMS (see Doyle 1979) and are regularly used in planning and automated reasoning devices (Pollock 1996). We can certainly see our alternatives generation procedure under such a perspective although the information conducting the process is provided on-line (during the decision aiding process) and not as an input (as it happens is most of the existing literature, for an exception see Pollock 2006).

The whole idea of revising the conclusion of a process as a result of new information is central in Non Monotonic Reasoning (NMR) formalisms (Ginsberg 1987; Makinson 2003). In Tsoukiàs (1991) it has already been suggested a relation between model revision in NMR and preference modelling. Our idea about generating alternatives shows several relations to this literature:

– a decision aiding process is naturally subject to updates (new information becoming available and existing information becoming obsolete and/or inconsistent) and revisions (of values, opinions and scenarios) two notions central in the study of NMR (see Gärdenfors 1988);
– expanding the set of conclusions derivable from given knowledge, adding defeasible reasoning is a suitable logical framework for our suggestion about the alternatives generation process starting from a partially described decision space. Since this space is only partially known we can proceed to multiple expansions which could (and actually are) defeasible, as soon as the client assess their satisfiability.

It is less obvious to us how the dimension of "creative" construction of alternatives can be considered within this framework, but this is only a special case of the more general problem; in most cases the dimensions which could be added, revised or updated are already implicitly considered in the problem formulation, but not yet explicitly considered due to the separability condition.

Concluding we are not afraid to state that is likely that other relations exist between our proposal and other artificial intelligence areas including argumentation theory, learning and knowledge discovery. But these are yet to be explored.

7 Conclusions

The paper presents a problem often neglected and/or underestimated in decision analysis: how the set of alternatives on which a decision support method/algorithm applies is constructed. Our effort to discuss this topic is part of a long term project aiming at establishing a characterisation of decision problems independent from methods and only relying on simple primitives, the set A of alternatives being one of these ones.

In the paper we have been able to show two results. The first consists in showing that the construction of A is itself a decision problem (allowing a recursion of decision problems) and thus, that it can be studied within our general framework. The second consists in showing that the crucial problem in constructing A is the generation of "unknown" alternatives, when the set presently available is considered to be unsatisfactory. Under such a perspective we have been able to show that generating such alternatives is practically possible through backtracking the recursion which generated the present set A and expanding/revising the set of separable dimensions describing the set.

We concluded showing that our research is strongly related to existing fields of research in design theory and artificial intelligence. Given the low interest of this topic in the mainstream literature, it is not surprising that most of these links are yet to be explored. We hope our contribution may motivate more efforts in this promising (for us) direction.

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MCDA Approaches for Efficient Strategic Decision Making

Nikos Tsotsolas and Spiros Alexopoulos

Abstract Strategic decisions are often complex and multifaceted and involve many different stakeholders with different objectives and priorities. Very often decision-makers (DMs), when confronted with such problems, attempt to use intuitive or heuristic approaches to simplify the complexity until the problem seems more manageable. In this process, important information may be lost, opposing points of view may be discarded, and elements of uncertainty may be ignored. A crucial issue, when dealing with strategic decisions, is the radical uncertainty about the present (e.g. lack or poor quality of information) and also about the future. The latter one addresses the seeming paradox—how can we evaluate the rationality of our decisions today if the most important fact that we know about future conditions is that they are unknowable? In the literature it is mentioned that robustness analysis is a way of supporting strategic decision making when dealing with uncertainties and ignorance. In the present chapter we discuss how facilitated forms of MCDA could tackle different aspects associated with strategic decision making and provide effective support in dealing with robustness of strategic decisions in designing complex strategies with long-term consequences. We finally present three case studies where MCDA approaches were used to tackle strategic decision problems.

1 Strategic Decisions

1.1 Strategic Choices

Strategic decisions in companies, organisations and governments are often complex, multifaceted and involve many different stakeholders with different priorities or objectives. Furthermore, strategic decision making consists of several sequential

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actions focusing on the achievement of a specific goal with several feedbacks and loops, so we may describe the whole process as a strategic decision circle (Lasswell 1956). Very often decision makers (DMs), when confronted with such problems, attempt to use heuristic and intuitive approaches to simplify the complexity until the problem seems more manageable. In this process, important information may be lost, opposing points of view may be discarded, and elements of uncertainty may be ignored. In short, there are many reasons to expect that during the evolution of a strategic decision circle the involved stakeholders will often experience difficulty making informed, thoughtful choices in a complex decision-making environment involving value trade-offs and uncertainty.

Competitiveness and efficiency depend heavily on how enterprises and organisations are organized, how they use and develop available human resources, how they harmonize technology and workers, and what kind of relations they maintain with suppliers, customers and other companies or organisations. Consequently, effective strategic decisions' support requires close observation and study of the external environment conditions, and also close monitoring of the organization's internal activities.

As a rule truly strategic actions differ fundamentally from optimized tactical moves. An organization that adapts a strategic approach, often takes the deliberate risk of creating discontinuities (creative destruction) with a view to exploiting new opportunities. This is achieved through changes such as the encouragement of improvements in the association of the organisation's resources with its environment.

Modelling and analysis play a key role in the interventions between the discipline of Operational Research (OR) and strategic decision-making. Strategic decisions have specific characteristics as described by Montibeller and Franco (2010):

- A strategic decision has been defined as one that is "*important, in terms of the actions taken, the resources committed, or the precedents is sets*"
- Strategic decisions are "*infrequent decisions made by the top leaders of an organisation that critically affect organizational health and survival*"
- The process of creating, evaluating and implementing strategic decisions is typically characterised by the consideration of high levels of uncertainty, potential synergies between different options, long term consequences, and the need of key stakeholders to engage in significant psychological and social negotiation about the strategic decision under consideration.

Strategic decision rarely is a one-off event that reaches a neat end point. On the contrary such decisions often lead to a new state of a system and thus create new needs, asking for new decisions on the same or different directions, generate feedback and reactions from the various DMs.

1.2 Decision-Making Framework for Strategy-Formulation

Generally speaking, the "main strategic choices" of an organization should take into account the organization's mode of action. Richard (1981) suggests a set of "strategic criteria" that permit an assessment of the organization's possibilities for survival and success, and verify the limitations of the economic system. These criteria can be apportioned into three groups or points of view, according to the organization's provisional horizon and the subsystem under study, namely:

- Competitiveness (analysis of the current external environment—a known field).
- Effectiveness (internal analysis of the company—a known field).
- Flexibility (analysis of the future external environment—unknown field that cannot be modelled).

The organisation's performance should aim at improving each of the above three groups of criteria. In other words, an organization is engaged in a strategic path whenever it chooses to alter the balance of its available resources with the environment.

David (2009) proposed a three-stage decision-making framework in which important strategy-formulation techniques can be integrated, comprising of an "input stage" (which corresponds to Richard's philosophy), a "matching stage" [Boston Consulting Group (BCG) Matrix, Strengths-Weaknesses-Opportunities-Threats (SWOT) Matrix etc] and a "decision stage" (decision support activities).

From the aforementioned, the need for new strategic decision analysis approaches, which could deal effectively with deeply uncertain, poorly characterized risks and long terms consequences, is apparent. The quantitative, decision-analytic framework of the Multi-criteria Decision Aid (MCDA) discipline, to be presented in more detail in the next section, offers a wide pallet of techniques designed to deal with problems which face multiple, conflicting goals and multiple stakeholders, such as the strategic decision-making problems. The goal of joint optimization of technical, financial and social aspects indicates the need of a collective, participating sociotechnical approach informed by both MCDA and "facilitated modelling" (presented in more detail in Sect. 3.1), focusing not only on addressing challenges involved, but also on exploiting the adaptability and innovativeness of stakeholders in achieving goals instead of over-determining technically the matter in which these goals should be attained (Fig. 1). It should also be noted that MCDA techniques are particularly appropriate for servicing the need of accountability of management, through the measurement of performance.

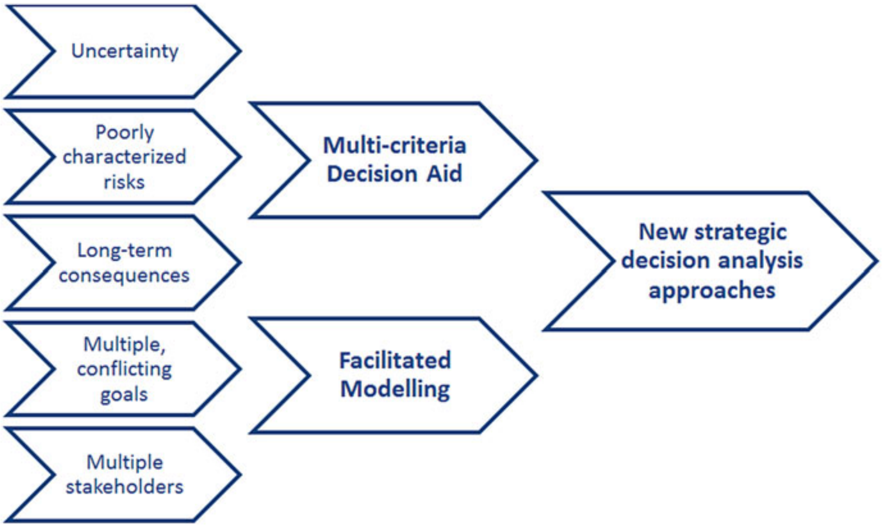


Fig. 1 The collective, participating approach of forming new strategic decision analysis approaches

2 The Role of MCDA in Strategic Decision Making

2.1 *Strategic Decision-Making as a Multicriteria Process*

Strategic decisions affect in a deep and often irreversible manner the future of a company, an organization, or even a country that chooses to explore now a part of its resources in order to reap fruits tomorrow—or, possibly, never. In this sense the strategic thinking works vice versa, simulating a distant future that dictates current selection actions. It becomes clear that strategic decision-making is a complex, multidimensional process (David 2009). Therefore a MCDA approach should be adopted, in order to take into account all the criteria involved in the analytical process of defining the scope of the decision, constructing a preference model, and supporting the decision (see Roy 1985; Roy and Bouyssou 1993; Belton and Stewart 2002; Figueira et al. 2005; Siskos 2008, for instance). A thorough collection of papers dealing with state-of-the-art trends in multicriteria analysis theory and practice was presented by Zopounidis and Pardalos (2010).

The well-known area of MCDA offers techniques designed to deal with situations, as the aforementioned, in which there are multiple conflicting goals for reaching strategic decisions (Roy 2005; Montibeller and Franco 2010). Furthermore, the process of creating, evaluating and implementing strategic decisions is typically characterised by the consideration of potential synergies between different options, long term consequences, and the need of key stakeholders to engage in significant psychological and social negotiation about the strategic decision under consideration. MCDA can efficiently tackle all these issues. However, the strategic decision and negotiation process among members of boards and committees does not take place in a political vacuum and political conflict is a reality. Thus, certain adaptations to the methods, tools and processes of MCDA are required, if it is to be effectively applied in such a context (Tsoukias et al. 2013). These adaptations have to tackle issues such as the probabilistic nature of the data and the uncertainty of future events and system states. Thus the robustness analysis as part of the MCDA approaches is a major issue in strategic decisions and the appropriate approaches and techniques shall be contained in different stages of any proposed methodology.

It is a fact that strategic decisions in an informed company, organisation or government shall be the result of the interaction between DMs and information-processing mechanisms. The measures taken, in order to meet a certain strategic goal, can create conflict when simultaneously trying to achieve other goals. Thus, strategic DMs seldom seek to maximize a single welfare objective; typically they are concerned about a bundle of strategic objectives, expressed by contributing variables or indicators, conditional on and constrained by applicable ethics or legislation (André and Cardenete 2008). Another important characteristic of the mechanism of strategic actions is that strategic decisions are a game among forward-looking stakeholders. As a result, the company or organisation current payoffs are equal to the "net present value" of its anticipated future actions (and resulting victories/losses), not just its present and past strategic choices. In this context actions of strategic DMs can be interpreted as efforts to design "efficient" strategies (those for which every objective is reached with the minimum loss for the other relevant objectives) to improve performance, as measured by well-defined indicators. Under a solely technical approach used in MCDA field, the term "efficient decision" could be described as a feasible solution of the strategic making problem if there is no other feasible solution that can achieve the same or better performance for all the criteria being strictly better for at least one criterion (André and Cardenente 2008). In this context the term Pareto-efficient strategies could be also used (Luptacik 2010).

Within this framework, the stage of strategy formulation, in which the objectives are set, the alternative solutions are designed, the costs are identified, the effects of solutions are estimated, the solutions are chosen and the strategy instruments are selected, is the one on which somebody shall focus through the prism of operational research. Moreover, a crucial point in this stage is the design of alternative solutions. The improvement of search for, and generation of, strategy alternatives leads to more effective and successful strategic decisions. It is impossible to choose a good strategy if all the designs under consideration are weak, no matter how thorough and sophisticated the evaluation of such alternative designs is. In order to confront with probable failures in strategic decision making due to poor designs, new design orientation calls for a broadening of thinking about design, examining combinations of substantive and procedural instruments and their interactions in complex strategy mixes (Howlett et al. 2015). This is why there are frameworks aiming to aid the strategic DMs to produce efficient strategies support evolutionary approaches in designing the strategy alternatives.

A number of research approaches have already identified the use of combining strategic management and MCDA, both under certainty and uncertainty i.e. mapping procedures that allow problems to be described in formal terms and then debated (e.g., Eden and Ackermann 1998) or decision making procedures to be analyzed (Hodgkinson et al. 1999). Furthermore, MCDA can be used to support strategic decision making in organizations by exploring the notions of strategic decisions and the strategic decision making process, by examining interconnectedness and long-term consequences as key characteristics of strategic decisions, and by considering the discursive nature of the processes within which strategic decisions are created and negotiated (Montibeller and Franco 2011), but real world applications seem to be limited until now. Montibeller and Franco (2010) made suggestions on how to implement these proposals, illustrating them with examples drawn from real-world interventions in which the authors participated as strategic decision support analysts.

2.2 Challenges in Applicability of MCDA in Strategic Decisions

The strategic decision problems are even more complex if we consider that, most of the times, conflicting—objectives must be best met by the joint optimization of technical, financial and even social aspects. Of course, the absence of certainty, the interference of management-power and the presence of complexity, as well as the unquestionable existence of wicked problems, also called social-messes (Ritchey 2011), shall not be an excuse of inaction in this field. Nobody could assert that a specific framework can tackle the whole extent of a strategic decision circle or guarantee optimal or robust solutions, but it could certainly increase rationality and accountability of top-management at a certain level. There is a lot of discussion between academics and practitioners concerning the complexity of strategy making and how representative could be a simplified strategic decision circle, which tries to capture that complexity and model the process using discrete stages, linear or most recently more complex ones, which include matrices and loops.

There is an on-going discussion on whether the performance-based strategic decisions, using systematic decision support tools, could reach optimum results. It is generally accepted that performance-based decision making efforts aim to:

- clarify the mission and prioritize objectives with an emphasis on the expected results,
- develop mechanisms for monitoring and reporting the achievement of those objectives, and
- use this information to make decisions about strategic actions, including making management more accountable.

In this area there are several challenges concerning the adaptation and application of appropriate decision techniques given the unique characteristics of the decision processes at the strategic level. One of the major characteristics of these processes is the long-time horizon of the impacts that most strategic decisions have. As Keeney (1992, 2013) states, the usual case is that their effects start to be apparent a long time after the decision has been reached and the decision process has been completed. During this long period several facts of the reality might have been changed or even the strategic objectives of the companies/organisations themselves might have been altered, so it's really difficult to predict how technical and financial scenarios may evolve in this future. Imagine that in a globalised economy scene a lot of decisions could be affected by factors coming from abroad and thus cannot be controlled or even foreseen in a trustworthy manner. Therefor a strategic decision circle actually should remain open in order to catch the effects that would occur after some time and handle them as feedbacks to be included into an on-going decision process.

Several challenges have to do also with technical complexity, which includes uncertainty ('epistemic', ethics values, political power) and decision complexity (inter-related choices, stakeholders' variety), as well as with social complexity, which includes social representations and communication channels. In general the strategic decisions may be described as 'messy' situations characterised by inter-relationships between different problem elements, many external and internal sources of ambiguity and conflicts, associated with both cognitive and emotional considerations of the problem (Franco and Rouwette 2011). That's why special attention shall be paid on how to address issues of robustness (Tsoukias et al. 2013) along with joint optimization of technical, economic and social issues at the different stages of the applied methodology and mostly in scenario planning, given the long-time horizon of the probable consequences of the selected strategies.

Furthermore, restrictions to the use of MCDA methods in strategic decision making also apply, depending a lot on the selection of specific method (possible problems may include: sensitivity to inconsistent data, difficulty to weight, inconsistencies between judgement and ranking criteria due to interdependence between criteria and alternatives, not logical results obtained etc.). Another important issue is the difficulty of the development of the appropriate model, which may require numerous simulations before use, as well as the collection of the necessary data, mainly in the cases where the models are sensitive to data. Moreover, sometimes the selected method or/and procedure may not be convenient for a specific framework. For a comprehensive summary of advantages, disadvantages and proposed suitable areas for application for the most common MCDA methods one can consult Velasquez and Hester (2013).

The aforementioned particularities, which are related to the specific aspect of strategic decisions and to the different points of view of the various stakeholders, could be efficiently tackled in a MCDA framework, in which these particularities could be modelled and affect proportionally to their importance the evaluation of alternatives and the reach of mutually accepted decisions (Salo and Hamalainen 2010). The task of achieving inclusion of all elements in a multicriteria model to be used in a strategic decision context is nothing but trivial. It requires enough creativity (Keisler 2002) in dealing with multiple objectives as well as in continuously building alternative options led by a probable evolutionary set of objectives (Montibeller and Franco 2011).

3 Facing the Challenges in MCDA Applications for Strategic Decisions

3.1 The Facilitated Mode of OR Consultancy

The most usual way to conduct OR consultancy for strategic decision making support in organisations is to adopt what is called the 'expert mode', where the operational researcher uses OR methods and models that permit an 'objective' analysis of the client's problem situation, together with the recommendation of optimal solutions. The 'expert mode' faces decision problems as real entities, thus the main task of the operational researcher is to represent the real problem that the client organisation is dealing with, avoiding 'biases' from different perspectives (Franco and Montibeller 2010).

Yet, more often than not, problems are socially constructed, thus the operational researcher has to help a management team drawn from the client organisation in negotiating a problem definition that can accommodate their different perspectives.

This process is a participative one, in the sense that participants are able to:

- jointly define the situation, structure it, and agree in a focus
- negotiate a shared problem definition by developing a model of organisational objectives
- create, refine and evaluate a portfolio of options/priorities
- develop action plans for subsequent implementation.

In these cases a participative OR consultancy process for strategic decision making support, other than 'expert mode', needs to be applied. This process should incorporate the exploration of the notions of strategic decisions and the decision making process, the examination of interconnectedness and long-term consequences as key characteristics of strategic decisions, and the consideration of the discursive nature of the processes within which strategic decisions are made.

Such a process was proposed by Franco and Montibeller (2010) incorporating 'facilitated decision modelling' (Eden 1990; Phillips 2007). In facilitated modelling, a management team or group, drawn from the client organisation, is typically placed as responsible for scoping, analysing and solving the problem situation of interest. The operational researcher acts not only as an analyst, but also as a facilitator to the client. Participants' interaction with the model reshapes the analysis, and the model analysis reshapes the group discussion (see Fig. 2).

Facilitated modelling is used as an intervention tool, which requires the operational researcher to carry out the whole intervention jointly with the client, and enables the accommodation of multiple and differing positions, possible objectives and strategies among participants (Checkland 1981; Eden and Ackermann 2004; Rosenhead and Mingers 2001; Williams 2008). As a result, strategic problems frequently require the facilitated mode, due to their complex social nature and

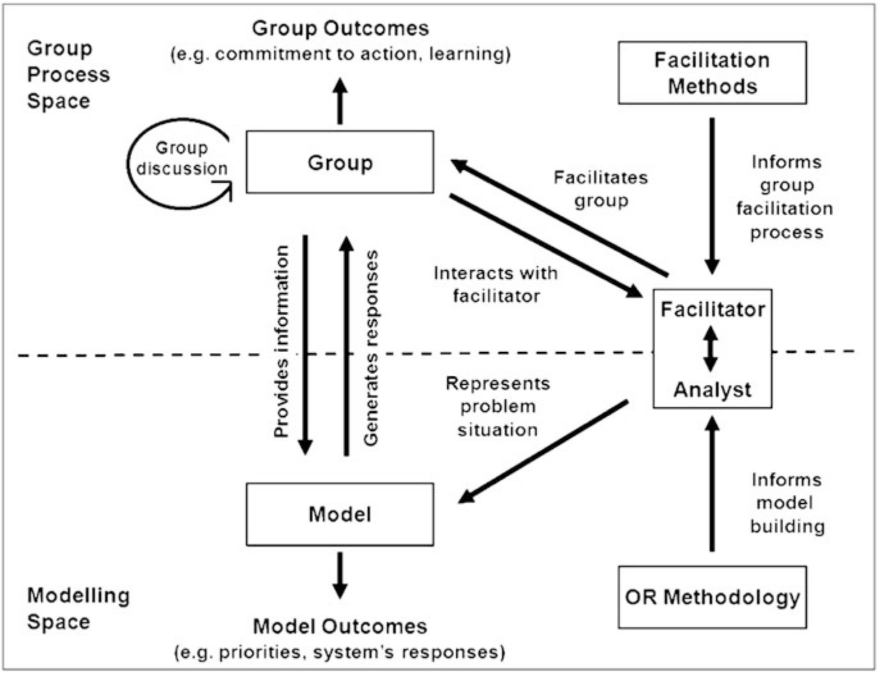


Fig. 2 Facilitated modelling in OR (source: Franco and Montibeller 2010)

qualitative dimensions, their uniqueness, and the need to engage a management team in the decision making process (Ackermann and Eden 2001; Friend and Hickling 2005).

In facilitated modelling, a management team or a group of strategic decision-makers is typically placed as responsible for scoping, analysing and solving the problem situation of interest by using formal models. The operational researcher acts not only as an analyst, but also as a facilitator to this team by jointly apply and often adapt the formal decision models through the implementation of strategy workshops, a form of strategic discourse through which decision making is also affected by linguistic interactions. Participants' interaction with the model reshapes the analysis, and the model analysis reshapes the group discussion.

The involvement of the facilitator is considered to be more requisite in specific stages of the strategic decision making process, starting from the initial phase of collecting and filtering the right information which is believed to be necessary for framing the problem and subsequently for model development. We have cases where a vast amount of data from different sources is available but their collection and their analysis might be time and cost consuming. Probably only a small portion of said data could provide the necessary, valuable information. On the other hand, if data is sparse, its information should be extracted indirectly or it can be appraised. For this kind of job the suitable facilitator could provide the right approaches helping the DMs to decide what the appropriate mix of data and estimations is.

As already mentioned, in strategic decision making DMs and facilitators shall use jointly their creativity in identifying, organizing and prioritizing the objectives because due to the endogenous complexity probably some of the objectives should be combined or associated with each other in a unique or unusual matter. Keeney (2013) describes a general framework using a mean-ends approach which could be adapted for managing the objectives in strategic decision making, starting from the generation of lists of objectives by the DMs, continues with the consolidation of the lists, the categorization and finally the prioritization of the categories as well as inside them. The suggested framework, which aims in transforming the mess of a complex amorphous problem into a structured entity, so that the problem can be communicated to a wide audience supporting the need for transparency and accountability, is not a trivial one.

The creativity of the DMs should be further stimulated by the facilitators in order to motivate them towards developing, extending and combining creative alternatives in an effort to satisfy the set of objectives. In the strategic decision field most of the times alternatives are comprised by a number of sub-options, often referred to as "portfolio of options", in terms of covering different aspects of the problem or/and sequences of future states. The role of the facilitator at this stage is firstly to support the creation of an initial set of alternatives which seems to be dynamic (Montibeller and Franco 2011)—unlike Roy's (1985) approach for a static set of alternatives—and secondly to serve the evolution of this set by presenting subsequent evaluations of the solutions, discuss them extensively and redesign better strategic options. Given the evolutionary nature of the different phases in managing the objectives, alternatives should also be approached in a dynamic way towards the continuous improvement in terms of performance and robustness.

Another stage in which the analyst may act as a facilitator is the selection of the appropriate method, or methods in cases of multistage problem solving, for evaluating the alternatives on a given set of objectives. Even though this stage seems to be more technocratic actually, as Roy and Slowinski (2013) advocate, the chosen method should be seen as a tool for a deeper analysis of the problem focusing on exploration, interpretation, debating and arguing, rather than a tool able to make a decision. This is why they suggest that through interaction between the facilitator and the DMs, an understandable and accepted by the DMs preference model shall be co-constructed according to the needs of the selected method. They also provide in their work a full set of questions, one crucial, five primary and two secondary ones, which can be used by the facilitators as a guideline for the selection of the proper method. These questions may also be applied in a progressive way by initially selecting one of the four categories (Lagrèze and Siskos 2001) in which the methods are found, and then evaluate in more details the methods inside the selected category.

3.2 The Importance of Robustness in Choice of Strategic Actions

An essential issue that shall be taken into consideration when implementing a strategic decision making process is the need for robustness analysis of the results of this process, given broad issues and multiple values being considered. Nevertheless, robustness can be defined in many ways by putting the focus on the different elements of the decision problem, namely the model, the data, the futures, the method, the algorithm, the technical parameters. If we want to deal with robustness in a holistic way we have to tackle each one of these elements (Tsotsolas and Alexopoulos 2017). A common point is that robustness is called to provide resistance or self-protection, as Roy mentioned (2010), against the existence of uncertainty, contingency and ambiguity of the past (historical data), the present (decision model) and the future (possible states) resulting to vague approximations and zone of ignorance. As far as the past and the present time are concerned the source of this situation might be the information shortage for the decision problem in question and the different interpretation of reality depending on the DMs' points of view. On the other hand, the uncertainty of the future states is even deeper and increased proportionally to the timeline, while on the same time is affected by the choice of each alternative decision.

Given this complexity, to seek for mere optimality might be very often a misleading approach to strategic decision problems by providing solutions that are not well-performed in different scenarios (or versions) of the reality and in different futures. Thus, the robustness of a model or/and of a solution should be assessed and evaluated each time so that the analyst shall be able to have a clear picture regarding the reliability and stability of the produced results. Robustness shall be expressed using measures, also referred as robustness criteria, which are understandable by the analyst and the DM. Based on these measures the DM may accept, or reject, or adapt the proposed decision model. Given the fact that uncertainty is present, influencing every decision-making context, and that it appears in several different ways, it should be neither omitted, nor relegated. Its importance shall be realized and it shall be considered in an appropriate manner. As robustness allows us to experiment with uncertainty, it is necessary to define its concept, its significance and to emphasize its importance in the MCDA field.

Even though robustness analysis has been intensively debated in the recent years under the MCDA context, there is still some confusion about the different meanings that the term "*robustness*" has received as pointed out by Mónica and Barberis (2006). For that reason it is necessary to consider the different notions behind the word "*robustness*" based on Vincke's approach (2003):

- Robust solution—good in all or in some cases—dealing with uncertainty of external environment and external factors (Kouvelis and Yu 1997)
- Robust conclusion—valid in all or most pairs (version, procedure)—dealing with system values and gap from reality (Roy 2010; Aissi and Roy 2010)

- Robust decision in dynamic context—keep open as many good plans as possible for the future—dealing with the unknown future (Rosenhead et al. 1972; Rosenhead 2002; Haasnoot et al. 2013)

By using the notion "robust solution" we are referring to a solution (or equally to a decision), which could be considered good enough in all or most cases (high inter-scenario robustness), or/and presents low variation under different cases (low inter-scenario risk). For the evaluation of a solution several robustness measures have been proposed, most them based on the three standard measures (absolute robustness, absolute deviation, relative deviation) proposed by Kouvelis and Yu (1997). Since these standard measures are considered to be conservative, because they tend to give the higher importance to the worst case, several of the proposed approaches try to take into consideration other cases approaching to a median or average case. These other measures allow the DMs to express a specific degree of optimism about future outcomes by selecting some really good solutions which show remarkable bad performance only in a minimum portion of cases. Nevertheless, in cases where a good solution might have extremely bad consequences that might be also irreversible or, in cases where uncertainty about the future is severe, the security provided by the pessimistic measures of Kouvelis and Yu is preferred.

Following that perspective, Montibeller et al. (2006) discussed the Goodwin and Wright (2001) approach for evaluating the performance of alternatives in different scenarios, where each decision alternative is a combination of strategic option in a given future scenario (a_i–s_j). They also extended this approach by introducing notions such as: different priorities across scenarios, elicitation of strategies' performance, analysing inter-scenario risk and inter-scenario robustness of options. According to their proposition, each one of the n strategic options a_i is evaluated on the m criteria under each s scenario, using a different model for each scenario: $V_s(a_i) = \sum \mathsf{w}_{s,k} \times v_{s,k}(a_i)$, where $w_{s,k}$ is the weight of the k-th criterion under the s-th scenario ($\sum w_{s,k} = 1$ for a given scenario) and $v_{s,k}(a_i)$ is the value of the i-th alternative on the k-th criterion (scaled from 0 to 100) under the s-th scenario. Notice that the model allows different weights for distinct scenarios, in order to reflect different future priorities.

A critical issue in evaluating the solutions over a set of cases is the generation or selection of these cases. Usually, in the literature cases are referred to as scenarios, where each scenario represents a probable instance of reality provided through a plausible set of parameters' values of the model that are considered as uncertain. Where the number of probable instances is huge then a representative set of scenarios is used.

Usually, the robustness measures, or the robustness criteria defined by these measures, are taken into account *a priori*, during the formulation of the project, along with the optimization criteria or by substituting them (see Aissi and Roy 2010 for more details on ways to integrate optimization and robustness criteria). However, *a posteriori* approaches are also considered, as a way to evaluate the robustness of a calculated solution, often referred to as stability analysis. In order to highlight the fact that the formal approaches involve concerns that must be taken into account *a priori*, Roy (2010) proposes the expression "robustness concern" instead of "robustness analysis".

According to Roy (2010) one of the main robustness concerns is the magnitude of the gap between the formal representation (model, procedures) of reality and the real-life context itself. It's necessary for the analysts to take into consideration, and to try to explain this to the DMs as well, that the decisions they try to reach will be:

- applied into the real world which probably will not be 100% compatible with the developed model
- actually evaluated according to a value system which also might not be in total compliance with the corresponding value system which was used for the development and application of the model

Instead of just presenting a set of robust solutions, it might serve better the aims of the analyst, who tries to confront any discordance between model and reality, if he/she provides a framework for the DM's choices by summarizing the results that show under what conditions some results are considered robust. The statements that are used to provide this summary are called "robust conclusions" (Aissi and Roy 2010). Therefore, a robust conclusion may state that a solution is good in all or in some versions/procedures, given that specific conditions are valid.

Another approach of robustness connects it with the dynamic context in which decisions are made. This approach is of particular interest when dealing with strategic decision making because of the multistage nature of many strategic decisions and the radical uncertainty of a long or even middle term future of the economic environment. Strategic decisions, in a degree higher than other strategic decisions, must be or can be staged. That is, the commitments made at the first stage of a decision do not necessarily define completely the future state of the system. There will be one or more future opportunities to modify or to define it further. These futures can be identified but their details are not known in advance and furthermore the initial commitments may affect the characteristics of the futures. The paradox, as Rosenhead (2002) points out, is how can we be rational in taking decisions today if the most important fact that we know about future conditions is that they are unknowable? The answer to the aforementioned paradox is the concept of flexibility. An initial decision (maybe the 1st stage of a multistage decision) is considered to be flexible if it keeps open attractive (i.e. good or at least acceptable) future options at specific points on a time line or when some kind of event creates a specific trigger. As Hites et al. (2006) state, the fewer obstacles a decision poses to future good decisions, the more flexible it is. Under this dynamic approach, a robust decision is one that does not undermine any possible future choice. The evaluation of the robustness of the decisions shall be done at each stage for each pair (alternative, future) by taking into consideration how these decisions will affect the context of future decisions. This specific robustness concern focuses on the continuous evolution of decisions which shall be adapted to various middle or long term futures.

According to this approach, let a_i be the initial alternative decision chosen from a set of decisions. Let S be the set of all possible plans realised in the future. Let S_i be a subset of S of attainable plan after decision a_i has been chosen. Let S^* and S_i^* be respectively the subset of S and S_i of "good" or "acceptable" plans. Then the robustness of a_i is measured in function of the subset of good plans, that is: $r_i = n(S_i^*)/n(S^*)$, where $n(S)$ is the number of elements in the set S. Obviously, the greater the value of r_i the more the decision is robust.

A sequence of actions a_i in a form of pathways could be considered as well, where an initial commitment to a short-term action may lead to another action when an adaptation tipping point is reached (Haasnoot et al. 2013). Each possible pathway could be considered from the beginning as a candidate action and evaluated as such.

Robust approaches in strategic decision-making could be perceived as an effort to trade some optimal performance for less sensitivity to assumptions, performing well over a wide range of versions and possible futures, and keeping options open (Lempert and Collins 2007). Relevant research suggests that this often adopted strategy is also usually identified as the most robust choice. Robust strategies may be preferable to optimum strategies when the uncertainty, usually taking the form of epistemic uncertainty (referred to a lack of complete knowledge of the economical and societal environment), is sufficiently deep and the set of alternative strategic options is sufficiently rich.

Given the necessity of dealing with robustness issues in strategic decision making, in order to confront uncertainty about the present and the future real-world states, holistic approaches shall be adopted, based on a robustness centre view, focusing on the determination of scenarios for the present, as well as for multiple futures, and on the evaluation of the options within and across the scenarios. Actually, such approaches may include the incorporation of the (procedure, version) approach of Roy (2010) with the ideas of Rosenhead et al. (1972) concerning the initial commitments leading to a set of representative future states and the inter-scenario robustness approach of Montibeller and Franco (2011). In this latter work even though the authors had discussed that one challenge of using the concept of robustness is that there are different ways of conceptualising it, they assessed robustness using only the notion of robust solution, based the work of Kouvelis and Yu (1997). Furthermore, the basis of their evaluation approach is the practical application of the multi-attribute value function of Goodwin and Wright (2001) as discussed in Montibeller et al. (2006). A holistic robustness approach in a MCDA framework shall use appropriate measures covering different notions of robustness, with the evaluation of each alternative under each plausible scenario. Moreover, it shall incorporate an extension of the scope of scenarios in relation to the ones proposed in Goodwin and Wright (2001) by including the notion of pair (procedure, version) used by Roy (2010) combined with the effect of subsequent actions on future states of the problem. Such an approach shall consist of the following steps:

- Definition of a set of k alternative actions, $A = \{a_1, a_2, \ldots, a_i, \ldots a_k\}$
- Setting of future states fs where $fs = 0, 1, 2, \ldots, q$, while $fs = 0$ is referring to the present time

- Definition of a set of plausible variable settings s = (procedure, version), using Roy's approach as an extension to the notion of scenario, in a future state *fs*, $S^{fs} = \{s^{fs}{}_{1}, s^{fs}{}_{2}, \ldots, s^{fs}{}_{j}, \ldots, s^{fs}{}_{m(fs)}\}$. The cardinality of S^{fs} is probably different for each future *fs*, and equal to *m(fs)*. It is very likely that for the distant futures the information about plausible variable settings maybe poor, so the cardinality of the S^{fs} will be decreased.

The set A of the alternative actions may evolve during the strategic decision circle and new, combined and updated actions might enter in A, so its cardinality $|A| = k$ will be increased. A suggestion could be that all previous versions of combined or updated actions shall remain in set A for comparison reasons. Furthermore, each pair (procedure, version) includes a number of parameters, called frailty points by Roy (2010), depending on the processing procedure in a certain method family and on the different version of reality's representation which is strongly connected to the decision model. The first set of parameters includes purely technical parameters (*e.g.* thresholds for replacing strict equalities, concordance level) as well as parameters which are in one way or another connected to the real problem (*e.g.* weights, preference and veto thresholds). This second subset of parameters could be also viewed as part of a version of the problem along with parameters directly connected with the real-life context and which could take the form of objective function and constraint matrix coefficients, constraints right-hand-side values, etc. (see Aissi and Roy 2010 for extended discussion on the notion of (p, v) pairs).

It could be even considered that each variable setting is also affected by the choice of an initial action a_{ic} at present time ($fs = 0$), referred as initial commitment by Rosenhead (2002), so the set of plausible variable settings could be represented as: $S^{fs}(a_{ic}) = \{s^{fs}{}_{1}(a_{ic}), s^{fs}{}_{2}(a_{ic}), \ldots, s^{fs}{}_{j}(a_{ic}), \ldots, s^{fs}{}_{m(fs)}(a_{ic})\}$ for $fs = 1, 2, \ldots, q$ given that the selection of choice a_{ic} could affect each *s* in the future. For the special case of $fs = 0$, present time, the set of plausible variable settings is not affected by the action *i*: $S^{0} = \{s^{0}{}_{1}, s^{0}{}_{2}, \ldots, s^{0}{}_{j}, \ldots, s^{0}{}_{m(0)}\}$.

For each alternative a_i an overall evaluation of its performance under each plausible variable setting $s^{fs}{}_{j}(a_{ic})$, denoted as $V(s^{fs}{}_{j}(a_{ic}), a_i)$, shall be calculated. This overall evaluation can be consisted of one or several performance measures depending on the family of procedures that are used.

Furthermore, the corresponding robustness of all alternative actions across the plausible variable settings shall be evaluated using three types of measures:

1. $R_{st}(s^{fs}{}_{j}(a_{ic}), a_i)$: The *Standard Type*, based on the definitions of Kouvelis and Yu (1997) as well as on the corresponding proposed variations by Roy (2010). This type of measures, which is the most commonly used, highlights solutions that are good enough in most scenarios and not very bad at any scenario.
2. $R_{cr}(s^{fs}{}_{j}(a_{ic}), a_i)$: The *Credibility Type*, based on the proposals of Siskos and Grigoroudis (2010) where the robustness of a solution is evaluated during post-optimality analysis by calculating stability and credibility measures.
3. $R_{cr}(s^{fs}{}_{j}(a_{ic}), a_i)$: The *Flexibility Type*, based on the ideas of Rosenhead et al. (1972). According to their approach an action a_i is considered to be robust, or

equally flexible, if a significant number of ‘good’ or at least ‘acceptable’ plans are kept open in future states *fs*.

The robustness measures that belonging to the aforementioned types shall be further elaborated and specified for different methods. They shall also be presented to the DMs through visual representations using software applications for a better comprehension and more efficient feedback as argued by Montibeller and Franco (2010) and by Siskos and Grigoroudis (2010).

4 Applications

Three case studies with MCDA approaches in strategic decision-making problems are presented in this section. The first one concerns the evaluation of strategic choices of a publishing company using ELECTRE II method (Alexopoulos et al. 2012), the second one concerns the design and the implementation of facilitated group decision making using MACBETH method (Bana e Costa et al. 2014) and the third one deals with the application of a 11-stages holistic framework for political decision-making using Stochastic UTA method (Tsotsolas and Alexopoulos 2017).

4.1 Evaluating Strategic Actions for a Greek Publishing Company

The decision-making status quo in the publishing sector is formed around two main axes. The first one is the on-going, fundamental transformation of the relationship between humans and information in the modern era. The second one relates to modern challenges of the industry, such as: diminishing circulation and readability of newspapers and magazines, advertising revenue migration to new digital media and free press publications, reader behaviour volatility, convergence of media, and need to create new value through leverage of technology, editing, production and research (Fidler 1997; Sorensen et al. 2007).

4.1.1 A Case Study: Developing Strategic Publishing Actions in Greece

After studying the publishing industry and interviewing publishing firms’ executives in Greece, a set of publishing actions to be evaluated were identified as follows. For a detailed overview regarding the structure of media market in Europe, economic characteristics of media industries, economies of scale and value-based pricing, inter-related markets, stages of production, advertising and free content, new media platforms, proposed key steps for market definition analysis, and issues regarding rapid change and convergence, one should consult the European Commission Report on Media Market Definitions (2003).

Sunday Newspaper Weekly newspaper circulating each Sunday with a coverage of national and international political, cultural, economic and sports news.

Daily Newspaper Daily newspaper circulating every weekday, except Sunday.

Sports Newspaper Daily newspaper focused on coverage of sporting events.

Classified Ads Newspaper Newspaper circulating once or twice a week with content exclusively comprising of small ads of any kind (supply and demand for: sales and rental of real estate, cars, appliances, finding a job, etc.).

Monthly Magazine Periodic edition, usually monthly, covering readers' informational and entertainment needs.

Free Press Free daily newspaper circulating all weekdays except Sunday.

Electronic Newspaper Edition «Twin» publication of a «traditional» newspaper on the Internet, which offers some or all of the content of the printed version in electronic form, enhanced with additional material such as additional text and audio-visual files.

Blog Site where text and multimedia files are posted.

TV Channel Television broadcasters have significant power to influence public opinion, and thereby attract high advertising incomings.

Radio Station Radio stations also have the power to influence public opinion and therefore attract advertising incomings, albeit not as great as TV channels.

Content Development for Use in Mobile Phones and Handheld Devices (Mobile Content) The rapid development of mobile phones (features bundled in devices), of mobile networks technology (3G networks), and the enthusiastic reception of new applications from users both in a business and in a lifestyle level, create demand for the development of appropriate content for distribution to mobile devices (newsletters, multimedia files, etc.).

Internet Portal This is a gate to the internet, leading to virtually unlimited independent sources of content.

4.1.2 Designing a Multicriteria Evaluation System

Following an analysis of the publishing industry in Greece and interviews with executives of publishing firms, a consistent family of nine evaluation criteria $F = \{g_1, g_2, \ldots, g_n\}$ is finally created according to three points of view (social, economic, business) and the policy of the publishing company, as presented below:

The Social Point of View

- {g1}: Informative action (contribution to informing the public).
- {g2}: Cultural action (contribution to cultivation of the public).
- {g3}: Encouragement of reader participation in the publishing product content (reception of user-generated content such as opinions and views, reviews, photos, reports from breaking news, etc.).

The Economic Point of View

- {g4}: Achieve profitability.
- {g5}: Achieve economies of scale (through exploitation of existing infrastructure, resources and synergies).

The Business Point of View

- {g6}: Brand name boosting.
- {g7}: Entry, or boosting of the firms' presence, in a publishing field where competition is already active.
- {g8}: Influence public opinion.
- {g9}: Achieve "disruptive innovation" (Christensen 1997, 2003) with steps leading to action in (a) a peripheral (niche) field of publishing business, and/or (b) adopting innovative technology, with a future potential to abstract market share from the competition.

Due to the qualitative nature of the above criteria the following ordinal scale is adopted for the evaluation of each strategic action and especially the role that each action could play on each concerned criterion:

4: Extremely positive, 3: Very positive, 2: Positive, 1: Rather positive, 0: Of no interest
This scale is adopted for all criteria (impacts) apart for criterion "achieve profitability" which is the only one of the nine criteria that can get negative values (the choice of an action could ultimately lead to loss). For this reason, the aforementioned ordinal scale was extended with four more values which are:
−1: Rather negative, −2: Negative, −3: Very negative, −4: Extremely negative
Executives of the Greek publishing firm (experts) were asked to evaluate, on the basis of the aforementioned preference scale, the attractiveness of each of the twelve potential publishing products, in respect to the nine criteria. More specifically scores where extracted by asking what role could the choice of a particular action play for the achievement of any subsequent impact.

It is noteworthy that the publishing firm's already existing activity range is very significant for the answers given, meaning that for the publishing action e.g. "Classified Ads Newspaper Publication" criterion "Presence Boosting" would receive a low rating from a publisher that already includes such a product in his portfolio, but will receive a high rating from another publisher, who does not hold such a product. The given scores are summarised in Table 1.

The criteria weights in the table above were determined by using the Simos method ("method of the cards") (Maystre et al. 1994; Siskos 2008). Following the

Table 1 Multicriteria evaluation of twelve publishing products and ELECTRE II parameters

Actions	Criteria								
	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	g_9
A1: Sunday newspaper	4	3	1	1	2	4	2	4	0
A2: Daily newspaper	4	3	1	0	2	3	1	3	0
A3: Sports newspaper	3	2	1	2	1	2	4	2	0
A4: Class. ads newspaper	3	0	2	3	2	1	0	1	0
A5: Monthly magazine	2	3	1	2	2	2	2	2	1
A6: Free press	3	3	2	1	3	1	4	2	2
A7: El. newspaper ed.	4	3	1	1	4	2	2	2	3
A8: Blog	4	3	4	1	3	1	4	2	4
A9: TV Channel	4	4	1	-1	2	4	2	4	2
A10: Radio station	3	3	2	0	2	3	4	3	1
A11: Mobile content	2	1	1	2	3	2	4	2	4
A12: Internet portal	4	3	3	−2	3	3	0	3	2
Criteria weights	0.11	0.03	0.03	0.23	0.11	0.16	0.11	0.17	0.05
v^1	2	2	2	1	2	2	2	2	3
v^2	2	3	3	2	2	2	2	2	3
s^1	0.78								
s^2	0.67								

steps of the Simos method, the DM (publisher) listed nine criteria $F = \{g_1, g_2, \ldots, g_9\}$ at 6 classes of equal weight (four white cards were used for increasing the difference of the weights between two successive classes). In this classification, criteria class $\{g_2, g_3\}$ is the least important (tail) while class $\{g_4\}$ is the most important (head of classification). The normalization of weights, according to the method, is carried out by rounding to the closest integer.

For the ranking of the twelve actions (publishing products) ELECTRE II method was chosen, as all criteria are true criteria, i.e. criteria with zero preference and indifference thresholds (see Appendix). The same method was applied in the late sixties by Abgueguen (1971, cited also in Roy 1985) in media planning problems to advertise products.

ELECTRE family methods are partially non compensatory methods allowing for a pairwise comparison of actions, in terms of outranking, which is based on the criteria concordance and the veto effect of each criterion (discordance). In case of the γ problematic (ranking), outranking relations are used to construct a ranking of the actions which is not necessary complete (methods ELECTRE II, III, IV, see Roy and Bouyssou 1993; Figueira et al. 2005).

ELECTRE II uses two sets of veto thresholds v^1 and v^2 (the first is more restrictive than the second one) and two concordance levels to construct two outranking relations (strong and weak outranking). Generally the following simple and systematic procedure is used by analysts to obtain these parameters: Two fictitious actions A and B are chosen, of which A outranks B on all criteria except

g_i. The analyst progressively raises B's g_i value to the point DM stops considering A outranks globally B. Then v_i equals $[g_i(B) - g_i(A)]$.

4.1.3 Implementation of ELECTRE II Method

The target of this study is to rank order the twelve proposed publishing products, so that the publisher can have a clear knowledge about his next business step.

In order to start the ELECTRE II algorithm (cf. Appendix), the decision analyst has to define two concordance thresholds (s^1, s^2) and two vectors of veto thresholds$\left(v_j^i,\ \ \forall\ i = 1, 2\ \text{ and }\ j = 1, 2, \ldots, n\right)$. Note that the veto threshold of a criterion represents the maximal allowable positive difference that could have an action over another one without disturbing the outranking of the first action by the second one due to the superiority of the second action on the big majority of criteria. The determination of these parameters is obtained interactively by questioning accordingly the DM. According to ELECTRE II method two outranking relations are built: the strong outranking relation S^1 is corresponding to the set of parameters $(s^1, \mathbf{v}^1)$ and the weak outranking relation S^2 is corresponding to the set of parameters $(s^2, \mathbf{v}^2)$. Of course S^1 is a subset of S^2. All the obtained values of the ELECTRE II parameters are comprised in Table 1.

After application of the concordance and discordance principle of the method, the obtained two outranking relations are presented in Figs. 3 and 4. In the outranking graph of Fig. 4 the dashed arrows correspond to weak outranking. The strong outranking graph shows the existence of two circuits, which are replaced in the method by fictitious actions including indifferent actions, as follows: C1 = {A6, A8}, C2 = {A3, A5}.

From outranking graphs two rankings were derived, a descending and an ascending one; the final result is the intersection of these two rankings which is a partial weak order Z (see Fig. 5).

Incomparable actions have been explained to the publisher as follows:

Action A4 (Classified Ads Newspaper) appears to be incomparable with most other actions as it is focused on meeting very specific readers' needs (information on buying, selling and renting) in contrast to the mainly informative nature and scope of other publishing products.

Action A9 (TV Channel) appears to be incomparable with actions A7 (Electronic Newspaper Edition), A3 (Sports Newspaper), and A5 (Monthly Magazine) as A9 is a media of a different nature in terms of content, access and meeting users' needs.

Action A2 (Daily Newspaper) appears to be incomparable with actions A6 (Sports Newspaper) and A8 (Blog), as these latter products cover niche needs of the user (reader) in contrast with daily newspaper's wide informative scope.

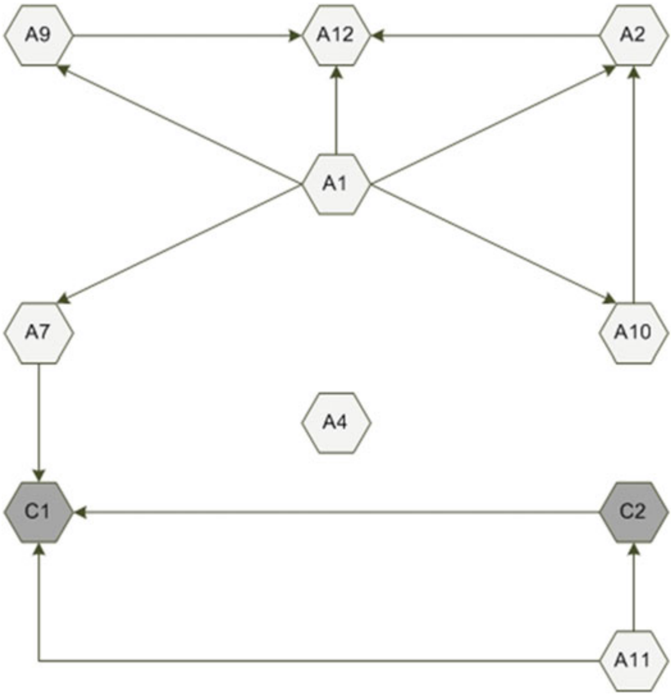


Fig. 3 Strong outranking relation with no circuits

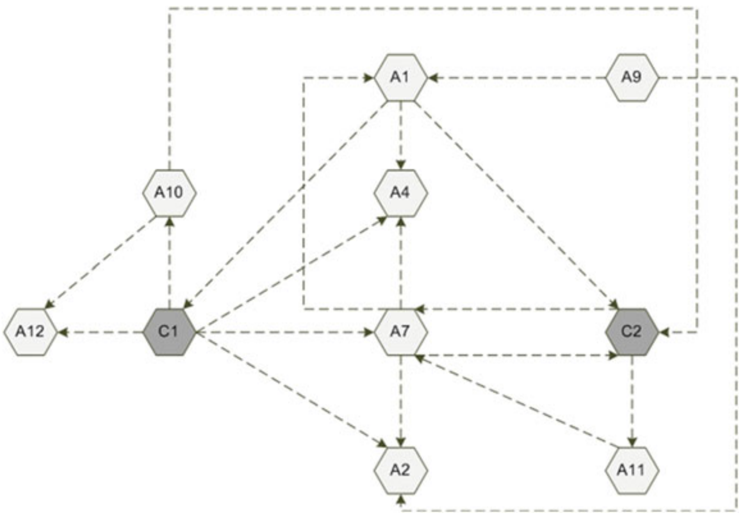


Fig. 4 Weak outranking relation with no circuits

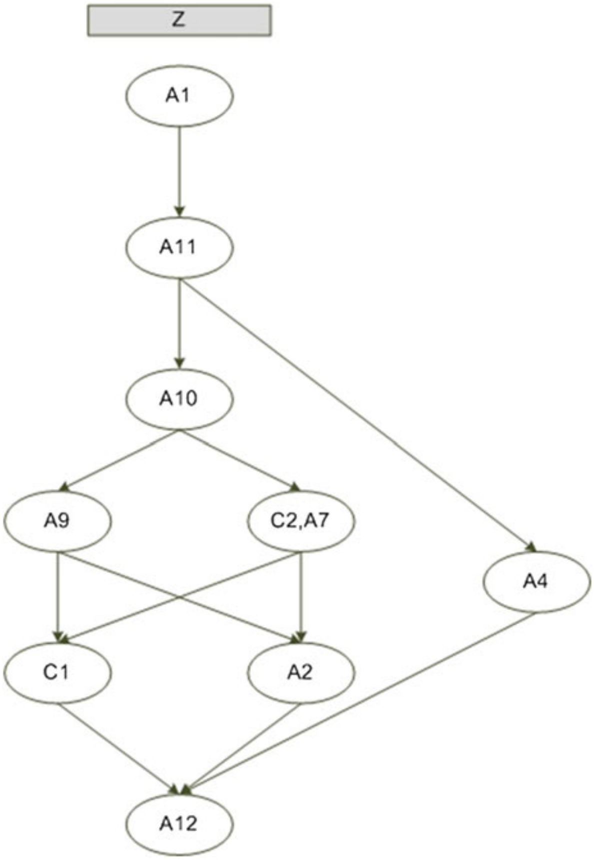


Fig. 5 ELECTRE II final ranking of publishing actions

After the removal of incomparabilities the twelve publishing products are ranked as follows:

1st: Sunday newspaper
2nd: Mobile content
3rd: Radio station, Classified ads newspaper
4th: TV channel, Electronic newspaper edition, C2 {Sports newspaper, Monthly magazine}
5th: C1 {Blog, Free press}, Daily newspaper
6th: Internet portal

Before his final decision for the financing of a global editorial action, the DM (the publisher) should also consider the implementation of suggested actions from an entrepreneurial point of view, taking into account parameters regarding not only the possible outcome (as expressed by criteria), but also preconditions and constraints such as (1) the availability of adequate assets for the funding of each action, and/or possible risk-aversion (i.e. in case a bank loan is necessary for funding an action),

(2) the consistency of a candidate action with the firm's vision, values' system, and culture, and (3) the consistency of a candidate action with the firm's priorities and possible business alliances.

4.2 Development of the Social Development and Human Rights Medium Term Strategic Plan for Pernambuco 2008–11

This case study is about the application of facilitating group decision making using the MACBETH Sociotechnical Approach in public strategic planning. The case has to do with Development of the Social Development and Human Rights Medium Term Strategic Plan for Pernambuco 2008–11, in which about 30 actors involved in a focused intervention context.

Even though there is plenty of common ground between private and public sector when dealing with strategic decision-making processes, there are also structural differences. Apart from the complex environment in which the public sector operates, often referred to as governmental superstructure, as a result of several involved authorities and bureaucratic procedures/normative guidelines that need to be followed, there are also a number of other factors that influence the decision process. One of these factors is the need for political power which a policy maker wants to satisfy.

In this case a smart sociotechnical approach was adopted through normative, prescriptive and constructive participation for a strategic planning with multi-criteria decision analysis and decision conferencing. The decision conferencing starts with the preparation phase where its objectives are agreed and the participants are selected and invited. It continues with the awareness of the key players for the issues under discussion. Within the main part of this process the issues are thoroughly explored, a decision model is build which is then explored towards the selection of the best alternative solutions. A shared understanding of the decision process and its outcome leads to the commitment for undertaking the appropriate actions for the proper implementation of the selected solution. Towards that direction the design of the social process should focus on transparent prioritisation, budgeting and resource allocation with multi-criteria analysis and decision conferencing. Phillips and Bana e Costa (2007) describe a social process for decision conferencing which starts with a kick-off meeting followed by several team meetings, which are reviewed by senior managers for realism and consistency. The process is concluded with a merge meeting in which the assessment of trade-offs and the exploration of the strategy portfolios are undertaken for the evaluation of the solutions and the assimilation of results.

The challenge when dealing with strategic decisions concerning political issues is to design a multicriteria interactive approach for strategic planning with the direct involvement of politicians. The methodology should be so attractive as to get the politicians to be willing to participate in the process as representatives of the population and be prepared to be present in open discussion sessions. Furthermore, the methodology should be applied through workshops or decision conferences organised in such a way that the effects of preferences and choices taken by participants during the sessions would be quickly reported in a friendly way. So, those effects could be easily understood by all the participants, thus enabling collective learning and the generation and debate of new ideas (Bana e Costa et al. 2002).

This project was a government initiative to create convergence on a strategy for Pernambuco's medium term social development and it engaged and aligned technical and political leaders of the new Secretary of State for Social Development and Human Rights (SEDSDH) and encouraged the participation of local experts.

The DM in this case was the SEDSDH and the objective of the intervention was to help SEDSDH to develop its medium term strategic plan (PPA 2008–2001). The method that was chosen was MACBETH socio-technical approach for strategic planning. The duration of the decision conferencing process was five consecutive days (from 11 to 15 June 2007) and the participants were about thirty technical and political actors. The process consultation team was comprised of 1 facilitator, 2 decision analysts and 2 experts.

The challenge in this strategic decision problem was to formulate, execute, monitor and evaluate, along with the society and other governmental entities, integrated public policies in the field of social development and human rights, which will allow transforming, in a conscientious and desired way, the social reality of the Pernanbucans who are living in a situation of vulnerability and risk, as supported by the following figures:

- 42% of the Pernanbucan population live with less then R$ 120/month (= € 32.6/month) per capita, finding themselves in a situation of vulnerability due to extreme or moderate poverty
- 33.3% are functional illiterates (15 years or older)
- The State of Pernambuco is the 8th economy among all 27 Brazilian States, but one of the lowest Human Development Indexes and one of the biggest Social Inequality Indexes

Two panels were formed, a Technical Panel and an Evaluation Panel with well-defined responsibilities and tasks in the process. The participants of the Technical Panel were experts of SEDSDH (representatives of the seven entities that integrate SEDSDH-departments and institutes). The tasks of the Technical Panel were to structure the objectives from SEDSDH mission, to conceive intervention actions (projects) and structures coherent programs (packages of projects) to achieve the objectives, and to organise factual information about the programs. Its duration was 3 days. The participants of the Evaluation Panel were Political decision-makers of SEDSDH, who are the secretary of state and the subsecretaries (leaders of the 7 units merged in SEDSDH). The tasks of the Evaluation Panel were to validate and weight the fundamental objectives, to evaluate the extent to which each program (package of projects) contributes to achieve the objectives, and to evaluate the doability of each program. In both panels several DSS were used to support structuring and multicriteria evaluation activities (Decision Explorer, STRAD, M-MACBETH, Equity).

The first task was the structuring of the underlying fundamental objectives to the SEDSDH's mission. Within this task, a group open-discussion of SEDSDH mission, major challenges and concerns was held. Each participant was asked to write (in post-its) the fundamental aspects, concerns and/or objectives that, in his/her opinion, better explain the mission. Then each participant was asked to place his/her own post-its in the wall, in such a way that the post-its would form groups of similar concerns. The post-its were read out loud, one by one, and their meaning discussed. Actions were separated from objectives. When agreed, each objective was entered in the Decision Explorer software, to generate a first cognitive map. This map represented the objectives written on the post-its as well means-ends relations between them (Fig. 6).

After two days of work and group discussions, the Technical Panel agreed of the main end-objectives and mean-objectives. The following three strategic objectives (SO) were later validated by the politicians and used to evaluate strategies:

- SO 1: Promote social inclusion and protection of people and families
- SO 2: Universalize, guarantee and promote human rights
- SO 3: Socialize the adolescent in conflict with the law and resocialize the jail population

MACBETH method (Measuring Attractiveness by a Categorical Based Evaluation Technique) was used for the multicriteria value measurement. MACBETH, is an interactive pairwise comparison approach to guide construction of a quantitative value model from qualitative value judgments. It uses a simple question-answer protocol that involves only two options in each question. The evaluator is asked to pairwise compare options by given a qualitative judgement (very weak, weak, moderate, strong, very strong, extreme) of the difference in attractiveness between these two options. For a set X of m options, the number of pairwise comparisons can vary from a maximum of $m(m-1)/2$ judgments, when all pairwise comparisons are made, to a minimum acceptable number of $m-1$ judgments, as when comparing only each two consecutive options in the ranking or one option with all of the other $m-1$ (however, it is recommended to ask for some additional judgments to perform several consistency checks).

MACBETH was used in this case for assessing the preference information of the 25 Projects against the Status Quo (SQ), which is considered to be the worse choice, meaning that its performances on all fundamental objectives SO1, SO2 and SO3 are equal to their lower references. For a more efficient application of the method a virtual action was described whose performances on all criteria are considered as benchmarks.

A MACBETH weighting process took place late in the fourth day. Three hypothetical programmes (HPs) were presented by the facilitator to the DM-team, each one assumed to give a good contribution to improve the Status Quo in one fundamental objective and no contribution in the others. While assessing MACBETH intracriterion preference information, as each judgement is entered

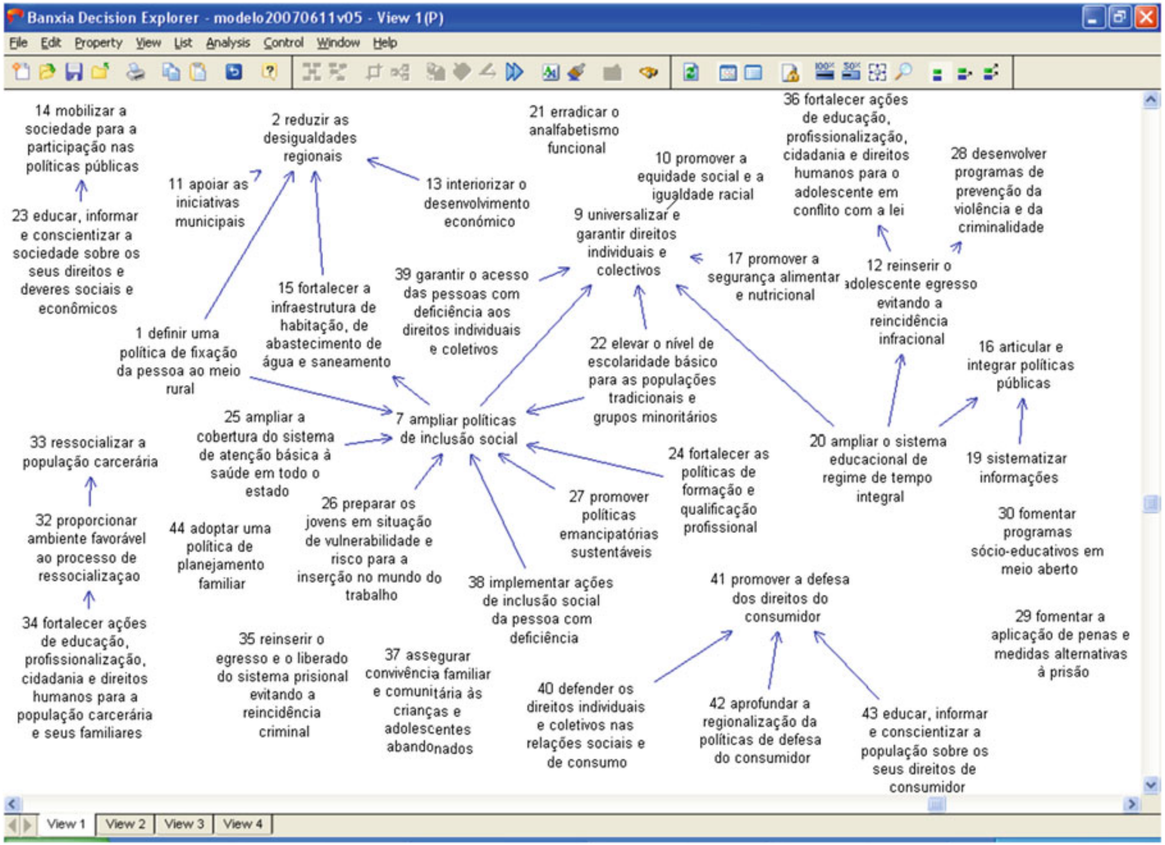


Fig. 6 The cognitive map in Decision Explorer software (source: Bana e Costa et al. 2014)

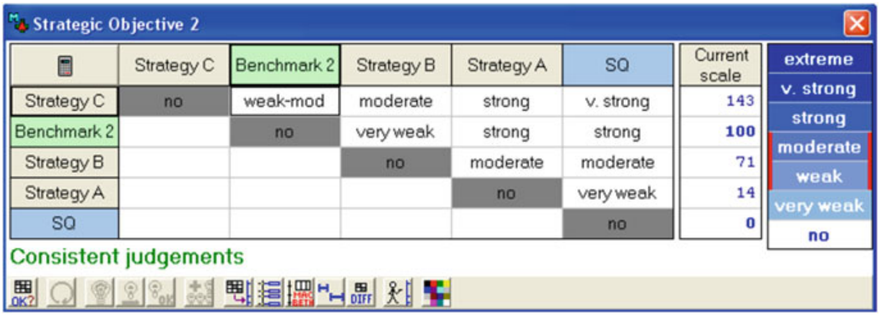


Fig. 7 Preference information and cardinal scale for Strategic Objective 2 (source: Bana e Costa et al. 2005)

in the matrix, its consistency with the judgments already inserted is checked and possible inconsistencies are detected (Fig. 7). If an inconsistency is detected, suggestions to overcome it are presented. Technically, this is done by a mathematical programming algorithm (Bana e Costa et al. 2005).

The software determines the interval within which each score of each option can vary when the other $m-1$ scores are fixed and still remain compatible with the matrix of judgments. This allows the adjustment of the scale by comparing differences of scores, to arrive to a cardinal scale.

For the overall evaluation of the strategies the next step was the weighting of the model's criteria. During this step the ranking of criteria weights is determined by ranking the "overall references" in terms of their overall attractiveness. Then the weights are quantified. Each strategy's overall performance corresponds to the sum of the products of each criterion weight and the strategy's score on the criterion (Table 2).

The 25 integrated programmes were also assessed by the DM-team in the light of their perceived "doability", that is, the extent to which the group envisaged or not significant obstacles to the implementation of a programme, whatever their nature is: political, technical, financial, administrative, logistical, legal, etc. Note that the higher the doability the lower the "effort" required to remove the obstacles and implement the programme. Finally, an analysis of the robustness of having selected all the programmes classified as pearls and oysters during the decision conferencing process was performed *a posteriori*.

4.3 Siting an Open Market Case Using Robust Facilitated Approach

The approach followed in this case (Tsotsolas and Alexopoulos 2017) is actually based on a facilitated robustness-central approach focusing on the determination of scenarios for the present as well as for multiple futures and on the evaluation of

Table 2 Scores of the programmes (source: Bana e Costa et al. 2014)

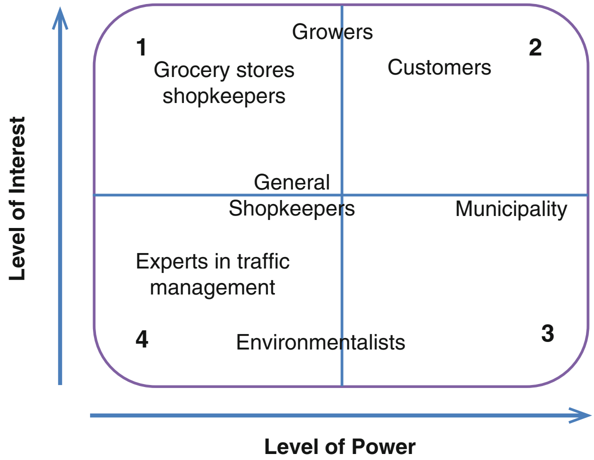
Ranking	Overall benefit	Contribution scores		
		O1	O2	O3
1.3	135	169	112	100
(1+8).1	128	133	147	100
4.1	127	128	135	118
6.2	123	141	135	82
4.2	104	100	124	91
1.5	103	100	112	100
7.1	103	69	100	164
8.2	102	69	159	100
1.1	100	100	100	100
7.5	96	54	100	164
5.1	91	62	112	118
6.1	89	100	124	36
7.3	87	59	59	164
1.2	85	100	100	45
5.2	85	54	59	164
8.1	79	100	112	9
7.4	68	21	53	164
3.2	62	72	35	73
7.2	60	3	53	164
1.4	48	54	41	45
3.4	28	15	41	36
3.1	23	18	18	36
3.3	19	8	12	45
2.1	18	26	24	0
2.2	11	10	24	0
	Weights:	0.46	0.27	0.27

the options within and across the scenarios using appropriate measures covering all three notions of robustness discussed in Sect. 3.2. Moreover, an extension of the scope of scenarios in relation to the ones proposed in Goodwin and Wright (2001) was adopted by including the notion of pair (procedure, version) used by Roy (2010) combined with the effect of subsequent actions on future states of the problem. This approach, which was consisted of 11 discrete stages, has been applied for the citing of an open market in central Greece. These discrete stages are presented in this section along with their specific implementation within the case study.

Stage 1 (Participation Scoping) The participants, meaning DMs, facilitators and stakeholders, in the decision circle are defined.

Participants Facilitator, Deputy Mayor, Chamber of Commerce Vice President. Two meetings: an introductory one (2 h) and the main meeting (4 h) to decide on the involved participants.

Fig. 8 Power/Interest Grid for siting an open market



Tool The DM in this process is actually the municipality but its officers would like to involve other stakeholders in this decision keeping in mind that a good or a bad choice may affect the opinion of the voters. The Power/Interest Grid approach (Fig. 8) was used as the main tool and the different stakeholders were placed at the appropriate quadrant considering the corresponding levels of power and interest. E.g. growers may have a bigger interest than customers because such a market may boost significantly their income but they have less (voting) power than the customers given the size of their population relating to the population of customers.

Result It was decided to involve the stakeholders that lie in quadrants 1, 2 and 3. Municipality officers were already involved, given the fact that they have the role of the developer of the new market. Furthermore, Chamber of Commerce, representing Grocery stores shopkeepers as well as General Shopkeepers, will participate in the decision process along with the Union of Agricultural Co-operatives (UAco) and the Consumers' Institute (INCU). From each one of the four stakeholders two representatives were designated. It was also decided that the experts in traffic management will get involved in the process to provide technical support but they would not be considered as stakeholders.

Stage 2 (Problem Definition) Through a continuous interaction among the participants, the selection and the exploitation of the appropriate quantitative as well as qualitative information (retrospective approach) and sound estimations (prospective approach) concerning the available resources are implemented.

Participants Facilitator, Municipality, Chamber, UAco, INCU, an expert in traffic management and an engineer appointed by the municipality. Two meetings: during the first one (4 h) the participants discussed in general about the needs that the new open market should satisfy and about the four alternative places where the new market could be created. The expert and the engineer were asked to collect technical information concerning the four places as well as concerning the estimated cost for the development. The second meeting was organised 2 weeks later and it lasted 5 h. The elementary consequences, which would occur if any of the alternative places was selected, have been discussed.

Tool Dialogue Mapping™ was used, which is a technique for diagramming meeting discussions (Fig. 9). The facilitator did the mapping using a shared display visible to all participants and a simple graphical "language", called IBIS (Issue Based Information System), for representing the discussion. Dialogue Mapping™ provided a central focus for the group, helping keep discussions on track. For each alternative place all the cloud of elementary positive and negative consequences were mapped and discussed. The software tool CompendiumNG was used for applying Dialogue Mapping™.

Result The four alternative places were selected: {"A1. Pedestrian road – town centre", "A2. Next to coach station", "A3. Parking of the court", "A4. Open area at northern entrance of the city"}. These places were analysed and the corresponding elementary consequences of each place were presented in CompendiumNG as pros and cons nodes and several details were attached to each node.

Stage 3 (Criteria Identification) Mean-ends analysis approaches are used, based on the framework proposed by Keeney (2013) for identifying, prioritizing and using multiple objectives, using tools such as cognitive maps.

Participants The same participants as in stage 2. They collaborated during the second meeting of stage 2, discussing the synthesis of cloud of elementary consequences into preference dimensions and criteria.

Tool Dialogue Mapping™ was used at this stage as well for a bottom-up approach, where the pros and cons nodes led to the creation of a list node, which included the criteria and the necessary information concerning the preference scales for each criterion.

Result A consistent family (Siskos 2008) of six criteria was created. The criteria and their corresponding preference scales are shown in Table 3:

The last criterion (Cost) was decided to be handled as probabilistic criterion and that's why a distributional evaluation was provided. Following the definition of the criteria the multicriteria evaluation table (Table 4) of the decision problem concerning the four alternative places was created.

Stage 4 (Method Selection) The MCDA method or the methods which are going to be used for the development of the decision model must fit to each specific problem as well as to the expectations of the participants.

Participants Only the facilitator.

Tool The questions guided approach of Roy and Słowinski (2013) was adopted for the selection of the appropriate MCDA method.

Result Our problem lies between (i) Type 1, given the fact that, as a result, a utility value is expected for each action because the Municipality Board, which shall take

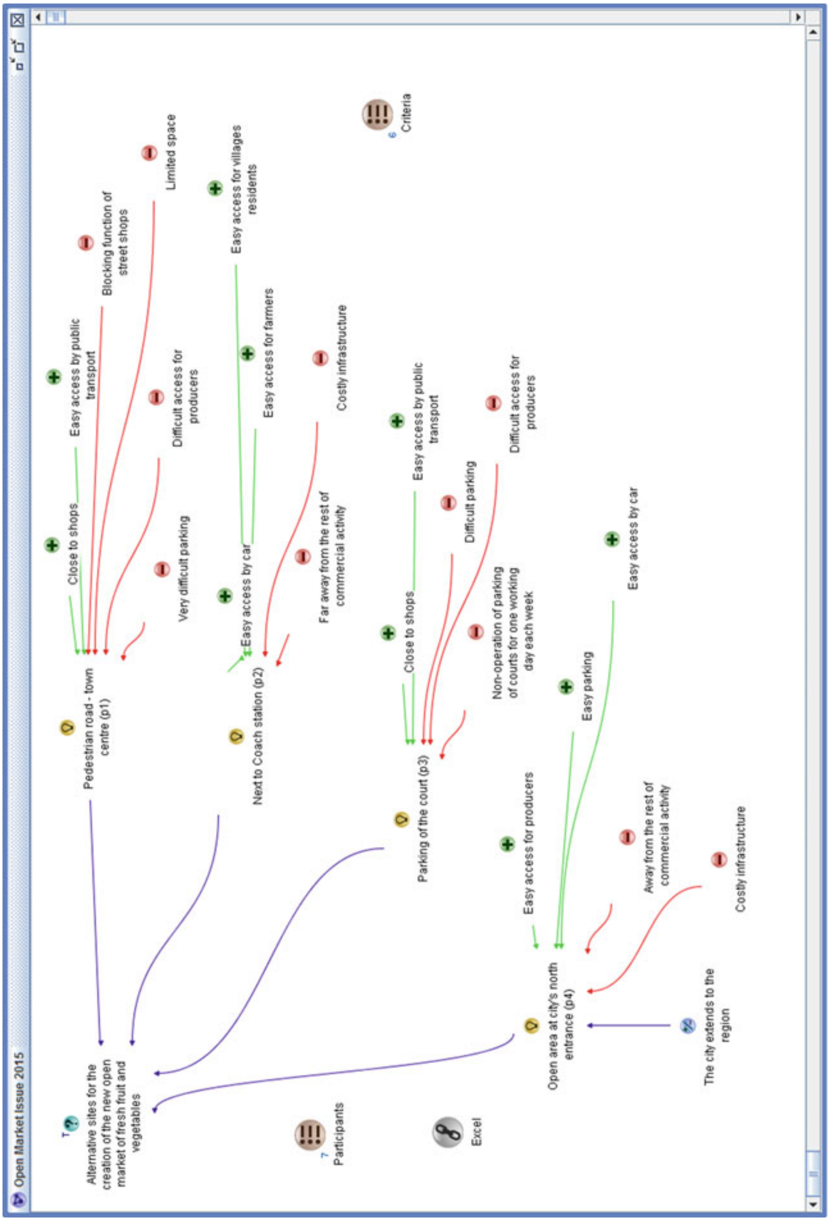


Fig. 9 A dialogue map for siting an open market

Table 3 Criteria information for siting an open market

Criterion name	Range	Measurement unit	Type	Monotonicity
Ease of access for farmers	1–5	Rate	Ordinal	Increasing
Public transport	0–1000	No of passengers per day	Metric	Increasing
Parking	1–5	Rate	Ordinal	Increasing
Proximity to services-stores	0–3000	km	Metric	Decreasing
Affecting other operations	1–5	Rate	Ordinal	Increasing
Cost	0–1000	k€	Metric	Decreasing

the final decision, should be able see a straight forward comparison among all alternative places, and (ii) Type 2, because it is considered as a good idea to ask the four different stakeholders to rank the initial set of alternative places according to their preferences by providing, each one of them, a complete or partial weak order. Furthermore, by taking also into consideration the probabilistic nature of one criterion (cost), as well as the compensated nature of the all criteria the Stochastic UTA method (Siskos et al. 2005) has been selected to be applied. The selection of this method is considered to be appropriate for our decision problem since its axiomatic characterization is acceptable in the considered decision context and since the existence of some weak points, having to do with the possible estimation of various compatible preference models, can be effectively tackled through the application of robustness analysis tools. The software TALOS (Christodoulakis 2015) has been selected to be used for the application of the Stochastic UTA in this case study, which also offers a wide range of robustness analysis tools.

Stage 5 (Preference Model Elicitation) A preferred strategy is a potential solution to a problem depending on judgments about the value or utility of expected outcomes for the participants in the strategic decision circle.

Participants Facilitator along with Municipality, Chamber, UAco, INCU who all of them act as Policy DMs at this stage.

Tool Application of Stochastic UTA in TALOS software using the four DMs' overall preference expressed by ranking the reference places A1, A2, A3 & A4.

Result A system of additive value functions was inferred, one barycentric value functions per DM. The results are shown in Table 5. It is apparent that a critical criterion is that of "Public Transport", which is the most important for 3 out of the 4 DMs and the second most important for the fourth one. Another important outcome is that the criterion "Cost" is only the third most important or even the forth for the DMs.

Stage 6 (Alternatives Reforming and Combination) Along with the criteria identification and the preference model elicitation stages, the initial set of alternatives may be evolved by reforming or/and combining actions in an effort to trade-off among competing objectives and values. This stage was not applied because it is decided that no alternatives' reforming or combination is considered necessary.

Table 4 Multicriteria table for siting an open market

	Criteria					
	Ease of access for farmers	Public transport	Parking	Proximity to services-stores	Affecting other operations	Cost (mean value, μ)*
Alternative places	Rate (↓)	No of passengers per day (↑)	Rate (↑)	km (↓)	Rate (↑)	k€ (↓)
A1. Pedestrian road—town centre	1	1000	1	100	1	100
A2. Next to coach station	5	500	5	3000	5	400
A3. Parking of the court	3	800	1	400	2	150
A4. Open area at city's north entrance	5	200	4	1500	5	300

*Standard deviation $\sigma = 4\% * \mu$

Table 5 Preference models for each DM

Decision makers	Criteria					
	Ease of access for farmers	Public transport	Parking	Proximity to services-stores	Affecting other operations	Cost
Municipality	17.71%	53.96%	7.08%	3.54%	3.54%	14.17%
Chamber	22.92%	24.00%	7.08%	23.75%	7.92%	14.33%
UAco	28.75%	26.25%	12.08%	8.75%	8.33%	15.83%
INCU	5.00%	51.99%	16.67%	9.17%	3.75%	13.42%

Stage 7 (Scenarios Building) Given the deep uncertainty of the strategic decision making context several plausible scenarios shall be developed in which specific combinations of parameters' values will be assumed.

Participants Only the facilitator.

Tool TALOS software was used to examine the affection of different levels of parameter δ (a small positive number so as to discriminate significantly two successive reference alternatives in UTA methods) for each one of the four preference models elicited in Stage 5.

Result Two levels of δ were selected, 0.1 and 0.05 for each one of the four preference models, so we have 8 different scenarios-versions.

Stage 8 (Future States Determination) Apart from multiple-scenarios, multiple-time frames shall be taken into consideration as a tool to tackle unforeseeable risks and uncertainties due to the long time horizon of strategic decision circles.

Participants Only the facilitator.

Tool Adaptation Pathways Map was used for representing the possible actions at present and at future states. A Scenario Analysis Matrix was also used for the discussion of how each possible future state affects the performance of each action.

Result In Fig. 10 (Adaptation Pathways Map) the four different alternative places for the present time are shown along with their subsequent actions after 5 years at future state 1 (only one future state was decided to be examined) for two different scenarios concerning the evolution of the demand, either stable or increased. It is assumed that for each initial chosen place a tipping point is reached after 5 years, and that new versions of these places shall be chosen at that time. Furthermore, in the Scenario Analysis Matrix (Table 6) the consequences over the performance of the initial places are described. At future state 1 an underground parking will have been built in the parking area of the courts and two different scenarios concerning the evolution of the demand of the market services were examined.

Stage 6 (Alternatives Reforming and Combination) Re-visit.

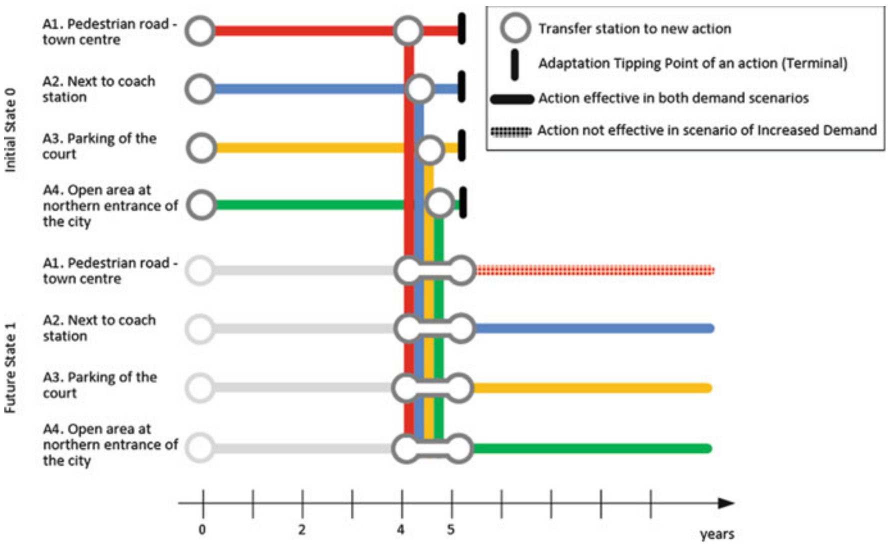


Fig. 10 Adaptation Pathways Map

Table 6 Scenario analysis matrix

	Future State 1: New underground parking	
	Scenarios	
	Stable demand	Increased demand
A1. Pedestrian road—town centre	No change	Not enough capacity
A2. Next to coach station	No change	Extra cost for extension
A3. Parking of the court	Increased performance in parking criterion Affecting less other operations	Increased performance in parking criterion Affecting less other operations Extra cost for extension
A4. Open area at city's north entrance	No change	Extra cost for extension

Participants Facilitator, Municipality, Chamber, UAco, INCU, an expert in traffic management and an engineer appointed by the municipality. A new meeting lasted 4 h for evaluating the combined alternative places which included initial state as well as future state 1.

Tool Extended discussion based on Dialogue Mapping™ used in Stage 3 as well as on Adaptation Pathways Map and Scenario Analysis Matrix used in Stage 8.

Result In Table 7 the new multicriteria evaluation of the 4 × 4 combined places for the two demand scenarios are shown, taking into consideration the situation as it will be in future state 1, 5 years from now. The choices that include place A1 for the future state under the scenario of increased demand were not included in this evaluation given the fact that place A1 could not serve the foreseen increased demand. Moreover, 6 out of the 28 evaluations were considered as not feasible

Table 7 Multicriteria table for siting an open market

Alternative Places	Demand	Criteria					
		Easy of access for farmers	Public transport	Parking	Proximity to services-stores	Affecting other operations	Cost (mean value, μ)*
		Rate (↓)	No of passengers per day (↑)	Rate (↑)	km (↓)	Rate (↑)	k€ (↓)
A1→A1	Stable	1	1000	1	100	1	100
A1→A2	Stable	5	500	5	3000	5	520
A1→A3	Stable	3	800	4	400	3	270
A1→A4	Stable	5	200	4	1500	5	420
A2→A1	Stable	1	1000	1	100	1	510
A2→A2	Stable	5	500	5	3000	5	400
A2→A3	Stable	3	800	4	400	3	560
A2→A4	Stable	5	200	4	1500	5	710**
A3→A1	Stable	1	1000	1	100	1	275
A3→A2	Stable	5	500	5	3000	5	575
A3→A3	Stable	3	800	4	400	3	150
A3→A4	Stable	5	200	4	1500	5	475
A4→A1	Stable	1	1000	1	100	1	410
A4→A2	Stable	5	500	5	3000	5	710**
A4→A3	Stable	3	800	4	400	3	460
A4→A4	Stable	5	200	4	1500	5	300
A1→A2	Increased	5	500	5	3000	5	670**
A1→A3	Increased	3	800	4	400	3	320
A1→A4	Increased	5	200	4	1500	5	520
A2→A2	Increased	5	500	5	3000	5	550
A2→A3	Increased	3	800	4	400	3	610
A2→A4	Increased	5	200	4	1500	5	810**
A3→A2	Increased	5	500	5	3000	5	725**
A3→A3	Increased	3	800	4	400	3	200
A3→A4	Increased	5	200	4	1500	5	575
A4→A2	Increased	5	500	5	3000	5	860**
A4→A3	Increased	3	800	4	400	3	510
A4→A4	Increased	5	200	4	1500	5	400

*Standard deviation σ = 4%*μ
**A threshold of 650 k€ for the Cost criterion was set and beyond that threshold the choice is considered as not feasible

according to the cost criterion threshold. So, the combined actions to be further examined for both demand scenarios are the following eight: A1→A3, A1→A4, A2→A2, A2→A3, A3→A3, A3→A4, A4→A3, A4→A4.

Stage 9 (Performance & Robustness Evaluation) The performances of each alternative option are evaluated for each scenario as well as its robustness within and across scenarios.

Participants Only the facilitator.

Tool Application of Stochastic UTA in TALOS software for calculating the utilities of the actions and the stability measures ASI (Hurson and Siskos 2014). MS Excel was used for the calculation of Kouvelis and Yu (1997) robustness measures and of their variations proposed by Roy (2010).

Result The values of ASI, measuring the credibility of each barycentric solution within each version of the problems, for the $4 \times 2 \times 2$ [(4 DMs) $\times$ (2 values of UTA δ) $\times$ (2 demand scenarios) $= 16$] versions of the problem were found in the range from 75.58% to 69.88%, with 2–3% higher values when using $\delta = 0.05$ instead of $\delta = 0.1$. All of these results are considered credible.

In Table 8 the highest utility value of each one of the 8 feasible alternative combined places in the 16 versions is shown in column (2), while in the next columns the three robustness measures proposed by Roy (2010) are given. For the calculations of these three measures we considered specific boundary values b and w also shown in the Table. Finally, in the last three lines of Table 6 the three inter-scenario robustness measures proposed by Kouvelis and Yu (1997) are given. Consequently, the analysis of these results led to the outcome that 2 out of the 8 alternative combined places could be considered as the most promising ones in terms of performance and robustness, namely A3→A3 and A4→A3.

Stage 10 (Decision) A good but not too risky option shall be selected for implementation and a detailed action plan towards an effective application of this option shall be set.

Participants Facilitator and the Decision Makers.

Tool The Municipality Board will reach the final decision based on the outcome of the decision process.

Result The final decision is expected to be reached during the first quarter of 2016. After the reaching of the decision the monitoring stage (11) shall begin.

Stage 11 (Monitoring) This stage provides milestones and sets triggers which can actually cover the DMs' need to constantly re-evaluate the results of the selected strategies and, if necessary, to go back in the strategic decision circle and decide on a new or revised strategy.

5 Conclusions and Further Research

The key aspect for developing efficient and robust strategies is to study and evaluate multiple scenarios for the present and the future. The role of facilitators in these and in several other cases is for sure very important, given the fact that they act as

Table 8 Performance & robustness results

Roy→	w = 0.5	(b,w)-absolute robustness		(b,w)-absolute deviation		(b,w)-relative deviation	
		b = 0.652		b = 0.146		b = 0.180	
Actions	Max Utility	$\min_s u_s(x)$	$r_{bw}(x)$*	$max_s[u^*_s - u_s(x)]$	$r_{bw}(x)$*	$max_s[(u^*_s - u_s(x))/u^*_s]$	$r_{bw}(x)$*
A1→A3	0.839	0.652	16	0.160	15	0.197	15
A1→A4	0.811	0.531	8	0.219	14	0.286	12
A2→A2	0.812	0.531	8	0.219	14	0.286	12
A2→A3	0.858	0.652	16	0.146	16	0.180	16
A3→A3	0.858	0.652	16	0.148	15	0.182	15
A3→A4	0.811	0.531	8	0.219	14	0.286	12
A4→A3	0.858	0.652	16	0.146	16	0.180	16
A4→A4	0.811	0.531	8	0.219	14	0.286	12
Kouvelis and Yu							
Absolute robustness		0.652					
Absolute deviation				0.146			
Relative deviation						0.180	

* $r_{bw}(x)$: the number of scenarios in which a solution is robust

catalysts in the decision process. However, the necessity of a dedicated DSS, which should act as the central point for entering, organising and analysing the available information and the produced results, is raised. Such a DSS should eliminate users' burden, which is a critical issue when dealing with strategic decision making processes.

Concluding, we believe that given the importance of strategic decision making for the survival and flourishing of any management and operational system, further developments in this field could not only produce opportunities for research on the several challenges already highlighted, but also have a real impact on MCDA practice. More studies on robustness of strategic decision paths under multiple scenarios are required, for example, about suitable operators and graphical displays for interacting with DMs and stakeholders. An open area for research in this field is how to deal effectively with a huge number of plausible variable settings given the long term consequences of strategic decisions. Given the special nature of the strategic decision making, it would be interesting to further assess the impacts of the approaches discussed in this chapter, and their effectiveness, within new case studies using facilitating approaches, as well as the overall usefulness of these approaches as a mean to increase our understanding of analytical decision support at the strategic level.

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Collaborative Decision Making for Small Groups Utilizing UTA Methods

Athanasios Spyridakos and Denis Yannacopoulos

Abstract Decision Aid process involving many stakeholders constitute a complex situation while requires the reconciliation of multiple views, interests and preferences. Multicriteria Disaggregation—Aggregation approaches such as UTA(*) and UTA II support the estimation of additive value preference models utilizing the Decision Makers (DMs) global preferences expressed by the pre-ranking of a limited set of alternative actions evaluated on a consistent family of criteria. This research work presents the exploitation of UTA methods and voting collective functions of Social Choice Theory in order to support decision aid process in a multi-agents decision environment. Also, the RACES systems developed to support small group decision aid process, accompanying the MINORA and MIIDAS system is presented and illustrated through a real world cases study.

1 Introduction

Decisions, either in business era or in social and political sector is usually the subject of many stakeholders involved directly or indirectly into the decision making process. In many cases, the final decision comes through a meshing and negotiation process of the different opinions, interests and preferences of the stakeholders participating in the decision making process. Also, every stakeholder has a different weight or impact in the decision taken. The existence of different views among the DMs ought to be handled and a final decision to be taken at the end of the day either through a dialogue processes which may lead to consensus or using voting process in order to identify the majority facing potential problems and conflicts.

Multicriteria Decision Aid (MCDA) approaches provide the methodological tools which can support, at a satisfactory level, the collaborative decision making in complex and unstructured decision problems. The last four decades a considerable

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number of methodological frames and software systems based on multicriteria decision aid analysis were developed in order to support situation of collaborative decision making. Most of them aim to the analysis and picturing of the different preference structures of the stakeholders participating in the decision making and to support the negotiation activities, focused to the achievement of consensus and to the reducing of the convergences among the different issues and points of view. Kersten (1985) developed the NEGO system, which supports the evaluation of DM's individual preferences handing the negotiation process. Bui (1987) combines Analytical Hierarchical Process (AHP) and ELECTRE methods (Roy 1990) in the Go-Op system, supporting the analysis of preferences attitudes of individuals within a group decision situation, through interactive and structured dialogues among the DMs. Dennis et al. (1988) presented PLEXYS which is based on the Multi Attribute Utility Theory (MAUT) and utilises a 10 level scale in order to support the alternatives' evaluation on the criteria. Also, provides a flexible way for handling the identification of the relative importance of the criteria. Multi Attribute Utility Theory is used by Vetchera (1991) incorporating interactive dialogues so as to re-arrange the individual preferences. The AHP was also employed by Carlsson et al. (1992) in Alicia and Sebastian systems in order to estimate models of the individual preferences which is used in a compromise processes, aiming to conclude to a decision with consensus among the stakeholders. The system JUDGES (Colson and Mareschal 1994) aims to support the uncovering of the consensuses and the conflicts among individual stakeholders and the categorisation of the alternative actions into seven groups of preference profiles through pair-wise analysis and graphical tools. ELECTRE III was used by Miettinen et al. (1997) in order handle the preferences elicitation through an explicit way where the preference data are imprecise.

Multicriteria Disaggregation–Aggregation (D-A) approaches (Siskos 1980; Jacquet-Lagrèze and Siskos 1982; Siskos and Yannacopoulos 1985; Greco et al. 2007, 2012; Figuera et al. 2009) leads to the assessment of additive value models based on: (a) the evaluation of the alternative actions into a consistent family of criteria, (b) the DM global preferences expressed by rank-ordering of a limited set of alternative actions (reference set), (c) Linear Programming techniques where an additive value model is estimated so as to reproduce, as close as possible, the initial global preferences of the DMs and (d) utilisation of interactive structured or unstructured dialogues with the DM where a set of feedbacks can be used triggered by the analysis of the estimated value preference model. The high interactive features of D-A approach as well as the capability of the method to support the analysis of DMs' preferences structures represented into additive value models, triggered many researches to utilise it in collaborative decision making situations. Jacquet-Lagreze and Shakun (1984) were the first who recognized the potentiality of D-A in collaborative decision support problems in order to support negotiations trying to achieve consensus or face conflicts. Later, Matsatsinis and Samaras (1997, 2001) proposed a framework based on UTASTAR method, where the individual preferences were assessed and a collective satisfaction model was estimated concluding to a decision. The UTA method feature to uncover the DM's preferences structures were also ulilised by Jarke et al. (1987) into the group decision support system MEDIATOR. Also, Matsatsinis and Delias (2004) presented protocols to support cases of decision making with multiple actors oriented to the features of D-A multicriteria decision aid analysis. A general frame concerning the adaptation of the UTA* for the acceptance of individual rankings into the linear programming subjective conditions presented by Siskos and Grigoroudis (2010). This approach provides a way so as to estimate a collective preference model and to picture and analyse the conflicts among the DMs.

This chapter is focused on the presentation and analysis of a methodological frame for exploiting UTA methods and Theory of Committees and Elections (TCE) in order to support the collaborative decision making. This combination was first presented by Spyridakos et al. (2001), where exploited Cook and Seiford voting collective technique and UTA II method in order to handle the collaborative Decision Making process with the construction of an additive value preference model for job evaluation. Later Spyridakos and Yannacopoulos (2015), Spyridakos (2012) and Yannacopoulos et al. (2014) presented an integrated approach for the utilization of UTA methods in collaborative decision making situations for small group of decision makers. This integration combining features of TCE and D-A UTA methods is further presented and analyzed in this chapter.

The chapter includes the introduction and three more sections. The second section is focused on the general frame of using UTA methods in collaborative decision making for small group of DMs. In the third section the methodological frame of synergistic utilisation of TCE and UTA methods is presented in details and is illustrated through a case study. The last section includes comments and perspectives for further research.

2 Collective Functions of Individual Preferences and UTA Methods

The UTA Methods of Multicriteria Disaggregation–Aggregation approach (Jacquet-Lagrèze 1982; Siskos 1980) for discrete alternative actions lead to the estimation of DMs' additive value preference model described in the following formulae:

$$U(g) = \sum_{i=1}^{n} p_i u_i (g_i), \quad u(g_{i*}) = 0, u\left(g_i^*\right) = 1, \text{for } i = 1, 2, .., n$$

$$\sum_{i=1}^{n} p_i = 1, \qquad p_i \geq 0, \qquad \text{for } i = 1, 2, .., n$$

where $g = (g_1, g_2, \ldots, g_n)$ is the evaluation vector of an alternative action on the n criteria, g_{i*} and g_i^* are the least and most preferable levels of the criterion g_i

respectively and $u_i(g_i)$, p_i are the value function and the relative weight of the i-th criterion.

The above described additive value model is estimated through a set of interactive steps functioned in a waterfall forms, where the DM is asked to express his/her global preferences by rank—ordering the actions of a limited reference set of the alternative actions evaluated into a consistent family of criteria (Roy 1985). Then the additive value model is assessed by solving the following linear programmes.

$$minF, F = \left(\sum_{\iota=1}^{\kappa} \left(\sigma^{+}(a_i) - \sigma^{-}(a_i)\right)\right)$$

s.t.

$$\sum_{i=1}^{n} p_i u_i\left(g_i\left(a_m\right)\right) + \sigma^{+}\left(a_m\right) - \sigma^{-}\left(a_m\right) - \sum\nolimits_{i=1}^{n} p_i u_i\left[g_i\left(a_{m+1}\right)\right] + \sigma^{+}\left(a_m + 1\right)$$
$$- \sigma^{-}\left(a_{m+1}\right) \geq \delta \; if a_m P a_{m+1}$$

or

$$\sum\nolimits_{i=1}^{n} p_i u_i\left[g_i\left(a_m\right)\right] + \sigma^{+}\left(a_m\right) - \sigma^{-}\left(a_m\right) - \sum\nolimits_{i=1}^{n} p_i u_i\left[g_i\left(a_{m+1}\right)\right]$$
$$+ \sigma^{+}\left(a_m + 1\right) - \sigma^{-}\left(a_{m+1}\right) = \delta \; if a_m I a_{m+1}$$
$$for\ m = 1, 2, .., n$$

$$\sum_{i=1}^{n} p_i = 1$$

$$p_i \geq 0, i = 1, 2, .., n$$

$$\sigma^{+}\left(a_j\right) \geq 0, \sigma^{-}\left(a_j\right) \geq 0, j = 1, 2, .., k$$

where δ is a small positive number; $g_i(a_m)$ the evaluation of the a_m action on the i-th criterion and $u_i(g_i(a_m))]$ the corresponding marginal value; and $\sigma^{+}(a_m)$, $\sigma^{-}(a_m)$ *the over(under)estimation errors concerning the m-th of the k actions, sorted in the ranking or*der.

The expression of DMs individual global preferences into the reference set is crucial for the implementation of UTA methods especially in cases of collaborative decision making. This characteristic is exploited by the proposed methodological frame and the system RACES developed to support the proposed methodological frame. The whole proposed process includes two alternative paths.

2.1 A Priori Aggregation of Individual Rankings

In the first path, we use a voting collective function coming from TCE in order to estimate a global ranking of the alternative actions by the individual ones and then we are moving forward to the assessment of a collective additive value model using the linear programming techniques presented above. The need of such voting collective functions triggers a lot of researchers more than two centuries ago. The pioneers Marquise De Condorcet (1785) and Borda (1781) described the first collective voting techniques, so as to support decision making in a more democratic and social way. Later, TCE was presented (Fishburn 1972; Truchon and Gordon 2009; Hwang and Lin 1988; Bargagliotti 2009; Fishburn and Brams 1981; Brams and Fishburn 2002), which includes methodological approaches aiming to provide ranking of alternative decisions as close as possible to the individual rankings. The most known methods for aggregating individual voting to collective ones are: (a) Dodgson (Black 1958), which proposed an approach which provides a ranking of the alternative actions based on the analysis of the changes to be done so as every alternative action to have preference majority on all the others. (b) The pair-wise comparison of the alternatives preference majority was used by Fishburn (1970) for the estimation of a collective ranking of the alternatives. (c) Kenemy and Snell (1972) studied the disagreement or dissimilarity between the consensus ranking and DMs' preferences and proposed a collective function. (d) One more significant work was done by Cook and Seiford (1978) who presented a techniques concluding to a collective ranking having the minimum summation of the absolute distances from all the individual rankings. Finally, Hwang and Lin (1988) presented a technique based on pair-wise comparison of the alternatives using the AHP (Saaty 1980) form of elicitation preferences and eigenvector.

A Representative set of collective voting techniques are presenting in the following:

Let be:

- n, the number of alternative actions and m the number of decision makers.
- a_j, j ϵ {1, . . . ,n} the set of alternative actions.
- V_{ij} the ranking of i-th DM on alternative action a_j (Ranking can also be assessed through P (preference) and I (indifference) structures, by expressing from the DM for every couple of alternatives (a_k, a_l) one of the following three case: a_k P a_l, a_k I a_l and a_l P a_k. This can be achieved in cases where the union of preference and indifference results a complete pre-order).
- p_i the weight of the i-th Decision Maker in cases where there is no equivalence among the DMs ($\Sigma p_i = 1$).

(a) **Borda Function (*Fb*)**

Borda function is based on the summation of the ranking of every alternative action,

$$Fb_i = \sum_{k=}^{m} V_{ki}$$

The total ranking is estimated by sorting in ascending form the alternative actions by Fb_i.

(b) **Condorcet Function** is described by the following**:**

$Fc_{jl} = \#(j, a_j\ P\ a_l\ and\ j \neq l)$ (Fc_{jl} represent the number of DMs who ranked a_j in better position than a_l.) or $Fc_{jl} = \Sigma\ (p_{j,})$, *where* $a_j\ P\ a_l$ *and* $j \neq l$, in case of weighted DMs.

$Fc(a_j) = min(Fc_{jl},\ k \neq l)$, representing the minimum number of DMs who ranked a_j in a better position for each of all the others.

The total ranking is assessed by sorting $Fc(a_j)$ in descending order.

(c) **Cook and Seiford**

- Calculation of the distances d_{jr} (absolute distance of Action a_j from position r).
  $$d_{jr} = \sum_{i=1}^{m} \left|V_{ij} - r\right|,\ j, r = 1..n \text{ or } d_{jr} = \sum_{i=1}^{m} p_i \left|V_{ij} - r\right|,\ j, r = 1 \ldots n$$
  for weighted DMs.
- Construction of the matrix $D = [d_{jr}]$.
- Solve the assignment problem, so as to minimize the summation of distances $\Sigma d_{jr.}$

(d) **Eigenvector Function**

This technique is based on the estimation of a vector of priorities and the following steps take place:

- Calculation of the indices $g_{kj} = \frac{w_{kj}}{w_{jk}}$, where $w_{kj} = \#(k, a_k P a_j)$, $k, j = 1 \ldots n$ or $w_{kj} = \sum_{i=1}^{n} p_i, a_k P a_j$ for the case of weighted DMs and represents the number of DMs who $a_k P a_j$. The matrix G = [gkj], k,j∈{1 . . . m} is reciprocal with positive elements.
- Calculation of the largest eigenvalue of the matrix G.
- Estimation of the eigenvector (W1, W2, . . . , Wn) of the largest eigenvalue.
- The eigenvector represents the priorities (importance) of the relative alternative actions.
- Sorting alternative actions by its priorities values in descending form.

(e) **Dodgson**

The following steps take place:

- Calculation of the indices G = [gkj], k,j∈{1 . . . m} with the same way as they are calculated in the eigenvector function technique.
- For every alternative action we calculate
  $$FD_j = \sum_{l=1}^{n} \frac{w_{jl} - w_{lj}}{2}, \forall l \in \{1 \ldots n\} \wedge w_{jl} < w_{lj}$$
  The alternative actions are ranked in an ascending form using the function FD_j.

2.2 A Posteriori Aggregation of Individual Preference Models

The second one is focused on the assessment of the individual additive value models of all the member of the DMs' group. Following the aggregation of the assessed models to a total one (mean or weighted mean) is taking place (a posteriori aggregation of individual preferences). Actually, the a posteriori aggregation of individual preference models approach provides the capability to estimate the individual preference models of all the stakeholders and then to aggregate them to a common additive value model. The analysis of every estimated individual additive value model in contrast to the collective one supports the need to analyse and support the revision or update of the preference structure of every individual, before moving to the aggregation of the collective one. A set of interactive feedbacks, concerning the review of the individual models can be implemented in a process aiming to improve the consensus.

The feedbacks of UTA methods function with two alternative and complementary ways. First, the estimated individual preference additive value models can be utilised in order to support every stakeholder to uncover his/her preference structures and to move to a reconsideration or refining of his/her preference model using the available feedbacks of the UTA methods. The other way concerns the feedbacks which are a result of the comparative analysis of the individual preference models and the collective one coming by the collective preference model. Divergences and different aspects are determined as well as points of consensus and key factors which can lead to a better convergence among the DMs. Feedbacks of the individual can also be considered and used in order to achieve a collaborative decision or to handle the negotiation process.

The level of consistency among the individual preferences and the estimated collective ranking is achieved by kendall's τ, (Kendall 1970), which ιs calculating by the following formulae:

Let $R_1, R_2, R_3, \ldots, Rn$ and $R'_1, R'_2, \ldots, R'_n$ are two ranking of the alternative actions $(a_1, a_2, a_3, \ldots, a_n)$ respectively and $(R_1, R'_1), (R_2, R'_2), \ldots, (R_n, R'_n)$ the $(½)n(n-1)$ pairs of the rankings.

Any pair of rankings (R_i, R'_1) and (R_j, R'_j) is *concordant* if $R_i \geq R_j$ and $R'_i \geq R'_j$ or $R_i \leq R_j$ and $R'_i \leq R'_j$.

Any pair of Rankings (R_i, R'_1) and (R_j, R'_j) is *discordant*, if $R_i > R_j$ and $R'_i < R'_j$ or if $R_i < R_j$ and $R'_i > R'_j$.

The Kendall's τ coefficient is defined as:

$$\tau = \frac{\text{Number of Concordant pairs–Number of Discordant Pairs}}{1/2\text{n}\,(\text{n} - 1)}$$

The value of τ varies into the range [−1, 1], where for τ = 1, the two ranking are totally identical (perfect agreement) and for τ = −1, the two rankings are totally different (perfect disagreement).

3 Methodological Approach and Illustration Example

For the purposes of the illustration of the methodological approach a case study is used where seven alternative actions are evaluated into six criteria. Also, eight DMs are involved with different importance on the decision making. Tables 1 and 2 presents the evaluation of the alternative actions (Alt1, Alt2, ..., Alt7) on the criteria (Crit.1, Crit.2, ..., Crit.6) including the preference monotonicity of the criteria. The process of the use of UTA methods for collaborative decision making is graphically presented in Fig. 1 (see also Siskos et al. 1993, 1998 for details about the MINORA and the MIIDAS systems). At the first steps the typical processes for multicriiteria decision aid approaches Criteria Modelling and the evaluation of the alternative actions on the criteria take places.

Then, a small subset of the alternative actions is selected, representative of the total set and familiar to the DMs so as to be able to express their preferences. For the needs of the presentation of the features of the proposed methodological approach in the illustration example the reference set is identical to the total set of alternative actions. The small group of DMs is asked to rank-order individually the alternative actions of the reference set expressing their global preferences. Table 2 includes the individual ranking of the DMs as well as their weight into the decision making.

Table 1 Illustration example

	Criteria					
Alternative actions	Crit. 1 (max)	Crit. 2 (min)	Crit. 3 (max)	Crit. 4 (max)	Crit. 5 (min)	Crit. 6 (max)
Alt1	1.23	2.34	3	4	3.4	2
Alt2	2.34	1.28	3	4	2	4.22
Alt3	2.67	4.11	4	3	4	5
Alt4	3	3.11	1	3	4	2
Alt5	3.11	2.98	4	2	3	3
Alt6	4.19	3.76	5	1	1	4
Alt7	3.55	1.69	2	5	5	1

Criteria and alternative actions evaluated on the criteria

Table 2 Illustration example: weights of the DMs and individual pre-rankings

	DM 1	DM 2	DM 3	DM 4	DM 5	DM 6	DM 7	DM 8
Weights	*0.25*	*0.05*	*0.05*	*0.05*	*0.05*	*0.10*	*0.25*	*0.20*
Alt1	5	4	2	2	6	5	5	3
Alt2	1	2	3	1	3	2	2	1
Alt3	3	1	2	4	4	3	3	3
Alt4	4	4	4	5	5	4	6	6
Alt5	6	5	5	6	6	4	5	4
Alt6	2	6	1	3	2	3	4	2
Alt7	7	3	6	4	1	1	1	5

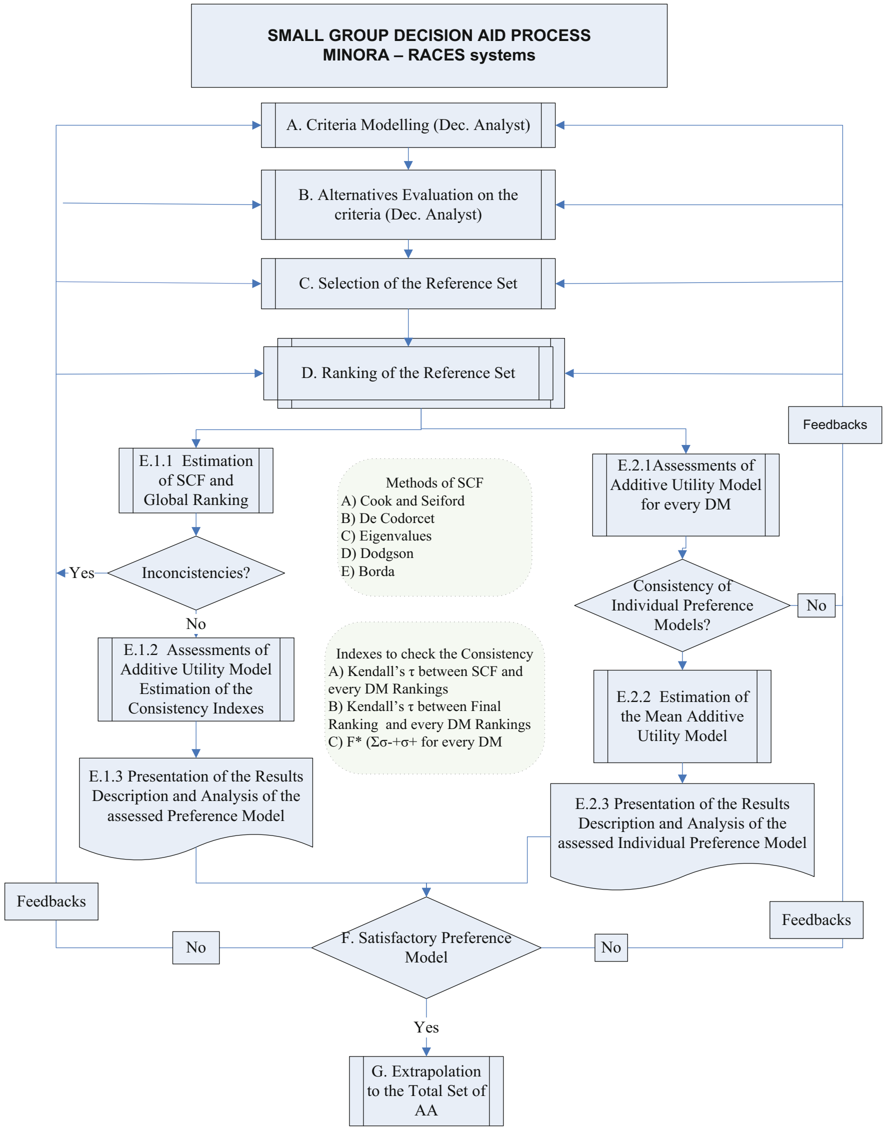


Fig. 1 Process flow of the collaborative approach of UTA methods for small groups

The utilisation of the UTA method can be implemented with two alternative paths separately or in a successive form.

3.1 A Priori Aggregation of the Individual Preferences

In this path we use one of the collective functions mentioned above for the estimation of a collective ranking. An easy way to select the most appropriate collective functions is to examine the Kendall's τ indexes. Kendall's τ mean and standard deviation can be a useful guide for the selection of the most representative collective total ranking. In our illustration example we select the eigenvector collective function. The estimated eigenvector and the collective ranking of the alternative actions is includes into the Tables 3 and 4.

The above estimated collective ranking is utilized for the assessment of the additive value model. The assessed additive value model (Figs. 2 and 3) can be considered consistent since the derived by the additive value model ranking is the same with the collective pre-ranking. The analysis of the estimated collective preference model can lead to significant outcomes as far as the collective preferences is concerned. For example it is crucial to examine the weights of the criteria, the consistency of the preference models (Over-under-estimation errors) the marginal value functions etc. These can trigger a new round of dialogues with the DMs in order to uncover agreements or differences among them and to conclude to the acceptance or not of the estimated collective additive value model.

Table 3 Illustration example: collective ranking (EigenVector Technique)

No	Alternative action	EigenVector	Ranking
1	Alt 2	8.5760	1
2	Alt 3	2.6011	2
3	Alt 6	2.4311	3
4	Alt 7	1.4051	4
5	Alt 1	0.6329	5
6	Alt 5	0.237	6
7	Alt 4	0.1391	7

Table 4 Estimated Weights of the Criteria after the post optimality analysis

	Weights		
Criterion	Min	Max	Barycenter
Crit1	0	0.4833	0.8351
Crit2	0	0.6759	0.1145
Crit3	0	0.93856	0.23893
Crit4	0	0.49444	0.21431
Crit5	0	0.47778	0.17067
Crit6	0	0.95556	0.17807

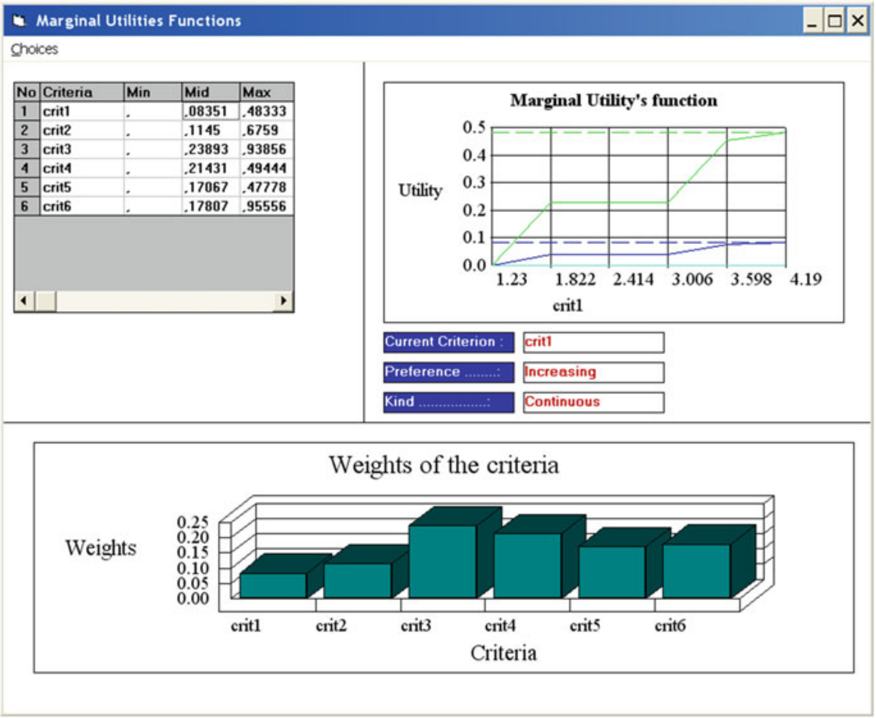


Fig. 2 Estimated weights of criteria—a priori aggregation of individual preferences

3.2 A Posteriori Collective Preferences Aggregation

A posteriori Collective Preference aggregation path functions with the opposite way. The eight individual preference models are estimated for every one of the participants. Then, the aggregation of the individual models to a collective one take places. Figures 4 present the complex graphs of the individual marginal value functions and the mean (weighted by the DMs' weights) ones estimated by the aggregation approach. Also, in Fig. 5 the collective additive value model is presented. The alternative actions are ranked according to the mean Value Model. The mean Kendall's τ of the estimated ranking with the individual ones is 0.55 with a standard deviation of 0.134244. In this case of the a posteriori aggregation approach of the individual preferences models it is worth to be examined: (a) the individual preference additive value models. (b) The differences among the individual preference models as well as the convergences or consensus between the individuals and the collective ones. For example in our case it is worth to examine the case of DM3 which is enough differentiate form the other DMs. The information coming from this analysis can support on the one hand the improving

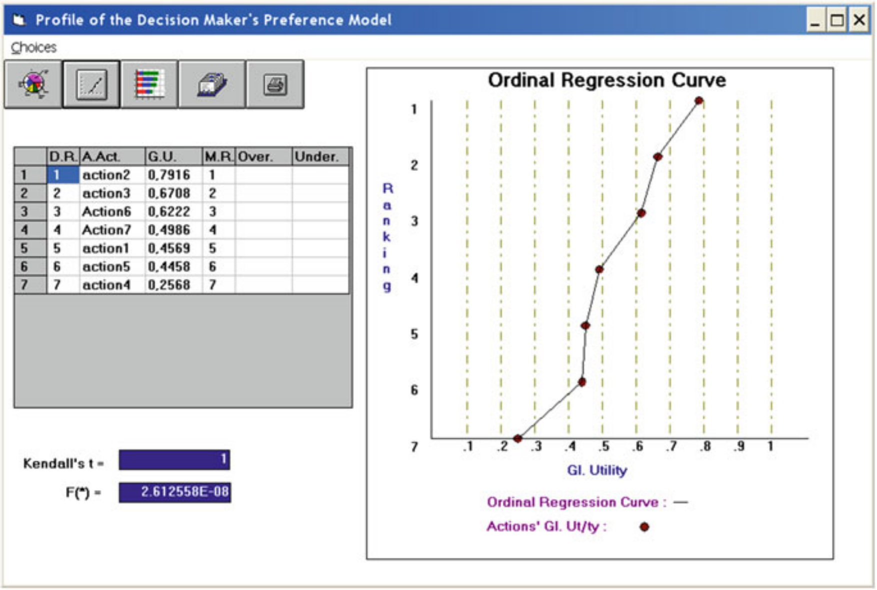
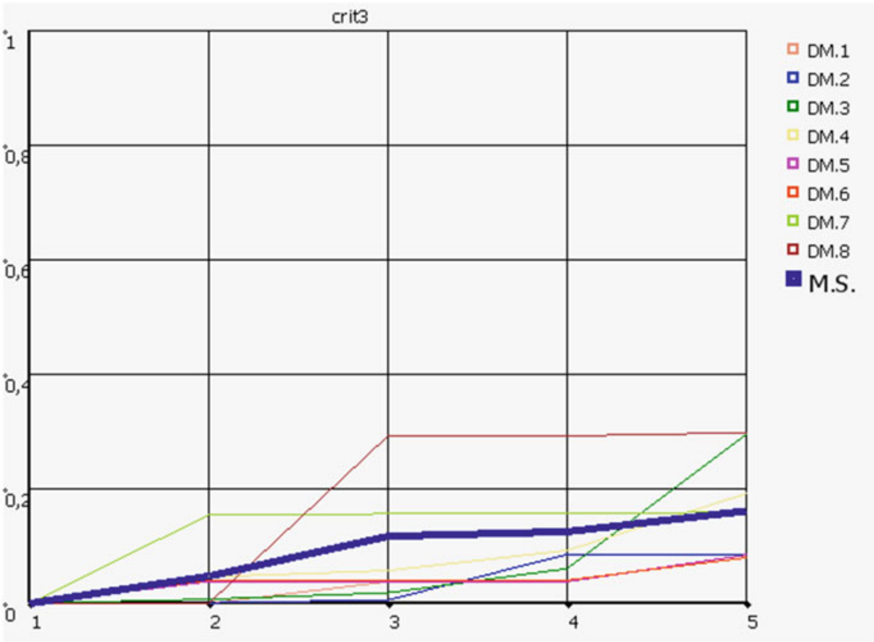


Fig. 3 A priori aggregation of individuals preferences. Global Values, Kendall's t, F(*) and ordinal regression curve

of the knowledge concerning the preference structures and can lead to feedbacks for a better consensus.

4 Conclusions and Perspectives

The chapter presents a general frame for the utilisation of UTA methods in collaborative decision making problems for small group of DMs. The main feature is the capability provided to analyse the individual preferences in an interactive way with all the participating stakeholders and to enrich the knowledge about the problem status. The presented methodological approaches provided new directions to the handling of small group decision making problems while allow to aggregate and analyse individual preferences with a flexible way in a process aiming to uncover the preference structures interactively. This interactive nature of UTA methods provides advantages to handle group decision problems with high level of discrepancies among the participating stakeholders and to exploit the opportunities to bring together the participants to the extent it can be done.



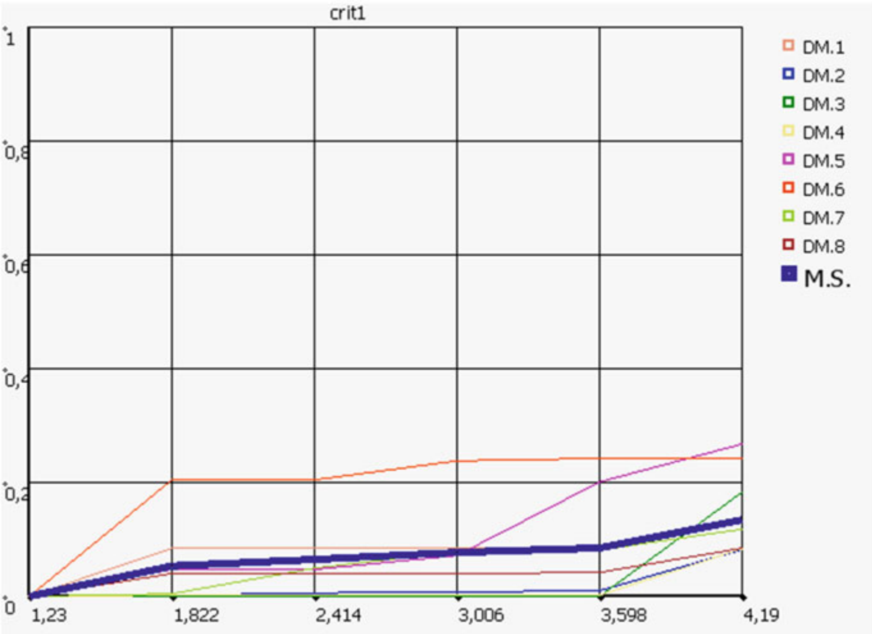
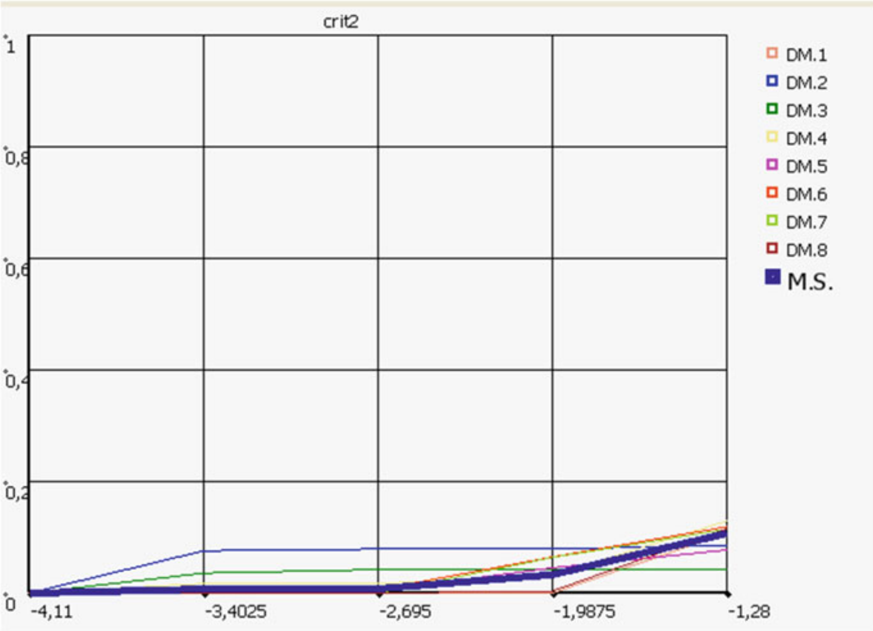


Fig. 4 Marginal value functions (individual and collective)



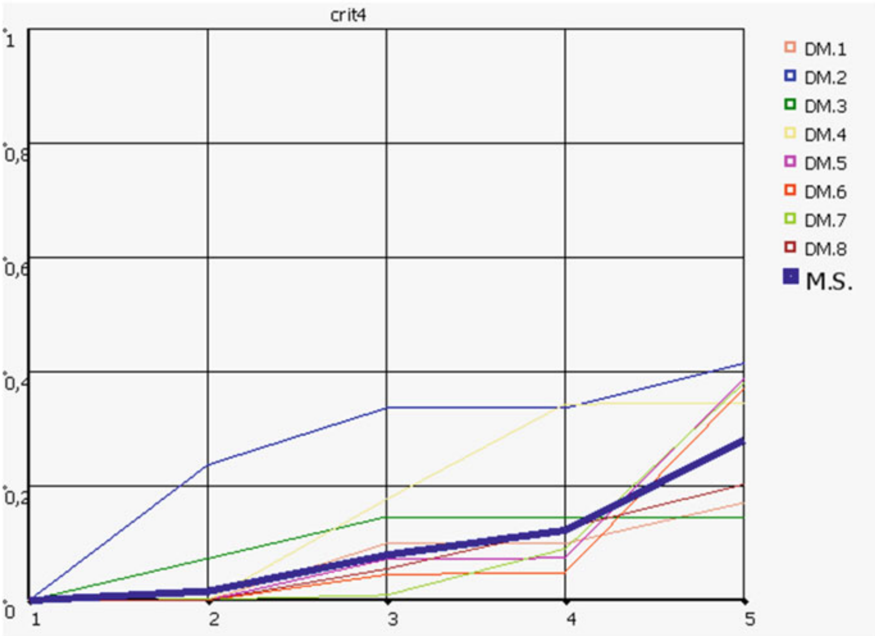
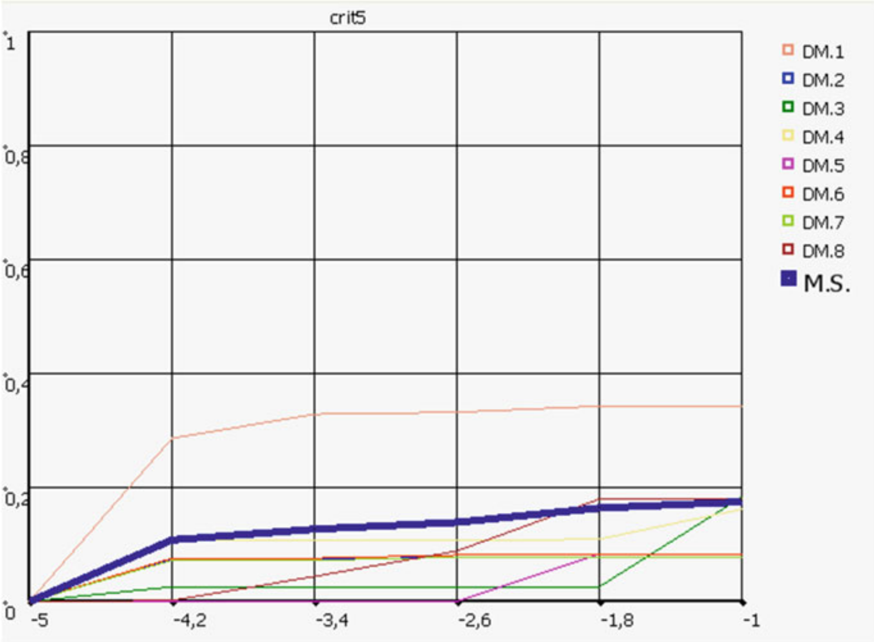


Fig. 4 (continued)



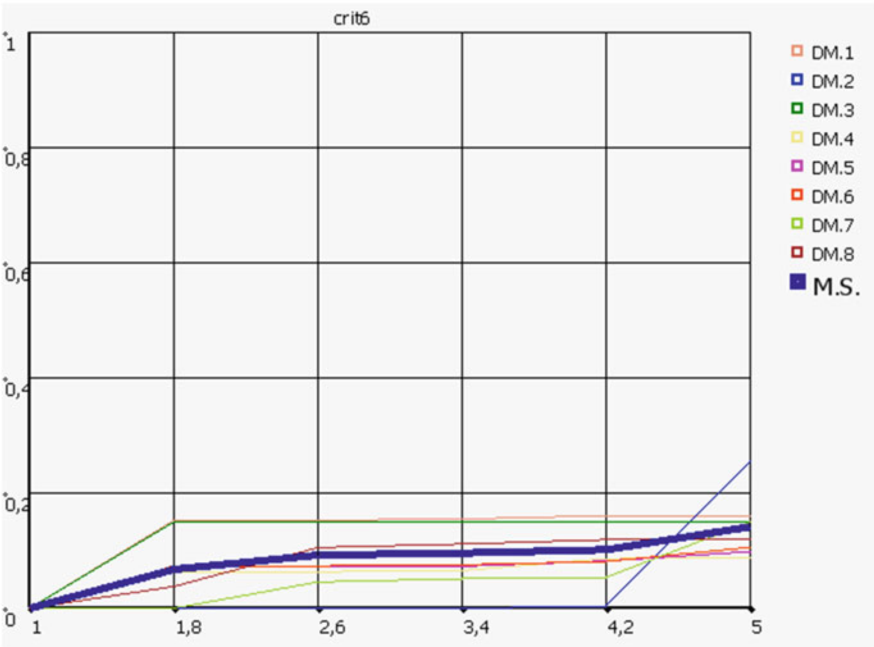


Fig. 4 (continued)

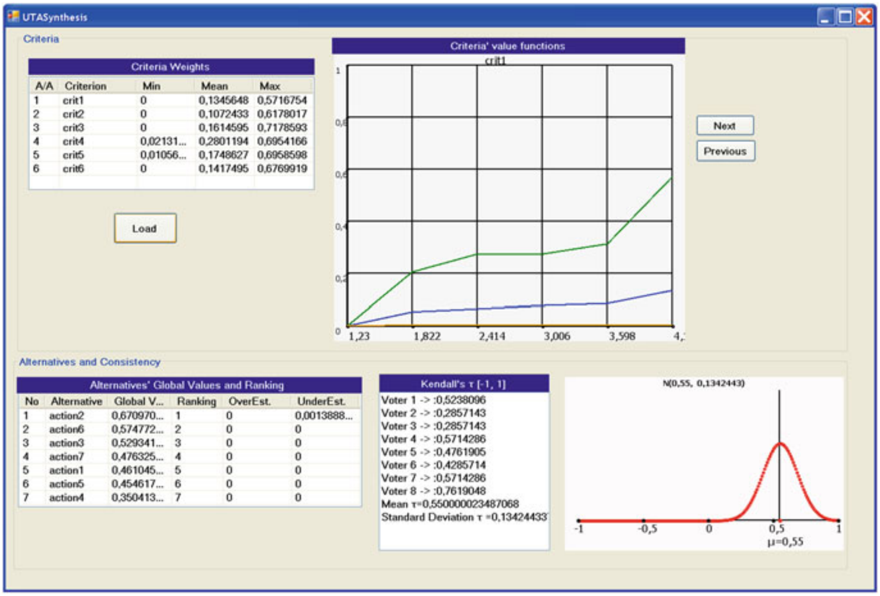


Fig. 5 Alternatives, Global Values and Kendall/s τ among voters and collective ranking

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Disaggregation Approaches for Multicriteria Classification: An Overview

Michalis Doumpos and Constantin Zopounidis

Abstract Multicriteria classification problems have been an very active area of research in MCDA for more than two decades. Such problems refer to the assignment of a given set of alternatives into predefined categories/classes. Preference disaggregation approaches provide a valuable basis for facilitating the construction of multicriteria classification models using a data-driven process. In this chapter, we provide an overview of the preference disaggregation techniques in multicriteria classification, covering the existing types of decision models, the approaches used for model inference, as well as robustness issues.

1 Introduction

Different types of decision problems can be identified depending on the characteristics of the problems that are of interest. For instance, in operations research, management science, and decision analysis, we typically distinguish between static and dynamic problems, deterministic and stochastic, problems involving a single decision maker versus group decision problems, etc.

In the field of multicriteria decision aiding (MCDA), the most common categorization of decision problems focuses on how the outcomes of the decision aiding process are formulated, i.e., choice, ranking, sorting, and description problematics. While choice and ranking problems are the ones most commonly considered

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in operations research/management science and MCDA, sorting or multicriteria classification has also attracted a lot of attention.

In multicriteria classification problems, a set of alternatives must be assigned to predefined performance categories, which are sorted from the category of best alternatives to the category consistent of the worst alternatives. Such problems arise in many domains in business and engineering. For instance, financial institutions use risk ratings to assess the creditworthiness of firms and individuals, customers provide satisfaction/quality ratings for products and services, the skills of personnel are evaluated by defining predefined skills groups, products and plants are rated by their energy efficiency and consumption, etc.

The wide range of applications of multicriteria classification problems has made them a very popular and active topic in the field of MCDA. Established decision models, originally developed for choice and ranking problems, have been adapted to support decisions in a classification setting and new modeling approaches have been introduced.

The aim of this chapter is to provide an overview of the advances in this area, adopting a preference disaggregation perspective. Preference disaggregation is involved with model development techniques that follow a regression-like scheme. Instead of asking the decision maker(s) (DM) to explicitly set the parameters of a decision model (e.g., the importance of the decision criteria), preference disaggregation follows a more flexible process, allowing the DM to provide the required information in an implicit manner through decision examples. Inferring the decision model from such examples, can greatly facilitate the decision aiding process. This framework has been widely used for multicriteria classification problems. In this chapter we present different disaggregation approaches and models for classification problems, and analyze some important research trends and developments in this area.

The rest of the chapter is organized as follows. Section 2 introduces the context of multicriteria classification problems, their characteristics, and the main types of MCDA classification decision models. Section 3 is devoted to the presentation of different approaches for constructing multicriteria classification models from data, in the context of the preference disaggregation paradigm, whereas Sect. 4 discusses issues related to the analysis of the robustness of the model construction approaches and the resulting models. Finally, Sect. 5 concludes the chapter and outlines some future research directions and challenges.

2 The Framework of Multicriteria Classification Problems

2.1 General Setting

Multicriteria classification can be considered in the general setting of discrete evaluation problems. Such problems involve the evaluation of the performance of a finite set X of choices (decision alternatives), through the consideration of n performance attributes (decision criteria). Thus, the basic piece of available information is a data matrix $\mathbf{X}$, with elements x_{ik} representing the given data for alternative i on criterion k. Each alternative can be represented by the vector $\mathbf{x}_i = (x_{i1}, x_{i2}, \ldots x_{in})$.

The data can be numerical (i.e., quantitative) measured on cardinal scales or qualitative expressed through ordinal scales. For the purposes of the presentation in this chapter, we shall assume that all criteria are expressed in maximization form, which implies that if $x_{ik} \geq x_{jk}$, then alternative i is at least as good as alternative j on criterion k. For instance, if two investment projects i and j differ only in terms of their return, then the project with the highest return is preferred.

The evaluation outcome in multicriteria classification problems involves the assignment of the alternatives to a set of q predefined categories (classes), which will be denoted by $C_1, C_2, \ldots, C_q$. The alternatives in each category have similar performance patterns and the definition of the categories is based on an ordinal setting. Thus, the categories do not simply provide a nominal (categorical) description of the alternatives' characteristics, as often assumed in a statistical and machine learning/data mining context. Instead, they represent an ordered performance rating. Without loss of generality, we shall assume that category C_1 includes the best alternatives and C_q is the category with the low performance alternatives. For instance, for a personnel evaluation system, C_1 will include the highly skilled and best performing employees, whereas employees in category C_q are those with the lowest skills and working performance.

It should be noted however, that alternatives belonging in the same category cannot be assumed to be all equally good. Thus, a category in a multicriteria classification problem does not represent an indifference class as in standard ranking problems, often considered in MCDA. In that sense, the indifference relation $\mathbf{x}_i \sim \mathbf{x}_j$, which indicates that the DM is indifferent between alternatives i and j, does not hold, in general.

As an example, consider the six investment projects (denoted by $\mathbf{x}_1, \ldots, \mathbf{x}_6$) shown in Fig. 1, The projects are described by their risk (a minimization criterion)

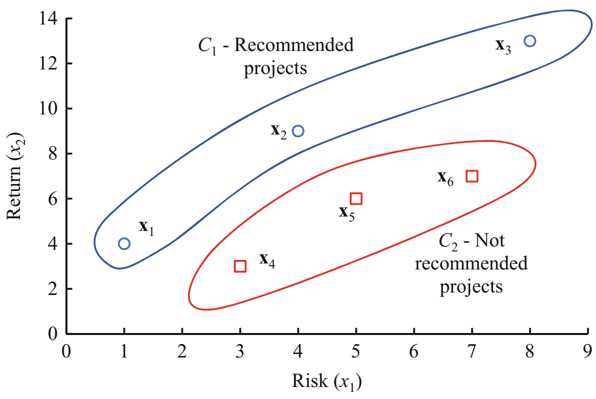

Fig. 1 Classification of investment project by their risk and return

denoted by x_1 and expected return (criterion x_2). Two categories are defined, namely the recommended projects (category C_1) and the not recommended ones (category C_2). It can be observed that category C_1 includes projects that have high return compared to their risk (their return/risk ratio exceeds 1.5), whereas category C_2 involves projects with low risk-adjusted returns (return/risk lower than 1.5). This classification does not imply that, for instance, projects 1 and 3 are equally good. In fact, a risk-averse DM would prefer project 1 against project 3. However, both projects are classified as efficient, implying that they are better options compared to the inefficient projects.

The categories in multicriteria classification problems are fixed and independent of the alternatives being evaluated. Thus, the evaluation result is expressed in absolute terms. For instance, a bank evaluates loan applications and accepts only those meeting some predefined (fixed) conditions. The acceptance/rejection decision rule does not depend on the loan applications under consideration; what matters is whether an applicant's creditworthiness meets the requirements imposed by the bank, but it is irrelevant whether the applicant is more creditworthy than others. Of course, in the course of time, as the decision environment changes, the decision rule must be adapted to accommodate various economic, business, technical and regulatory requirements. In the above example, during economic/banking crises the evaluation of loan applications is more stringent compared to times of economic growth.

In some cases, the categories may also be defined in relative terms. For instance, in the above example, the categories could have been defined in a different manner, such that category C_1 involves of efficient projects and category C_2 the inefficient ones. A project i is considered as being efficient if there is no other project j, such that:

- the return of project j is at least as high as the return of project i, but its risk is lower, i.e., there is no project j with $x_{j1} < x_{i1}$ and $x_{j2} \geq x_{i2}$, or
- the risk of project j is at least as low as the risk of project i, but its return is higher, i.e., there is no project j with $x_{j1} \leq x_{i1}$ and $x_{j2} > x_{j2}$.

This is a relative definition of the two categories, because it implicitly depends on the projects under consideration. For instance, a new investment project 7 with risk $x_{71} = 3$ and return $x_{72} = 10$, would be classified as efficient, because none of the existing projects matches its risk-return profile. However, project 2 has risk $x_{21} = 4$ and $x_{22} = 9$, which shows that it is dominated by project 7. Thus, the addition of the new project 7 leads to a different classification for project 2, even through there is no change in its risk-return profile. Under this scenario, this problem does not have the characteristics of a multicriteria classification problem, unless the distinction between efficient/inefficient project is based on a fixed rule. For instance, project 7 could be considered as efficient compared to the reference projects 4–6, without this affecting the characterization of project 2, which can also be considered as efficient when compared to the reference projects 4–6. In this case, projects 1–3 are considered as typical examples of efficient projects and projects 4–6 are typical inefficient projects, without making any reference to an exact definition of efficiency.

According to the above discussion, it is evident that multicriteria classification has different characteristics compared to the ranking problematic. Deriving a ranking of the alternatives and then grouping the alternatives by their ranks (e.g., assign the top 10% to C_1, the next 10% to C_2, etc.), does not provide an answer in a classification setting, where the categories are defined a priori. Therefore, typical MCDA models for choice and ranking problems are not directly applicable in a classification setting. On the one hand, classification models require the definition of a decision rule to assign the alternatives to the categories. On the other hand, the model building process must take into account the nature of the classification problematic.

2.2 Decision Models

Evaluation problems in multicriteria classification can be modeled through a variety of different forms of decision models, which are available in the field of MCDA. Formally, a multicriteria classification model can be considered as a mapping $F(\mathbf{x}, \beta) \to \{C_1, \ldots, C_q\}$ that aggregates the available information about the criteria and provides recommendations about the classification of the alternatives. The model is explicitly defined by a set of parameters β, which may relate to the relative importance of the criteria or other information about the aggregation process.

In the following subsections, we briefly describe the two most commonly used types of decision models for classification problems, namely value functions and outranking models. However, it is worth noting that other decision modeling forms are also applicable and deserve mention. For instance, decision rule models have been successfully used for multicriteria classification purposes, originally deriving ideas from the fields of data mining and machine learning. Rough sets in the most widely used approach of this type in MCDA. A comprehensive presentation of this approach can be found in the work of Greco et al. (2001). Fuzzy-based models is another popular approach. For instance, applications of models based on Choquet and Sugeno integrals for multicriteria classification, can be found in works such as those of Grabisch and Nicolas (1994) and Roubens (2002), whereas Grabisch and Labreuche (2008) provide an overview of such approaches.

2.2.1 Value Function Models

Multiattribute utility/value theory (MAUT/MAVT) has played a central role in the field of MCDA since its axiomatization by von Neumann and Morgenstern (1944). While the term "utility theory" is usually used in the context of decisions under uncertainty, "value theory" is used for deterministic cases. Given that in this chapter we do no address problems under uncertainty, we shall only refer to value models.

MAVT models are expressed in functional form, aggregating multiple criteria into a composite indicator. Depending on the criteria independence conditions, different forms of value functions can be defined. The simplest and most widely used form is the additive value function, which implies that the criteria are mutually preferential independent (Keeney and Raiffa 1993):

$$V(\mathbf{x}) = \sum_{k=1}^{n} w_k v_k(x_k) \tag{1}$$

where $w_k \geq 0$ is the weighting constant for criterion k and $v_k(x_k)$ is the associated marginal value function. This is a compensatory model, with the weights representing the trade-offs between the criteria. The marginal value functions decompose the overall performance score into partial scores at the criteria level; they are non-decreasing for criteria in maximization form (e.g., profit related criteria) and non-increasing for minimization criteria (e.g., risk criteria).

The value function is usually scaled in [0, 1], by imposing the condition $w_1 + w_2 + \cdots + w_n = 1$ and scaling the marginal values functions such that the worst performance corresponds to 0 and the best performance to 1. Thus, alternatives with higher global value (i.e., close to 1) are the best ones.

The additive model (1) can be extended to more general forms, by weakening the preferential independence assumptions. For instance, a multiplicative model can be expressed as follows:

$$1 + \lambda V(\mathbf{x}) = \prod_{k=1}^{n} [1 + \lambda w_k v_k(x_k)] \tag{2}$$

where $\lambda > -1$ is a scaling constant, such that $1 + \lambda = \prod_{k=1}^{n} [1 + \lambda w_k]$. If $w_1 + w_2 + \cdots + w_n = 1$, then $\lambda = 0$ and the multiplicative function reduces to the additive one.

Under the more general setting, the multilinear value function can be considered:

$$\begin{aligned} V(\mathbf{x}) = &\sum_{k=1}^{n} w_k v_k(x_k) + \sum_{k=1}^{n} \sum_{\ell>k} w_{k\ell} v_k(x_k) v_\ell(x_\ell) \\ &+ \sum_{k=1}^{K} \sum_{\ell>k} \sum_{z>\ell} w_{k\ell z} v_k(x_k) v_\ell(x_\ell) v_z(x_z) + \ldots \\ &+ w_{123\ldots} v_1(x_1) v_2(x_2) v_3(x_3) \cdots \end{aligned} \tag{3}$$

This general form includes the additive and multiplicative models as special cases. However, the additional complexity of the multilinear model makes it difficult to use, mainly in cases where many criteria are involved. Nevertheless, Keeney and Raiffa (1993) note that even when their underlying assumptions do not hold, additive and multiplicative are reasonable approximations to the general case.

The simplest way to use a value function model for multicriteria classification purposes, is through the following threshold-based decision rule:

$$t_\ell < V(\mathbf{x}_i) < t_{\ell-1} \Leftrightarrow \mathbf{x}_i \in C_\ell \tag{4}$$

where $t_0 = 1 > t_1 > t_2 > \cdots > t_{q-1} > t_q = 0$ are thresholds that distinguish the classes. This approach is adopted in the UTADIS method and its variants (Doumpos and Zopounidis 2002).

Alternative decision rules can also be considered. For instance, Greco et al. (2010) considered an example-based rule, under which an alternative i is classified in category C_ℓ if:

1. $V(\mathbf{x}_i) < V(\mathbf{x}_j)$ for every alternative j from categories $C_1, \ldots, C_{\ell-1}$, and
2. $V(\mathbf{x}_i) > V(\mathbf{x}_j)$ for every alternative j from categories $C_{\ell+1}, \ldots, C_q$.

Obviously, the threshold and example-based assignments lead to identical results under the same value function model.

A more complex approach was proposed by Zopounidis and Doumpos (2000) through the MHDIS method (Multi-group Hierarchical DIScrimination), which is based on a hierarchical discrimination (classification) scheme. In MHDIS, a problem with q categories, is decomposed into $q-1$ binary classification tasks, each described through a pair of value functions. More specifically, starting from the category of best performing alternatives (C_1), a pair of value functions V_1 and $V_{\neg 1}$ is used to identify the alternatives that should be assigned to category C_1, as follows:

$$\text{if } V_1(\mathbf{x}_i) > V_{\neg 1}(\mathbf{x}_i), \text{ then alternative } i \text{ is assigned to } C_1$$

For the alternatives not assigned to C_1, a second pair of value functions V_2 and $V_{\neg 2}$ is used to identify those that should be assigned to category C_2:

$$\text{if } V_2(\mathbf{x}_i) > V_{\neg 2}(\mathbf{x}_i), \text{ then alternative } i \text{ is assigned to } C_2$$

The classification process is continued in the same manner for the remaining categories. In the lowest level of this sequential/hierarchical process, the alternatives that remain unclassified are distinguished between those that should be assigned to category C_{q-1} and the ones of category C_q, using the pair of value functions V_{q-1} and $V_{\neg(q-1)}$:

$$\begin{aligned} &\text{if } V_{q-1}(\mathbf{x}_i) > V_{\neg(q-1)}(\mathbf{x}_i), \text{ then alternative } i \text{ is assigned to } C_q, \\ &\qquad \text{otherwise alternative } i \text{ is assigned to } C_q \end{aligned}$$

2.2.2 Outranking Relations

Outranking models in MCDA were first introduced by Roy (1968) with the ELECTRE methods (ELimination Et Choix Traduisant la REalité). Such models have a relational form, with an outranking relation S defined between a pair of alternatives (i, j), such that

$$\mathbf{x}_i \, S \, \mathbf{x}_j \Rightarrow \text{alternative } i \text{ is at least as good as alternative } j$$

Outranking methods provide an operational framework for modeling such binary relations and exploiting them for decision aiding. Overviews of ELECTRE methods and other outranking approaches can be found in Brans and De Smet (2016), Figueira et al. (2010, 2016) and Martel and Matarazzo (2016).

In the context of multicriteria classification problems, a typical outranking scheme is based on comparing the alternatives with a set of profiles $\mathbf{r}_1, \mathbf{r}_2, \ldots, \mathbf{r}_{q-1}$ representing the boundaries of the categories. Each profile $\mathbf{r}_\ell$ corresponds to a separating boundary between categories C_ℓ and $C_{\ell+1}$, defined as a vector of boundary levels for each decision criterion, i.e., $\mathbf{r}_\ell = (r_{\ell 1}, r_{\ell 2}, \ldots, r_{\ell n})$. Given the profiles, the outranking relations $\mathbf{x}_i \, S \, \mathbf{r}_\ell$ and $\mathbf{r}_\ell \, S \, \mathbf{x}_i$ are used to compare each alternative with the profiles and derive its assignment to one of the categories.

This is the framework employed in the ELECTRE TRI method. Extensions based on different specifications of the profiles have also been considered. For instance, Fernández et al. (2017) proposed the use of multiple boundary profiles, whereas the used of central profiles was explored in Almeida-Dias et al. (2010, 2012). Bouyssou and Marchant (2015) discuss the connections between theses two schemes (boundary versus central profiles).

The ELECTRE TRI uses two assignment rules based on the results of the pairwise comparisons between the alternatives and the profiles:

- Optimistic (pseudo-disjunctive) assignment: alternative i is assigned to category C_ℓ, where ℓ corresponds to the largest index such that $\mathbf{r}_{\ell-1} \, S \, \mathbf{x}_i$ and $\mathbf{x}_i \, \neg S \, \mathbf{r}_{\ell-1}$, with $\neg$ denoting the negation operation; if there is no profile that satisfies these conditions, then the alternative is assigned to category C_1.
- Pessimistic (pseudo-conjunctive) assignment: alternative i is assigned to category C_ℓ, where ℓ is the lowest index such that $\mathbf{x}_i \, S \, \mathbf{r}_\ell$ (if no profile meets this condition, then the alternative is assigned to category C_q).

The two rules define a range of assignments $[C_O, C_P]$, where C_O is the category resulting from the optimistic rule and C_P is the assignment of the pessimistic procedure. Cases where $C_O \neq C_D$ arise under incomparability conditions, i.e., when the characteristics of an alternative make it not directly comparable to some of the profiles ($\mathbf{x}_i \, \neg S \, \mathbf{r}_\ell$ and $\mathbf{r}_\ell \, \neg S \, \mathbf{x}_i$, for at least one $\ell = 1, 2, \ldots, q$).

The construction of the outranking relation S in the ELECTRE TRI model is based on a two step process, where the evidences supporting S are first analyzed (concordance) and, then, the evidence against the relation are considered (discordance). The process follows a weighted voting scheme with veto conditions (Figueira et al. 2010, 2016).

Other outranking models for multicriteria classification problems that are based on the principles of ELECTRE methods have been proposed in several works, such as Belacel et al. (2007), Fernández and Navarro (2011), Sobrie et al. (2013) and Perny (1998).

Similar approaches have also been proposed in the context of other outranking techniques, such as the PROMETHEE method, which is based on a preference relation and a flow-based scoring model that extends the principles of the Borda count. For instance, Nemery and Lamboray (2008) proposed the FlowSort method, a direct extension of PROMETHEE to classification problems, whereas Doumpos and Zopounidis (2004) proposed a similar procedure using an PROMETHEE-based model, which does not require the specification of category profiles.

3 Approaches for Inferring Multicriteria Classification Models from Decision Examples

In the framework of preference disaggregation analysis, the parameters of a decision model are inferred from a sample of m decision instances $X' = \{\mathbf{x}_i, C_i\}_{i=1}^{m}$. This sample (referred to as the reference set) may consist of decisions about alternatives considered in past situations or decisions about a set of alternatives which can be easily judged by the DM (Jacquet-Lagrèze and Siskos 2001).

Formally, the model that is most compatible with the information in the reference set, is defined by parameters $\widehat{\beta}^*$ such that:

$$\widehat{\beta}^* = \arg\min_{\widehat{\beta}\in\mathcal{A}} L[Y_{X'}, F(X', \widehat{\beta})] \tag{5}$$

where $F(X', \widehat{\beta})$ denotes the outputs of a model with parameters $\widehat{\beta}$ for the alternatives in X', $\mathcal{A}$ is the set of acceptable parameter values, and $L(\cdot)$ is a function that measures the differences between the recommendations of the model and the given assignments $Y_{X'}$ for the reference alternatives. If the solution of the above problem (5) is judged satisfactory, then the inferred parameters $\widehat{\beta}^*$ can be used to extrapolate the model to any other alternative outside the reference set.

The preference disaggregation framework for multicriteria classification problems is analyzed in the book of Doumpos and Zopounidis (2002), whereas a more recent overview discusses the connections to the statistical learning paradigm (Doumpos and Zopounidis 2011).

In the following subsections we outline the use and implementation of preference disaggregation approaches for constructing MCDA classification models.

3.1 Model Inference for Value Functions

For a value function model, problem (5) can be expressed in a mathematical programming form. In particular, the inference of a classification model (weights of the criteria, marginal value functions, and classification thresholds) from the reference examples can be expressed as the following optimization problem, which is based on the threshold-based classification rule (4):

$$\begin{aligned}
\min \quad & \sum_{\ell=1}^{q} \frac{1}{m_\ell} \sum_{\mathbf{x}_i \in C_\ell} (\sigma_i^+ + \sigma_i^-) && && (6)\\
\text{s.t.} \quad & V(\mathbf{x}_i) + \sigma_i^+ \geq t_\ell + \delta && \forall \mathbf{x}_i \in C_\ell,\ \ell = 1, \ldots, q-1 && (7)\\
& V(\mathbf{x}_i) - \sigma_i^- \leq t_\ell - \delta && \forall \mathbf{x}_i \in C_\ell,\ \ell = 2, \ldots, q && (8)\\
& t_\ell - t_{\ell+1} \geq \varepsilon && \ell = 1, \ldots, q-2 && (9)\\
& V(\mathbf{x}_*) = 0,\ \ V(\mathbf{x}^*) = 1 && && (10)\\
& V(\mathbf{x}) \geq V(\mathbf{x}') && \forall \mathbf{x} \geq \mathbf{x}' && (11)\\
& \sigma_i^+,\ \sigma_i^- \geq 0 && i = 1, \ldots, m && (12)
\end{aligned}$$

The objective function minimizes the total weighted classification error, where the weights are defined on the basis of the number of reference alternatives from each category ($m_1, \ldots, m_q$). The incorporation of weights in the objectives function provides a straightforward way to handle cases where there is considerable imbalance in the number of reference alternatives in each category, which may lead to biased results (for a more involved approach to handle this issue, see Liu et al. 2018). The error variables σ^+ and σ^- are defined through constraints (7) and (8) as the magnitude of the violations of the classification rules (4), with δ being a small positive constant used to ensure the string inequalities. Constraint (9) ensures that the class thresholds are defined in a decreasing sequence (ε is a small positive constant), whereas constraint (10) defines the scale of the value model between 0 and 1, with 0 corresponding to the performance of the least preferred alternative $\mathbf{x}_*$ and 1 corresponding to the performance of an ideal action $\mathbf{x}^*$. Finally, constraint (11) ensures that the model is non-decreasing with respect to the performance criteria (assuming all criteria are in maximization form).

For the case of an additive value function, the above optimization problems can be written in linear programming form, using a piece-wise linear modeling approach to describe the marginal values functions (for the details, see Doumpos and Zopounidis 2002 and Jacquet-Lagrèze and Siskos 1982). This is the basic formulation used in the UTADIS method (Doumpos and Zopounidis 2002).

Alternative model fitting objectives can also be defined. For instance, instead of using one error variable to describe the error for an alternative, multiple errors can be defined, each corresponding to violations of successive category thresholds. This is helpful, in multi-category problems, because it enables the distinction between small errors (an alternative from category C_ℓ is misclassified to $C_{\ell-1}$ or $C_{\ell+1}$) and larger ones (the divergence between the model's output and the actual assignment of an alternative exceeds one category).

Formally, for a reference alternative i from category C_ℓ, a series of downgrade errors $\sigma_{i\ell}^+, \sigma_{i,\ell+1}^+, \ldots, \sigma_{i,q-1}^+$ can be defined. These errors refer to violations of the thresholds $t_\ell, \ldots, t_{q-1}$. A downgrade of alternative i (as opposed to its given assignment C_ℓ) occurs when $V(\mathbf{x}_i) < t_\ell$. If the downgrade is limited to one notch (i is assigned to $C_{\ell+1}$), then $t_{\ell+1} < V(\mathbf{x}_i) < t_\ell$, and the error variables are $\sigma_{i\ell}^+ = t_\ell - V(\mathbf{x}_i) + \delta > 0$ and $\sigma_{i,\ell+1}^+ = \cdots = \sigma_{i,q-1}^+ = 0$. If there is a two-notch downgrade (i is assigned to $C_{\ell+2}$), then $V(\mathbf{x}_i) < t_{\ell+1} < t_\ell$, and the error variables are $\sigma_{i\ell}^+ = t_\ell - V(\mathbf{x}_i) + \delta$, $\sigma_{i,\ell+1}^+ = t_{\ell+1} - V(\mathbf{x}_i) + \delta$, and the others equal to 0. Thus, the total downgrade error is $\sigma_{i\ell}^+ + \sigma_{i,\ell+1}^+$. The same interpretation extends to larger downgrades. Upgrade errors $(\sigma_{i2}^-, \ldots, \sigma_{i\ell}^-)$ can be defined in a similar manner. More specifically, a reference alternative i assigned by the DM to category C_ℓ, is upgraded by the model if $V(\mathbf{x}_i) > t_{\ell-1}$. If the upgrade is limited to one notch (the alternative is assigned by the model to $C_{\ell-1}$), then $t_{\ell-1} < V(\mathbf{x}_i) < t_{\ell-2}$ and the error variables are $\sigma_{i,\ell-1}^- = V(\mathbf{x}_i) - t_{\ell-1} + \delta > 0$ and $\sigma_{i1}^- = \cdots = \sigma_{i,\ell-2}^- = 0$. If there is a two-notch upgrade, then $V(\mathbf{x}_i) > t_{\ell-2} > t_{\ell-1}$ and the error variables are $\sigma_{i,\ell-2}^- = V(\mathbf{x}_i) - t_{\ell-2} + \delta$, $\sigma_{i,\ell-1}^- = V(\mathbf{x}_i) - t_{\ell-1} + \delta$, and the others equal to 0. Thus, the total upgrade error is $\sigma_{i,\ell-1}^- + \sigma_{i,\ell-2}^-$. The same interpretation extends to larger upgrades.

With this modeling of the error variables, the previous optimization model can be reformulated as follows (Doumpos et al. 2015):

$$\min \quad \sum_{\ell=1}^{q} \frac{1}{m_\ell} \sum_{i \in C_\ell} \sum_{k=1}^{q} (\sigma_{ik}^+ + \sigma_{ik}^-) \tag{13}$$

$$\text{s.t.} \quad V(\mathbf{x}_i) + \sigma_{i\ell}^+ \geq t_\ell + \delta \qquad \forall\, \mathbf{x}_i \in \{C_1, \ldots, C_\ell\},\ \ell = 1, \ldots, q-1 \tag{14}$$

$$V(\mathbf{x}_i) - \sigma_{i\ell}^- \leq t_{\ell-1} - \delta \qquad \forall\, \mathbf{x} \in \{C_\ell, \ldots, C_q\},\ \ell = 2, \ldots, q \tag{15}$$

$$t_\ell - t_{\ell+1} \geq \varepsilon \qquad \ell = 1, \ldots, q-2 \tag{16}$$

$$V(\mathbf{x}_*) = 0, \ \ V(\mathbf{x}^*) = 1 \tag{17}$$

$$V(\mathbf{x}) \geq V(\mathbf{x}') \qquad \forall\, \mathbf{x} \geq \mathbf{x}' \tag{18}$$

$$\sigma_{i\ell}^+,\ \sigma_{i\ell}^- \geq 0 \qquad \forall\, i,\ \ell \tag{19}$$

Another natural extension is to consider the minimization of the number of misclassified alternatives, instead of the magnitude of the errors (Zopounidis and Doumpos 1998). Under this scheme, problem (6)–(12) is transformed to a mixed-integer optimization problem by considering the errors $\sigma^\pm$ as binary 0–1 variables. The same idea can also be applied to the above variant (13)–(19), as shown in Doumpos et al. (2016). The main difficulty, however, with such mixed-integer programming formulations, is that they are generally difficult to solve to optimality, particularly when the reference set is large.

The construction of classification models in the form of value functions, can also be formulated under the example-based assignment rule (Greco et al. 2010). For instance, using continuous error variables, the following optimization model is derived:

$$\min \quad \sum_{i,j} (\sigma_{ij}^{+} + \sigma_{ij}^{-}) \tag{20}$$

$$\text{s.t.} \quad V(\mathbf{x}_i) - V(\mathbf{x}_j) + \sigma_{ij}^{+} \geq \delta \qquad \forall\, \mathbf{x}_i \in C_\ell,\ \mathbf{x}_j \in C_\ell^{>},\ \ell = 1, \ldots, q \tag{21}$$

$$V(\mathbf{x}_i) - V(\mathbf{x}_j) - \sigma_{ij}^{-} \leq -\delta \qquad \forall\, \mathbf{x}_i \in C_\ell,\ \mathbf{x}_j \in C_\ell^{<},\ \ell = 1, \ldots, q \tag{22}$$

$$V(\mathbf{x}_*) = 0,\ \ V(\mathbf{x}^*) = 1 \tag{23}$$

$$V(\mathbf{x}) \geq V(\mathbf{x}') \qquad \forall\, \mathbf{x} \geq \mathbf{x}' \tag{24}$$

$$\sigma_{ij}^{+},\ \sigma_{ij}^{-} \geq 0 \qquad i,\ j = 1, \ldots, m \tag{25}$$

where $C_\ell^{>}$ denotes the set of categories $\{C_{\ell+1}, \ldots, C_q\}$ and $C_\ell^{<}$ denotes the set of categories $\{C_1, \ldots, C_{\ell-1}\}$. Similarly to the previous models, weights can be introduced for the error variables in the objective function to take into account the importance and size of each category. The main disadvantage of this optimization formulation compared to the previous ones that adopt the threshold-based approach, is the much larger number of constraints, which may raise some computational issues for large reference sets.

3.2 Inferring Outranking Models

The inference of multicriteria classification models from assignment examples in the context of outranking methods, is generally more involved compared to the approaches described above for value functions. This is due to the complex structure of most outranking models, which makes it impossible to infer their parameters from data through analytical optimization techniques.

In the context of the ELECTRE TRI method, Mousseau and Słowiński (1998) were the first to propose a disaggregation model for model inference using assignment example. In the proposed approach, the authors focused only on the pessimistic assignment rule, which is simpler to model. Moreover, the discordance test was not considered. With these simplifying assumption, an optimization formulation was proposed in non-linear and non-convex form. From a computational point of view, however, such a formulation is only applicable to small-scale reference sets.

Later, several variants of the above approach were presented, all based on linear programming formulations, focusing on specific sets of parameters of the ELECTRE TRI method. For instance, Mousseau et al. (2001) focused on inferring the weights of the criteria while assuming the rest of the parameters fixed. A similar approach was also considered by Dias et al. (2002) as well as Ngo The and Mousseau (2002), who presented linear programming models for inferring the category profiles, while Dias and Mousseau (2006) showed that the parameters involved in the discordance test (veto thresholds) can be inferred from assignment examples using mixed-integer linear programming. It should be noted that all these approaches only considered the pessimistic assignment rule, similarly to the original work of Mousseau and Słowiński (1998). An extension to the optimistic rule for inferring the weights was presented by Zheng et al. (2014), using mixed-integer linear programming formulations.

A more general approach (again based on the pessimistic rule) was proposed by Doumpos and Zopounidis (2002), who combined linear programming models with simple heuristics to infer all parameters of ELECTRE TRI. The proposed approach involved a two-step procedure, in which the first step involved a heuristic process for the specification of the preference parameters for the concordance and discordance tests, while the second step used these parameters to define the weights using linear programming. This two-step approach, however, does not ensure that the "optimal" model is obtained, because the parameters are inferred sequentially, rather than as a whole.

More recently, metaheuristics have been used to overcome the computational complexity of inferring more general outranking models. For instance, Goletsis et al. (2004) used a genetic algorithm for the development of an ELECTRE-type outranking model in a two-group problem involving ischemic beat classification. Doumpos et al. (2009) used the differential evolution algorithm to infer all the parameters of ELECTRE TRI with both the optimistic and pessimistic assignment procedures, focusing on large-scale instances of reference sets. Similar approaches have also been presented in the context of other outranking techniques. For instance, Belacel et al. (2007) used the reduced variable neighborhood search metaheuristic to infer the parameters of the PROAFTN method from a set of reference examples. Sobrie et al. (2013) also used a metaheuristic search approach for a majority rule sorting approach. Genetic algorithms were used by Covantes et al. (2016) for the THESEUS method, as well as by Van Assche and Smet (2016) for the FlowSort method.

4 Robustness Issues

One of the most important issues in disaggregation techniques involves the robustness of the inferred decision models. Roy (2010) described in detail the *robustness concern* in decision aiding, arguing that it is raised by *vague approximations* and *zones of ignorance* that cause the formal representation of a problem to diverge from the real-life context, due to: (1) the way imperfect knowledge is treated, (2) the inappropriate preferential interpretation of certain types of data (e.g., transformations of qualitative attributes), (3) the use of modeling parameters to grasp complex aspects of reality, and (4) the introduction of technical parameters with no concrete meaning.

The robustness concern in the context of preference disaggregation arises because, often, multiple decision models can be inferred in accordance with the information embodied in the set of reference decision examples. This is particularly true for reference sets that do not contain inconsistencies, but it is also relevant when inconsistencies exist.

For instance, consider the optimization formulation (6)–(12) under the case of a fully consistent reference set. In this case, the error variables are all equal to zero, and the optimization model translates to a system of feasible constraints:

$$\begin{aligned} & V(\mathbf{x}_i) \geq t_\ell + \delta && \forall \mathbf{x}_i \in C_\ell,\ \ell = 1, \ldots, q-1 \\ & V(\mathbf{x}_i) \leq t_\ell - \delta && \forall \mathbf{x}_i \in C_\ell,\ \ell = 2, \ldots, q \\ & t_\ell - t_{\ell+1} \geq \varepsilon && \ell = 1, \ldots, q-2 \\ & V(\mathbf{x}_*) = 0,\ \ V(\mathbf{x}^*) = 1 && \\ & V(\mathbf{x}) \geq V(\mathbf{x}') && \forall \mathbf{x} \geq \mathbf{x}' \end{aligned} \tag{26}$$

Assuming that the value function is additive with piece-wise linear marginal value functions, this is actually a system of linear constraints. The size of the corresponding feasible polyhedron is associated with the robustness of the results and can be affected by a number of factors. The most important of these factors relate to the adequacy of set of reference examples and the complexity of the selected decision modeling form. The former is immediately related to the quality of the information on which model inference is based (Vetschera et al. 2010), which needs to be considered in combination with the complexity of the model. More complex model require higher quality data of larger size to be inferred in a meaningful manner. Expect for its size, other characteristics of the reference set are also relevant, such as the existence of noisy data, outliers, the existence of correlated criteria, etc. (Doumpos and Zopounidis 2002).

Traditional disaggregation techniques based on value function models, such as the family of the UTA methods, use linear programming post-optimality techniques (Siskos and Grigoroudis 2010) in order to build a representative additive value function defined as the average solution of some characteristic extreme points of the feasible polyhedron (26). Other approaches for selecting the most representative decision model include the regularization approach of Doumpos and Zopounidis (2007), the analytic center formulation of Bous et al. (2010), and the max-min model of Greco et al. (2011). Such approaches seek to identify (analytically) central solutions to the polyhedron defined by (26), which are expected to be more robust to changes in the data and the setting of the analysis. The experimental results presented in Doumpos et al. (2014) are supportive of this setting.

Recently, alternative approaches have been proposed that enable the formulation of recommendations based on multiple decision models. These approaches follow a more general perspective, which is applicable not only to value function models, but also outranking relations, too. Two main schemes can be identified in this framework.

The first is uses simulation techniques, which are based on sampling, at random, different solutions (classification models) from a feasible region. This approach was first considered in the context of the SMAA method for choice and ranking problems (Lahdelma et al. 1998; Lahdelma and Salminen 2001). The simulation process provides an approximate description of all models compatible with the classifications for the reference set and enables the formulation of a range of recommendations associated with probabilistic measures of confidence (see, for instance, Tervonen et al. 2009). This approach works best when sampling from a polyhedron of feasible solutions, i.e., when the classification model can be expressed in the form of linear constraints. Sampling from non-convex regions is much more difficult.

The second scheme is based on analytical approaches. In the context of additive value models, Greco et al. (2010) introduced a modeling framework that takes into account all decision models compatible with the constraints (26). Their approach is based on the definition of necessary and possible assignments. The set of necessary assignments N_i for a non-reference alternative $i \notin X'$ consists of the classes in which i is classified by all models compatible with the reference set. On the other hand, the set of possible assignments P_i includes the results supported by at least one decision model. This framework is general enough to be applicable to different types of decision models. For instance, except for value models, it has been extended to outranking approaches and rule-based models (Kadziński and Ciomek 2016; Kadziński et al. 2016).

Hybrid approaches have also been proposed. For instance, Kadziński and Tervonen (2013) considered a combination of robust analytic procedures based on the specification of the necessary and analytic assignments with simulation techniques. The latter provide further information in probabilistic form about the necessary and possible assignments. Simulation-based methods, however, only provide an approximate description of the problem data and they can be computationally intensive for larger data sets involving many alternatives and criteria.

5 Conclusions and Future Research

Multicriteria classification problems arise in many decision making situations in different areas and they have become an important topic in the theory and practice of MCDA. Preference disaggregation approaches have been widely used for constructing multicriteria classification models from data.

In the overview presented in this chapter, we described the main approaches, covering different modeling forms, model inference techniques, and further discussed issues related to robustness, thus highlighting the current status and trends in this area.

Despite the huge progress achieved in this active field of MCDA, there are still many challenges and opportunities for further research. Robustness is one of the most challenging areas. While significant research has been made on developing robust decision making approaches, measuring robustness through analytical measures that can be applied to complex and large-scale instances, remains a challenge. This is also related to reporting and visualization of results derived from robustness analysis. The connections with other established areas such as robust optimization and robust statistical learning, are also worth the consideration. Moreover, the advances in big data analytics and the emergence of new application areas where big data are highly relevant, raise challenges for scaling up existing MCDA classification approaches to large data sets. Finally, applications to complex real-world cases as well as further experimental testing and validation is required to get further insights into the properties of existing and new approaches.

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Multiple Criteria Approaches for Customer Satisfaction Measurement

Evangelos Grigoroudis and Yannis Politis

Abstract Customer satisfaction can be perceived as a multicriteria evaluation problem, where the overall satisfaction with the provided service/product depends on a set of satisfaction criteria. The main aim of the chapter is to present an overview of multiple criteria approaches for customer satisfaction measurement and analysis. In this context, the MUSA method, being the most representative approach, is presented, while several recent advances, including extensions and alternative approaches are discussed. The MUSA method is a collective preference disaggregation model following the principles of ordinal regression analysis (inference procedure) under constraints. The method is used for the assessment of a set of marginal satisfaction functions in such a way that the global satisfaction criterion becomes as consistent as possible with customer's judgments. The main objective of the method is to assess collective global and marginal value functions by aggregating individual judgments. The main advantages of the MUSA method, in addition to its ability to properly handle ordinal data, are its flexibility due to the linear programming formulation, as well as its ability to provide an integrated set of results capable to analyze customer needs and expectations and justify their satisfaction level.

1 Introduction

Customer satisfaction is one of the most important issues concerning business organizations of all types, which is justified by the customer-orientation philosophy and the main principles of continuous improvement of modern enterprises. For

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this reason, customer satisfaction measurement is considered as the most reliable feedback, taking into account that it provides in an effective, direct, meaningful and objective way the customers' preferences and expectations.

Several approaches have been developed to evaluate customer satisfaction (see Grigoroudis and Siskos (2010) for a detailed list of the existing methods). These approaches examine the customer satisfaction evaluation problem from very different perspectives and may include simple quantitative tools, statistical and data analysis techniques, consumer behavioral models, etc. However, in all these approaches the data of the problem are based on the customers' judgments, directly collected from them. Also, customer satisfaction is considered as a multivariate evaluation problem given that customer's overall satisfaction depends on a set of variables representing product/service characteristic dimensions.

Many of these approaches do not consider the qualitative form of customers' judgments, although this information constitutes the main satisfaction input data. In simple words, the data are usually obtained via questionnaires directly from customers and have a qualitative (ordinal) rather than a quantitative nature. The convenient approach is such case is to consider that the differences between the levels of ordinal scales are equal and treat them as linear interval scales. However, this is a rather strong assumption that cannot be justified a priori, while several studies underline the nonlinear behavior of customers, especially in the case of customer satisfaction (Grigoroudis and Siskos 2010). Furthermore, in several cases, the measurements provide by the classical and data analysis approached are not sufficient enough to analyze in detail customer satisfaction.

Based on the previous, Multiple Criteria Decision Aid (MCDA) methods seem appropriate in the customer satisfaction evaluation problem. In particular, customer satisfaction can be perceived as a multicriteria evaluation problem, where the overall satisfaction with the provided service/product depends on a set of satisfaction criteria.

The MUSA (MUlticriteria Satisfaction Analysis) method proposed in this context is the most known MCDA model for measuring and analyzing customer satisfaction. The MUSA method is a collective preference disaggregation model following the principles of ordinal regression analysis (inference procedure) under constraints. It uses linear programming techniques for its solution with a methodological frame developed by Siskos et al. (1998). The MUSA method is used for the assessment of a set of marginal satisfaction functions in such a way that the global satisfaction criterion becomes as consistent as possible with customer's judgments. The main objective of the method is to assess collective global and marginal value functions by aggregating individual judgments.

The main advantages of the MUSA method, in addition to its ability to properly handle ordinal data, are its flexibility due to the linear programming formulation, as well as its ability to provide an integrated set of results capable to analyze customer needs and expectations and justify their satisfaction level. As a result, the MUSA method may provide a decision-aid tool and an integrated benchmarking system.

Since its introduction, the MUSA method has been implemented in many different cases in the banking sector (Mihelis et al. 2001; Grigoroudis et al. 2002), in the shipping sector (Siskos et al. 2001), in the education sector (Politis and Siskos 2004), in logistics (Politis et al. 2014), for assessing the quality of web providers (Grigoroudis et al. 2008), for estimating the preferences of e-customers (Grigoroudis et al. 2007), etc.

In addition, several extensions of the MUSA method have been proposed during the recent years. For example Grigoroudis and Politis (2015) introduced additional constraints in the basic linear programming formulation of the method in order to improve the stability of the provided results. Joao et al. (2010) used a dummy variable regression technique with additional constraints and employed the least square approach in order to provide more stable results than the original MUSA method. In a different context, Angilella et al. (2014) proposed MUSA-INT, an alternative approach that takes into account positive and negative interactions among satisfaction criteria. Politis and Grigoroudis (2017) incorporated the concept of Six Sigma analysis in customer satisfaction measurement by introducing the principles of Kano's model in order to derive important information for the selection of strategic actions. Aouadni and Rebai (2016) proposed the fuzzy MUSA method in order to make the method capable of accepting and processing fuzzy scores as input and producing a satisfaction function with fuzzy coefficients.

The main aim of this chapter is to present an overview of MCDA approaches for customer satisfaction measurement and analysis. In this context, the main part of the chapter is devoted to the presentation of the MUSA method and the recent advances, including extensions and alternative MCDA approaches. The chapter is organized in five more sections. The next section is devoted to the MUSA method and discusses the provided results and the robustness analysis. Section 3 presents several indicative extensions of the MUSA method, including the modeling of interacting criteria, additional properties and preferences, as well as alternative optimality criteria. Other MCDA methods for customer satisfaction evaluation based on fuzzy sets theory and outranking approaches are discussed in Sect. 4, while Sect. 5 summarizes some concluding remarks and outlines future research topics.

2 The MUSA Method

2.1 Basic Models

The MUSA (MUlticriteria Satisfaction Analysis) method is a multicriteria preference disaggregation approach that provides quantitative measures of customer satisfaction, considering the qualitative form of customers' judgments (Siskos et al. 1998; Grigoroudis and Siskos 2002). The main objective of the MUSA method is the aggregation of individual judgments into a collective value function, assuming that customer's global satisfaction depends on a set of n criteria or variables representing service/product characteristic dimensions. This set of criteria is denoted as $\mathbf{X} = \{X_1, X_2, \ldots, X_n\}$ where a particular criterion i is represented as a monotonic variable X_i. This way, the evaluation of customer's satisfaction can be considered as a multicriteria analysis problem.

The MUSA method assesses global and partial satisfaction functions Y^* and X_i^*, respectively, given customers' judgments Y and X_i. The method follows the principles of ordinal regression analysis under constraints using linear programming techniques (Jacquet-Lagrèze and Siskos 1982; Siskos and Yannacopoulos 1985; Siskos 1985). The ordinal regression analysis equation has the following form:

$$Y^* = \sum_{i=1}^{n} b_i X_i^* \quad \text{with} \quad \sum_{i=1}^{n} b_i \tag{1}$$

where n is the number of criteria, b_i is the weight of criterion i, and the value functions Y^* and X_i^* are non-decreasing functions in the ordinal scales Y and X_i, respectively, and normalized in the interval $[0, 100]$.

The normalization constraints for the value functions Y^* and X_i^* can be written as follows:

$$\begin{cases} y^{*1} = 0, y^{*\alpha} = 100 \\ x_i^{*1} = 0, x_i^{*\alpha_i} = 100 \;\; \text{for } i = 1, 2, \ldots, n \end{cases} \tag{2}$$

where y^{*m} and x_i^{*k} are the values of the m-th global satisfaction level and the k-th satisfaction level of the i-th criterion, respectively, α is the number of global satisfaction levels, and α_i is the number of satisfaction levels for the i-th criterion.

Furthermore, because of the ordinal nature of Y and X_i, the following preference conditions are assumed:

$$\begin{cases} y^{*m} \leq y^{*m+1} \iff y^m \preceq y^{m+1} & \text{for } m = 1, 2, \ldots, \alpha - 1 \\ x_i^{*k} \leq x_i^{*k+1} \iff x_i^k \preceq x_i^{k+1} & \text{for } k = 1, 2, \ldots, \alpha_i - 1 \text{ and } i = 1, 2, \ldots, n \end{cases} \tag{3}$$

where y^m and x_i^k are the m-th global satisfaction level and the k-th satisfaction level of the i-th criterion, respectively, and $\preceq$ means 'less preferred or indifferent to'.

The MUSA method infers an additive collective value function Y^*, and a set of partial satisfaction functions X_i^* from customers' judgments. The main objective of the method is to achieve the maximum consistency between the value function Y^* and the customers' judgments Y.

Based on the modeling presented above, and introducing a double-error variable, the ordinal regression equation becomes as follows:

$$\tilde{Y}^* = \sum_{i=1}^{n} b_i X_i^* - \sigma^+ + \sigma^- \tag{4}$$

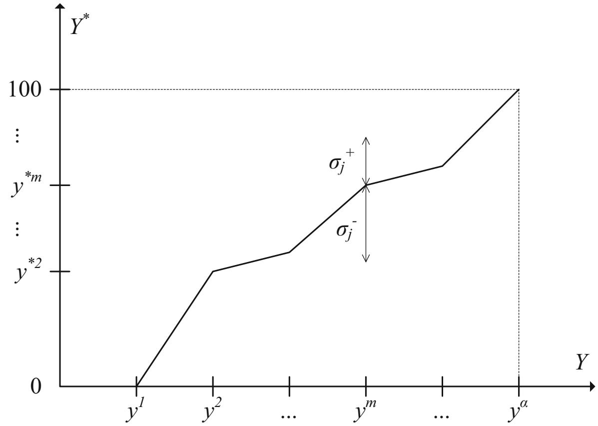


Fig. 1 Error variables for the *j*-th customer

where $\tilde{Y}^*$ is the estimation of the global value function Y^*, and σ^+ and σ^- are the overestimation and the underestimation error, respectively. Since formula (4) should hold as much as possible for every customer, a pair of error variables is assessed for each customer separately as shown in Fig. 1.

Through formula (4) it is easy to note the similarity of the MUSA method with the principles of goal programming modeling, ordinal regression analysis, and particularly with the additive utility models of the UTA family (Jacquet-Lagrèze and Siskos 1982, 2001; Siskos and Yannacopoulos 1985; Despotis et al. 1990; Siskos et al. 2005).

According to the aforementioned definitions and assumptions, the customers' satisfaction evaluation problem may be formulated as a linear program (LP) in which the goal is the minimization of the sum of errors under the constraints:

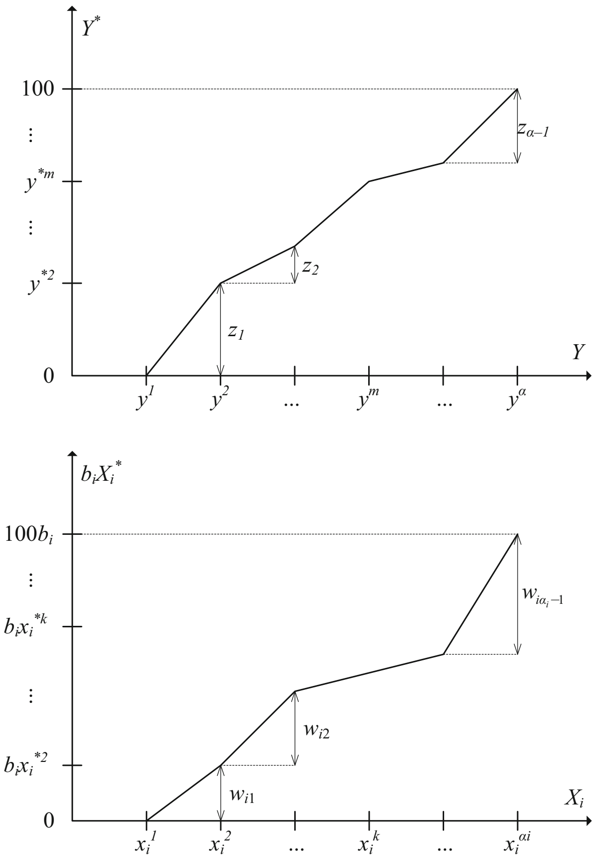
a) ordinal regression equation (4) for each customer,
b) normalization constraints for Y^* and X_i^* in the interval $[0, 100]$, and
c) monotonicity constraints for Y^* and X_i^*.

Removing the monotonicity constraints, the size of the previous LP can be reduced in order to decrease the computational effort required for the search of the optimal solution. This is effectuated via the introduction of a set of transformation variables, which represent the successive steps of the value functions Y^* and X_i^* (Siskos and Yannacopoulos 1985; Siskos 1985). The transformation equation can be written as follows (see also Fig. 2):

$$\begin{cases} z_m = y^{*m+1} - y^{*m} & \text{for } m = 1, 2, \ldots, \alpha - 1 \\ w_{ik} = x_i^{*k+1} - x_i^{*k} & \text{for } k = 1, 2, \ldots, \alpha_i - 1 \text{ and } i = 1, 2, \ldots, n \end{cases} \tag{5}$$

It is important to note that using these variables, the linearity of the model is achieved since Eq. (4) presents a non-linear model.

Fig. 2 Transformation variables z_m and w_{ik} in global and partial value functions



Using Eq. (5), the initial variables of the MUSA method can be written as:

$$\begin{cases} y^{*m} = \sum_{t=1}^{m-1} z_t \quad \text{for } m = 2, 3, \ldots, \alpha \\ x_i^{*k} = \sum_{t=1}^{k-1} w_{it} \quad \text{for } k = 2, 3, \ldots, \alpha_i \text{ and } i = 1, 2, \ldots, n \end{cases} \tag{6}$$

Assuming that the j-th customer has expressed his/her satisfaction judgments y^{t_j} and $x_i^{t_{ij}}$ using the ordinal scales Y and X_i, respectively, i.e. $y^{t_j} \in Y = \{y^1, y^2, \ldots, y^{y_j}, \ldots y^\alpha\}$ and $x_i^{t_{ij}} \in X_i = \left\{x_i^1, x_i^2, \ldots x_i^{t_{ij}}, \ldots, x_i^{\alpha_i}\right\}$ for $i = 1, 2, \ldots, n$ and introducing the z_m and w_{ik} variables, the final LP formulation of the method may be written as follows:

$$\begin{cases} [\min]\, F = \sum_{j=1}^{M} \sigma_j^+ + \sigma_j^- \\ \text{subject to} \\ \sum_{i=1}^{n} \sum_{k=1}^{t_{ij}-1} w_{ik} - \sum_{m=1}^{t_j-1} z_m - \sigma_j^+ + \sigma_j^- = 0 \ \ \forall j \\ \sum_{m=1}^{\alpha-1} z_m = 100 \\ \sum_{i=1}^{n} \sum_{k=1}^{t_{ij}-1} w_{ik} = 100 \\ z_m, w_{ik}, \sigma_j^+, \sigma_j^- \geq 0 \ \ \forall i, j, k, m \end{cases} \tag{7}$$

where M is the number of customers.

Under the assumption that Y^* and X_i^* are monotonic and strictly increasing functions, a generalized MUSA model may be developed. In such case, it is possible to avoid potential instability, where the optimal solution of the previous LP gives $b_i = 0$ for some criteria X_i or $y^{*m} = y^{*m+1}$, $x_i^{*k} = x_i^{*k+1}$ (see also Jacquet-Lagrèze and Siskos 1982). Taking into account the hypothesis of strict preferences, the conditions of Eq. (3) become as follows:

$$\begin{cases} y^{*m} < y^{*m+1} \iff y^m \prec y^{m+1} & \text{for } m = 1, 2, \ldots, \alpha - 1 \\ x_i^{*k} < x_i^{*k+1} \iff x_i^k \prec x_i^{k+1} & \text{for } k = 1, 2, \ldots, \alpha_i - 1 \text{ and } i = 1, 2, \ldots, n \end{cases} \tag{8}$$

where $\prec$ means 'strictly less preferred'.

Based on Eq. (8), the following conditions occur:

$$\begin{cases} y^{*m+1} - y^{*m} \geq \gamma \iff z_m \geq \gamma & \text{for } m = 1, 2, \ldots, \alpha - 1 \\ x_i^{*k+1} - x_i^{*k} \geq \gamma_i \iff w_{ik} \geq \gamma_i & \text{for } k = 1, 2, \ldots, \alpha_i - 1 \text{ and } i = 1, 2, \ldots, n \end{cases} \tag{9}$$

where γ and γ_i are the preference thresholds for the value functions Y^* and X_i^*, respectively.

These thresholds represent the minimum step of increase for Y^* and X_i^* and it can be proved that the minimum weight of a criterion X_i becomes $\gamma_i(\alpha_i - 1)$.

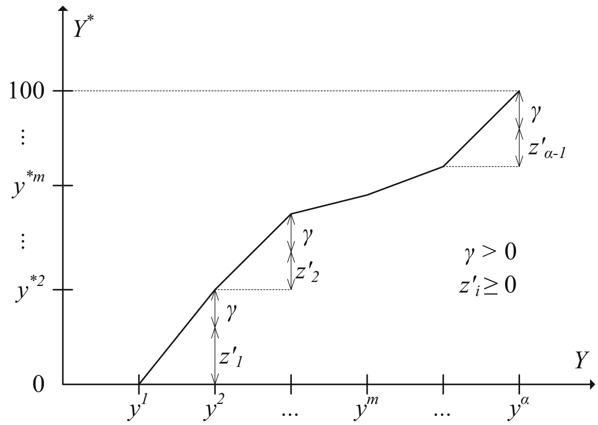


Fig. 3 Preference threshold for the value function Y^*

Using the new variables $z'_m = z_m - \gamma$ and $w'_{ik} = w_{ik} - \gamma_i$ (see Fig. 3), the generalized MUSA method reads:

$$\begin{cases} [\min] F = \sum_{j=1}^{M} \sigma_j^+ + \sigma_j^- \\ \text{subject to} \\ \sum_{i=1}^{n} \sum_{k=1}^{t_{ij}-1} w'_{ik} - \sum_{m=1}^{t_j-1} z'_m - \sigma_j^+ + \sigma_j^- = \gamma \left(t_j - 1\right) - \sum_{i=1}^{n} \gamma_i \left(t_{ij} - 1\right) \quad \forall j \\ \sum_{m=1}^{\alpha-1} z_m = 100 - \gamma\, (\alpha - 1) \\ \sum_{i=1}^{n} \sum_{k=1}^{t_{ij}-1} w_{ik} = 100 - \sum_{i=1}^{n} \gamma_i\, (\alpha_i - 1) \\ z'_m, w'_{ik}, \sigma_j^+, \sigma_j^- \geq 0 \;\; \forall i, j, k, m \end{cases} \tag{10}$$

This model consists the generalized form of the MUSA method, since the basic form (Eq. 7) is a special case where $\gamma = \gamma_i = 0, \forall i$.

The principles and the initiative methodological frame of the MUSA method have been developed by Siskos et al. (1998) and Grigoroudis et al. (2000), while a discussion and a more detailed presentation of the method may also be found in Grigoroudis and Siskos (2002, 2010).

2.2 Results and Indices

The satisfaction criteria weights represent the relative importance of the assessed satisfaction dimensions and they can be calculated using the following formula:

$$b_i = \frac{1}{100} \sum_{t=1}^{\alpha_i - 1} w_{it} \quad \text{for } i = 1, 2, \ldots, n \tag{11}$$

The estimated value/satisfaction functions are the most important results of the MUSA method, considering that they show the real value, in a normalized interval [0, 100], that customers give for each level of the global or marginal ordinal satisfaction scale. The form of these functions indicates the customers' degree of demanding and they can be calculated through:

$$\begin{cases} y^{*m} = \sum_{t=1}^{m-1} z_t & \text{for } m = 2, 3, \ldots, \alpha \\ x_i^{*k} = 100 \dfrac{\sum_{t=1}^{k-1} w_{it}}{\sum_{t=1}^{\alpha_i - 1} w_{it}} & \text{for } k = 2, 3, \ldots, \alpha_i \text{ and } i = 1, 2, \ldots, n \end{cases} \tag{12}$$

Replacing z_m and w_{ik} with z'_m and w'_{ik}, formulas (11) and (12) may give the solution of the generalized MUSA method.

Furthermore, the assessment of a performance norm, globally and per satisfaction criteria, may be very useful in customer satisfaction analysis and benchmarking. The average global and partial satisfaction indices, S and S_i, respectively, are used for this purpose, and may be assessed according to the following equations:

$$\begin{cases} S = \frac{1}{100} \sum_{m=1}^{\alpha} p^m y^m \\ S_i = \frac{1}{100} \sum_{k=1}^{\alpha_i - 1} p_i^k x_i^{*k} \quad \text{for } i = 1, 2, \ldots, n \end{cases} \tag{13}$$

where p^m and p_i^k are the frequencies of customers belonging to the y^m and x_i^k satisfaction levels, respectively.

The average satisfaction indices are basically the mean value of the global or marginal value functions, normalized in the interval [0, 1].

Other important results of the MUSA method refer to the average global and partial demanding indices, which represent the average deviation of the estimated value curves from a 'normal' (linear) function. These indices are normalised in the interval $[-1, +1]$ and reveal the demanding level of customers. They are assessed based on the following formulas:

$$\begin{cases} D = \dfrac{\sum\limits_{m=1}^{\alpha-1}\left(\frac{100(m-1)}{\alpha-1} - y^{*m}\right)}{100\sum\limits_{m=1}^{\alpha-1}\frac{m-1}{\alpha-1}} & \text{for } \alpha > 2 \\ S_i = \dfrac{\sum\limits_{k=1}^{\alpha_i-1}\left(\frac{100(k-1)}{\alpha_i-1} - x_i^{*k}\right)}{100\sum\limits_{k=1}^{\alpha_i-1}\frac{k-1}{\alpha_i-1}} & \text{for } \alpha_i > 2 \text{ and } i = 1, 2, \ldots, n \end{cases} \tag{14}$$

where D and D_i are the average global and partial demanding indices, respectively.

Demanding indices are used in customer behavior analysis. They may also indicate the extent of company's improvement efforts: the higher the value of the demanding index, the more the satisfaction level should be improved in order to fulfill customers' expectations.

Considering the output of improvement efforts, it can be assumed that it depends on the importance of the satisfaction dimensions and their contribution to dissatisfaction as well. The average improvement indices show the improvement margins on a specific criterion, and they are assessed according to the following equation:

$$I_i = b_i\,(1 - S_i) \quad \text{for } i = 1, 2, \ldots, n \tag{15}$$

These indices are normalized in $[0, 1]$ and it can be proved that $I_i = 1$ iff $b_i = 1 \wedge S_i = 0$ and $I_i = 0$ iff $b_i = 0 \vee S_i = 1$ for $i = 1, 2, \ldots, n$.

All the above indices and the results provided by the MUSA method can be combined in order to develop a series of helpful diagrams. Grigoroudis and Siskos (2010) proposed the following diagrams:

a) Action diagrams: They are developed by combining weights and average satisfaction indices and may indicate the strong and the weak points of customer satisfaction and define the required improvement efforts.
b) Improvement diagrams: They may be developed by combining the average improvement and demanding indices and they can determine the output or the extent of improvement efforts.

2.3 Fitting and Stability

In order to evaluate the reliability of the results provided by the MUSA method, the level of fitting to the customer satisfaction data and the stability of the post-optimality analysis results, have to be assessed.

The fitting level of the MUSA method refers to the assessment of a preference collective value system (value functions, weights, etc.) for the set of customers with the minimum possible errors. For this reason, the optimal values of the error variables indicate the reliability of the value system that is evaluated.

Several fitting measures may be used depending on the optimum error level and the number of customers. Grigoroudis and Siskos (2002) propose the following simple average fitting index AFI_1:

$$AFI_1 = 1 - \frac{F^*}{100M} \tag{16}$$

where F^* is the optimal value of the objective function of LP (7) (or LP (10)).

AFI_1 is normalized in the interval $[0, 1]$, and it is equal to 1 if $F^* = 0$, that is when the method is able to create a preference value system with zero errors. On the other hand, AFI_1 takes its worst value only when the pairs of the error variables take the maximum possible values.

An alternative fitting indicator is based on the percentage of customers with zero error variables. This means that, for these customers, the estimated preference value systems fits perfectly with their expressed satisfaction judgments. This average fitting index AFI_2 can be assessed as follows:

$$AFI_2 = \frac{M_0}{M} \tag{17}$$

where M_0 is the number of customers with $\sigma^+ = \sigma^- = 0$.

Finally, AFI_3 is a fitting indicator that examines separately every level of global satisfaction, and calculates the maximum possible error value for each one of these levels:

$$AFI_3 = 1 - \frac{F^*}{M \sum_{m-1}^{\alpha} p^m \max\{y^{*m}, 100 - y^{*m}\}} \tag{18}$$

AFI_3 is an alternative formulation of AFI_1, which takes into account the maximum values of the error variables for every global satisfaction level, as well as the number of customers that belongs to this level.

As noted by Grigoroudis and Siskos (2010), all of the aforementioned average fitting indicators are highly affected by potential inconsistencies in customer satisfaction judgments. Therefore, the examination of all these indices may give a more complete view for the fitting ability of the MUSA method.

Other alternative indicators and tools that can be used in order to assess the fitting level of the MUSA method include the following:

a) Variance diagram of the added value curve: It shows the value range that the customers' set gives for each level of the ordinal satisfaction scale and therefore can be considered as a confidence interval for the estimated added value function.

b) Prediction table of global satisfaction: It calculates the percentage of correctly classified customers by the MUSA method. This depends on the comparison of the actual global satisfaction level (as expressed by the customers) and the predicted global satisfaction level (as calculated by the MUSA method). The higher the number of customers that are classified by the MUSA to the same satisfaction level with the one actually expressed by customers, the higher the prediction capability of the MUSA method.

A post-optimality analysis stage is also included in the MUSA method in order to face the problem of multiple or near optimal solutions. Considering that the method is based on LP modelling, post-optimality analysis can give insight about the stability of the provided results (Siskos 1984; Siskos and Grigoroudis 2010). The MUSA method applies a heuristic method for near optimal solutions search, where the final solution is obtained by exploring the polyhedron of near optimal solutions, which is generated by the constraints of LP (7) or (10). During the post-optimality analysis stage of the MUSA method, n LPs (equal to the number of criteria) are formulated and solved. Each LP maximizes the weight of a criterion and thus the solutions give the internal variation of the weights of all criteria, and consequently give an idea of the importance of these criteria in the decision-maker's preference system (Siskos et al. 2005).

The post-optimality analysis LPs have the following form:

$$\begin{cases} [\max]\ F' = \sum\limits_{k=1}^{\alpha_i - 1} w_{ik} \\ \text{subject to} \\ F \leq F^* + \varepsilon \\ \text{all the constraints of LP (7) (or LP (10))} \end{cases} \qquad \text{for} \quad i = 1, 2, \ldots, n \tag{19}$$

where F^* is the optimal value of the objective function of LP (7) (or LP (10)) and ε is a small percentage of F^*.

The average of the optimal solutions given by the n LPs (19) may be considered as the final solution of the problem. In case of instability, a large variation of the provided solutions appears and the final average solution is less representative.

The observed variance in the post-optimality matrix indicates the degree of instability of the results. Thus, the mean value of the normalized standard deviation of the estimated weights can be used as an average stability index (*ASI*) of the method:

$$ASI = 1 - \frac{1}{n} \sum_{i=1}^{n} \frac{\sqrt{n \sum\limits_{t=1}^{n} \left(b_i^t\right)^2 - \left(\sum\limits_{t=1}^{n} b_i^t\right)^2}}{100\sqrt{n-1}} \tag{20}$$

where b_i^t is the estimated weight of the i-th criterion in the t-th post-optimality analysis LP, while *ASI* is normalized in [0, 1].

Grigoroudis and Siskos (2010) discuss additional stability measures in the context of the MUSA method. For example, the range of the weights during post-optimality analysis is also able to provide valuable information for the robustness of the provided results. These ranges may give a confidence interval for the estimated weights, and can identify possible competitiveness in the criteria set, i.e., the existence of certain customer groups with different importance levels for the satisfaction criteria.

3 Extensions of the MUSA Method

3.1 Additional Properties and Preferences

The LP formulation of the MUSA method gives the ability to consider additional constraints regarding special properties of the assessed model variables. One of the most interesting extensions concerns additional properties for the assessed average indices. The introduction of additional constraints in the basic linear programming formulation of the MUSA method can improve the stability of the provided results. Grigoroudis and Politis (2015) examined two cases of modelling additional information and properties in order to improve the robustness of the MUSA method. The first refers to the desired properties of the collective preference system (i.e., additional properties for the assessed average indices), while the second case concerns customer preferences on satisfaction criteria importance.

In the case of average satisfaction indices, a reasonable approach is to assume that the global average satisfaction index S is an aggregation of the partial average satisfaction indices S_i. If a weighted sum aggregation formula is used, then the following property occurs:

$$S = \sum_{i=1}^{n} b_i S_i \tag{21}$$

Similarly, a weighted sum formula may be assumed for the average demanding indices:

$$D = \sum_{i=1}^{n} b_i D_i \tag{22}$$

Formulas (21) and (22) can be rewritten in terms of the MUSA variables z_m and w_{ik} and may be easily introduced as additional constraints in the basic LP of the MUSA method. However, such constraints should be used carefully, since their form does not guarantee a feasible solution of the LP, especially in case of inconsistencies between global and partial satisfaction judgments. For this reason, these constraints may be rewritten using a goal programming formulation.

Additional preferences may also refer to customer preferences on satisfaction criteria importance, where customers are asked either to judge the importance of a satisfaction criterion using a predefined ordinal scale, or rank the set of satisfaction criteria according to their importance. Using an approach similar to the UTADIS method (Zopounidis and Doumpos 2001), the problem may be formulated through a LP. The modeling procedure include the following steps:

a) Define a set of ordered importance category (e.g., very important, important, less important). If a total of q such categories are set, the problem is to find $q - 1$ thresholds, which define the rank and, therefore, label each one of these ordered categories.
b) Using these thresholds as variables and incorporating a set of overestimation and underestimation errors for each customer, write the main constraints of the LP.
c) Add constraints about the minimum values of the thresholds in order to increase the discrimination of the importance classes.

A detailed presentation and discussion of the previous weights estimation model may be found in Grigoroudis and Spiridaki (2003) and Grigoroudis et al. (2004), including some real-world applications.

Taking into account the previous modelling, the LP, which refers to the customer preferences on the importance of the satisfaction criteria, and the LP of the original MUSA method may be combined in a Multiobjective Linear Program (MOLP), given the two different sets of error variables.

Usually the competitive nature of the multiple objective in MOLP problems does not allow to find a solution that optimizes all objective functions. This competiveness may be observed in the proposed model particularly if there are inconsistencies between satisfaction performance and satisfaction importance judgments, as directly expressed by customers.

The previous MOLP problem may be solved using any MOLP technique (e.g., compromise programming, global criterion approach, etc.). Grigoroudis and Politis (2015) proposed a heuristic approach based on a lexicographic concept, consisting of the following steps.

a) The objective function of the basic MUSA model is chosen to be optimized in the first step of the proposed procedure, considering that it is most important to produce a model as consistent as possible with the customers' performance judgments.
b) In the second step, the procedure optimizes the objective function of the weights estimation model, implying that the next important optimality criterion refers to inferring a preference model as consistent as possible with the customers' importance judgments.
c) The additional desired properties of the MUSA variables are considered as the less important optimality criterion, thus in the last step, the objective function of the model referring to the desired properties of S and D is chosen to be optimized.

This assumed importance of the optimality criteria in the proposed lexicographic approach may be modified. In any case, the main purpose of the proposed extension is to examine whether additional information about the weights of the criteria and additional constraints regarding the desired properties of S and D can improve the results of the MUSA method.

3.2 Interacting Criteria

The original MUSA method is not able to represent positive and negative synergies between specific features of a product or a service, since it considers an additive utility function and, consequently, one of its major underlying hypothesis is preference independence. This is an important issue because it is a common experience that in the evaluation of a product or a service, some features could positively or negatively interact. For example, in the evaluation of a supermarket, prices and special offers have, usually, a negative interaction. For this reason, Angilella et al. (2014) proposed the MUSA-INT method which is able to handle positive and negative synergies between couples of criteria, using an approach similar to the multicriteria method UTAGMS-INT (Greco et al. 2014).

In order to describe the method, the following elements are considered:

a) $I = \{1, 2, \ldots, n\}$ is the set of satisfaction criteria.
b) $Syn^+ \subseteq I^{(2)}$, with $I^{(2)} \subseteq I$ is the set of all couples of criteria for which there is a positive interaction.
c) $Syn^- \subseteq I^{(2)}$, with $I^{(2)} \subseteq I$ is the set of all couples of criteria for which there is a negative interaction.
d) syn^+_{pq} is a function non-decreasing in both its two arguments representing the strength of the positive interaction between criteria p, $q \in I$ such that $\{p, q\} \in Syn^+$.
e) syn^-_{pq} is a function non-decreasing in both its two arguments representing the strength of the negative interaction between criteria p, $q \in I$ such that $\{p, q\} \in Syn^+$.

The method is composed of three main successive phases. In the first phase, a value function Y^* representing the satisfaction of all customers is estimated with a minimal sum of overestimation and underestimation errors. During the second phase, a minimal set of couples of interacting criteria is identified, where minimality refers to the inclusion. Finally, the aim of the third phase is to find a value function that discriminates as much as possible satisfaction levels for both marginal and global value functions. From a computational point of view, each phase consists in solving a specific Mixed Integer Linear Program (MILP).

In this approach, the ordinal regression equation has the following form:

$$Y^* = \sum_{i=1}^{n} X_i^* + \sum_{\{p,q\} \in I^{(2)}} syn_{pq}^{+}\left(X_p, X_q\right) - \sum_{\{p,q\} \in I^{(2)}} syn_{pq}^{-}\left(X_p, X_q\right) - \sigma_j^{+} + \sigma_j^{-} \tag{23}$$

Similarly to the UTAGMS_INT method (Greco et al. 2014), the following options for the positive and negative interactions present in the value function (23) for each couple of criteria $\{p, q\} \in I^{(2)}$ are considered:

S1) $syn_{pq}^{+}\left(X_p, X_q\right)$ and $syn_{pq}^{-}\left(X_p, X_q\right)$ are not mutually exclusive, such that in the evaluation space of the two criteria there is a switch between positive interaction and negative interaction; in some parts of the space the positive interaction prevails and in some others the negative interaction prevails, or even, there is no interaction,

S2) $syn_{pq}^{+}\left(X_p, X_q\right)$ and $syn_{pq}^{-}\left(X_p, X_q\right)$ are mutually exclusive, and

S3) only one of the two interactions is considered (e.g., the positive one).

In order to have as simple model as possible, i.e. with the lowest possible number of interactions, it is supposed that each criterion i can interact with at most one another criterion. Therefore, in case of option (S1), for each couple of criteria $\{p, q\} \in I^{(2)}$, the following binary variable β_{pq} is introduced:

$$\beta_{pq} = \begin{cases} 1 & \text{if} \quad \{p, q\} \in I^{(2)} \text{ are interacting} \\ 0 & \text{if} \quad \{p, q\} \in I^{(2)} \text{ are not interacting} \end{cases} \tag{24}$$

Thus, the following constraints are considered in the first MILP problem:

$$E_{(S1)} \begin{cases} \beta_{pq} \in \{0, 1\} \\ \sum\limits_{q \in I \setminus \{p\}} \beta_{pq} \leq 1 \quad \forall p \in I \\ syn_{pq}^{+}\left(x_p^{\alpha_p}, x_q^{\alpha_q}\right) \leq \rho\beta_{pq} \\ syn_{pq}^{-}\left(x_p^{\alpha_p}, x_q^{\alpha_q}\right) \leq \rho\beta_{pq} \end{cases} \tag{25}$$

where ρ is a positive real constant representing an upper bound for syn_{pq}^{+} and syn_{pq}^{-} (e.g., $\rho = 1$), and the second constraint ensures that each criterion can interact with at most one another criterion.

In case of option (S2), there are introduced as many binary variables $\delta_{pq}^{+}, \delta_{pq}^{-} \in \{0, 1\}$ as twice the couples of criteria. The meaning of every binary variable is the following:

$$\delta_{pq}^{+}\left(\delta_{pq}^{-}\right) = \begin{cases} 1 & \text{if} \quad \{p, q\} \in I^{(2)} \text{ are positively (negatively) interacting} \\ 0 & \text{if} \quad \{p, q\} \in I^{(2)} \text{ are not positively (negatively) interacting} \end{cases} \tag{26}$$

For every couple of criteria $\{p,q\} \in I^{(2)}$, three situations can arise:

a) p and q are interacting positively ($\delta^+_{pq} = 1$)
b) p and $q$are interacting negatively ($\delta^-_{pq} = 1$)
c) p and $q$are not interacting ($\delta^+_{pq} = \delta^-_{pq} = 0$

In consequence, the following constraints are included in the first MILP:

$$E_{(S2)} \begin{cases} \delta^+_{pq}, \delta^-_{pq} \in \{0, 1\} \\ \delta^+_{pq} + \delta^-_{pq} \leq 1 \;\; \forall \{p,q\} \in I^{(2)} \\ syn^+_{pq}\left(x_p^{\alpha_p}, x_q^{\alpha_q}\right) \leq \rho\delta^+_{pq} \\ syn^-_{pq}\left(x_p^{\alpha_p}, x_q^{\alpha_q}\right) \leq \rho\delta^-_{pq} \\ \sum\limits_{q \in I\setminus\{p\}} \left(\delta^+_{pq}, \delta^-_{pq}\right) \leq 1 \;\; \forall p \in I \end{cases} \tag{27}$$

where ρ can be set for example equal to 1, the second constraint ensures that there are not positive and negative interactions simultaneously for the same couple of criteria and the last constraint ensures that each criterion can interact with at most another one criterion.

In case of option (S3):

a) If there are only positive interactions, then the corresponding set of constraints $E_{(S3^+)}$ is obtained form $E_{(S2)}$ by adding $\delta^-_{pq} = 0 \; \forall\{p,q\} \in I^{(2)}$.
b) If there are only negative interactions, then the corresponding set of constraints $E_{(S3^-)}$ is obtained form $E_{(S2)}$ by adding $\delta^+_{pq} = 0 \; \forall\{p,q\} \in I^{(2)}$.

Finally, the MILP formulation includes some technical constraints concerning monotonicity and boundary conditions on the synergies, the global, as well as the marginal value functions.

In particular, monotonicity constraints ensure that the marginal values x_i^{*k} for $i = 1, 2, \ldots, n$ and $k = 1, 2, \ldots, \alpha_i$ and the global value y^{*m} for $m = 1, 2, \ldots, \alpha$ are non-decreasing functions of x_i^k and y^m, respectively, while interaction functions $syn^+_{pq}\left(x_p^{k_p}, x_q^{k_q}\right)$ are non-decreasing functions of both their two arguments $x_p^{k_p}, x_q^{k_q}$ for $k_p = 1, 2, \ldots, \alpha_p$, $k_q = 1, 2, \ldots, \alpha_q$ and $\forall\{p,q\} \in I^{(2)}$. Boundary conditions ensure, that for every customer, the utility presenting the worst satisfaction level is equal to zero, while the utility presenting the best satisfaction level on each criterion is equal to one. In consequence, the set of constraints common to all the options described before is the following:

$$
\left.
\begin{array}{l}
Y^* = \sum_{i=1}^{n} X_i^* + \sum_{\{p,q\}\in I^{(2)}} syn_{pq}^{+}\left(X_p, X_q\right) - \sum_{\{p,q\}\in I^{(2)}} syn_{pq}^{-}\left(X_p, X_q\right) - \sigma_j^+ + \sigma_j^-
\end{array}
\right.
$$

$$
\left.
\begin{array}{l}
x_i^{*k+1} \geq x_i^{*k} \quad \text{for } k = 1, 2, \ldots, \alpha_i - 1 \\
y^{*m+1} \geq y^{*m} + d \quad \text{for } m = 1, 2, \ldots, \alpha - 1 \\
syn_{pq}^{+}\left(x_p^{k_p}, x_q^{k_q}\right) \geq syn_{pq}^{+}\left(x_p^{k'_p}, x_q^{k'_q}\right) \\
syn_{pq}^{-}\left(x_p^{k_p}, x_q^{k_q}\right) \geq syn_{pq}^{-}\left(x_p^{k'_p}, x_q^{k'_q}\right) \\
x_p^{*k_p} + x_q^{*k_q} + syn_{pq}^{+}\left(x_p^{k_p}, x_q^{k_q}\right) - syn_{pq}^{-}\left(x_p^{k_p}, x_q^{k_q}\right) \geq \\
x_p^{*k'_p} + x_q^{*k'_q} + syn_{pq}^{+}\left(x_p^{k'_p}, x_q^{k'_q}\right) - syn_{pq}^{-}\left(x_p^{k'_p}, x_q^{k'_q}\right) \\
\text{with } k_p \geq k'_p \text{ and } k_q \geq k'_q \\
k_p, k'_p = 1, 2, \ldots, \alpha_p, k_q, k'_q = 1, 2, \ldots, \alpha_q, \forall \{p, q\} \in I^{(2)}
\end{array}
\right\} \text{(monotonicity constraints)}
$$

$$
\left.
\begin{array}{l}
y^{*1} = 0, x_i^{*1} = 0 \quad \text{for } i = 1, 2, \ldots, n \\
syn_{pq}^{+}\left(x_p^1, x_q^1\right) = syn_{pq}^{-}\left(x_p^1, x_q^1\right) = 0 \;\; \forall \{p, q\} \in I^{(2)} \\
\sum_{i=1}^{n} x_i^{*\alpha_i} + \sum_{\{p,q\}\in I^{(2)}} syn_{pq}^{+}\left(x_p^{\alpha_p}, x_q^{\alpha_q}\right) + \sum_{\{p,q\}\in I^{(2)}} syn_{pq}^{-}\left(x_p^{\alpha_p}, x_q^{\alpha_q}\right) = 1
\end{array}
\right\} \text{(boundary constraints)} \tag{28}
$$

Depending on the choice of (S1), (S2) or (S3), constraints $E_{(S1)}$, $E_{(S2)}$, $E_{(S3^+)}$, $E_{(S3^-)}$ are added, accordingly, while the objective is the minimization of the sum of errors. The above MILP returns the utility function Y^* and, moreover, for option (S1) the set *Syn* of couples of criteria that can interact positively and negatively, and for options (S2) and (S3), the sets Syn^+ and Syn^- of couples of positively and negatively interacting criteria.

The second phase of the method concerns the identification of a minimal set of couples of interacting criteria. In order to identify a minimal set *Syn* or a minimal pair (Syn^+, Syn^-) of sets of couples of interacting criteria, while possibly accepting a small deterioration of the approximation error resulting from the previous phase, the following MILP problem has to be solved:

$$
\left\{
\begin{array}{l}
[\min]\, f \\
\text{subject to} \\
\text{constraints (17) plus } E_{(S1)}, E_{(S2)}, E_{(S3^+)}, E_{(S3^-)} \text{ accordingly} \\
\sum_{j=1}^{M} \left(\sigma_j^+ + \sigma_j^-\right) \leq F^* + \varepsilon
\end{array}
\right. \tag{29}
$$

where $f = \sum_{\{p,q\}\in I^{(2)}} \beta_{pq}$ for option (S1) or $f = \sum_{\{p,q\}\in I^{(2)}} \left(\delta_{pq}^+ + \delta_{pq}^-\right)$ for options (S2), (S3), F^* is the optimal value of the minimization of total error and ε is a small number. The parameter ε in MUSA-INT controls the trade-off between the number of criteria interacting and the total approximation error of the value function.

In the third phase, the most discriminating function has to be found. In order to find a value function Y^* discriminating as much as possible all levels of satisfaction by the marginal value functions X_i^*, or by the global value function, while keeping the same number of interacting couples of criteria, as obtained from (Eq. 29), two MILP problems have to be solved. The first one tends to discriminate as much as possible the satisfaction levels of the global value function:

$$\begin{cases} [\max]\, d \\ \text{subject to} \\ \text{constraints (18)} \\ \sum_{\{p,q\}\in I^{(2)}} \beta_{pq} \leq optsyn \ \text{ for (S1)} \\ \sum_{\{p,q\}\in I^{(2)}} \left(\delta_{pq}^{+} + \delta_{pq}^{-}\right) \leq optsyn \ \text{ for (S2) and (S3)} \end{cases} \tag{30}$$

where d is a variable present in the constraint $y^{*m+1} \geq y^{*m} + d$ and $optsyn$ is the optimal value of the objective function of MILP (Eq. 29).

The solution of MILP (Eq. 30) gives a value function maximizing the minimal difference $y^{*m+1} - y^{*m}$, $m = 1, 2, \ldots \alpha - 1$. In fact, the minimum of those differences is equal to d_{global}, i.e. the optimal value of d given by MILP (Eq. 30). A similar MILP problem can be solved when trying to find the most discriminating function not only with respect to the global value, but also with respect to the marginal value functions.

The three-phase method described in this section can be considered as the standard procedure proposed by Angilella et al. (2014), while finding other minimal sets of couples of interacting criteria and introducing Robust Ordinal Regression (ROR) methodology (Greco et al. 2008) in order to evaluate customer satisfaction using a set of compatible preference models, constitute some extensions of the methodology.

3.3 Least Square Approach

An alternative to the MUSA method in order to overcome some stability problems with the estimates has been proposed by Joao et al. (2010). This approach also aggregates the individual customer satisfaction criteria into an overall value function, but it makes use of a dummy variable regression technique with additional constraints. Moreover, contrary to the MUSA method, they proposed to apply more than one regression technique, starting with a dummy variable regression technique employing the least squares approach and then iteratively use a robust method of regression such as M-regression.

According to the original variables of the MUSA method, the coding procedure is performed considering the highest level as the reference level (M1), namely $x_i^{\alpha_i}$ for $i = 1, 2, \ldots, n$ and y^{α} for the highest level of the overall satisfaction scale (see Table 1).

Table 1 Dummy variables X_{ik} and Y_k coding for criterion and overall levels

Criterion i	X_{i0}	X_{i1}	...	$X_{i(\alpha_i-1)}$	Overall	Y_0	Y_1	...	$Y_{(\alpha-1)}$
Level $0 = x_i^0$	1	0	...	0	Level $0 = y^0$	1	0	...	0
Level $1 = x_i^1$	0	1	...	0	Level $1 = y^1$	0	1	...	0
...	...	...	...	...	...	...	...	...	...
Level $\alpha_i - 1 = x_i^{\alpha_i-1}$	0	0	...	1	Level $\alpha - 1 = y^{\alpha-1}$	0	0	...	1
Level $\alpha_i = x_i^{\alpha_i}$	0	0	...	0	Level $\alpha = y^{\alpha}$	0	0	...	0

The model is based on a dummy variable regression, which for the j-th customer can be represented by:

$$\sum_{i=1}^{n}\sum_{k=0}^{\alpha_i-1} D_{ik}X_{ik} - \sum_{m=0}^{\alpha-1} Z_m Y_m - \sigma_j = 0 \tag{31}$$

where, D_{ik} and Z_m are the dummy variable regression parameters.

The final form of the M1 problem can be written as follows:

$$\begin{cases} [\min]\ F = \sum\limits_{j=1}^{M} \sigma_j^2 \\ \text{subject to} \\ \sum\limits_{i=1}^{n}\sum\limits_{k=0}^{\alpha_i-1} D_{ik}X_{ik} - \sum\limits_{m=0}^{\alpha-1} Z_m Y_m - \sigma_j = 0 \ \text{ for } j = 1, 2, \ldots, M \\ \sum\limits_{i=1}^{n} D_{i0} = \text{constant}\,(< 0)\ D_{i(\alpha_i-1)} \leq 0 \\ D_{ik} \leq D_{i(\mathrm{k}+1)} \ \text{ for } k = 0, 1, \ldots, \alpha_i - 2 \\ Z_0 = \text{constant}\,(< 0)\ Z_{\alpha-1} \leq 0 \\ Z_m \leq Z_{m+1} \ \text{ for } m = 0, 1, \ldots, \alpha - 2 \end{cases} \tag{32}$$

Each dummy variable parameter represents the difference in the value of a level minus the value of the reference level according to:

$$\begin{cases} Z_m = y^{*m} - y^{*\alpha} \ \text{ for } m = 0, 1, \ldots, \alpha - 1 \\ D_{ik} = x_i^{*k} - x_i^{*\alpha_i} \ \text{ for } k = 0, 1, \ldots, \alpha_i - 1 \text{ and } i = 1, 2, \ldots, n \end{cases} \tag{33}$$

The dummy variable regression parameters, Z_m and D_{ik} in overall and partial value functions are graphically represented in Fig. 4. After the estimation of these dummy variables, the values y^{*m} and x_i^{*k} can be calculated. The range of the values across the levels of a criterion is a measure of the 'weight' of that criterion, and is calculated according to $x_i^{*\alpha_i} - x_i^{*0}$. The 'weight' of a criterion is normalized to

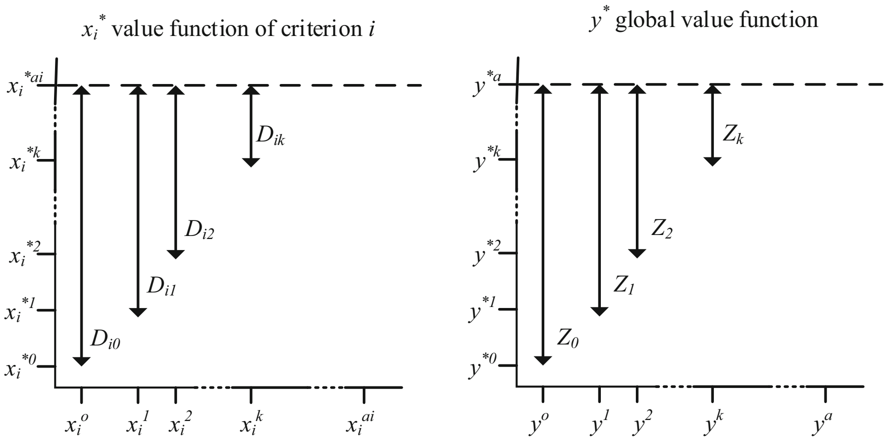


Fig. 4 Graphical representation of the dummy variable regression parameters

ascertain the relative weight according to:

$$b_i = \frac{x_i^{*\alpha_i} - x_i^{*0}}{\sum\limits_{t=1}^{n} \left(x_t^{*\alpha_i} - x_t^{*0}\right)} \tag{34}$$

The normalized values $\overline{x}_i^{*k}$ for $k = 0, 1, \ldots, \alpha_i$ and $\overline{y}^{*m}$ for $m - 0, 1, \ldots, \alpha$ are calculated by:

$$\overline{x}_i^{*k} = \frac{x_i^{*k} - x_i^{*0}}{x_i^{*\alpha_i} - x_i^{*0}} \quad \text{and} \quad \overline{y}^{*m} = \frac{y^{*m} - y^{*0}}{y^{*\alpha} - y^{*0}} \tag{35}$$

The normalized values and the relative weights provide a basis for interpreting the results. The method was tested using three alternative forms of coding: differences to an upper reference level (M1), differences to a lower reference level (M2), and consecutive differences between levels (M3).

In order to improve the estimates obtained by the dummy variable regression method, Joao et al. (2010) used M-regression which is a ‘robust’ method of regression allowing them to deal with the presence of outliers. According to Birkes and Dodge (1993) the least squares regression performs well if the population of errors is normally distributed but when the data contains outliers, least squares (LS) may perform poorly. The least absolute deviation (LAD) optimization procedure used by MUSA, is appropriate when the data contain outliers, however presents stability problems. To overcome these stability problems and in order to have a method that performs well when in presence of outliers, Joao et al. (2010) proposed to use iteratively a robust method of regression after the first estimates of M1.

Therefore, contrary to the original MUSA method, they proposed to apply more than one regression technique, starting with a dummy variable regression technique employing the least square approach and then iteratively using a robust method of regression such as M-regression. In M-regression the advantages of LAD and LS can be combined. The main advantage of LAD estimates over LS estimates is that they are not so sensitive to outliers. When there are no outliers, however, LS estimates may be more accurate.

The authors compared the results, with real data sets, obtained by the dummy variable regression method with the results obtained by the MUSA method. They concluded that the results provided by the dummy variable regression method are more stable than the ones of the MUSA method. Furthermore, the method was tested using three alternative forms of coding: differences to an upper reference level (M1), differences to a lower reference level (M2), and consecutive differences between levels (M3). Their comparison revealed that the results obtained for the relative criteria weight, as well as for the value functions are independent of the coding procedure used, and therefore any level can be used as a reference level without changing the results. Finally, after the comparison of the results obtained by M1 and MUSA, the authors used iteratively M-regression. From the results obtained with M-regression they concluded that it is valuable to use M-regression iteratively combining the advantages of LAD and LS.

4 Other Approaches

4.1 Fuzzy MUSA Method

In real life, the problem of imprecise, uncertain, or vague qualitative data due to the lack of knowledge or ill-defined information is rather common. This is also the case with data concerning customer satisfaction. For this reason, Aouadni and Rebai (2016) proposed an extension of the MUSA method, into a fuzzy environment. The objective was to make the method capable of accepting and processing fuzzy scores as an input and producing a satisfaction function with fuzzy coefficients (i.e., fuzzy partial satisfaction functions and fuzzy global satisfaction). They proposed to combine a continuous genetic algorithm with the fuzzy MUSA method in order to obtain a robust solution of the problem.

The fuzzy MUSA method involves steps similar to those of the classic MUSA method:

Step 1: Define the triangular fuzzy numbers of the linguistic variable
In their study, Aouadni and Rebai (2016) used the triangular fuzzy numbers (TFN) to define the fuzzy set $\tilde{A}$ on the universal set of real numbers. The mathematical

Table 2 Triangular fuzzy numbers of linguistic variable

Linguistic variable	Rating
Very unsatisfied	(0,0,1)
Unsatisfied	(0,1,2)
Fair	(1,2,3)
Satisfied	(2,3,4)
Very satisfied	(3,4,4)

formula of membership function of TFNs is defined as follows:

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-a}{b-a} & x \in (a, b] \\ \frac{c-x}{c-b} & x \in [b, c) \\ 0 & \text{otherwise} \end{cases} \tag{36}$$

TFNs are represented as triplets of three real numbers (a, b, c), where $a < b < c$. The membership function increases from 0 to 1 in range $(a, b]$ in a linear fashion and decreases from 1 to 0 in range $[b, c)$. At point b, $\mu_{\tilde{A}}(b) = 1$, and at points a and c, $\mu_{\tilde{A}}(a) = \mu_{\tilde{A}}(c) = 0$. The authors, in their work adopted five fuzzy linguistic terms by triangular fuzzy numbers to express un-quantified matters (see Table 2).

Step 2: Create LP with fuzzy numbers
The LP formulation minimizes the sum of errors, similarly to the original MUSA method. All the parameters of the original MUSA method are fuzzy, as well as the ordinal regression analysis equation. The proposed formulation is similar to the fuzzy UTASTAR method, which is a fuzzy extension of the UTASTAR method (see Patiniotakis et al. 2011).

Step 3: Solve using genetic algorithm
In order to solve the formulated LP, Aouadni and Rebai (2016) propose the use of a genetic algorithm, consisting of the following steps:

a) Generate initial population: The initial population refers to model variables, i.e., fuzzy variables w_{ik} and z_m.
b) Selection: In the selection process, two parents from the population are selected and crossed by using a fitness function.
c) Crossover operator: After choosing two individuals from the current population as parents and in order to generate two children, the authors randomly generated one position in order to cross and have a new chromosome.
d) Mutation operator: The mutation procedure is based on the previous step and refers to the fuzzy variables w_{ik} and z_m.
e) Fitness function: The fitness function corresponds to the original objective function of the fuzzy LP, i.e., the minimization of the sum of errors σ^+ and σ^-.
f) Convergence criterion: The genetic algorithm stops after a priori fixed number of generations. In Aouadni and Rebai (2016) this is fixed at 100,000 generations.

Step 4: Defuzzification

Aouadni and Rebai (2016) use the theorem of Roubens (1991) in order to compare the fuzzy numbers. A fuzzy numbers comparison is achieved by mapping fuzzy numbers onto real axis, where a natural order exists, and then compare real numbers instead of fuzzy ones. Roubens proved that a good ranking function for triangular fuzzy numbers is:

$$\Re = \frac{a + 2b + c}{4} \tag{37}$$

where (a, b, c) is a TFN.

4.2 Outranking Approaches

Outranking multicriteria methods have also been applied in customer satisfaction measurement. In their work, Costa et al. (2007) have tried to implement the outranking multicriteria methodology ELECTRE TRI in order to classify customers according to their satisfaction.

ELECTRE TRI is a multiple criteria sorting method that assigns alternatives to pre-defined categories (Yu 1992). The assignment of an alternative a results from the comparison of a with the profiles defining the limits of the categories. Let F denote the set of the indices of the criteria $g_1, g_2, \ldots, g_m$ ($F = \{1, 2, \ldots, \mathrm{m}\}$) and B the set of indices of the profiles defining $p + 1$ categories ($B = \{1, 2, \ldots, p\}$), b_h being the upper limit of category C_h and the lower limit of category C_{h+1}, $h = 1, 2, \ldots, p$ (see Fig. 5, where the profiles b_{p+1} and b_0 correspond to the ideal and the anti-ideal alternatives, respectively).

ELECTRE TRI builds an outranking relation S i.e., validates or invalidates the assertion aSb_h, meaning that *'a is at least as good as b_h.'* Preferences restricted

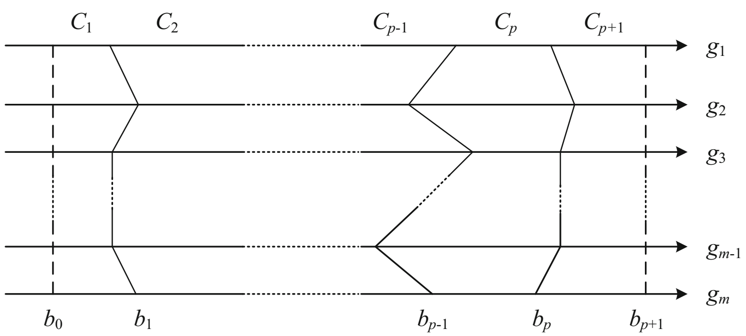


Fig. 5 Definition of categories using limit profiles

to the significance axis of each criterion are defined through pseudo-criteria. The indifference and preference thresholds, $q_j(b_h)$ and $p_j(b_h)$, respectively, constitute the intra-criterion preferential information. They account for the imprecise nature of the evaluations $g_j(a)$. $q_j(b_h)$ specifies the largest difference $g_j(a) - g_j(b_h)$ that preserves indifference between a and b_h on criterion g_j. $p_j(b_h)$ represents the smallest difference $g_j(a) - g_j(b_h)$ compatible with a preference in favor of a on criterion g_j.

The ELECTRE TRI algorithm is based on the following calculations (Mousseau et al. 2000):

- The partial concordance indices $c_j(a, b_h)$ (or $c_j(b_h, a)$), expressing the extent to which the statement *'a is at least as good as b_h (or b_h is at least as good as a) considering criterion g_j'* is true.
- The global concordance index $C(a, b_h)$ (or $C(b_h, a)$), expressing the extent to which the statement *'a outranks b_h (or b_h outranks a) considering all the criteria'* is true.
- The discordance indices $d_j(a, b_h)$ (or $d_j(b_h, a)$), expressing the extent to which the criterion g_j is opposed to the statement *'a is at least as good as b_h (or b_h is at least as good as a)'* is true.
- The degree of credibility of the outranking relation $\sigma(a, b_h)$ (or $\sigma(b_h, a)$), expressing the extent to which the statement *'a outranks b_h (or b_h outranks a) according to the global concordance index $C(a, b_h)$ (or $C(b_h, a)$) and to the discordance indices $d_j(a, b_h)$ (or $d_j(b_h, a)$)'*, $\forall j \in F$ is true.
- The resulting outranking relation, which is the translation of the obtained fuzzy outranking relation S by means of a λ-cut threshold ($0.5 \leq \lambda \leq 1$). λ is considered as the smallest value of the credibility index compatible with the assertion *'a outranks b_h'*, i.e., $\sigma(a, b_h) \geq \lambda \Rightarrow aSb_h$. The following binary relations P (preference), I (indifference) and R (incomparability) are defined:

$$\begin{aligned} aIb_h &\Rightarrow aSb_h \text{ and } b_hSa \\ aPb_h &\Rightarrow aSb_h \text{ and not } b_hSa \\ aRb_h &\Rightarrow \text{not } aSb_h \text{ and not } b_hSa \end{aligned} \tag{38}$$

In order to determine the category to which an alternative a should be assigned, two assignment procedures are available, the pessimistic and the optimistic one. In both cases, an alternative a is compared successively to b_i, for $i = p, p - 1, \ldots, 0$, where b_{h-1} and b_h denote the lower and upper profile of the category C_h. The assignment of alternatives follows the following rules:

a) If aPb_i and $b_{i+1}Pa$ or aIb_{i+1}, then a is assigned to category $i + 1$ in both the optimistic and the pessimistic assignment procedures.
b) If aPb_i and aRb_{i+1}, aRb_{i+2}, $\ldots$, aRb_{i+k}, $b_{i+k+1}Pa$, then a is assigned to category $i + 1$ or to the category $i + k + 1$, according to the pessimistic or the optimistic assignment procedures, respectively.

Costa et al. (2007) tried to implement the previous procedure in customer satisfaction measurement. The first step of their proposed approach refers to the identification of the service to be evaluated by customers, while in the next step the criteria that will be used to assess customer satisfaction are defined. In the third step the importance and performance scale of satisfaction criteria is specified based on the works of Bana e Costa (1990), Herrera and Costa (2001). The next step refers to the customer satisfaction survey, where performance and importance customers' judgments for each one of the satisfaction criteria are collected. Data are analyzed in the fifth step, considering the following:

- *Analysis of sample behavior*: Performance and importance data are analyzed using descriptive statistics measures (e.g., coefficient of variation, asymmetry, kurtosis) in order to assure the degree of homogeneity of the sample. In addition, the Chauvenet's criterion is applied in order to identify and eliminate possible outliers (see for example Dally and Riley 1998).
- *Selection of preference and indifference thresholds*: The preference (p_j) and indifference (q_j) thresholds for each criterion j should be defined in order to consider the imprecise nature of customers' judgments. In the proposed approach, since these thresholds are associated with the dispersion of customer evaluation in the sample, Costa et al. (2007) suggest to set $p_j = q_j = \min\{CV_j, I/2\}$, where CV_j is the coefficient of variation of the performance judgments of the j-th satisfaction criterion and I is the interval in the satisfaction scale.
- *Define the equivalence classes*: Based on the above, the necessary satisfaction categories, as well as their respective limits (upper and lower profiles) should be defined.
- *Apply the ELECTRE TRI algorithm*: In this final step, the ELECTRE TRI algorithm is applied in order to classify customers to one of the predefined satisfaction categories.

As discussed by Costa et al. (2007), the previous approach produces two different classification results:

a) The pessimistic (most demanding) classification, where a customer is classified into a generic class h, if his/her performance judgments are at least as good as the $h-1$ profile on a significant number of criteria (with a minimum degree of credibility σ).
b) The optimistic (less demanding) classification, where a customer is classified into a generic class h, if his/her performance judgments are just below the h profile on a significant number of criteria (with a minimum degree of credibility σ).

The degree of credibility is a measure of the reliability of the resulting classification, being defined from an integration between the concept of agreement (how much customer's judgments 'agree' with the classification) and the concept of disagreement (how much customer's judgements 'disagree' with the classification).

5 Concluding Remarks

Customer satisfaction is one of the most important issues concerning business organizations and therefore measuring customer satisfaction in an effective and reliable manner is very crucial in order to have an objective feedback about customers' preferences and expectations.

Although several approaches have been developed to evaluate customer satisfaction, multicriteria methods can be regarded as the most appropriate ones considering that they take advantage of the multiple criteria nature of customer satisfaction. Customer satisfaction can be regarded as a multivariate evaluation problem given that customer's global satisfaction depends on a set of variables representing product/service characteristic dimensions.

In this chapter, multiple criteria approaches for customer satisfaction measurement are presented, focusing on the most representative one that is the MUSA method. As it is a preference disaggregation approach mostly used in customer satisfaction measurement, several extensions have been proposed since the introduction of the original MUSA method, in an attempt to enrich the provided results and take more reliable and meaningful information about customers' preferences. These extensions were also presented in this chapter along with other outranking approaches used for customer satisfaction measurement.

However, since, in most of the cases, the proposed approaches have been implemented in limited samples, their results cannot be generalized. More representative samples about different business sectors are needed in order to have more reliable information about the credibility of the provided results. These different approaches can be implemented with various samples in order to compare their results and take interesting information about the most appropriate approaches for different characteristics of the customers' satisfaction data. A software including all the different multiple criteria approaches for measuring customer satisfaction could be developed for this reason.

Different extensions of the presented approaches as well as the possibility to consider the preference disaggregation paradigm in other MCDA methods may also be examined in future research efforts.

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Projects Portfolio Selection Framework Combining MCDA UTASTAR Method with 0–1 Multi-Objective Programming

Isaak Vryzidis, Athanasios Spyridakos, and Nikos Tsotsolas

Abstract The evaluation of projects portfolio effectiveness is a complex and diverse topic linked to the strategic planning, the efficiency of project implementation teams, the social and economic environment, the availability of resources etc. The appropriate projects selection constitutes one of the key points to ensure the total portfolio success by including different selection criteria regards not only to projects efficiency but also to their effectiveness. Efficiency reflects whether the project management team used effectively the organization's resources in order to accomplish the initial plan and project goals, while effectiveness determines whether the results of a project meet the objectives set by the organization's top management team. In this chapter we are discussing an approach for the selection and evaluation of projects portfolio based on two multicriteria methodological frames: (a) The Multi Criteria UTA(*) method of Disaggregation—Aggregation approach (D-A) with which the alternative actions are evaluated according to the business strategic objectives and (b) the Multi-objective (0–1) Linear Programming techniques, which are utilised to select a subset of the alternative projects considering the estimated with the D-A approach multicriteria global values of the alternative projects, the additional objectives related to the external environment, the internal and external policy restrictions, the availability of resources and the specific market conditions. The incorporation of stochastic criteria into the analysis to evaluate the alternative projects under uncertainty is also presented in the following sections. The aforementioned approaches are illustrated through a case study concerning the projects portfolio selection of a contraction firm.

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1 Introduction

The project management together with an efficient projects selection is important for the competitiveness of organizations within the today's dynamic and unpredictable environment. The last decades, firms and organizations, which are projects process organised, are focusing on the effective projects portfolio selection in order to group them together for the achievement of the organizational strategic objectives and for an effective allocation of the available resources (human, material, cash flow).

The effectiveness and the total success of the projects are related not only to the implementation factors (Atkinson 1999; Ika 2009; Patanakul and Milosevic 2009; Westerveld 2003; Yu et al. 2005) but also to parameters measured mainly after the project's completion. The performance on these parameters is influenced by a suitable portfolio selection linking the strategy with projects in order the project management team to manage them accordingly and then track their contribution to the firm's development and change. Managing a projects portfolio, measuring and tracking their progress and assessing their future impacts and benefits include dynamic features such as the uncertainty, the complexity, the time, the risk, the influence of the stakeholders involved, the influence of external factors, the interaction with other projects at the organization-enterprise level, the viability of the original plan, the degree of projects alignment with the strategic objectives, etc. Moreover, each project is unique with different goals and inputs requiring different project management techniques (Shenhar and Dvir 2007) to efficiently implement them and balance the various conflicting parameters within an environment that is continuously changing. The successful implementation of a project and/or a portfolio of projects according to the initial plan is a prerequisite for an overall project success. For this reason, it is necessary to analyse the feasibility of the projects desired outcomes in accordance with the available resources and policy restrictions during the selection phase. Therefore, the selection process needs to include criteria related to efficiency in addition to criteria that estimates the project results after the project life cycle and for different stakeholder perspectives.

In general, the selection of the projects portfolio (APM 2012; PMI 2008) constitutes a semi-structured decision problem as:

- The outcomes of projects cannot be precisely predicted due to the uncertainties characterizing the operational environment.
- The undertaken projects reserves resources resulting to availability limitations and leading to the exclusion of other projects.
- There are a lot of conflicting and competitive factors to be taken into consideration for the selection of the projects (income, quality, preparation for the future, etc.).
- There is no a step by step procedure that can fit to all cases for the projects evaluation by taking into account different point of views without compromises among the selection criteria.

The selection process of projects' portfolios, especially in the cases where the needs of a later assessment are considered, faces specific challenges which should be tackled under a well-defined and sound methodological approach. These challenges are summarised in the following points:

- *Linearity:* A lot of existing models aggregate the criteria in a linear way without taking into consideration the possible variation in their relative importance at different level of performance on each criterion. Criteria weights and non-linear criteria functions should be part of the project selection process in order the models to be closer to the real world leading to more realistic final selections.
- *Consistent family of criteria:* Another important point to be taken into account when modelling project selection problems is the need to use a consistent family of criteria (monotony, proficiency, non-redundancy) (Bouyssou 1990). This ensures not only that there is no criterion that will probably affect the project evaluation process at a later stage, but also that the criteria are independent of each other and the same result from a point of view is not taken twice.
- *Different criteria for each case:* Each project is unique and the factors determining its effectiveness vary for each case. So, a comprehensive selection methodology should allow each decision maker groups to determine the important parameters of each project based on their experience and the available knowledge.
- *Management of qualitative parameters:* There is a need to follow reliable processes of managing the quality parameters in the problem of project selection. It is not a solution to turn all the parameters into cost and sum them together. The process should describe how exactly the quality and quantitative parameters are synthesized into a final conclusion and ensure that a realistic and rational model is utilised.
- *Linking efficiency to strategic goals:* The overall success of projects is directly linked to the defined strategic goals. Influenced by the work of Shenhar et al. (2001), projects should be evaluated on the basis of the achievements according to the strategic goals that triggered them. Their effectiveness shall be estimated based on the reasons that led to their selection. Therefore, at the selection stage, the criteria to be selected should reflect this necessary link with the strategic objectives.
- *Management of uncertainty:* Uncertainty related to a project is met during the implementation stages and also after the implementation while evaluating its effectiveness. It is not certain from the beginning that the assumptions that were considered at the initial analysis will continue to be valid in future stages. So, there is a necessity to include the uncertainty at the selection stage.
- *Evaluating the satisfaction of stakeholders:* A major problem in the evaluation of projects is the different views and perceptions of the stakeholders involved about effectiveness. Different outcomes have different importance for the organization—company, the management team, the customers, the society and the wider external environment. For that reason, the involvement of stake-

holders at the selection stage or at least the analysis and incorporation of their needs is essential.

In the methodological framework outlined in a subsequent section, these challenges are effectively addressed through a structured project selection process that aids with appropriate tools the decision of the top management team and/or the portfolio manager. Specifically, an approach is discussed, which links the evaluation criteria during the selection process to the strategic objectives of an organization by modelling the preferences of the decision-maker on the alternative projects. The synthesis of the qualitative and quantitative parameters in a reliable manner for the project selection problem is implemented through estimated value functions taking into account their non-linear form and relative importance. This is achieved by utilising multi-criteria methods, which are further used to check the consistency of the used criteria through a process of iterations and feedbacks. Also, the methodological framework under discussion allows the decision analysts to include stochastic criteria in the analysis for the selection parameters under uncertainty.

As already mentioned, the business strategic goals need to be included in the portfolio selection process conforming to the new trends in the project management discipline. The project management is becoming more strategic and business oriented (Shenhar 2015) and the project managers have been characterized by Shenhar et al. (2001) as the new strategic leaders. Therefore, the linking of the available projects to the strategy and the management of the complexity of projects selection process are vital points, which require further research.

The chapter consists of an introduction and four more sections. The second section includes a background for project selection in the project management literature and an overview of the notions of effectiveness and efficiency. The proposed methodological framework for projects portfolio selection is presented in the third section of the chapter. Then, in the fourth section an illustration example is developed for the analytical presentation of the methodological framework. Finally, some concluding remarks together with further exploitations are presented in the last section.

2 Background in Projects Portfolio Selection

Portfolio managers are responsible for the selection, prioritization and control of the organisation's projects and programmes in regards with its strategic goals and resources capacity (APM Body of Knowledge 2012). The selected portfolio needs to be balanced according to the taken risks, resources usage, cash flow capacity and linked to the business strategic objectives. Therefore, several selection methods have been developed and proposed over the years to aid firms and organisations prioritize and organize their projects. These methods generally fall into the two following broad categories (Iyigun 1993; PMI 2004):

- **Benefit measurement methods**, which are focusing on the development of a measurement system estimating the potential benefits for each project. These methods are the most common approaches used in practice and the majority of them are benefit contribution or economic models. Specifically, in these models the benefits and predicted value of each project is estimated and presented in terms of Benefit Cost Analysis (BCA), Return on Investment (ROI), Discounted Cash Flow Analysis, Net Present Value (NPV), Opportunity Cost, etc. Moving away from the financial models, another type of methods included in this category are the Scoring Models which conclude to an overall project score through the aggregation of different weighted criteria. These models could be a separate category, especially in the case where Multi-Criteria Decision Aid (MCDA) methods has been utilised. In the methodology presented in Sect. 3, the multi-criteria Disaggregation—Aggregation UTA methods are used to estimate an additive value system leading to a projects prioritization (criteria weights, marginal utility functions).
- **Constrained optimization methods**, which are mathematical models and algorithms aiding the decision maker to determine an optimal set of actions. These methods are suitable for large and complex selection processes in order to ensure that the selected projects comply with the organization's resources constraints and the external restrictions (market regulation, laws, etc.). Methods and techniques included in this category are linear programming, non-linear programming, dynamic programming, integer programming, multi-objective programming, stochastic programming and fuzzy mathematical programming.

The bibliography work of Supachart Iamratanakul et al. (2008) identifies another four categories in addition to the above two, which are the Simulation and Heuristics Models, Cognitive Emulation Approaches (decision-tree approaches, statistical approaches, etc.), Real Options and Ad Hoc Models. The detailed description of the above methodologies exceeds the purpose of this chapter book and emphasis will be given to important points of the selection process. One of them, which mentioned previously, is the integration of the needs and desires of various stakeholders in the analysis. Stakeholders could influence the projects positively or negatively and early identification of them will be beneficial to assess their impact (Hill 2009). Apart from their impact to projects, stakeholders are important from the perspective of their satisfaction. Van Aken (1996) defines that a project is successful when the satisfaction of all stakeholders has been met. Therefore, the ideal situation is to involve the various stakeholders during project selection process and link the projects to their needs and interests. Although, this is not achievable in all the cases and impossible to include all stakeholders during the project selection phase, a stakeholders analysis by mapping their interest and power or influence (Eden and Ackermann 1998) could aid the selection team to estimate the risks and feasibility for each project.

Another parameter which affects the selection process in practice is the perception of top management team for project success. The projects selection criteria and the evaluation criteria of project success are the two sides of the same coin.

For example, if a project is characterized as successful when it is implemented in time, within the budget constraints and according to the quality standards, then the selection process will emphasize more on the operational point of view. On the other hand, if project success is linked to criteria such as the end-user's satisfaction, the organizational benefits, the project personnel satisfaction, the client satisfaction, etc., the selection criteria will focus more to the strategic objectives and the various stakeholders. Jugdev and Muller (2005) explain that "the project management can have strategic value when a clear connection is made between how efficiently and effectively project is done and how the project's products and services provide business value". At this point, in order to avoid any confusion, the following concepts should be distinguished:

- Efficiency: expresses if the organization's resources were used effectively to achieve the project objectives and whether or not the project management team has successfully implemented the initial plan. It focuses mainly on criteria related to the implementation of the projects, such as the "golden" triangle, risk management, etc.
- Effectiveness: focuses on the results of the project after the implementation and expresses the achievements in regards with the business and strategic objectives. It is related to the success of the final product including the customer and end-user satisfaction, the added business value, the benefits to various stakeholders, etc.

The total project success is achieved when both efficiency and effectiveness are ensured (Baccarini 1999). Therefore, the project selection process needed to include those parameters that will ensure the projects efficiency and those that examine the projects effectiveness. It is important for the total project success to link the effectiveness parameters to the projects through the selection process in order the project management team to focus on delivering the business and strategic value that is expected from the undertaken projects. Shenhar et al. (1997, 2001) explain that effectiveness has three dimensions: (1) the customer satisfaction which can be measured a few weeks after project execution, (2) the company's short-term benefits (e.g. earnings, market share) which can be measured after 1 or 2 years, and (3) long-term benefits which can be estimated after about 4 or 5 years. The long term benefits of a project are not easily determined. A selection process, which includes long-term parameters (preparation of the business for future challenges), could help to relate directly the long-term impacts to the added business value. Also, every dimension of project effectiveness does not have the same weight through the time, but it changes. In the short term, the top management team is more interested in the effective implementation of the project by satisfying the original plan. After implementation, the importance of the project management efficiency begins to decrease to a point where the impact on the client will dominate. Finally, in the medium and long term, interest is shifting respectively to direct and indirect business benefits (Fig. 1). Therefore, it is clear that projects are so important for the overall business success in short-term and long term and a structured and detailed selection process could ensure that this could be achieved.

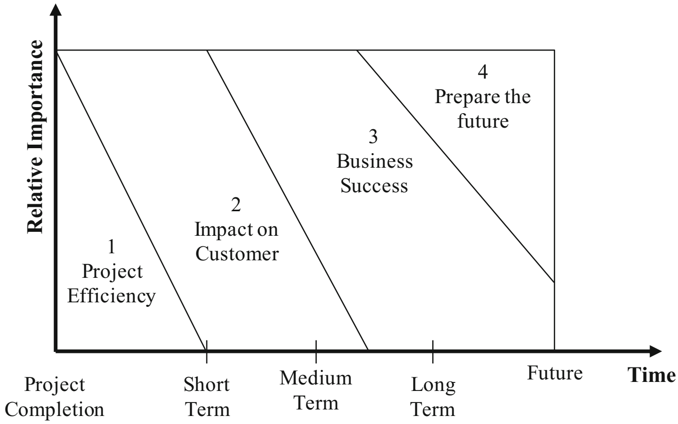

Fig. 1 Relative importance of success dimensions through time (Shenhar et al. 2001)

One question that usually needs to be addressed at the projects selection phase is in what extend and how detail the analysis of the above parameters will be sufficient. This depends mainly from the nature and type of the alternative projects which have some interest for the top management team. Several classifications exist in the literature to distinguish the projects that could help the management team to determine the critical parameters and the level of the analysis required. Five project types has been developed from Westerveld and Gaya Walters (2001) based on the desired project goals set at the selection phase and the external factors influencing the project implementation. These project types are:

I. Product Orientation Projects: are the ones which are considered as a synthesis of different disciplines for the achievement of an end product defined by the client. An example is the restoration of the drainage system in a school building. In this category, emphasis is given to the cost, time and quality (iron triangle).
II. Tool Orientation Projects: are the ones which are considered as a process that leads to an end product by using the appropriate tools and techniques to maximise the efficiency of the resources usage. Emphasis is given to the iron triangle and the resources restrictions. An example is the mechanical equipment maintenance needed to be done for the whole train fleet of an organisation. The key point is the minimization of the inactive time of maintenance personnel and simultaneously to ensure no impact to the organisation operations.
III. System Orientation Projects: are the ones which are considered as a system of contracting partners and project organisation that leads to an end defined product including the demands of users and various stakeholders. An example is the building of a new school by taking into account the needs of residents, families and teachers in the initial design.
IV. Strategy Orientation Projects: are the ones which are considered as an organisation from directly involved parties that targets to fulfill the needs of a client

and end—user under external stakeholder restrictions. The satisfaction of the client, the end users, the contracting partners and the project personnel (internal project stakeholders) is critical for the overall project success.

V. Total Project Management Projects: requiring general management of all stakeholders to meet their needs. For example, many different groups, such as local residents, government partners, builders, etc. were involved in the pedestrian and touristic regeneration of the historic center of Athens. Balancing their needs is an important parameter for the success of the project.

It is clear that "one size does not fit all the projects" (Shenhar et al. 2001) and there is not a set of selection criteria that can be used in all the cases. The Multi-Criteria analysis and the Decision Theory have a lot to offer in this field, especially if the available knowledge from the project management is utilised for the formulation and construction of the decision problem. Decision making treats every case separately according to each business characteristics, the external environment and the preferences of the decision maker by linking the strategy to the projects. In the next section a methodological framework in respect to the project management requirements is discussed in detail.

3 Methodological Framework for Projects Portfolio Selection

Following several works in which a combination of multicriteria approaches are suggested (Badri et al. 2001; Mavrotas et al. 2003, 2006), we are discussing a methodological approach for the selection of projects' portfolio, which on the one hand links the selection criteria to the organizational strategic objectives and on the other supports the handling of factors influenced by the external environment and business restrictions. The methodological approach under discussion is based on a synergistic exploitation of the Multicriteria Disaggregation—Aggregation UTA (*) method (Siskos 1980, 1983; Siskos et al. 1993) and the Multi-objective Linear Programming techniques (Ehrgott and Wiecek 2005; Evans and Steuer 1973; Korhonen 2005; Korhonen and Wallenius 1990; Zeleny 1974). Also, special treatments are applied in order to handle the uncertainty on project parameters and outcomes.

The methodological framework under discussion is based on two Multicriteria Decision Aid approaches: (a) the Disaggregation—Aggregation UTA methods with which an additive value system is estimated linking directly the potential outcomes of alternative projects with the business strategic orientations and (b) the Multi-Objective (0–1) Linear Programming techniques (MOLP) which allows the projects selection by taking into account the decision maker's preferences, parameters related to the external environment (e.g. economical risk, political uncertainty, market competitiveness, social needs) and the constraints due to resources availability, policy restrictions or business situation. The framework for the projects portfolio selection consists of two phases: (1) evaluation of projects utility functions, (2)

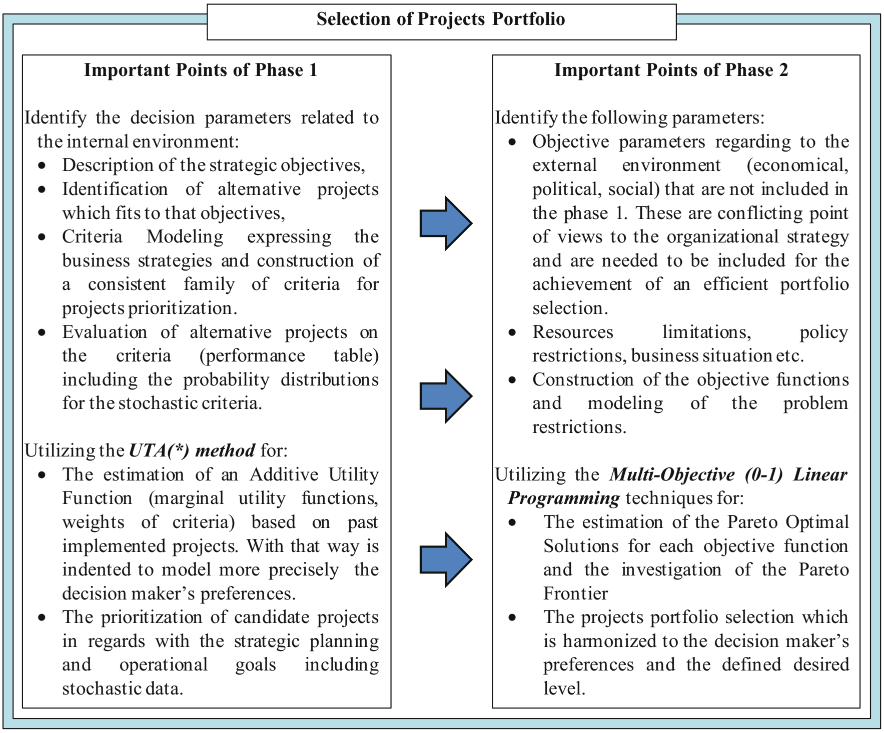

Fig. 2 Illustration of the important points of the proposed approach for Projects Portfolio Selection

selection of project (or portfolio of projects) using multiple objectives. These two phases together with the respective outcomes are presented in Fig. 2.

In the first phase of the proposed approach the UTA(*) is utilized in order to achieve the assessment of a value system encapsulating the evaluators' preferences that is described in the following formulae:

$$U(g) = \sum_{i=1}^{n} p_i u_i\,(g_i)$$
$$u\,(g_{i*}) = 0,\ u\,(g_{i*}) = 1, \text{for i} = 1, 2, \ldots, \text{n}$$
$$\sum_{\text{i}=1}^{\text{n}} \text{p}_\text{i} = 1,\ p_i \geq 0, \text{for i} = 1, 2, \ldots, \text{n}$$

where $\text{g} = (\text{g}_1, \text{g}_2, \ldots, \text{g}_\text{n})$ is the performance vector of an alternative project on the n criteria; g_{i*} and $g_i{*}$ are respectively the least and most preferable levels of the criterion g_i; $u_i(g_i)$ and p_i are the value of the performance g_i and the relative weight of the i-th criterion (Keeney 1996; Keeney and Raiffa 1976).

This value system can be obtained utilizing the MINORA system (Siskos et al. 1993) the spine of which is the disaggregation-aggregation UTA (*) method. In Fig. 2 the major steps of the methodological frame are presented, which are described in the following:

(a) **Criteria Modeling:** Criteria Modeling is crucial for the evaluation process resulting in a consistent family of criteria (Bouyssou 1990) so as to provide a supplemented view of the alternative projects regarding its performance. This set of criteria allows us, to measure the consistency and appropriateness of the alternative projects with respect to the three principles that ensure the consistency of the criteria family (Roy 1985).
(b) **Construct the set of alternative projects:** Let's define $A = \{a_j, j = 1, 2, \ldots, m\}$ as the finite set of all those alternative actions to be considered and evaluated by the decision-maker within the decision-making process, which will eventually lead to the selection of one of these actions (Roy and Bouyssou 1993). A project is considered to belong to the set A if it is likely to take place.
(c) **Projects evaluation on the criteria:** The evaluation of the projects on the consistent family of criteria takes places into this procedure. A set of rules and techniques, designed during the criteria modeling procedure, has to be followed in order to assign the corresponding values of the projects for every criterion.
(d) **Selection of the reference set:** From the total number of the alternative projects a small number is selected (reference set). The members of the reference set have to be representative of the whole set of alternative projects in order to take into account the different aspects of them. Also, they have to be known to the DMs so as to express their preferences fluently. In order to ensure the above mentioned requirements in this proposed approach we use a set of previous implemented projects which constitute the reference set for the assessment of the additive value which will be further used for the evaluation of the alternative projects under consideration.
(e) **DMs' pre-ranking of the reference set:** The DMs express their global preferences by rank ordering (weak order) the alternative projects of the reference set.
(f) **Assessment of the Evaluation Model:** The UTA (*) method estimates the weighting factors p_i as well as the value functions $u(g)$ (piecewise linear) of the criteria using special linear programming techniques. Suppose a ranking (weak order) is given on a set of reference projects $A_r = (a_1, a_2, \ldots, a_k)$, where the objects are rearranged in such a way that a_1 is the head and a_k is the tail of the ranking and for every pair of consecutive projects for evaluation (a_m, a_{m+1}) holds either $a_m P a_{m+1}$ (preference) or $a_m I a_{m+1}$ (indifference).

    UTA(*) solves the linear program below which, because of the transitivity of the (P,I) preference system has k constraints only. Special post-optimality analysis techniques are also applied to test the stability of the estimated weights

(Grigoroudis and Siskos 2002; Jacquet-Lagreze and Siskos 1982; Siskos and Yannacopoulos 1985):

$$\begin{cases} [\min]\, F,\ F = \sum_{i=1}^{k} \left(\sigma^{+}(\mathrm{a_i}) + \sigma^{-}(\mathrm{a_i})\right) \\ \textit{Subject to}: \\ \sum_{i=1}^{n} \mathrm{p_i u_i}\left[\mathrm{g_i}(\mathrm{a_m})\right] - \sigma^{+}(\mathrm{a_m}) + \sigma^{-}(\mathrm{a_m}) - \sum_{i=1}^{n} \mathrm{p_i u_i}\left[\mathrm{g_i}(\mathrm{a_{m+1}})\right] + \sigma^{+}(\mathrm{a_{m+1}}) - \sigma^{-}(\mathrm{a_{m+1}}) \geq \delta \text{ if } \mathrm{a_m P a_{m+1}} \\ \qquad\qquad or \\ \sum_{i=1}^{n} \mathrm{p_i u_i}\left[\mathrm{g_i}(\mathrm{a_m})\right] - \sigma^{+}(\mathrm{a_m}) + \sigma^{-}(\mathrm{a_m}) - \sum_{i=1}^{n} \mathrm{p_i u_i}\left[\mathrm{g_i}(\mathrm{a_{m+1}})\right] + \sigma^{+}(\mathrm{a_{m+1}}) - \sigma^{-}(\mathrm{a_{m+1}}) = 0 \text{ if } \mathrm{a_m I a_{m+1}} \\ \text{for m} = 1, 2, \ldots, \text{k-1} \\ \sum_{i=1}^{n} \mathrm{p_i} = 1, \quad \mathrm{p_i} \geq 0, \text{ for } \mathrm{i} = 1, 2, \ldots, \mathrm{n} \\ \sigma^{+}(\mathrm{a_j}) \geq 0, \quad \sigma^{-}(\mathrm{a_j}) \geq 0, \text{για j} = 1, 2, \ldots, \mathrm{k} \end{cases}$$

where δ is a small positive number; $g_i(a_m)$ the evaluation of the $\mathrm{a_m}$ object on the *i*-th criterion and $u^i[g^i(a^m)]$ the corresponding marginal value; and $\sigma^+(a_j)$, $\sigma^-(a_j)$ the under (over)estimation errors concerning the *j*-th object.

The additive value model is applied into the reference set for the estimation of the marginal values, the global values of the alternative projects and the produced ranking by the global values. If there is a significant uncertainty on at least one of the criteria, the evaluation of the alternative projects will be achieved by transforming these criteria into stochastic ones in the extrapolation step. In that case the marginal utility of the criterion g_i for the project *a* will be estimated from the following formulae:

$$u_i\left(g_i(\alpha)\right) = \sum_{\mathrm{T}=1}^{\mathrm{q_i}} \mathrm{d_i^\alpha}\left(g_i^T\right) u_i\left(g_i^T\right)$$
$$\mathrm{d_i^\alpha}\left(g_i^T\right) \leq 1,\ \mathrm{d_i^\alpha}\left(g_i^T\right) \geq 0,\ \textit{for } T = 1, 2, \ldots, q_i$$
$$\sum_{\mathrm{T}=1}^{\mathrm{q_i}} \mathrm{d_i^\alpha}\left(g_i^T\right) = 1$$

where q_i and d_i^α are respectively the number of possible values and the distributional evaluation of the alternative project α on the *i*-th criterion, $d_i^\alpha\left(g_i^T\right)$ is the probability that the performance of project *a* on the *i*-the criterion is g_i^T and $u_i\left(g_i^T\right)$ is the marginal utility function estimated with UTA(*) previously.

(g) **Feedbacks**: The final accepted additive value model is assessed through iterative procedures. During this process the current additive value model is presented and analyzed to the DMs as well as the inconsistencies (over and under-estimation errors). Every iteration leads to a modification of the parameters influencing this parameters related to the additive value model (criteria, evaluation of the alternative actions on the criteria, reference set, pre-ranking). Finally an acceptable additive value model is assessed. Also, through trade off analysis procedures, the evaluation model can be modified so as to eliminate specific and crucial over and under–estimation errors.

(h) **Robustness analysis**: This is an important step before the adoption of additive value model. The robustness of the preference model is influenced by both the preferences of the decision maker and the choices made within the preference modelling process (set of criteria, evaluation of the alternative actions on the criteria, selecting a set of reference actions). Whenever solving a Linear Problem of a Multi-Criteria model, it is necessary to assess the robustness of the n-dimensional subspace of solutions. An important goal is to assess indices that can express the level of robustness of this n-dimensional subspace (Mavrotas et al. 2015; Tsotsolas and Alexopoulos 2017).
(i) **Extrapolation:** The assessed additive model is used in order to assign a value (utility) to the alternative projects under consideration. The utility of every project constitutes the sum of the marginal utilities of the criteria for this object. This value system is used in order to rank order the whole set of evaluation projects. Also, the ordinal regression curve is designed, providing a visual way to picture the results.

In the second phase the selection of projects portfolio is achieved with the utilization of the Multi-Objective (0–1) Linear Programming techniques (MOLP) (Ehrgott and Wiecek 2005; Evans and Steuer 1973; Korhonen 2005; Korhonen and Wallenius 1990; Zeleny 1974). The purpose of implementing MOLP is to identify those projects which are closest to the desired objective goals given by the decision maker for both internal and external environment. The major steps of this methodological frame are described below:

(a) **Construction of the objective functions:** The first objective goal is the maximization of the global utilities estimated in the previous phase of the proposed methodological frame. Other objective functions related to the external environment (economical, political, social, etc.) are identified by taking into account the firm's nature and activity.
(b) **Modeling the restrictions of the selection problem:** In this step the resources requirements and the policy restrictions of the alternative projects are identified. The linear functions related to these constraints are also constructed.
(c) **Calculation of the pay-off table:** The aim of this step is to estimate the projects that optimize each objective function under the portfolio restrictions. The extreme pareto (Ehrgott 2012) optimal solutions are identified by solving the h linear problems presented below:

$$
\begin{aligned}
&\mathrm{Max}\ \left(Z_1 = U\ (a_1)\, x_1 + U\ (a_2)\, x_2 + \cdots + U_\lambda\, (a_\lambda)\, x_\lambda\right)\\
&(\mathrm{Min}\,/\mathrm{Max})\, Z_I = g_I\,(x) = c_{I1}x_1 + c_{I2}x_2 + \cdots + c_{I\lambda}x_\lambda,\, I = 2, \ldots, h\\
&\text{subjected to}\\
&a_{11}x_1 + a_{12}x_2 + \cdots + a_{1\lambda}x_\lambda\ (\geq)\ (\leq)\ (=)\ b_1\\
&a_{21}x_1 + a_{22}x_2 + \cdots + a_{2\lambda}x_\lambda\ (\geq)\ (\leq)\ (=)\ b_2\\
&\ldots\ldots\\
&\alpha_{\zeta 1}x_1 + a_{\zeta 2}x_2 + \cdots + a_{\zeta\lambda}x_\lambda\ (\geq)\ (\leq)\ (=)\ b_\zeta\\
&x_j = \{0, 1\}\,, j = 1, 2, \ldots, \lambda, I = 1, 2, \ldots, h
\end{aligned}
$$

MIN/MAX	$g_1(x)$	$g_2(x)$	...	$g_h(x)$	$X = \{x_1, x_2, .. x_\lambda\}$
$g_1(x)$	$g_{11}(x)$	$g_{12}(x)$	...	$g_{1h}(x)$	x_1
$g_2(x)$	$g_{21}(x)$	$g_{22}(x)$	...	$g_{2h}(x)$	x_2
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$g_h(x)$	$g_{h1}(x)$		...	$g_{hh}(x)$	x_λ
MIN	$g_1'(x)$	$g_2'(x)$	...	$g_h'(x)$	
MAX	$g_1''(x)$	$g_1''(x)$	...	$g_h''(x)$	

Fig. 3 General form of the pay-off table

where λ the total number of the alternative projects, I the number of the objective functions, ζ the number of the restriction functions, $U(a_j)$ the global utility of the alternative project a_j, c_{Ij} the performance of project j on the I-th objective function. The values of $x_j = \{0,1\}$ are indentified, where $x_j = 1$ if the project is selected and $x_j = 0$ if the project is not selected.

From the solution of the above linear problems a pay-off table (Fig. 3) is created which includes, for each linear problem solved (optimizing the corresponding objective function), the vector x (indicate the selected projects for each solution), the values of the objective functions g_I (x), and the equivalent maximum—minimum of the objective functions.

(d) **Define the desired levels for each Objective function:** The decision maker is asked to determine the desired levels $Z_{I\text{-target}}$ for each objective function (Z_I) within the range of maximum and minimum values estimated in the previous step ($Z_{I\text{-min}}$, $Z_{I\text{-max}}$).

(e) **Implementation of the desired goals technique for the portfolio selection:** In this step the optimal pareto solution closest to the desired goals defined previously by the decision maker is investigated. Therefore, a 0–1 LP is formed where the objective functions become restriction functions and the variables $d_i^+, d_i^-, i = 1, 2, \ldots,$ h are additionally introduced. These variables represent the difference of the values on the objective functions from the desired ones. The aim of solving this linear program is to achieve the smallest overall deviation from the defined targets. The errors are normalized by the factors:

$$r_I = \frac{\max Z_I}{Z_I}$$

The following Linear Problem is solved:

$$(\text{Min})\ \Sigma = r_1(d_1^+ + d_1^-) + r_2(d_2^+ + d_2^-) + \ldots + r_h(d_h^+ + d_h^-)$$

Subjected to

$$
\begin{aligned}
&c_{11}x_1 + c_{12}x_2 + \ldots + c_{1\lambda}x_\lambda - d_1^+ + d_1^- = Z_1 \\
&c_{21}x_1 + c_{22}x_2 + \ldots + c_{2\lambda}x_\lambda - d_2^+ + d_2^- = Z_2 \\
&\ldots \\
&c_{h1}x_1 + c_{h2}x_2 + \ldots + c_{h\lambda}x_\lambda - d_h^+ + d_h^- = Z_h \\
&a_{11}x_1 + a_{12}x_2 + \ldots + a_{1\lambda}x_\lambda\ (\geq)\ (\leq)\ (=)\ b_1 \\
&a_{21}x_1 + a_{22}x_2 + \ldots + a_{2\lambda}x_\lambda\ (\geq)\ (\leq)\ (=)\ b_2 \\
&\ldots \\
&a_{\zeta 1}x_1 + a_{\zeta 2}x_2 + \ldots + a_{\zeta\lambda}x_\lambda\ (\geq)\ (\leq)\ (=)\ b_\zeta \\
&x_j = \{0, 1\}, j = 1, 2, \ldots, \lambda\ \kappa\alpha\iota\ d_I^+ \geq 0, d_I^- \geq 0, I = 1, 2, \ldots, h \\
&c_{11} = U(a_1), c_{12} = U(a_2), \ldots, c_{1\lambda} = U(a_\lambda),
\end{aligned}
$$

The results are presented to the decision-maker and if he is satisfied, then the procedure is finished. If he is not satisfied or the errors are significant, then the decision-maker may proceed to revisions of the desired goals until a satisfactory and acceptable solution is calculated.

4 The Case Study

The above described Multi-criteria approach was used for the projects evaluation of a small Greek construction company which intends to design the bidding plan for the next year. The decision maker indentifies a set of 10 alternative projects that fits to the company's profile and business plan, while a set of 12 previous implemented projects had been selected for the estimation of the additive utility model in order to provide projects with known results to the DM for the easier expression of his preferences. The crucial aims of this case study are the projects prioritization, the projects selection and the portfolio optimization in accordance with the strategic objectives, the internal—external environment and the resources restrictions, respectively.

The criteria used had been divided into two categories. The one category is related to the internal environment points of view and includes the following criteria:

- Expected net income (K€, increasing preference), which is a stochastic criterion that takes into account uncertainty on the estimation of a precise value for the net-income. For the net income of every project a Gaussian distribution was estimated with a mean value and a standard deviation (see Table 1).
- Knowhow (scale 1–5, increasing preference), which is a qualitative criterion indicating the level of firm's existing knowledge and specialization about each project.
- Future perspectives (scale 1–5, increasing preference), which is a qualitative criterion specifying the potential opportunities that could be produced from the undertaken of each project under consideration.

- Additional Strategic Elements (scale 1–5, increasing preference). It is a qualitative criterion, which measures the projects correlation to the firm's strategy excluding the above three point of views.

The second category is related to the external environment and includes the following two criteria:

- Business Risk (scale 1–5, decreasing preference), which is a qualitative criterion measuring the risk not to achieve the expected project outcome and the possible influence of the external environment to project execution.
- Competition (scale 1–5, decreasing preference). It is a qualitative criterion indicating the competitiveness in the market from other construction companies which could bid for the same projects.

Important parameter for the selection of the projects is the capability to implement them efficiently. The main restrictions are related to the available resources (human and material) and cash flow limitations, which border the number of projects to be selected for implementation. The decision maker defines three key resources categories for the achievement of an effective project management and efficient portfolio implementation. These categories are the following:

- Type A—Average monthly work load (man/months). The accepted total monthly workload is varied between 40 and 50 man/months.
- Type B—Required equipment and machinery, which are distinguished into three categories. For the category B1, B2 and B3 the maximum availability for the year is five, four and three, respectively. Also, for the rational utilization of the available resources a minimum value of three, two and one is correspondingly indicated to the three categories.
- Type C—Cash flow monthly restriction (K€). This restriction is direct related to the required liquidity for the projects implementation. The decision maker indentifies a maximum available cash flow to 220 K€ according to the additional firm's liabilities.

The decision maker had indentified an additional policy restriction that the total expected net income (mean value) and the average standard deviation for the undertaken projects shall be more than 750 K€ and less than the average standard deviation of all alternative projects, respectively.

The rating of the potential alternative projects (referred with code names p1, p2, . . . , p10) together with the resources requirements are presented in Table 1. A set of iterative procedures has been implemented for the construction of a consistent family of criteria according to the strategic planning (internal environment) and for the representative modeling of decision maker's preferences. The additive value model was assessed by utilizing the UTA(*) method in the MINORA system and was based on DMs pre-ranking of 12 past projects (referred with the code names pr1, pr2, . . . , pr12). The performance table of these projects to the consistent family of criteria and the decision maker's ranking are illustrated in Fig. 4, respectively. The final accepted value model is presented in Figs. 5a, b, 6a, b, 7, 8a (marginal

Table 1 Rating of potential alternative projects to the selection criteria and resources requirements

	Internal environment				External environment		Resource Type 3				
Projects	Expected Net Income $N(m_j,\sigma_j)$	Knowhow	Future	Strategy	Business Risk (R_j)	Competition (C_j)	A (a_j)	B1 (b_{1j})	B2 (b_{2j})	B3 (b_{3j})	C (c_j)
p1	N(130,10)	3	2	2	2	4	11	1	0.5	0	25
p2	N(420,15)	2	3	3	4	2	18	0	1	1	80
p3	N(80,7)	4	1	2	3	3	5	2	0	0	15
p4	N(200,10)	1	5	3	1	5	12	1	1	0	50
p5	N(300,9)	3	2	2	5	1	15	0	1	0	90
p6	N(170,5)	4	3	3	3	2	13	0	1.5	0.5	32
p7	N(350,20)	5	3	2	2	3	21	1	0	0	40
p8	N(230,18)	1	2	5	2	2	7	1	0	0	22
p9	N(95,12)	4	5	1	3	4	8	1	0	1	15
p10	N(145,10)	2	2	2	1	3	11	0	1	2	18

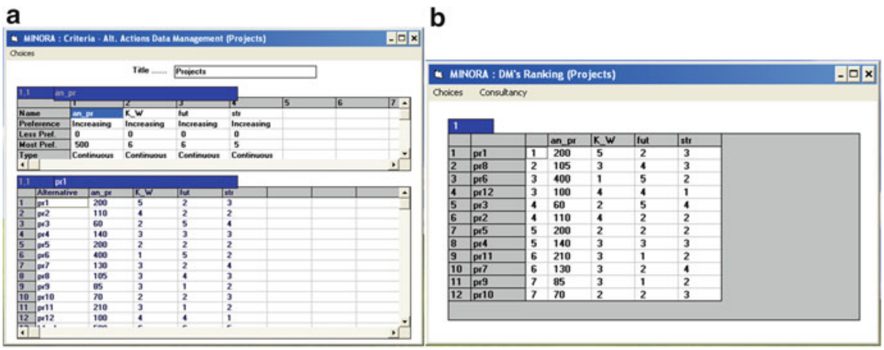

Fig. 4 (**a**) Past Projects Performance Table and (**b**) DM's Ranking

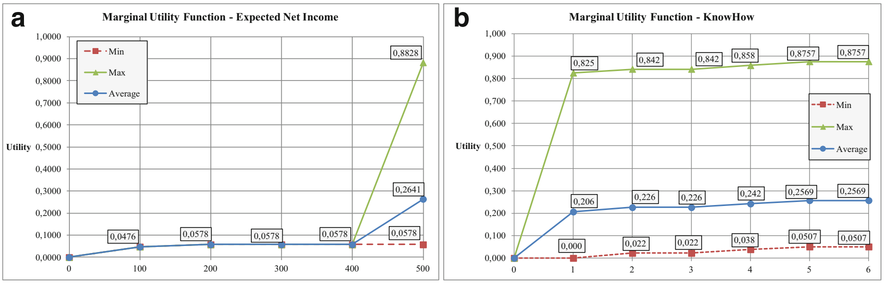

Fig. 5 Value function of the criteria (**a**) "Expected Net Income" and (**b**) "KnowHow"

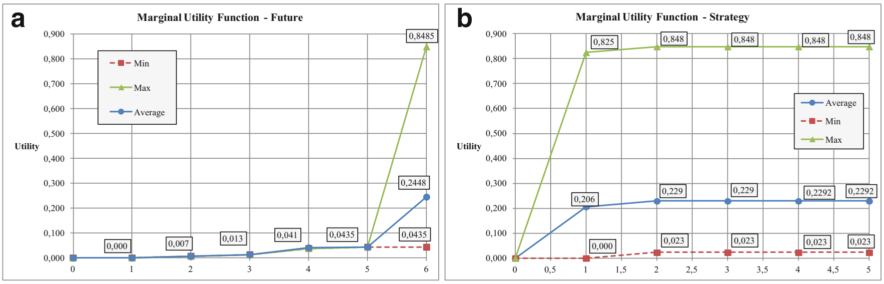

Fig. 6 Value function of the criteria (**a**) "Future" and (**b**) "Strategy"

utility functions, weights of the criteria and ordinal regression curve). This assessed additive utility model was used for the evaluation of the 10 alternative projects according to the firm's strategy. The marginal utility of the stochastic criterion Expected Net Income together with the Gaussian distribution of each project and the global utilities are presented in Figs. 8a and 9, respectively.

In the second phase according to the proposed methodology, the selection of projects portfolio is accomplished by taking into account the global utilities (Fig. 9),

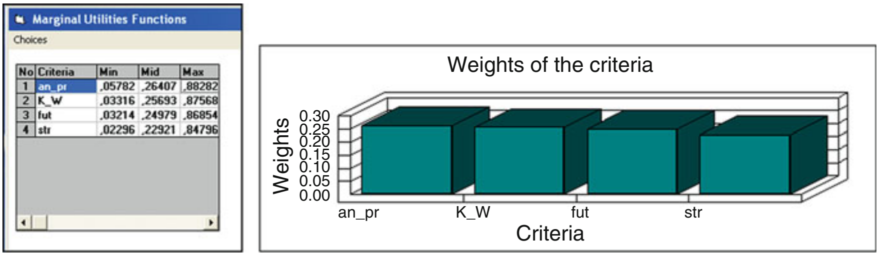

Fig. 7 The estimated weights of the criteria

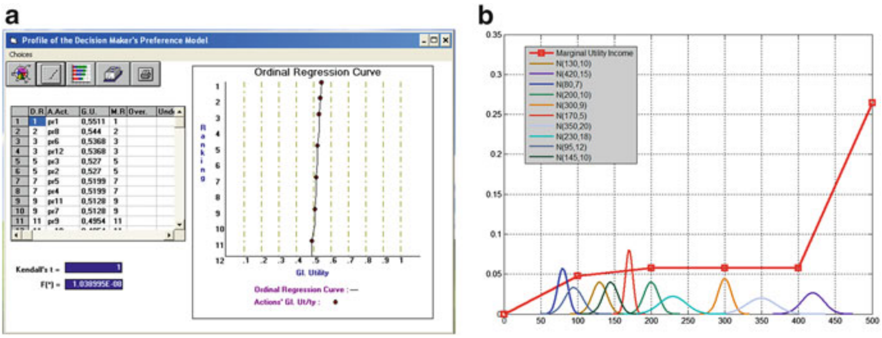

Fig. 8 (**a**) Ordinal Regression Curve and (**b**) Gaussian distributions for each alternative project

No	A. Actions	G.U.
1	p7	0,572505
2	p2	0,548397
3	p6	0,539224
4	p4	0,536797
5	p9	0,536037
6	p5	0,530075
7	p10	0,514275
8	p1	0,512775
9	p3	0,509359
10	p8	0,503402

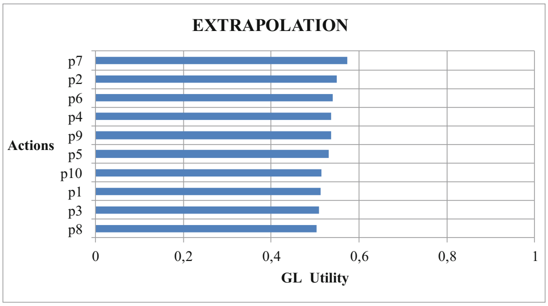

Fig. 9 Extrapolation to the whole set of jobs

the parameters related to the external environment (Table 1, Business Risk and Competition) and the resources availability (Table 1). Therefore, the following Multi-Objective Linear Programming Problem was created:

Let $x = (x_1, x_2, \ldots, x_{10})$ the vector of the unknown values, $x_j \in \{0,1\}$:

$$\text{Maximize Global Utilities} : g1\ (x) = U_1x_1 + U_2x_2 + \cdots + U_{10}x_{10}$$

$$\text{Minimize Business Risk} : g2\ (x) = R_1x_1 + R_2x_2 + \cdots + R_{10}x_{10}$$

$$\text{Minimize Competition} : g3\ (x) = C_1x_1 + C2x_2 + \cdots + C_{10}x_{10}$$

Subjected to conditions concerning (the values of a_j, b_{ij}, c_j are presented in Table 1):

- **Resources Restrictions:**

Resource A ($40 \leq A \leq 50$):	$a_1x_1 + a_2x_2 + \cdots + a_{10}x_{10} \geq 40$ $a_1x_1 + a_2x_2 + \cdots + a_{10}x_{10} \leq 50$
Resource B ($3 \leq B1 \leq 5$):	$b_{11}x_1 + b_{12}x_2 + \cdots + b_{110}x_{10} \geq 3$ $b_{11}x_1 + b_{12}x_2 + \cdots + b_{110}x_{10} \leq 5$
($2 \leq B2 \leq 4$):	$b_{21}x_1 + b_{22}x_2 + \cdots + b_{210}x_{10} \geq 2$ $b_{21}x_1 + b_{22}x_2 + \cdots + b_{210}x_{10} \leq 4$
($2 \leq B3 \leq 4$):	$b_{31}x_1 + b_{32}x_2 + \cdots + b_{310}x_{10} \geq 1$ $b_{31}x_1 + b_{32}x_2 + \cdots + b_{310}x_{10} \leq 3$
Resource C ($C \leq 220$ K€):	$c_1x_1 + c_2x_2 + \ldots + c_{10}x_{10} \leq 220$

- **Business Policy Restrictions**

(1) Expected Total Net Income (mean value) ≥ 750 K€:	$m_1x_1 + m_2x_2 + \ldots + m_{10}x_{10} \geq 750$
(2) The average SD of the undertaken projects $\leq$ Total average SD of all alternative projects:	$\frac{1}{k}(\sigma_1x_1 + \sigma_2x_2 + \cdots + \sigma_{10}x_{10}) \leq \frac{1}{10}\sum_{j=1}^{10}\sigma_j = 11,6$

k: the number of selected projects
$x_j \geq 0$, $j = 1, 2, \ldots, 10$

The pay-off table (Fig. 10) has been calculated by solving the three linear programming problems (Maximize Global Utilities Minimize Business Risk and Minimize Competition subjected respectively to conditions). Then, a pareto optimal solution closer to decision maker's desired level is estimated, by using the desired goals method. The desired level is the following point (Global Utilities, Business Risk, Competition) = (2.35, 11, 12). The decision maker accepted the indicated projects' selection due to high political and economical uncertainty. Higher utility values can be achieved only by significant increase of business risk and competition. The last policy condition has been checked manually after the estimation of the selected portfolio. The average standard deviation of the selected projects is less than the average standard deviation of all alternative projects and equal to 9.25.

Projects	project 1	project 2	project 3	project 4	project 5	project 6	project 7	project 8	project 9	project 10	Utility	Business Risk	Competition
Max_U	0	1	1	1	0	0	0	1	1	0	2,634	13	16
Min_Risk	0	0	1	1	0	0	1	0	0	1	2,133	7	14
Min_Competition	0	1	1	0	1	0	0	1	0	0	2,091	14	8
Desired Level 1	0	1	1	1	0	1	0	0	0	0	2,134	11	12

Fig. 10 Pay—off Table—Selection of Projects Portfolio with Desired Goal Method

5 Conclusions

The contribution of the proposed methodological frame is focused on specific issues for an effective projects' selection supporting portfolio managers in this area. A structured process is provided to evaluate the alternative projects by taking into consideration the strategic planning, the risks of the external environment, the availability of business resources and the uncertainty of the future outcomes. The synergetic utilization of multicriteria disaggregation—aggregation methods with the multi-objective linear programming techniques allows the complexity management of projects selection problem with the active participation of the DM.

Also, the utilisation of the proposed approach cannot be bordered only to construction firms. The last decades, firms are organized into a project based form because this kind of structure provides flexibility in the internal operation and supports the effective utilisation of the available resources, the operational cost reduction and the achievement of higher quality results. Appropriate adaptations of the proposed methodological frame can be applied in firms and organizations following projects oriented operational structures.

This research work constitutes one step forward in the research of an efficient portfolio selection method aiming to link the desired strategic goals with the expected project achievements. One direction of future research is the exploitation of the proposed approach to support strategic decision making teams (Montibeller and Franco 2010) by checking the feasibility of alternative strategic plans through the direct interaction between the organizational governance and the executive managers. The enriched of the proposed process with the robustness analysis techniques is another future perspective.

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Applying the Disaggregation-Aggregation Paradigm for Crude Oil Pipeline Risk Management

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Abstract Pipelines is the most efficient (and hence popular) mean to transport crude oil and natural gas. However, there exist several reasons that could trigger a failure of pipelines and the following consequences to people's properties, human health, and the environment. To this end, pipeline risk management is a primary concern for Oil and Gas companies. Since multiple factors contribute to the risk level of a pipeline, in this work we apply the aggregation-disaggregation paradigm of MCDA to assess the risk of every part of a crude oil pipeline. The presented method considers multiple dimensions (criteria), it is able to deal with the uncertainties in the criteria measurements, and it aggregates the preferences of multiple experts. We focus on a crude oil pipeline owned by the Nigerian Petroleum Development Company, and we used experts' opinion to get the evaluations of the alternatives on the criteria set. To deal with the inherent uncertainty, we applied stochastic UTA, a method that allows a probabilistic distribution to get used for alternatives evaluations. We were able to estimate the significance weight for every criterion, its marginal utility function, a final ranking of the segments, and valuable insights about how those ranks are achieved. In particular, it became apparent that for the specific location of the pipeline, the external interference criterion has

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greater importance than in other regions. In fact, it becomes a criterion of primary importance (in tandem with the corrosion criterion).

1 Introduction

Fossil fuels (coal, oil, and natural gas) remain the core of global energy, despite the recent major focus on renewable energy sources. Fossil fuels production sites are commonly geographically distant from the major consumption centers, thus transportation is a critical part of the supply chain. The primary mean of transporting crude oil and natural gas is through pipelines. To get an immediate grasp of pipelines' efficiency when compared with other transportation means, let us consider the case of CEPA (Canadian energy pipeline association): CEPA's pipeline network transports 3 million barrels of oil every day. The equivalent number of rail cars would be 4200 and that of tanker tracks would reach 15,000 vehicles!

However, there exist several reasons that could trigger a failure of pipelines and the following consequences to people's properties, human health, and the environment. To this end, pipeline risk management has appeared in the literature (Muhlbauer 2004; Mohitpour et al. 2010) as a distinct thread to control and mitigate the risk for Oil and Gas companies, and to tackle issued like corrosion (Gomes et al. 2013); structural and manufacturing defects (Kishawy and Gabbar 2010); construction digging (Liang et al. 2012); natural disasters (Petrova 2011); or even human errors (Skogdalen and Vinnem 2011). Moreover, factors like aging of the pipelines, crossing high-population density areas, and polluting water resources increase the need as well as the complexity of pipelines risk management.

It is clear that pipeline risk assessment should consider multiple dimensions to identify the parts of the network where risk is critical (or just higher). After all, trying to assess the risk using a single dimension approach is equivalent to deliberately discarding certain aspects of reality. Relying on a single dimension is prone to dictating an idiosyncrating point of view as objective (Roy 1996). Moreover, these dimensions (e.g., operational, economical) can hardly be described by precise and certain metrics. There is a great amount of uncertainty that characterizes the estimated of the values of those dimensions. This is why, in risk assessment of pipeline is typical to rely on expert judgment (Dawotola et al. 2011). However, for companies it is very important (for legitimation as well as for validation reasons) to be able to understand the decision model of the experts.

In this work we apply the aggregation-disaggregation paradigm of MCDA (Siskos et al. 2005) to assess the risk of every part of a crude oil pipeline. The presented method considers multiple dimensions (criteria), it is able to deal with the uncertainties in the criteria measurements, and it aggregates the preferences of multiple experts. By using the proposed method, Oil & Gas companies could i) assess the level of risk for their pipeline network parts, ii) Analyze the decision model of experts, and use it to extrapolate future risk assessments, and iii) Handle the (eventually different) preferences of multiple experts.

The next section provides a concise discussion about the factors that commonly affect pipeline failures, a brief overview of other works that try to tackle similar problems like the one under question in this work, and the basic elements of the problem's case study. In Sect. 3, we highlight the principle elements of the mathematical model, while in Sect. 4 we present the actual components of our application, namely the family of relevant criteria and the pertinent results. A short discussion concludes the paper.

2 Background

2.1 Pipeline Failure Factors

Pipeline integrity is a major problem for oil companies, especially when the condition of its components is deteriorating due to aging. Perhaps the most evident cause of failure is *corrosion* (Bolzon and NATO 2011). Air, water and soil pollution caused by corrosion leaks are of major consideration, as oil companies are obliged by legal and regulatory framework to apply preventive measures. Corrosion itself can take many shapes: sweet corrosion (CO_2 corrosion), which appears mainly either as pitting (localized attack that results in rapid penetration and removal of metal at small discrete area) or as mesa attack (a form of localized CO_2 corrosion under medium-flow conditions)" (Popoola et al. 2013); sour corrosion (H_2S corrosion) which is the most catastrophic for the drill pipe and takes place when H_2S is mixed with water; oxygen and galvanic corrosion, microbiologically induced corrosion, etc.

Then, a number of possible manufacturing defects can be encountered. Although for pipeline construction low-carbon steel or low-alloy steel is commonly used, manufacturing defects account for failures at a rate of around 10% (Kiefner 2007). Some indicative types of defects are hook cracks (laminations that exist in the weld zone that curves), cold welding (two metals which come into contact, melt and finally become one piece), mismatched skelp edges, centerline cracking, etc.

There are also a number of external factors that influence the risk level for a pipeline. Excavation (construction digging) is the most usual cause of pipeline accidents, associated with third party interference (Han and Weng 2011). Excavation can also damage indirectly an underground pipeline system, making it vulnerable to corrosive effects. Natural disasters can be really dangerous for pipeline infrastructures. Earthquakes, hurricanes and tornadoes can cause severe damage to pipeline distribution systems. Damage can also be induced indirectly by flooding, as standing waters create favorable conditions for bacteria. In addition, considering third party interference, terrorism, vandalism and theft have become a major concern, especially for certain African or Middle-East countries (Anifowose et al. 2012). Last, human errors, intentional (i.e., workers feel overconfident about how to cope with a situation, but in reality their estimations are wrong) or unintentional (actions committed or omitted with no prior thought) contribute as well to the increase of the risk level of pipelines (Castiglia and Giardina 2013).

To conclude, there are several attributes under which the elements of a pipeline network are observed, described, measured etc. However, the aim of this work is not to represent an exhaustive list about the "empirical" knowledge available or collected about pipelines, but to outline the factors that shape the preferences of the decision makers. We eventually capture these preferences in terms of criteria, as we will explain in Sect. 3.

2.2 Related Works

In Cagno et al. (2000) authors collected expert judgments by an ad hoc questionnaire and integrated with the historical data for an urban gas pipeline network. Based on factors like laying location, diameter and laying depth they created a tree-like structure to assign a class of failure rate. Then, they asked each expert to compare the pipeline classes pairwise, in order to apply the AHP methodology and eventually deliver significance weights for pipeline classes. The weights obtained represent the experts' estimate (index) of the propensity-to-failure for each class. AHP was also used in Dey (2002) to develop a project selection model of cross-country petroleum pipelines. The top-level dimensions are technical analysis (including technical factors like pipeline length, approachability, etc.), environmental impact assessment (e.g., failure and normal operation of pipelines), and socio-economic impact assessment (comprising factors like employment, rehabilitation, etc).

In Markowski and Mannan (2009) authors build a fuzzy logic system around the Layer of Protection Analysis (LOPA) (American Institute of Chemical Engineers 2001). They develop a fuzzy risk index based on two dimensions: failure frequency rate, and severity of mitigated consequences. They applied their method on a gasoline pipeline network located in central part of Poland, and they used generic data based on available databases as well as expert opinion to fill the required input data.

Expert elicitation with fuzzy set theories was also used in Yuhua and Datao (2005) to evaluate the probability of the events in a fault tree. Having selected experts, authors assigned them with a weighting factor that represented their quality, and asked them to express in linguistic terms about the failure probability of pipeline installation. Then they converted linguistic terms to fuzzy numbers, and fuzzy numbers into a fuzzy possibility score. Last, they transformed that score into a fuzzy failure probability to announce an importance measure of every basic event of the fault tree. For a more comprehensive review of related works the interested reader is directed to Han and Weng (2011).

However, our method focuses on assessing the risks rather than on identifying the causes of the accidents, is able to deal with heterogeneous data and handle various probability distributions for their uncertainties, reveals the decision model of experts (thus making it available for future risk assessments extrapolations), and it delivers a robustness report of the recommended decisions.

2.3 Case Study

This work focuses on a crude oil pipeline owned by the Nigerian Petroleum Development Company (NPDC). This specific pipeline was constructed in 1989 and transports crude oil within the southwestern region of Nigeria ever since. Its diameter is 24 in. and its length 340 km, while its operating pressure and temperature are 100 bar and 26.8 °C, respectively. The infrastructure was constructed by carbon steel, with a concrete type coating. The same pipeline was the subject of the work of Dawotola et al. (2011). In fact, we used the experts' opinion as described in Dawotola et al. (2011) to get the evaluations of the alternatives on the criteria set. In the original setting, the pipeline is divided into three segments (X1, X2, X3) and six pipeline experts were invited and were provided with information concerning pipeline repair history, design parameters, inspection records and current operating conditions. In particular, those experts were invited to estimate failure assessments for identified failure mechanisms of the pipeline in terms of probabilities. Moreover, in that work, the expected cost of failure was estimated through a database of historical costs. We used those parameters to evaluate the alternatives' performance on our set of criteria, as explained in Sect. 4.1.

3 Methodology

3.1 Basic Elements of the Algorithm

The disaggregation-aggregation (D-A) paradigm (Jacquet-Lagreze and Siskos 1982; Siskos and Yannacopoulos 1985; Siskos et al. 1993; Matsatsinis and Delias 2003; Delias and Matsatsinis 2007) aims at analyzing the behavior and the cognitive style of the Decision Maker. Since the D-A paradigm is well established, in this section we shall not explain it in detail, but we will just outline the basic elements. For an analytical presentation the interested reader is forwarded to Siskos et al. (2005). Because one of the inherent characteristics of the problem is the uncertainty of the alternatives performance, we choose to apply Stochastic UTA that was originally introduced in Siskos (1983) and exemplified in Siskos and Assimakopoulos (1989).

As it happens in every D-A application, in order to build the evaluation model we need to define a set of alternatives $A = \{a_1, a_2, \ldots, a_m\}$ and a consistent family of n evaluation criteria $G = \{g_1, g_2, \ldots, g_n\}$. Stochastic UTA assumes that for each criterion, the performance of an alternative $a \in A$ is not fixed but it involves a probability distribution. Let g_{i*} be the worst level of the measurement scale of the g_i criterion, and similarly let g_i^* be the best level of the scale. Following this notation, the variable scale for g_i will be $\left[g_{i*}, g_i^*\right]$. The evaluation of an alternative $a \in A$ is formulated as a density function δ_i^a, where

$$\sum_i \delta_i^a \left(g_i^j\right) = 1 \text{ for the discrete case}$$

and

$$\int \delta_i^a \left(g_i^j\right) dg_i = 1 \text{ for the continuous case}$$

The aim of the method is to provide an additive formula that will eventually represent the cognitive style of the DM. The multi-attribute utility function will have the form of

$$u\left(\boldsymbol{g}\right) = \sum_{i=1}^{n} w_i u_i\left(g_i\right)$$

subject to the following normalization constraints:

$$\begin{cases} u_i\left(g_{i*}\right) = 0, \forall i = 1, \ldots, n \\ \sum_{i=1}^{n} u_i\left(g_i^*\right) = 1, \forall i = 1, \ldots, n \\ w_{ij} = u_i\left(g_i^{j+1}\right) - u_i\left(g_i^j\right) \geq 0 \\ u_i\left(g_i^l\right) = \sum_{i=1}^{l-1} w_{il}, \forall i, l > 1 \end{cases}$$

where $u_i\left(g_i^j\right)$ is the marginal value of the performance on the i$^{\text{th}}$ criterion, and w_{ij} are scaling factors which are to be estimated. To fairly represent the cognitive style of the DM, the additive value function must guarantee the following properties for any pair of alternatives $\{a_i, a_j\} \subset A$:

$$u\left(\boldsymbol{\delta}^{a_i}\right) > \left(\boldsymbol{\delta}^{a_j}\right) \iff a_i \succ a_j \ \text{(preference)}$$

$$u\left(\boldsymbol{\delta}^{a_i}\right) = \left(\boldsymbol{\delta}^{a_j}\right) \iff a_i \sim a_j \ \text{(indifference)}$$

where $\boldsymbol{\delta}^a$ is the vector of distributional evaluations of alternative a, and $u(\boldsymbol{\delta}^a)$ is its overall expected utility.

Considering a single criterion, the marginal utility follows the von Neumann-Morgenstern form, i.e.,

$$u_i\left(\delta_i^a\right) = \sum_j \delta_i^a\left(g_i^j\right) u_i\left(g_i^j\right), \ \text{if } g_i \text{ discrete}$$

and

$$u_i\left(\delta_i^a\right) = \int_{g_{i*}}^{g_i^*} \delta_i^a\left(g_i\right) u_i\left(g_i\right) dg_i, \ \text{if } g_i \text{ continuous}$$

The next step is a typical step for UTA methods, the introduction of two error functions $\sigma^+$and $\sigma^-$by writing the following expressions for each pair of consecutive alternatives in the reference ranking:

$$\Delta\left(a_j, a_{j+1}\right) = u\left(\delta^{a_j}\right) - \sigma^+\left(a_j\right) + \sigma^-\left(a_j\right) - u\left(\delta^{a_{j+1}}\right) + \sigma^+\left(a_{j+1}\right) - \sigma^-\left(a_{j+1}\right)$$

Then, we are solving the linear problem that has an objective function the minimization of the sum of these errors. In particular,

$$minF = \sum_{j=1}^{k} \sigma^+\left(a_j\right) + \sigma^-\left(a_j\right)$$

subject to:

$$\text{for} \quad j = 1, 2, \ldots, k-1$$

$$\Delta\left(a_j, a_{j+1}\right) > \lambda, \text{if } a_j \succ a_{j+1}$$

$$\Delta\left(a_j, a_{j+1}\right) = 0, \text{if } a_j \sim a_{j+1}$$

$$\sum\nolimits_{i,l} w_{il} = 1$$

$$w_{il} \geq 0, i = 1, 2, \ldots, n; l = 1, 2, \ldots, a_{i-1}$$

$$\sigma^+\left(a_j\right) \geq 0, \sigma^-\left(a_j\right) \geq 0, j = 1, 2, \ldots, k$$

λ being a small positive number.

At the final stage we check for the existence of multiple or near optimal solutions during a post-optimality step. More specifically, during the post-optimality stage, many LPs are formulated and solved, which maximize repeatedly the weight of each criterion. The mean value of the weights of these LPs is taken as the final solution, and the observed variance in the post-optimality matrix indicates the degree of instability of the results. Thus, an Average Stability Index (ASI) may be assessed as the mean value of the normalized standard deviation of the estimated weights (see also Grigoroudis and Siskos 2002).

4 Pipeline Risk Assessment

4.1 Risk Assessment Criteria

In Nigeria (where the case's study pipeline network lies) there is a huge issue of pipeline sabotage, majorly expressed through oil bunkering, pipeline vandalisation/fuel scooping and oil terrorism (Onuoha 2008). Therefore, the first criterion that we introduce is the *external interference* criterion. Since sabotage actions exhibit regularity, we represent the probability of a failure due to this factor with a normal distribution. The parameters (mean and standard deviation) of this distribution are defined by the experts.

Lack of maintenance is a major factor in Nigeria, which cause indirectly defects associated with corrosion. Nigeria's sweet oil does not contain any hydrogen sulfide, so sour corrosion does not pose a threat. On the other hand, the presence of carbon dioxide (CO_2), when mixed with water can cause severe damage to the pipelines. Most of the main pipelines in Nigeria are over 30 years old and aging also affects the integrity of the infrastructure. As discussed in Cobanoglu (2014) the Poisson distribution is usually used in reliability systems to fit the probability distribution of pipeline failures due to corrosion, however the normal distribution could give a fair approximation as well. Once again the experts defined the parameters for the *corrosion* criterion.

An additional *operational error* criterion is introduced to capture the manufacturer and construction installation causes, equipment failures or human errors. The importance of this criterion is expected to be small, yet not negligible, so to assure the exhaustiveness property for the family of criteria, we suggest its introduction through a triangular distribution since experts can estimate the ceiling (maximum value) for this variable.

Last, it is clear that all the above risk factors can be mitigated if excessive monitoring and maintenance actions are applied. It is also clear that such a strategy is not feasible due to its high cost. Therefore, to balance the decisions with the cost factor, we introduce the *level of investment fund for maintenance* criterion. To describe this criterion we applied a verbal, ordinal scale (low, moderate, high) and a relevant discrete distribution. Once again experts defined the detailed parameters.

Actually, the way the parameters were set is the following: In Dawotola et al. (2011), experts assessed the probability of failure due to every factor, and based on those assessments they were ranked based on their contribution to knowledge. We used the lower and upper limits of those probabilities to define the scales for every criterion (except for the "Cost"). Then, we broke down those scales into five segments, and defined the middle point as the mean value. For the top-ranked experts, we set the standard deviation to the minimum value (since they proved more confident in their estimations). For the bottom-ranked experts, we used larger standard deviations (equal to the mean because their estimations proved to contribute no knowledge at all).

All experts but one gave the same ranking (X3 to be the least risk prone segment, then X2, then X1). However, expert no. 4 differentiated by assessing X2 as the least risk-prone segment, then X3 and then X1. This can be explained by the fact that, according to Dawotola et al. (2011), X3 segment has more control valves that involve manual operations compared to X1 and X2 and therefore is more vulnerable to a failure due to operational error. We can plausibly assume that the operational error criterion is most important for expert no. 4, and that it led him to a different ranking.

An important note with respect to the evaluation criteria is that they comprise a plethora of individual factors (e.g., the external interference criterion includes the possibility of terrorism attacks, theft, third party digging, etc.), as it was discussed in Sect. 2.1. By defining a criterion as the probability to have a failure because of any of those factors, the decision makers can abstract from a low level of detail, and observe their general impact, like we present in the next section.

4.2 A Dedicated Software Tool

In order to solve the pertinent linear problems, a special decision support system, TALOS (Christodoulakis 2015) was applied. TALOS is a dedicated DSS that supports decision makers to evaluate and rank alternatives that are characterized over multiple criteria. It focuses on integrating uncertainty by allowing probabilistic distributions to represent the alternatives' performances on the criteria set. It delivers a final ranking for the alternatives (and the corresponding decision model) that is consistent with the decision makers' preferences. TALOS has been programmed with Visual C# on Microsoft Visual Studio .NET 2012. Linear problems are solved by the Simplex method. The software product includes 50 forms that guide users to enter data, define the solving parameters, and get the results (criteria weights, marginal utility functions, global utilities, stability indices, etc). The structure of the DSS is illustrated in Fig. 1.

It has been developed by using reusable components (subroutines, functions). The output of one component can be the input for the next. The basic components that have been developed are:

- Input Units and Data Transformation Units
  - Multiple criteria evaluation matrix
  - Preferences
  - Models' parameters

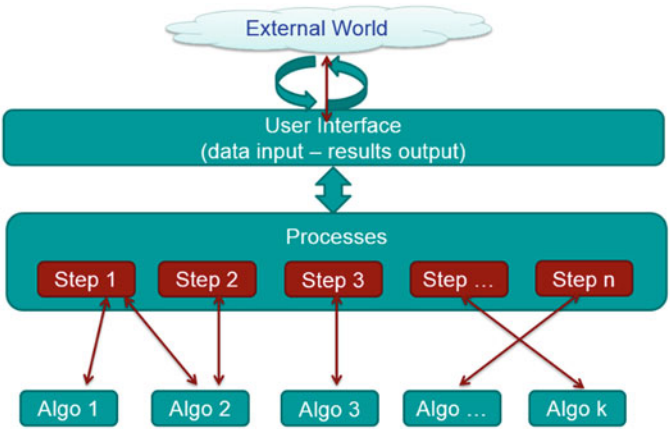


Fig. 1 The structure of the DSS

- Model Analysis
  - LP solver
  - Stochastic UTA
  - SMAA—Stochastic multiobjective acceptability analysis (Lahdelma et al. 1998)
  - UTA GMS (Greco et al. 2008)
  - Extreme ranking (Kadziński et al. 2012)
- Post-optimality analysis (Siskos and Grigoroudis 2010)
  - Maximum UTA
  - Max-Min UTA
  - Maximum W
  - Max-Min W
  - Manas-Nedoma

TALOS uses XMCDA (Bisdorff et al. 2009), a standard that defines a grammar over XML to handle data relevant in a MCDA context. It uses a graphical user interface that assumes a main form (MDI Parent) which hosts all the other forms supporting the various functions (MDI Child) (see Fig. 2).

Ultimately, TALOS uses its graphical interface to guide the user over five steps:

1. Criteria definition: The user inputs the evaluation criteria. For each criterion, the user should provide a proper name, its unit, its type, its monotony, the number of intervals, as well as their labels (in case of quantitative criterion) and the optimal performance (in case of quantitative criterion) (see Fig. 3).

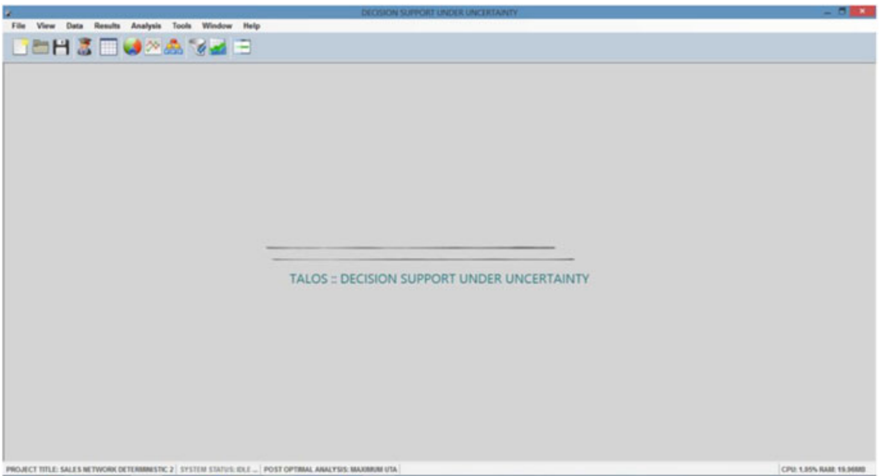


Fig. 2 The first screen (main form) of TALOS

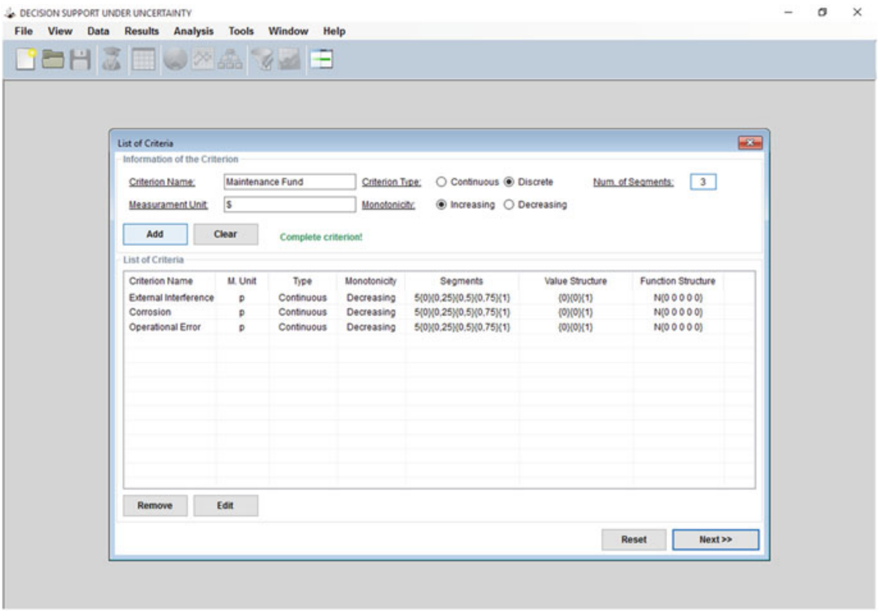


Fig. 3 Defining the evaluation criteria through the TALOS interface

2. Alternatives definition: For each alternative, the user should define the probability distribution for every criterion (Fig. 4).
3. Algorithm choice: The user selects one method among Stochastic UTA, SMAA, UTA GMS, Extreme Ranking, and among Max UTA, Max-Min UTA, Max W, Max-Min W, Manas-Nedoma for the post-optimality phase.
4. Ranking: The user provides an indicative ranking of the alternatives that she has entered during the previous phase. The interface allows a friendly drag-and-drop technique to declare preference or indifference between alternatives.
5. Decision Model Selection: TALOS solves the problem and provides numerous charts and tables to present the results. In the next paragraph we present the most interesting results for the pipeline risk evaluation problem.

4.3 Results

The results we present in this section are the typical, rich results that the D-A paradigm methods provide. The stochastic UTA method that we applied, solves the initial linear problem to find an optimal solution, and then during the post-optimality phase, it solves as many as twice the number of criteria new linear problems (each problem aiming at maximizing/minimizing the weight of one criterion), to

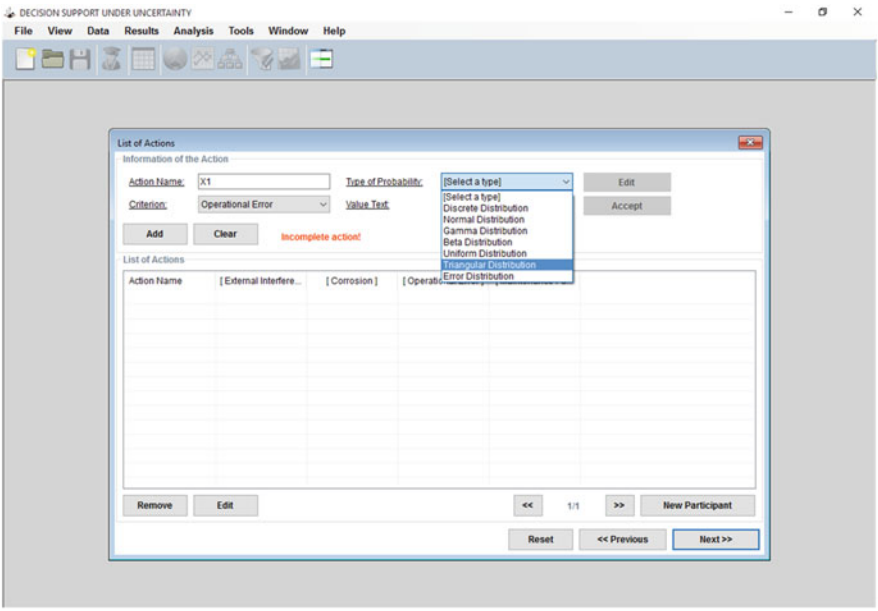


Fig. 4 Defining the alternatives and their vectors of performance over the criteria through the TALOS interface. The list of available probability distributions is shown

discover near optimal solutions. In the following, we shall comment if the results are averaged, or if they correspond to a special linear problem solution. First, the most visible output is the significance weights for the criteria. We shall remind that criteria weights sum up to 1, so every criterion's weight trade-offs the weight of another's. The weight of a criterion is calculated as the average value of the utilities that the last level of that criterion's scale got in the solutions of the LPs. The relevant results can be observed in Fig. 1. External Interference proved to be as much important as the corrosion criterion (0.25 weight for each). In the oil and gas pipelines literature, factors that are relevant to corrosion appear to be most important ones, however, it looks like the specific location of the case study has suffered a lot from thefts and terror attacks, so experts are equally concerned about the external interference factors.

In Fig. 5 we can also observe the shape of the utility function for every criterion (the maximum, the average, and the minimum cases). We can see that for the operational error dimension, experts are very strict, and that even a low probability (of 0.043) is sufficient to return a zero utility. For the corrosion dimension, a pipeline segment can get some credit (positive utility) if it has a probability of failure (due to corrosion failure mechanism) less than 0.075, which is actually the middle point of the scale that experts provided for this criterion. Things are somehow different in the external interference dimension. We regard a rather large scale (from 0.087 to 0.322), while experts allow having a positive utility for probabilities as

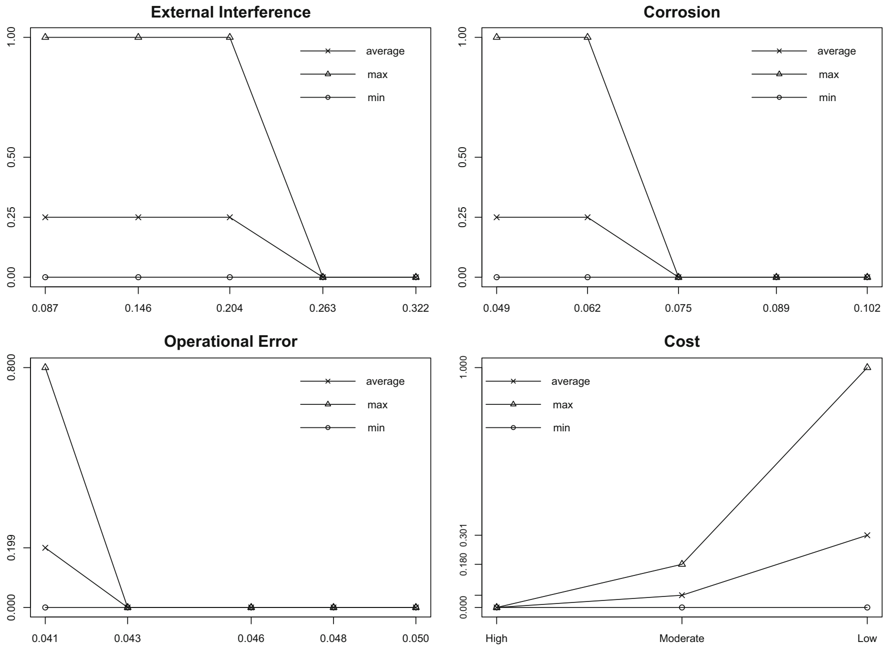
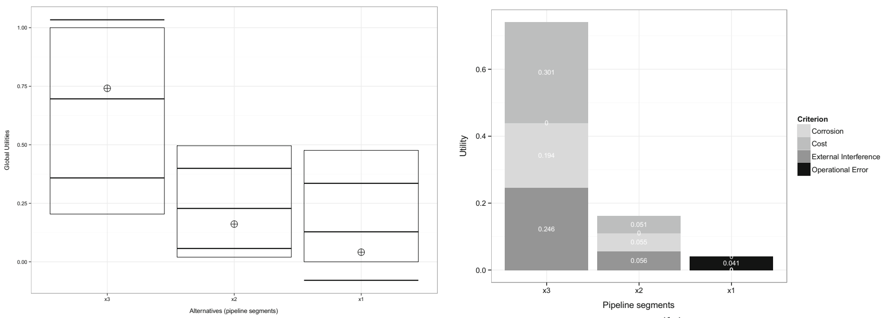


Fig. 5 Marginal utility functions for the criteria family

high as 0.263. Regarding the cost dimension, we see that the difference (in terms of utility gain), between the levels Moderate-Low is suggestively larger than the corresponding pair of levels High-Moderate. In particular, the "High" level returns zero utility, and the gain of the "Moderate" level is 0.180. Since the "Low" level returns a utility of 1, the gain for the pair Moderate-Low is 0.820, more than four times larger.

Having solved many linear problems, we are able to observe the variation of the solutions, and illustrate it in Fig. 6 (a). More specifically, we plot one box per alternative (pipeline segment), where the upper edge is the maximum global utility that this pipeline segment achieved among all solutions. Similarly, the bottom edge is the minimum global utility that the segment achieved. Then, we plot three horizontal lines per segment (thicker lines). The middle one is drawn at the average value, while the other two are drawn at the points of [mean value − standard deviation] and [mean value + standard deviation]. Last, the first, initial, supposedly optimal solution is depicted with a crossed circle inside the boxes.

We can see that the pipeline segment X3 is performing suggestively better than the other two segments, while between X2 and X1, the difference (either among the mean values, or the best/worst values, or even the optimal values) is small. However, the variation for the X3 segment is large: the distance between the points of [mean value − standard deviation] and [mean value + standard deviation] is more that 0.75. This is an indication that the performance of X3 is very much



(a) (b)

Fig. 6 Details for the evaluation of pipeline segments: (**a**) variation of the performances of pipeline segments over the different linear problems, (**b**) contribution of every criterion to the pipeline segment performance

dependent on which criterion we are optimizing for. Therefore, and in order to have a better insight, we plot the contribution of each criterion to the global utility of every pipeline segment in Fig. 6 (b). We regard that X3 owns its compelling performance primarily to the “Cost” criterion, and then to the “External Interference” criterion. An interesting note here is that X3 collects zero utility from the “Operational Error” criterion, a criterion where only X1 achieves a positive figure.

5 Conclusions

Integrity and maintenance of pipelines in a cost effective way are of major consideration for oil and gas industry companies. A pipeline accident can have disastrous consequences on human health and the environment. To mitigate the pertinent risks while maintaining a realistic cost for risk management, companies should prioritize the areas (pipeline segments) according to their attached risk. In this work, we propose four high-level criteria that can guide the prioritization process. However, due to the inherent uncertainty, it is hard as well as costly to get exact evaluations of the segments over the criteria set. Therefore, we applied a method that allows a probabilistic distribution to get used for these evaluations. Following the disaggregation-aggregation paradigm, we were able to estimate the significance weight for every criterion, its marginal utility function, a final ranking of the segments, and valuable insights about how those ranks are achieved. This actually a disaggregated decision model that the company can apply to extrapolate future decisions. Through the application of the proposed method, it became apparent that for the specific location of the pipeline, the external interference criterion has greater importance than in other regions. In fact, it becomes a criterion of primary importance (in tandem with the corrosion criterion). Further improvements of this project may include, modifying the set of criteria by adding new ones or by creating a hierarchical scheme by inserting the low level factors into the criteria family.

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International Cooperation for Clean Electricity: A UTASTAR Application in Energy Policy

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Abstract Energy policy making is a complex, multidisciplinary process that usually requires the assessment of a large number of factors. Consequently, Multiple Criteria Decision Making, which is a sub-discipline of Operational Research, has long been employed as an approach to addressing problems of this domain. This paper aims to explore how the preference disaggregation-aggregation paradigm, which infers a preference model from given global preferences on a set of reference alternatives, can support decision making in energy policy design and implementation. In this direction, a detailed literature review of multicriteria analysis applications in this domain is conducted, in which a knowledge gap regarding preference disaggregation approaches can be observed. The UTASTAR model is, then, described in detail and implemented in an energy policy application regarding the potential development of clean electricity projects through the cooperation between European Union member states and 22 neighbouring countries with which the Union has already established ties towards economic and energy market integration. The results of the study show that European countries outside the Union feature better potential for hosting clean energy projects compared to Middle East and North African countries; finally, the analysis suggests that UTASTAR can also provide concrete insight into the criteria weighting dynamics, as inferred by the global preferences of the decision makers.

1 Introduction

Energy policy making is de facto a very complex, multidisciplinary process. It is true that energy used to be considered a secondary issue following economic growth, instead of pushing it, and thus would not be in the forefront (Bloom 1982)

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of national or international priorities. Nowadays, however, that the systematic threat of climate change appears to be the most challenging issue the global community will be facing in the twenty-first century (Fuss et al. 2008) and that the energy sector lies in the heart of climate mitigation policy, a growing number of criteria must be taken into account when formulating energy-related policy, and priorities among evaluation axes have been shifted, from following least-cost approaches to focusing on—for example—issues such as energy security, sustainability, competitiveness and GHG reduction potential.

As a result, the challenging process of developing effective and robust energy policy requires the systematic use of simple methodological frameworks that can, on the one hand, prioritise the evaluation criteria against which decisions must be made and, on the other hand, investigate the relationship between policy objectives and available alternatives, in order to fully assess the latter (Doukas 2013). Supporting energy policy making can be achieved in various ways, including but not limited to sustainable energy planning, evaluating energy policy instruments or strategies, assessing different power generation technologies, evaluating actions towards responding new policies, and selecting viable energy projects.

It is evident, therefore, that energy policy making must employ effective decision support tools, in the form of computational frameworks that can incorporate this diverse range of aspects into their process. In this respect, Multiple Criteria Decision Making (MCDM) frameworks, which by default facilitate the evaluation of a large number of alternatives by taking into consideration a large number of evaluation criteria, can provide the capacity and flexibility to address such issues. In this context, MCDM methodologies have been widely used as decision support tools for designing energy and environmental policies as well as sustainable energy planning (Greening and Bernow 2004; Pohekar and Ramachandran 2004).

It should be noted that multicriteria analysis involves a set of methods or models enabling the aggregation of multiple evaluation criteria to choose one or more actions from a given set (Siskos et al. 2005); that is, in traditional MCDM approaches, the decision makers' preference models are known and broken down into the respective evaluation criteria, and the analyst seeks to aggregate the efficiency of each alternative against each criterion into the missing global preference. However, in such a multidisciplinary problem domain that is energy policy, there are times when the stakeholders (i.e. decision makers) are reluctant or unable to fully provide their preference models in a way that can be used in the context of the traditional MCDM philosophy. It is in this direction that Jacquet-Lagrèze and Siskos (1982) introduced the disaggregation-aggregation approach, based on the disaggregation paradigm, which aims at analysing the behaviour (i.e. the global preference) of the decision makers and inferring their preference models, in order to later use these models when seeking the global preference in a different problem of the same domain.

Preference disaggregation models have been widely used in the literature in a number of problem domains and scientific fields. One such set of MCDM models, for example, is the UTA (UTilités Additives) family, several variants of which have been applied in financial management, marketing, quality management and human resources management applications (Grigoroudis et al. 2012). These models, however, have been underexploited in the field of Energy Policy. The aim of this paper, therefore, is to explore how UTASTAR (Siskos and Yannacopoulos 1985), an improved version of the original UTA model (Jacquet-Lagrèze and Siskos 1982), can contribute to supporting energy policy making.

The following section provides a detailed overview of MCDM applications in the energy policy literature, focusing on the few UTASTAR applications as opposed to traditional multicriteria analysis methods. Section 3 introduces the UTASTAR methodological framework and algorithm, while Sect. 4 presents an original application while drawing from the existing literature and Sect. 5 summarises the main points and findings of the study.

2 A Review of Applications in Energy Policy

As explained in the previous section, multicriteria analysis models have been extensively used in the energy policy domain, since several key aspects of energy technologies, projects and policy instruments—such as the social and environmental dimensions—are usually disregarded by other decision support methods (Van den Bergh et al. 2000), which focus on market-related aspects (Doukas 2013). Pohekar and Ramachandran (2004) note that there has been an enormous shift in energy-related studies during the past decades, from energy demand forecasting and single-criteria methods to delving into the social and environmental frameworks dimensions of sustainable energy planning and MCDM respectively.

Traditional MCDM methodologies that have mostly been utilised in this focus area include the Analytic Hierarchy Process (AHP), the Analytic Network Process (ANP), the ELECTRE family, the Multi-Attribute Utility Theory (MAUT), the PROMETHEE family, and TOPSIS in energy planning, energy policy, technology and environmental impact assessment, project selection and energy efficiency action evaluation applications.

The most extensively used methods across all application areas appear to be ELECTRE and AHP; the ELECTRE family of methods seem to be preferred when assessing different power generation or transport technologies (e.g. Beccali et al. 1998; Roulet 2002; Wen et al. 2016), as well as for the evaluation of energy efficiency measures and actions (e.g. Patlitzianas and Psarras 2007; Bojkovic et al. 2010); while the latter is usually preferred in energy planning applications (e.g. Akash et al. 1999; Tzeng et al. 2005; Sadeghzadeh and Salehi 2011) and research studies with regard to the evaluation of alternative renewable energy projects (e.g. Nixon et al. 2010; Yi et al. 2011; Kaya and Kahraman 2011a). These two frameworks are followed by PROMETHEE (e.g. Ren et al. 2009; Ghafghazi et al. 2010) and TOPSIS (e.g. Doukas and Psarras 2009; Gao et al. 2011), in terms of frequency. Finally, the Multi-Attribute Utility Theory has been widely applied in energy planning (e.g. Loken et al. 2009) and policy evaluation (e.g. Konidari and Mavrakis 2007) and seems to be preferred in environmental impact assessment studies (e.g. Linkov et al. 2006) compared to the other models, while there exist a limited number of recent ANP applications (Liu and Lai 2009; Kabak and Dağdeviren 2014; Xu et al. 2015).

There also exist MCDM applications in which more than one models have been applied, as part of an integrated methodological framework. For example, Erdoğan and Kaya (2016), in order to determine the right region for the construction of a nuclear power plant, use a fuzzy AHP method for determining the evaluation criteria weights and a fuzzy TOPSIS approach for ranking the alternative locations. In a similar approach, Kaya and Kahraman (2011a) propose an integrated methodology for calculating the criteria weights by means of a fuzzy AHP procedure and then assessing the environmental impact with fuzzy ELECTRE.

Table 1 provides a detailed overview of MCDM applications in energy policy support studies, by classifying them into different application areas and methodologies, based on the work of Doukas (2013) and further elaborated and updated.

Despite the proliferation of MCDM applications in energy policy studies, preference disaggregation models have not been widely used. UTASTAR, in particular, has been used in a number of studies outside the energy domain (for example, Grigoroudis et al. 2012; Manolitzas et al. 2013; Haider et al. 2015). Especially with regard to energy policy, other variants of the original UTA method have been used to support policy making. For example, Diakoulaki et al. (1999) used UTADIS (Devaud et al. 1980), a UTA variant that is popular primarily in financial management applications, in order to characterise the economic and energy structure of each country. Another recent example can be found in Androulaki and Psarras (2016), who developed a preference disaggregation methodological framework based on UTA II (Siskos 1980) in the aim of assessing a large number of onshore and offshore gas supply pipeline corridors for Greece across three evaluation axes: economics of supply, security of supply and international cooperation conditions.

The only UTASTAR applications with direct energy policy implications found in the literature are the works of Papapostolou et al. (2016, 2017). In these studies, Papapostolou et al. delve into the international cooperation mechanisms that the recent Renewable Energy Directive (2009/28/EC) established, and develop a UTASTAR-based framework for evaluating five countries of the North African region (in the first study) and seven of the Western Balkan region (in the second study) across three evaluation axes (investment framework, social conditions, and energy and technological issues), in order to support European Union (EU) member states in selecting joint project partners. Building on these applications and slightly modifying the evaluation criteria and scope, we argue that the UTASTAR preference disaggregation model can contribute to a significant extent to energy policy making.

3 The UTASTAR Method

The regression-based UTASTAR model (Siskos and Yannacopoulos 1985) adopts the aggregation-disaggregation principle, that is seeks to analyse the behaviour of

Table 1 Overview of traditional MCDM applications in energy policy domains

Application area	Multiple-criteria decision making methodological framework					
	AHP	ANP	ELECTRE	MAUT	PROMETHEE	TOPSIS
Energy planning	Akash et al. (1999) Barin et al. (2009) Sadeghzadeh and Salehi (2011) Yedla and Shrestha (2003) Shanian and Savadogo (2006) Tzeng et al. (2005)		Beccali et al. (1998) Haurant et al. (2011)	Loken et al. (2009) McCarthy et al. (2007) McDaniels (1996) Michalik et al. (1997) Yan et al. (2011)	Diakoulaki and Karangelis (2007) Ren et al. (2009)	Chu (2002) Kaya and Kahraman (2011b) Montanari (2004) Niu et al. (2009)
Energy policy instruments assessment	Elkarmi and Mustafa (1993) Kahraman and Kaya (2010) Lee et al. (2009)		Mousavi et al. (2017)	Flamos et al. (2004) Jones et al. (1990) Konidari and Mavrakis (2007) Voropai and Ivanova (2002)	Madlener et al. (2007)	Doukas and Psarras (2009) Doukas et al. (2014) Ruan et al. (2010)
Energy technology assessment	Gerdsri and Kocaoglu (2007) Lee et al. (2008) Lee et al. (2011) Pilavachi et al. (2009) Zongxin and Zhihong (1997)	Kabak and Dağdeviren (2014)	Beccali et al. (1998) Beccali et al. (2003) Cavallaro (2010) Georgopoulou et al. (1998) Karagiannidis and Perkoulidis (2009) Madlener et al. (2009) Papadopoulos and Karagiannidis (2008) Perkoulidis et al. (2010) Roulet (2002) Siskos and Hubert (1983) Wang et al. (2009) Wen et al. (2016)	Erol et al. (2011)	Cavallaro (2009) Goumas and Lygerou (2000)	Vahdani et al. (2001)

(continued)

Table 1 (continued)

Application area	Multiple-criteria decision making methodological framework					
	AHP	ANP	ELECTRE	MAUT	PROMETHEE	TOPSIS
Environmental impact assessment	Kaya and Kahraman (2011a)	Liu and Lai (2009)	Kaya and Kahraman (2011a) Khodabakhshi and Jafari (2010)	Beynon and Wells (2008) Kapepula et al. (2007) Linkov et al. (2006) Palma et al. (2007)	Martin et al. (2003) Geldermann et al. (2000) Tuzkaya et al. (2009) Zhang et al. (2009)	Awasthi et al. (2010)
Evaluation of energy efficiency actions	Lee et al. (2007) Ren et al. (2009) Wong and Li (2008)	Xu et al. (2015)	Avgelis and Papadopoulos (2009) Bojkovic et al. (2010) Neves et al. (2008) Patlitzianas and Psarras (2007)		Ghafghazi et al. (2010)	Nikas et al. (2018)
Selection of energy projects (e.g. RE projects, CDM projects, etc.)	Cowan et al. (2010) Erdoğan and Kaya (2016) Heo et al. (2010) Kahraman et al. (2009) Kahraman and Kaya (2010) Kaya and Kahraman (2011a) Nixon et al. (2010) Yi et al. (2011)		Banias et al. (2010) Flamos et al. (2004) Georgiou et al. (2008) Haralambopoulos and Polatidis (2003) Karakosta et al. (2008)	Golabi et al. (1981) Mirasgedis and Diakoulaki (1997) Nussbaumer (2009) Theodorou et al. (2010) Drupp (2011)	Doukas et al. (2006) Doukas et al. (2008) Haralambopoulos and Polatidis (2003)	Doukas et al. (2010) Erdoğan and Kaya (2016) Gao et al. (2011) Gomez-Lopez et al. (2009) Jiang et al. (2009)

Source: Doukas (2013); own elaboration

the decision maker and analytically model their preference model, broken down into evaluation weights for each criterion; in fact, since UTASTAR primarily relies on the global preference of the decision makers and thus offers unbound freedom with regard to the complexity of preference model construction, it also aims at analysing preference dynamics along each criterion's scale by breaking it down into smaller intervals and attributing different weights to them.

Global preference is analysed by means of a set of reference actions/alternatives on which the decision maker is asked to provide their ranking; this means that the decision maker must rank these reference actions explicitly against the selected evaluation criteria or, equally, that the selected criteria are consistent, i.e. exhaustive and non-redundant. These reference actions comprise the set AR, which can be (a) a set of past decision alternatives for which the global preference is known a priori or can easily be elucidated; (b) a subset of the current decision alternatives $AR \subseteq A$, which is meaningful only in the case of a large set A and the extraction of a subset AR on which ranking can easily be elucidated from the decision maker; or (c) a set of fictitious actions, the performance values on the criteria of which can be easily judged by the decision maker.

The UTASTAR method, specifically, as a variation—and improvement—of the original UTA method (Jacquet-Lagrèze and Siskos 1982) that aims at inferring a set of additive value functions from an initial ranking on a number of reference functions (Grigoroudis et al. 2012), is based on the criteria aggregation model (additive value function and constraints) of the following form:

$$u(g) = \sum_{i=1}^{n} p_i u_i\left(g_i\right)$$
$$\begin{cases} \sum_{i=1}^{n} p_i = 1 \\ ui\left(gi^*\right) = 0, ui\left(gi^*\right) = 1, pi \geq 0 \quad \forall i = 1, 2, \ldots, n \end{cases}$$

where u_i is a marginal value or utility function, which is a non-decreasing real-valued function that is normalized in [0, 1] for each criterion g_i, and p_i is its weight.

The original UTA algorithm, in particular, modifies this additive value model by introducing a potential error $\sigma(a)$ relative to the additive value function, as follows:

$$u^{'}\left[g(a)\right] = \sum_{i=1}^{n} u_i\left[g_i(a)\right] + \sigma(a)$$
$$\begin{cases} \sum_{i=1}^{n} u_i\left(gi^*\right) = 1 \\ ui\left(gi^*\right) = 0 \quad \forall i = 1, 2, \ldots, n \end{cases}$$

This potential error $\sigma(a)$ is linked to every alternative action $a \in AR$ and must be minimized. Building on this specification of the UTA method and acknowledging that this error function is not adequate for the global dispersion around the monotone curve to be minimised, the UTASTAR model introduces a double positive (overestimation and underestimation) error function:

$$u^{'}\left[g(a)\right] = \sum_{1}^{n} ui\left[gi(a)\right] - \sigma^{+}(\alpha) + \sigma^{-}(\alpha) \qquad \forall a \in \boldsymbol{AR}$$

In order to fully assess the additive value and marginal utility functions towards reaching a ranking that is as consistent with the decision makers' behaviour as possible, the algorithm then employs special linear programming techniques.

Initially, the global value of all *m* reference alternatives is expressed in terms of marginal values $ui(gi)$ and, subsequently, in terms of marginal weights wij (upon each of the $\alpha i - 1$ intervals $[gi^{j}, gi^{j+1}]$ into which the scale of criterion gi is divided, i.e. the difference $ui(gi^{j+1}) - ui(gi^{j})$ of the marginal utilities between two successive values gi^{j} and gi^{j+1}):

$$\begin{cases} ui\left(gi^{1}\right) = 0 & \forall i = 1, 2, \ldots n \\ ui\left(gi^{j}\right) = \sum_{t=1}^{t=j-1} wit & \forall i = 1, 2, \ldots n \quad \text{and} \quad j = 2, 3, \ldots \alpha i - 1 \end{cases}$$

Subsequently, drawing from the decision makers' ranking of the reference alternatives, the difference between each pair of consecutive reference alternatives is expressed so as to incorporate the respective overestimation and underestimation errors:

$$\begin{aligned} \Delta\left(a_k, a_{k+1}\right) = &\left\{u\left[\boldsymbol{g}\left(a_k\right)\right] - \sigma^{+}\left(a_k\right) + \sigma^{-}\left(a_k\right)\right\} \\ &- \left\{u\left[\boldsymbol{g}\left(a_{k+1}\right)\right] - \sigma^{+}\left(a_{k+1}\right) + \sigma^{-}\left(a_{k+1}\right)\right\} \end{aligned}$$

Finally, in order to ensure the strict preference of an alternative over its subsequent alternative, according to the ranking of *AR*, a decision maker's threshold δ is defined, which is a very small positive number (e.g. 1–2%). Usually, a very weak order is selected initially, meaning a very small preference threshold, thus allowing for reaching a set (polyhedron) of feasible solutions and then strengthening the preference by increasing this number in order to minimise the polyhedron towards the optimal solution. At this point, the following linear programming problem must be solved:

$$\begin{cases} \min z = \sum_{k=1}^{m} \left[\sigma^{+}\left(a_k\right) + \sigma^{-}\left(a_k\right)\right] \\ \text{subject to :} \\ \left.\begin{array}{l} \Delta\left(a_k, a_{k+1}\right) \geq \delta \quad if\ a_k \succ a_{k+1} \\ \Delta\left(a_k, a_{k+1}\right) = 0 \quad if\ a_k \approx a_{k+1} \end{array}\right\} \forall k \\ \sum_{i=1}^{n} \sum_{j=1}^{ai-1} wij = 1 \\ wij \geq 0, \quad \sigma^{+}\left(a_k\right) \geq 0, \quad \sigma^{-}\left(a_k\right) \geq 0 \quad \forall \text{i, j, k} \end{cases}$$

4 A Preference Disaggregation Approach to Formulating Energy Policy

This is not the first time that international cooperation in the aim of developing joint energy projects is supported by means of multicriteria analysis. For example, Flamos et al. (2004) developed an integrated development and environmental additionality assessment methodology, based on the ELECTRE Tri method of the ELECTRE family, in order to evaluate potential Clean Development Mechanism projects with regard to the additionality condition that must be met in order for projects to be eligible under the mechanism. Karakosta et al. (2008) proposed a similar methodological approach based, too, on the ELECTRE Tri outranking MCDM model, aiming at the assessment of energy technology transfer alternatives under the Kyoto Protocol. Other examples of multicriteria analysis regarding Clean Development Mechanism candidate projects include PROMETHEE (Diakoulaki et al. 2007), ELECTRE III (Georgiou et al. 2008), and MAUT-based approaches (Nussbaumer 2009; Drupp 2011).

Although international cooperation for clean electricity primarily through large-scale renewable energy projects, as promoted for example by the Renewable Energy Directive, substantially differ in scale and requirements from projects under the Clean Development Mechanism, there are also similarities. As Schroeder (2009) notes, renewable energy projects constitute a large share of the projects developed under the Mechanism; renewable energy sources do offer a fine alternative for achieving two of the main objectives of the Mechanism, after all: effectively reducing carbon emissions and contributing to sustainable development. It is in this perspective, we draw from the sole UTASTAR application in the field of energy policy (Papapostolou et al. 2016) and expand its scope, by considering a much larger pool of candidate countries in the aim of international cooperation for clean electricity within the European Union.

More specifically, starting from the five North African countries (Algeria, Egypt, Libya, Morocco and Tunisia) of said study, we added EU neighbours in the East and South and ended up with the following pool of candidate countries: Albania, Algeria, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina (B&H), Egypt, Former Yugoslav Republic of Macedonia (FYROM), Georgia, Israel, Jordan, Kosovo, Lebanon, Libya, Moldova, Montenegro, Morocco, Russia, Serbia, Tunisia, Turkey and Ukraine (Table 2). These countries, apart from Russia, are all members of the Energy Community (European Parliament 2015) and/or the European Neighbourhood Policy (Cadier 2013). In the context of this application, two professors from the National Technical University of Athens, whose research interests and activities include international energy policy, were selected as decision makers.

The objective of this study is to explore and evaluate the cooperation potential between EU Member States and neighbouring countries towards developing clean

Table 2 Members of the Energy Community and the European Neighbourhood Policy that are included in the case study

Countries	Member of the Energy Community	Member of the European Neighbourhood Policy	Included in the case study
Albania	✓		✓
Algeria		✓	✓
Armenia	✓	✓	✓
Azerbaijan		✓	✓
Belarus		✓	✓
Bosnia	✓		✓
Egypt		✓	✓
FYROM	✓		✓
Georgia	✓	✓	✓
Israel		✓	✓
Jordan		✓	✓
Kosovo	✓		✓
Lebanon		✓	✓
Libya		✓	✓
Moldova	✓	✓	✓
Montenegro	✓		✓
Morocco		✓	✓
Norway	✓		
Palestine		✓	
Russia			✓
Serbia	✓		✓
Syria		✓	
Tunisia		✓	✓
Turkey	✓		✓
Ukraine	✓	✓	✓

electricity projects. Drawing from the original application, we modify the assessment framework and consider the following evaluation criteria:

g1. OECD country risk rating 2016 (OECD 2016)
g2. Ease of doing business index (The World Bank 2016)
g3. Global Competitiveness index (World Economic Forum 2013)
g4. Social Hotspot index (SHDB 2015)
g5. Household Indicator (based on World Energy Outlook 2014)
g6. Electric power transmission and distribution losses (The World Bank 2013a)
g7. Energy production and use growth (based on data from The World Bank 2013b)
g8. Age of technology fleet
g9. Share of fossil fuels in electricity production (based on data from IEA 2014)

Table 3 Energy production and use growth rate, based on data from The World Bank (2013b)

Countries	Energy production and use					Growth rate
	2007	2008	2009	2010	2011	
Albania	679.862	697.004	722.584	724.563	770.340	9.11%
Algeria	1075.194	1070.725	1151.451	1112.402	1138.913	3.31%
Armenia	954.730	1009.761	879.931	837.930	914.954	0.00%
Azerbaijan	1411.557	1520.314	1334.166	1279.553	1369.351	0.00%
Belarus	2918.198	2932.099	2790.068	2900.220	3097.713	7.37%
B&H	1381.122	1552.585	1620.090	1689.932	1864.555	19.45%
Egypt	896.348	914.943	919.068	883.918	908.220	0.51%
FYROM	1474.712	1469.664	1367.358	1396.127	1511.246	5.91%
Georgia	818.551	745.548	778.161	795.286	914.675	16.61%
Israel	2898.153	3129.128	2873.876	3042.434	2980.176	0.00%
Jordan	1251.682	1176.195	1190.065	1089.807	1045.196	0.00%
Kosovo	1179.569	1267.742	1381.957	1405.041	1411.507	7.87%
Lebanon	1034.922	1322.134	1590.249	1471.095	1382.391	2.05%
Libya	2725.888	2870.791	3058.635	3281.077	2157.484	0.00%
Moldova	938.597	938.348	891.029	984.625	971.407	3.55%
Montenegro	1927.979	2067.968	1646.312	1898.288	1815.530	0.00%
Morocco	487.449	503.076	505.188	527.283	560.441	10.81%
Russia	4709.846	4823.132	4531.287	4827.811	5057.521	7.08%
Serbia	2248.155	2290.125	2070.229	2141.055	2236.088	2.23%
Tunisia	883.981	912.674	877.221	974.840	919.397	0.79%
Turkey	1438.535	1403.255	1372.287	1455.834	1526.345	7.68%
Ukraine	2996.211	2910.661	2487.036	2886.995	2768.924	0.00%

Criterion g7, in particular, was calculated for years 2007–2011 (latest available data) in Table 3, using the following formula (and assuming negative values to be zero):

$$Growth = \frac{EnergyUse2011 - 0.25\sum_{2007}^{2010} EnergyUsei}{0.25\sum_{2007}^{2010} EnergyUsei} \cdot 100\%$$

Finally, criterion g8 is a qualitative index assessing the age and depreciation of every electricity generation unit of a candidate country, based on its technology.

Table 4 summarises the scores of each candidate country for each evaluation criterion.

As explained in the previous section, the reference set AR can be a set of past actions, for which the ordering is known a priori and considered as the decision makers' global preference, a subset of the alternatives $AR \subseteq A$ that the decision makers can easily rank, or a set of fictitious actions, the scores in each criterion of

Table 4 Candidate countries' scores for the nine evaluation criteria

Countries	OECD country risk rating	Ease of doing business rank	Global Competitiveness index	Social Hotspot database index	Energy Development index—Household Indicator	Electric power transmission and distribution losses	Energy production and use growth (%)	Age of technology fleet	Share of fossil fuels in electricity production
	g1	g2	g3	g4	g5	g6	g7	g8	g9
Albania	6	58	3.8	138.59	0.380	28	9.11	4	0
Algeria	4	156	3.8	215.88	0.516	18	3.31	4	99.6
Armenia	6	38	4.1	179.11	0.502	12	0	2	42.44
Azerbaijan	5	65	4.5	155.2	0.522	14	0	1	94.02
Belarus	7	37	4	91.26	0.550	11	7.37	2	99.17
B&H	7	81	4	130.76	0.401	8	19.45	2	63.27
Egypt	6	122	3.6	216.96	0.395	11	0.51	3	90.95
FYROM	5	10	4.1	76.57	0.229	19	5.91	3	75.96
Georgia	6	16	4.2	167.22	0.531	8	16.61	3	19.63
Israel	3	52	4.9	147.09	0.440	4	0	2	98.49
Jordan	5	118	4.2	216.33	0.391	14	0	2	99.64
Kosovo	7	60	4	105	0.274	13	7.87	1	97.22
Lebanon	7	126	3.8	202.81	0.491	10	2.05	1	98.92
Libya	7	188	3.7	234.41	0.453	19	0	3	100
Moldova	7	44	3.9	127.06	0.487	25	3.55	2	93.8
Montenegro	7	51	4.2	116.25	0.318	16	0	3	44.8
Morocco	3	68	4.1	175.85	0.466	16	10.81	4	86.42
Russia	4	40	4.2	79.12	0.586	10	7.08	3	66.01
Serbia	6	47	3.8	94.58	0.274	14	2.23	2	65.8
Tunisia	4	77	4.1	183.23	0.497	15	0.79	2	92.8
Turkey	4	69	4.4	117.16	0.460	15	7.68	3	78.98
Ukraine	7	80	4.1	102.36	0.546	11	0	3	45.62

which enable the decision makers to easily provide their global preference. Given that a ranking of five countries was available from Papapostolou et al. (2016), this set could have been used as reference; however, the number of alternatives in *AR* is to a large extent dependent on the number of criteria; for a set of nine evaluation criteria, a reference set of five countries would be insufficient for forming a useful global preference model. More importantly, however, this application's decision makers are different from the decision makers of Papapostolou et al. (2016), thus the resulting ordering of the latter would not be consistent with the decision makers' behaviour of this case study. Consequently, a set of 15 fictitious countries was created so as to facilitate the decision makers into expressing their global preference: these countries would differ from one another only in 2–3 criteria, every time.

In order to initiate the UTASTAR algorithm, every criterion was broken down into equal intervals, based on its scale:

- $[g1*, g1^{*}] = [7, 6, 5, 4, 3, 2, 1, 0]$
- $[g2*, g2^{*}] = [189, 142, 95, 48, 1]$
- $[g3*, g3^{*}] = [1, 3, 5, 7]$
- $[g4*, g4^{*}] = [500, 400, 300, 200, 100, 0]$
- $[g5*, g5^{*}] = [0, 0.25, 0.5, 0.75, 1]$
- $[g6*, g6^{*}] = [30, 25, 20, 15, 10, 5, 0]$
- $[g7*, g7^{*}] = [30, 25, 20, 15, 10, 5, 0]$
- $[g8*, g8^{*}] = [1, 2, 3, 4, 5]$
- $[g9*, g9^{*}] = [100, 90, 80, 70, 60, 50, 40, 30, 20, 10, 0]$

By breaking each criterion scale into smaller intervals, UTASTAR can explore the dynamics along the scales, since the weight of a criterion can be considered to be dynamic and change as an alternative's score moves along its scale.

After expressing the global value of the 15 reference countries in terms of marginal values *ui*(*gi*) and, subsequently, in terms of marginal weights *wij*, and then expressing the difference between two subsequent countries (as resulted from the global preference provided by the decision makers) in the latter form, the linear programming problem of Sect. 3 is solved for a preference threshold of 1%, seeking to minimize the sum of all over- and underestimation errors. Indeed, we found that $z^* = 0$, meaning that there exists at least one solution of *wij*, for which the (weak) ordering provided by the decision makers is met. Should the solution have been $z^* \neq 0$, the order would not have been consistent and the decision makers would have been asked to reconsider their global preference.

It should be noted that the existence of at least one solution does not mean that this is unique, but rather that there actually exist a feasible set (or polyhedron, bound by the problem's constraints) of near optimal solutions. One way to address this is to calculate all of the solutions that minimise and maximise each *wij* and then assume the barycentre of all to be the most representative solution (Papapostolou et al. 2016). Siskos et al. (2005) mention a number of other approaches to reaching a small number of solutions. One such approach is to exaggerate the order strength, by changing the objective function of the linear programming problem into maximising the preference threshold. After following this approach, the preference threshold is found δ max $= 1.725\%$, for which we can be certain that the size of the polyhedron of near optimal solutions is minimised. In fact, after trying to implement the barycentre approach, we notice that the solution's stability is extremely high, hence the solution that is consistent with the decision makers' global preference can be considered unique. After having calculated the weights wij, the utility functions of the 22 case study countries must be expressed in terms of marginal values $ui(gi)$ and, subsequently, in terms of marginal weights wij, so as to rank them. For example, the utility function of Albania and Algeria are the following:

$$\begin{aligned}\mathrm{u\,(Albania)} &= \mathrm{u1(6) + 0.21u2(95) + 0.79u2(48) + 0.4u3(3) + 0.6u3(5) + 0.39u4(200)}\\ &\quad \mathrm{+ 0.61u4(100) + 0.48u5(0.25) + 0.52u5(0.5) + 0.6u6(30) + 0.4u6(25)}\\ &\quad \mathrm{+ 0.82u7(10) + 0.18u7(5) + u8(4) + u9(0)}\\ &= \mathrm{w11 + w21 + w22 + 0.79w23 + w31 + 0.4w32 + w41 + w42 + w43}\\ &\quad \mathrm{+ 0.61w44 + w51 + 0.52w52 + 0.4w61 + w71 + w72 + w73 + w74}\\ &\quad \mathrm{+ 0.18w75 + w81 + w82 + w83 + w91 + w92 + w93 + w94 + w95}\\ &\quad \mathrm{+ w96 + w97 + w98 + w99 + w90}\end{aligned}$$

$$\begin{aligned}\mathrm{u\,(Algeria)} &= \mathrm{u1(4) + 0.3u2(189) + 0.7u2(142) + 0.6u3(3) + 0.4u3(5) + 0.16u4(300)}\\ &\quad \mathrm{+ 0.84u4(200) + 0.94u5(0.5) + 0.06u5(0.75) + 0.6u6(20) + 0.4u6(15)}\\ &\quad \mathrm{+ 0.66u7(5) + 0.34u7(0) + u8(4) + 0.96u9(100) + 0.04u9(90)}\\ &= \mathrm{w11 + w12 + w13 + 0.7w21 + w31 + 0.4w32 + w41 + w42 + 0.84w43}\\ &\quad \mathrm{+ w51 + w52 + 0.06w53 + w61 + w62 + 0.4w63 + w71 + w72 + w73}\\ &\quad \mathrm{+ w74 + w75 + 0.34w76 + w81 + w82 + w83 + 0.04w91}\end{aligned}$$

Finally, the global value for every country may be calculated. The resulting order of the case study neighbouring countries is presented in Table 5.

It is interesting to observe that the results are quite consistent with the ranking of the five North African countries in Papapostolou et al. (2016), with the exception of Egypt which seems to rank higher than Tunisia. This can be attributed to a

Table 5 Final ranking of the 22 case study candidate countries

Rank	Country	u(g)	Rank	Country	u(g)
1	Montenegro	0.787884	12	Israel	0.498563
2	Ukraine	0.784662	13	B&H	0.498359
3	Georgia	0.759328	14	Kosovo	0.480509
4	Albania	0.7298	15	Moldova	0.46645
5	Russia	0.705	16	Egypt	0.450402
6	Armenia	0.672273	17	Azerbaijan	0.436033
7	FYROM	0.615772	18	Tunisia	0.410867
8	Turkey	0.603442	19	Algeria	0.321556
9	Serbia	0.591644	20	Libya	0.287144
10	Morocco	0.568274	21	Jordan	0.284193
11	Belarus	0.533598	22	Lebanon	0.280934

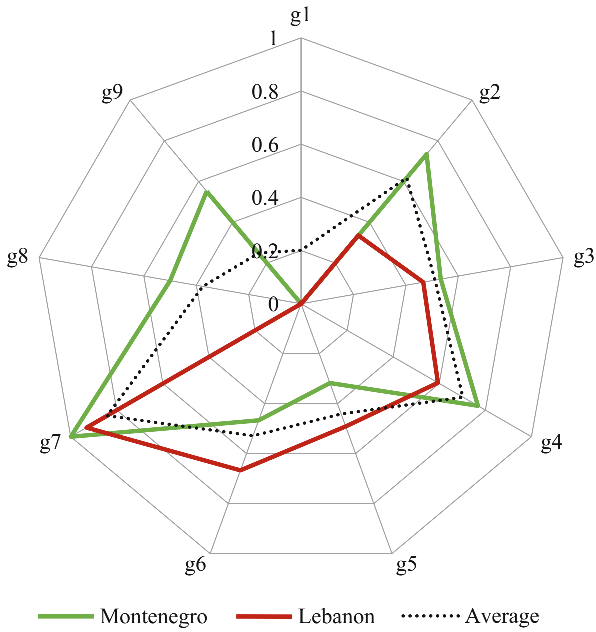

Fig. 1 Radar chart for the top (Montenegro), average and bottom (Lebanon) ranking countries

number of reasons. First of all, different decision makers inevitably provide different global preferences, which are in turn disaggregated into different preference models; secondly, the criteria used in this application are slightly different; finally, the set of reference actions *AR* is also different from the one used to evaluate the North African region. It is imperative, therefore, to note that the selection of the set of reference alternatives is of vital importance since it is upon these that the decision makers will express their global preference.

Some conclusions regarding the decision makers' preference model can be drawn by looking at the rankings of Table 2 and the example radar chart (Fig. 1) of the top, average and bottom ranking countries: It appears that social indicators, such as access to electricity (as expressed by the Household Indicator) and transmission and distribution losses, are not as important to the decision makers as investment-related criteria or indicators of energy security and sustainability.

This is also evident from the global utility function, as a result of our analysis after adding the corresponding weights *wij* for each criterion:

$$u(g) = 0.021u(g1) + 0.152u(g2) + 0.149u(g3) + 0.105u(g4) + 0.095u(g5) \\ + 0.086u(g6) + 0.025u(g7) + 0.132u(g8) + 0.235u(g9)$$

By observing the global utility function, we can see that, indeed, the most important criteria according to the decision makers' initial ranking are the fossil fuel dependence of the current power generation mix, followed by the perceived ease of doing business and global competitiveness, as opposed to the overall risk of the candidate countries, as estimated by OECD.

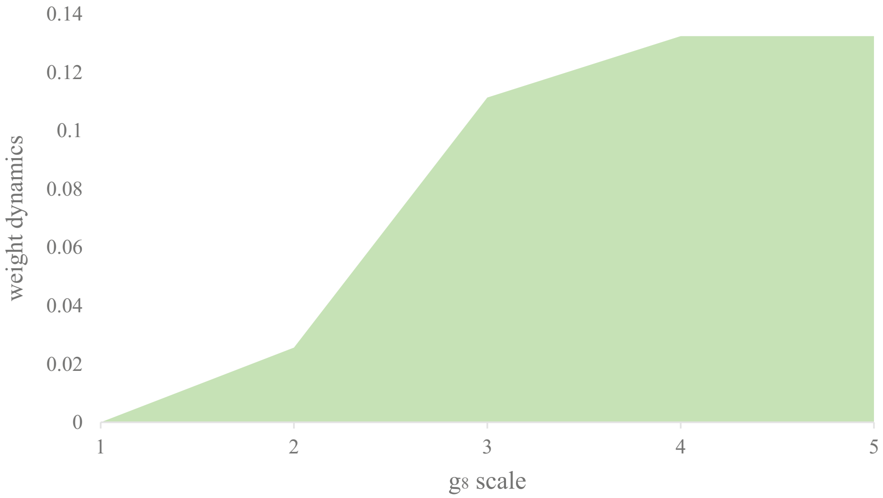

Fig. 2 Weight dynamics along the scale of the age of technology fleet evaluation criterion

As a preference disaggregation model, which depends solely on the global preference of the decision makers, UTASTAR also allows for in-depth analysis of the weights along the criteria scales. For example, for criterion g8, we can see how the weight changes dynamically as we move along the scale [1, 5] (Fig. 2), indicating that an average performance of a country in its power generation units age boosts the country's overall performance significantly more than a perfect score in this criterion, in a potential tradeoff analysis.

The weights for every sub-interval of each criterion scale are presented in Fig. 3.

5 Conclusions

Given their multidisciplinary nature, problems within the problem domain of energy policy usually require analysis based on a number of factors, making multicriteria decision aid an attractive, viable approach. Despite the large proliferation of a variety of traditional MCDM methods in this respect as explored in a detailed literature review, however, preference disaggregation is still underexploited as a multicriteria analysis approach. In this study, we argue that the disaggregation-aggregation paradigm in multiple criteria decision making can support decision makers and contribute to energy policy making. In this direction, a global preference disaggregation model of the UTA family, UTASTAR, is described in detail and implemented in the context of the challenging task of evaluating EU neighbouring countries as candidate hosts of clean power generation projects. Drawing from the existing literature, a set of nine evaluation criteria is put together, covering aspects from the economic, social, technological and energy security dimensions.

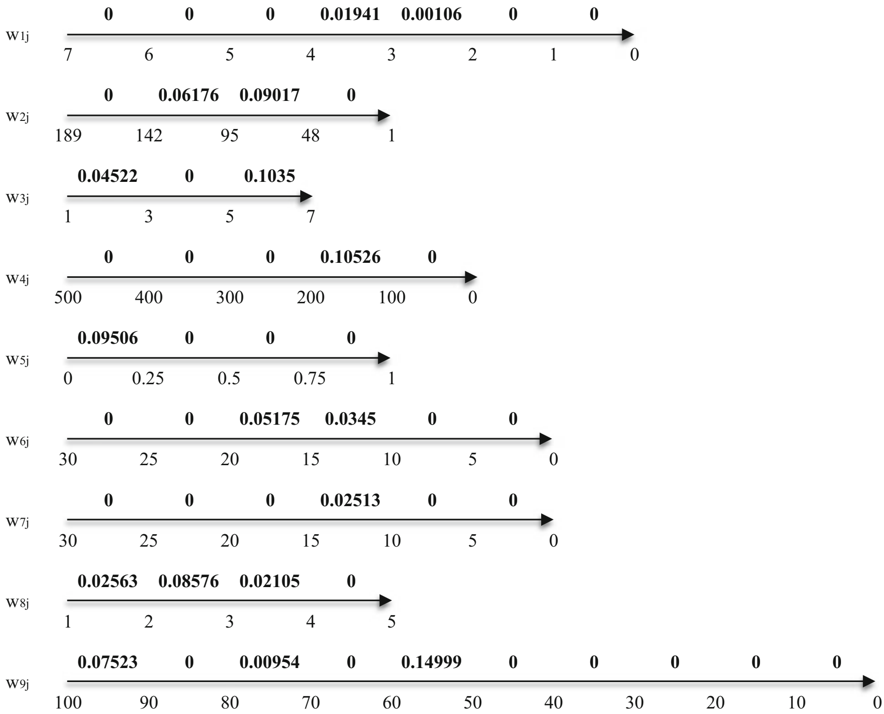

Fig. 3 Weights w_{ij} for all intervals of each criterion scale

Our pool of candidate countries consists of members of the Energy Community on the one hand, and the European Neighbourhood Policy on the other, with which international ties towards political, economic and energy market integration already exist and provide ideal grounds for clean electricity through international cooperation.

The results of our analysis, based on the UTASTAR method, indicate that European countries (outside the Union) on average rank better—and thus are perceived to be more attractive—than countries of the South and East. Aside from the ranking, the proposed methodology also allows us to draw conclusions concerning the inferred preference model of the decision makers, by providing a detailed overview of how each criterion weighs as well as of exactly what levels of each criterion are important, or more important that others, to the decision makers. From a methodological point of view, however, it is evident that these results are primarily meaningful for the given set of reference countries, implying that the end preference model as expressed by the decision makers can to some extent be influenced by the performance and number of the reference alternatives. Furthermore, the latter is in fact largely dependent on the number of the evaluation criteria: the more criteria the analysis uses, the larger the set of reference actions must be; in any other case, the ranking the decision makers provide on the reference alternatives will not be adequate to accurately transfer their global preferences that UTASTAR seeks to disaggregate.

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Developing Regional Strategies Based on Tourist Behaviour Analysis: A Multiple Criteria Approach

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Abstract Tourism is a vital sector of the Greek economy that undoubtedly needs support for its strategic planning. In this work, we provide policy makers with a strategic plan for a touristic destination strategy. Our recommendations have a regional scope and are results of a large survey that was conducted at the airports of the island of Crete. Having collected more than 5000 questionnaires, we applied a multiple criteria customer satisfaction methodology to assess tourists' satisfaction. This multiple criteria analysis is combined with some demographic statistics, as well as it is followed-up by a loyalty analysis. Eventually, we were able to deliver a strategic plan with the shape of a SWOT analysis. This plan confirms that tourists visiting Crete are heterogeneous, yet the competitive advantage of the destination is unanimously its environment, and the dominant patterns of the touristic product should not be challenged. However, the plan also suggests marginal improvements that could contribute to improving tourists' satisfaction.

1 Introduction

Tourism is a vital sector of the Greek economy and a major contributor of its economic development. Recent studies (published periodically at http://www.insete.gr—a non-profit civil partnership supported by the national professional body of the tourism sector) estimate that the direct contribution of tourism to the Greek gross domestic product (GDP) is around 9%. Should we consider the indirect effects to the national economy, the overall contribution of tourism is estimated at more than

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20% of the GDP. In particular, for certain regions (Crete, South Aegean, Ionian), tourism contributes more than 50% to the regional GDP, making tourism the most critical economic activity.

The need to support this critical sector with effective strategic planning is therefore quite straightforward. However, it is not clear what should be the focus of such a strategy design. Historically, the focus was on individual touristic organizations (e.g., hotels) (Ward 1998). Later, the concept of touristic destination emerged as the principal element (Wang and Pizam 2011), while governmental efforts push to widen the scope at a national level (Witt et al. 2013). There are two main reasons that make the touristic destination level more suitable for this work: First, the global trend that indicate that destinations are the biggest brands in the travel industry (Chaperon 2017; Morgan et al. 2011), and second, country-specific circumstances. More specifically, Greece is a country where the importance of tourism varies significantly across regions. Moreover, due to political turbulences, a national strategic plan is not yet established, allowing regions to take initiative on the touristic strategy design.

Focusing on touristic destinations, a critical competitive advantage for the corresponding regions is tourists' satisfaction (Fuchs and Weiermair 2004). Tourist satisfaction itself, for a particular destination, can be improved by harmonizing tourists' expectations with the destination's performance (Kozak 2002). The importance of service quality evaluation in general, and of the tourism product in particular, through customer satisfaction measurement is reinforced by the necessity of adopting a "continuous improvement" philosophy and understanding customer perceptions (e.g., needs, expectations) (Song et al. 2012). Generally, the main reasons for measuring customer satisfaction are comprehensively summarized by (Evangelos Grigoroudis and Siskos 2010). Outlining some of the major arguments, we regard customer satisfaction to constitute the most reliable market information. It provides a business organization with the ability to evaluate its current position against competition, and design its future plans accordingly. Moreover, the main principles of continuous improvement require the development of a specific customer satisfaction measurement process. This way, any improvement action is based on standards that take into account customer expectations and needs. Finally, customer satisfaction measurement may help business organizations to understand customer behavior, and particularly to identify and analyze customer expectations, needs, and desires.

A common approach to measure tourist satisfaction is the confirmation/disconfirmation paradigm (Bowen and Clarke 2002; Michalkó et al. 2015; Vasconcelos et al. 2015). A relevant method is the HOLSAT model, which is a characteristic approach used to evaluate satisfaction from a particular destination (Tribe and Snaith 1998). The model is based on the disconfirmatory paradigm outlined before and adopts the philosophy of the SERVQUAL model (Parasuraman et al. 1991). The main results of the HOLSAT model focus on the difference between "expectation" and "experience" scores for each attribute, which gives a quantitative measure of the level of satisfaction shown by the vacationers (Truong and Foster 2006).

Despite the context and the multivariate nature of tourist satisfaction measurement (Jannach et al. 2014), Multiple Criteria Decision Analysis (MCDA) has not been widely applied in evaluating service quality in the tourism industry. Rozman et al. (2009) apply the DEX method, which combines traditional MCDA approaches and elements of expert systems and machine learning, in order to assess tourist farm service quality. An AHP model, combined with fuzzy TOPSIS, is applied in (Hsu et al. 2009) for a preference analysis for tourist choice of destination in Taiwan. In Tsitsiloni et al. (2013), authors use a multiple criteria methodology to combine satisfaction importance and performance results and provide a SWOT analysis for the whole set of the tourist satisfaction criteria.

The aim of this work is to support the formulation of a strategy plan for a specific touristic destination, by analyzing tourists' behavior through a multiple criteria methodology. We used an established method from the family of aggregation-disaggregation methods to elaborate on tourist satisfaction, and eventually deliver strategic recommendations through a SWOT analysis. The next section describes the application context and the foundations of the multiple criteria method. Then we present some general statistics that describe the population, before focusing on the satisfaction analysis. Finally, we pipeline the results of the multiple criteria method into a qualitative strategy technique, a SWOT map.

2 Methodology

2.1 Application Context

The data for this study was collected from inbound individual adult tourists who had arrived by charter flights at Crete, Greece. The survey was realized through personal interviews based on a structured questionnaire. The interviews were conducted at the two big, international airports of the island (N. Kazantzakis & Y. Daskalogiannis) a few minutes before boarding. The questionnaire was translated into six languages (English, French, German, Italian, Swedish and Russian) and it consisted of six sections: personal data, travel data, staying details, satisfaction, loyalty, special topics. Interviews began in June, 2008 and finished 4 months later, October 2008. The final population interviewed reached 5144 tourists, adult men and women.

In order to select the satisfaction dimension, we made an initial list of relevant criteria based on the literature of customer satisfaction for tourism destinations (Arabatzis and Grigoroudis 2010; Karakitsiou et al. 2007; Pizam et al. 1978; Tsai and Wang 2017; Yuksel 2001), and then, survey sponsors (local stakeholders) made the adjustments they considered practical. Finally, we used the following set of satisfaction dimensions (criteria):

(1) Accommodation: Refers to the characteristics of accommodation e.g., room, staff, service, cleanliness, etc.

(2) Eating: This particular criterion refers to the food related activities, offered inside or outside the accommodation facilities and includes food quality, the variety of dishes, the environment (decoration, aesthetics), the provided services, the prices, etc.
(3) Environment—People: A rather composite criterion that describes the natural environment, the climate conditions, the local architecture, as well as the behavior, and the friendliness of the locals.
(4) Infrastructures—Safety: Besides feeling safe, in this criterion we ask about the information available to tourists, public spaces, etc.
(5) Entertainment: This criterion refers to the entertainment/recreation options offered to tourists during their stay and includes the available choices, the service offered, the venues, the prices, etc.
(6) Airports: This dimension concerns the characteristics of the service provided in island's airports.
(7) Local transportation: By local transportation we mean bus and taxi services, rented cars, etc. The criterion includes all the characteristics of the provided services (availability, service from personnel, prices, etc.).

Every item is a question for which tourists are asked to express their satisfaction using a 5-point ordinal scale (dissatisfied, somehow dissatisfied, neither satisfied nor dissatisfied, somehow satisfied, satisfied).

2.2 The MUSA Method

The MUSA (MUlticriteria Satisfaction Analysis) method is an established multicriteria preference disaggregation approach, which provides quantitative measures of customer satisfaction considering the qualitative form of customers' judgments. A detailed presentation of the method can be found in (E. Grigoroudis and Siskos 2002; Evangelos Grigoroudis and Siskos 2010) while it have been applied in several domains, from healthcare (Manolitzas et al. 2014) to tourism (Muhtaseb et al. 2012). The basic mathematical formulation can be found in the appendix, however in the following paragraph we briefly present its essential concepts. The main objective of the MUSA method is the aggregation of individual judgments into a collective value function, assuming that client's global satisfaction depends on a set of n criteria or variables representing satisfaction dimensions. We use the notation X_i to represent a criterion i with a monotonic variable. The MUSA method infers an additive collective value function Y^* and a set of partial satisfaction functions X_i^*, given customer's global satisfaction Y and partial satisfaction X_i according to criterion i (ordinal scaling). The main objective of the method is to achieve the maximum consistency between the value function Y^* and the customers' judgments Y. Based on the modeling of preference disaggregation approach, the ordinal regression equation becomes as follows:

$$\widetilde{Y^*} = \sum_{i=1}^{n} b_i X_i^* - \sigma^+ + \sigma^- \text{ with } \sum_{i=1}^{n} b_i = 1$$

where $\widetilde{Y^*}$ is the estimation of Y^*, b_i is the weight of the i^{th} criterion, n is the number of criteria, and σ^+, σ^- are the overestimation and the underestimation errors, respectively.

MUSA provides the following key results:

- *Criteria weights*: The weights are value trade-offs among the criteria. They represent the relative importance of the assessed satisfaction dimensions.
- *Average satisfaction indices*: The level of customers' satisfaction in a range of $0-100\%$. They can be considered as the basic performance norms.
- *Average demanding indices*: They represent the average deviation of the estimated value functions from a "normal" function, and they are calculated according to the shape of global and partial value functions. These indices are used in customer behavior analysis, but they may also indicate the extent of company's improvement efforts: the higher the value of the demanding index, the more the satisfaction level should be improved in order to fulfill customers' expectations.
- *Average improvement indices*: These indices represent the improvement efforts and they depend on the importance of satisfaction criteria and their contribution to dissatisfaction as well. They suggest the improvement margins on a specific criterion, and hence its priority rank.

3 Results

3.1 General Statistics

To describe the age distribution of the sample population, we cut the age into five groups (younger than 24, 25–34 years old, 35–44, 45–60, and older than 61 years old). The percentage of the first four levels seems quite balanced in the overall population (see Fig. 1a), while the last category is suggestively less frequent. However, the percentages vary significantly across prefectures. These differences are illustrated in Fig. 1b, where the vertical axis crosses the horizontal one at the percentage that corresponds to the total sample (percentages of Fig. 1a). We can observe that in the Heraklion prefecture, the age group of young tourists (younger than 24 years) is over-represented. Likewise, in Chania, we observe an over-representation of the top-three elder age groups.

Prefectures' visitors are also nationality-wise different. The top-five most popular nationalities per area are presented in Tables 1–4. The numbers in these tables correspond to the percentage of each nationality with respect to the total visitors of that particular area.

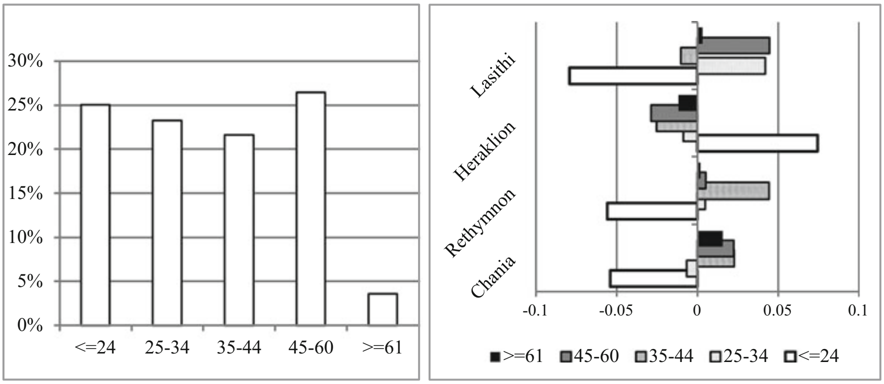

Fig. 1 (**a**) Frequency distribution for the entire sample per age level. (**b**) Differences in the age levels' frequencies per prefecture

Table 1 Most popular nationalities for Chania

Nationality	Percentage
Swedish	17.87
Norwegian	16.27
Danish	16.07
German	11.20
British	10.60

Table 2 Most popular nationalities for Rethymon

Nationality	Percentage
German	18.49
French	11.50
Russian	9.46
British	7.57
Norwegian	7.42

Table 3 Most popular nationalities for Heraklion

Nationality	Percentage
British	18.32
German	17.97
Dutch	12.91
French	9.20
Italian	7.54

Table 4 Most popular nationalities for Lasithi

Nationality	Percentage
French	29.06
British	19.69
German	14.53
Italian	8.44
Other	5.78

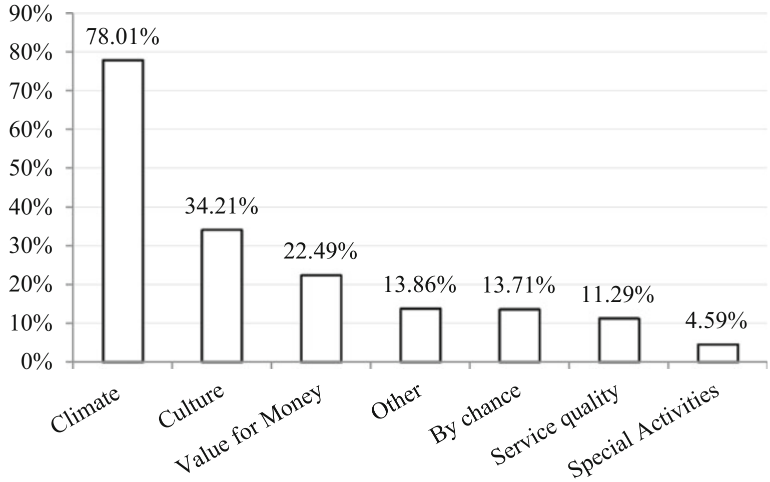

Fig. 2 Reasons that guide touristic destination selection

To investigate the reasons why tourists choose the region of Crete as their destination, we used a direct question. In particular, we asked them to choose between "Climate-Natural Beauty (sun-sea)"; "Culture (history, archaeological monuments)"; "Value for money"; "Service Quality"; "Special Activities" (agro-tourism etc.); and "By chance (last minute reservation)". We allowed multiple checking of responses. There was also an additional open-ended response to fill, if applicable. The popularity of these reasons is presented in Fig. 2 where the superiority of "Climate" is evident.

As long as for the length of staying, the mean value is calculated to be 10.18 days for the total sample, and this value does not differ significantly among prefectures. However, there are two peaks in the frequency distribution: on 7 days, and on 14 days, a fact that is in accordance with the way that tour operators organize their vacations' packages for Crete.

3.2 Satisfaction Analysis

In this paragraph we present the results for the total sample. We have also conducted multiple tests by filtering data on tourists' nationality, age, place of stay, etc. We noticed some marginal differences among groups, however in order to keep the presentation of results in scope, we present here only some highlights.

With respect to nationality, Russians are in general more satisfied while the least satisfied are Dutch tourists. Italians consider the accommodation's elements as the most significant, Russians the food-related elements, and Dutch the environment-people criterion. Satisfaction indices are also negatively correlated with the educational level, and the income of tourists.

The overall satisfaction index is 84.22%. The best performing criterion is "Environment-People" (88.89%), and the worst performing one is the "Airports" one (73.27%). The performance for every criterion can be seen in Fig. 3, where the dashed line plots the overall satisfaction index. We may recall at this point that the overall index is calculated as a weighted sum of the marginal indices, considering the criteria significance weights. These weights are depicted in Fig. 4. Quite remarkably, the most important criterion is the best performing one, while the worst performing criterion is the least important one. This fact is reflected in the corresponding action diagram (Fig. 5), where "Airports" seem to be a

Fig. 3 Satisfaction indices for each criterion. The dashed line indicated the overall performance

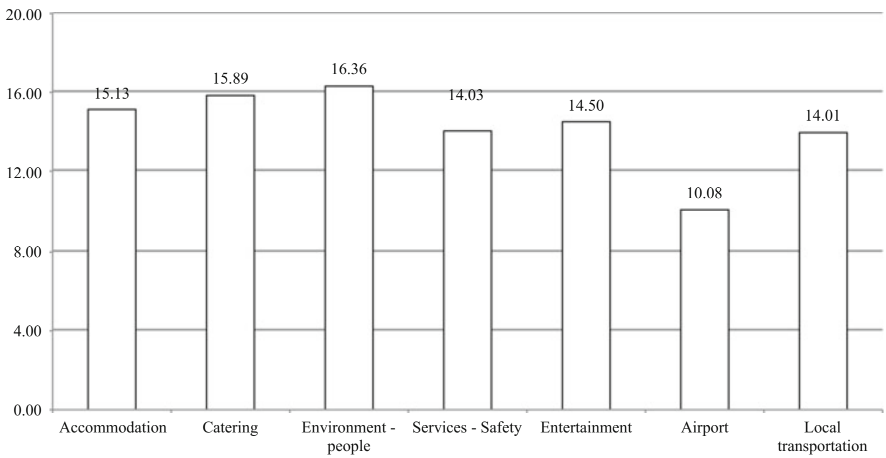

Fig. 4 Significance weights of the criteria. The weight of each criterion indicates its relative importance

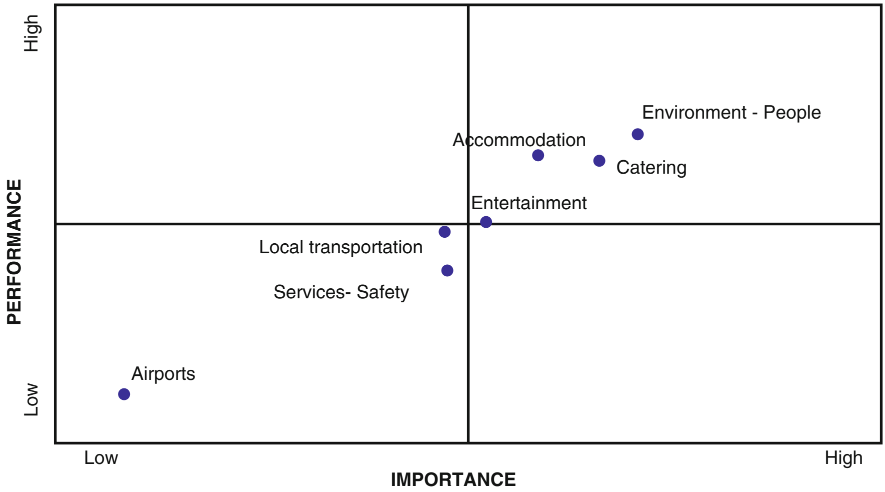

Fig. 5 Action Diagram for the overall satisfaction (high-level criteria). The placement of criteria in the plot correspond to their relative order

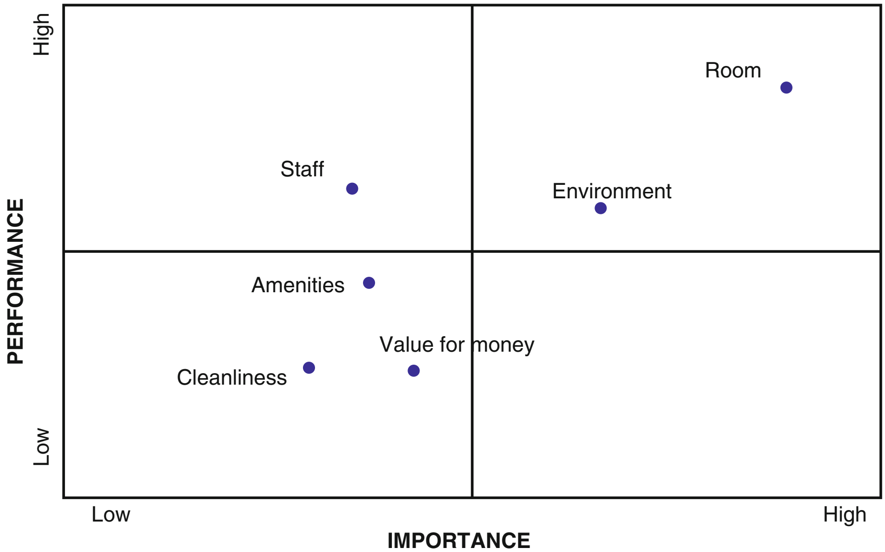

Fig. 6 Action Diagram for the "Accommodation" criterion. The placement of sub-criteria in the plot correspond to their relative order

typical "status quo" criterion, and "Environment—People" a typical "Leverage opportunity", meaning that it can be used as an advantage against competition.

Considering the satisfaction dimensions of the "Accommodation" criterion (Fig. 6; Table 5), the highest performance is reached by the most important sub-

Table 5 Satisfaction analysis for the "Accommodation" criterion

Sub-criterion	Satisfaction Index	Weight
Room	89.44%	22.78%
Staff	87.22%	14.35%
Amenities	85.09%	14.67%
Value for money	83.12%	15.53%
Cleanliness	83.20%	13.49%
Environment	86.77%	19.19%

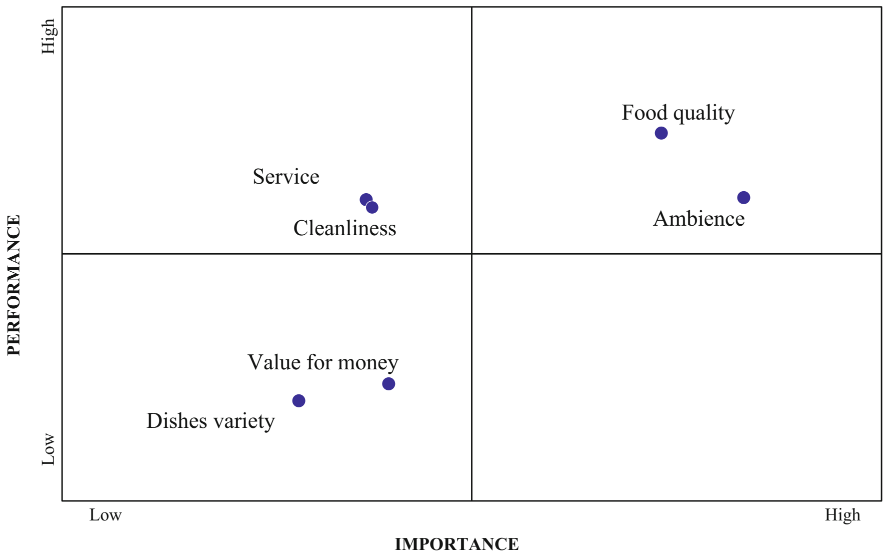

Fig. 7 Action Diagram for the "Eating" criterion. The placement of sub-criteria in the plot correspond to their relative order

criterion (i.e., the "Room"). The fact that the sub-criterion "Staff" achieves high performance with simultaneously low importance is an indication that it should be exploited more (either by transferring resources to a more important criterion, or by administering a plan to augment its contribution to satisfaction). Correspondingly, for the satisfaction dimension of the "Catering" criterion, we regard that the tourism product of Crete performs well in the important dimensions (food quality and ambience), while it performs poorly to less important sub-criteria (e.g., dishes variety). In this dimension, we identify "Service" and "Cleanliness" as opportunities for further exploitation (Fig. 7; Table 6).

In the "Environment—People" criterion we meet the top two performing sub-criteria among the entire set. These are the "Climate" and the "Natural environment" (Fig. 8; Table 7). However, the dimension of "Hospitality—locals" deserves special attention since it has the same importance with "Climate" and "Natural environment", but it does not reach the same satisfaction levels.

Table 6 Satisfaction analysis for the "Catering" criterion

Sub-criterion	Satisfaction Index	Weight
Food quality	88.13%	19.21%
Dishes variety	84.11%	14.36%
Service	87.12%	15.26%
Value for money	84.36%	15.54%
Cleanliness	87.02%	15.33%
Ambience	87.16%	20.30%

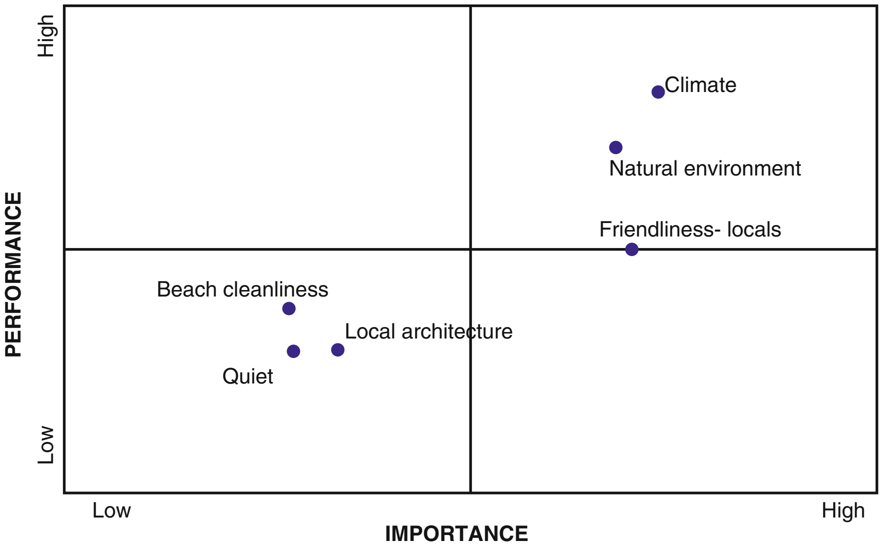

Fig. 8 Action Diagram for the "Environment—People" criterion. The placement of sub-criteria in the plot correspond to their relative order

Table 7 Satisfaction analysis for the "Environment—People" criterion

Sub-criterion	Satisfaction Index	Weight
Climate	96.85%	21.24%
Natural environment	93.27%	20.20%
Beach cleanliness	83.13%	12.21%
Quiet	80.34%	12.32%
Local architecture	80.44%	13.41%
Friendliness—locals	86.83%	20.62%

The "Infrastructures—Safety" criterion includes one of the overall best performing sub-criteria, the "Feeling safe". At the same time, it includes one of the worst performing sub-criteria, the "Roads—sidewalks". However, the tourism destination of Crete is favored by the fact that "Feeling safe" is far more important than "Roads—sidewalks" (Fig. 9; Table 8).

The variety of entertainment options and airports' control services are the two single satisfaction dimensions with the poorest performance. Figures 10 and 11 and

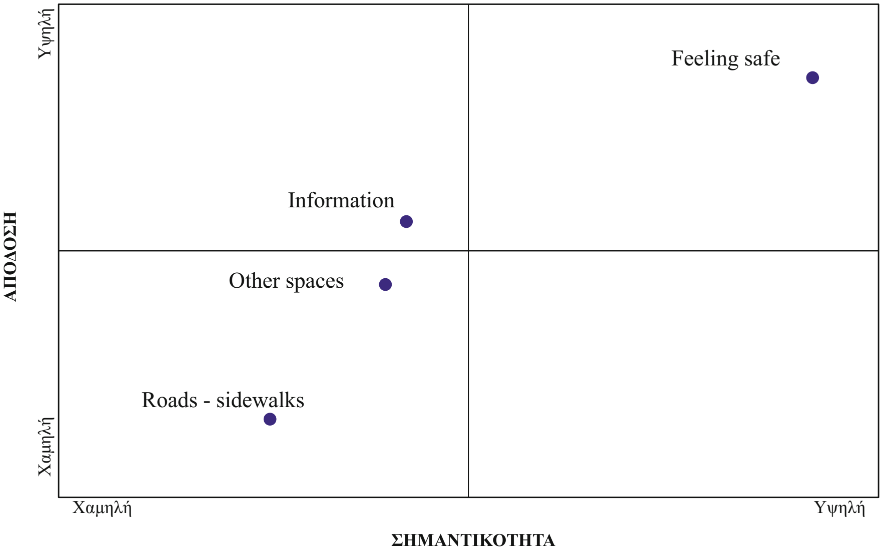

Fig. 9 Action Diagram for the "Infrastructures—Safety" criterion. The placement of sub-criteria in the plot correspond to their relative order

Table 8 Satisfaction analysis for the "Infrastructures—Safety" criterion

Sub-criterion	Satisfaction Index	Weight
Information	77.60%	22.73%
Roads—sidewalks	60.03%	17.78%
Other spaces	72.03%	22.00%
Feeling safe	90.35%	37.49%

Tables 9 and 10 plainly suggest taking actions to improve tourists' satisfaction to those particular dimensions.

In general, we observe that Crete as a tourism destination achieves high satisfaction levels for the important dimensions, while its weaknesses remain mainly in less important dimensions. There are few exceptions to this observation: the variety of the entertainment options, and the airports' control services. The worst performing sub-criteria are "Road safety" and "Roads—sidewalks" (Fig. 12; Table 11). On the other hand, the top performing sub-criteria are "Climate", "Natural Environment", and "Feeling safe".

3.3 Loyalty Analysis

Loyalty can be measured via various approaches (Hill and Alexander 2006; Sato et al. 2016). Because of its importance for a touristic destination, in this work, we applied three different techniques. First, we examined returning visitors, i.e., tourists

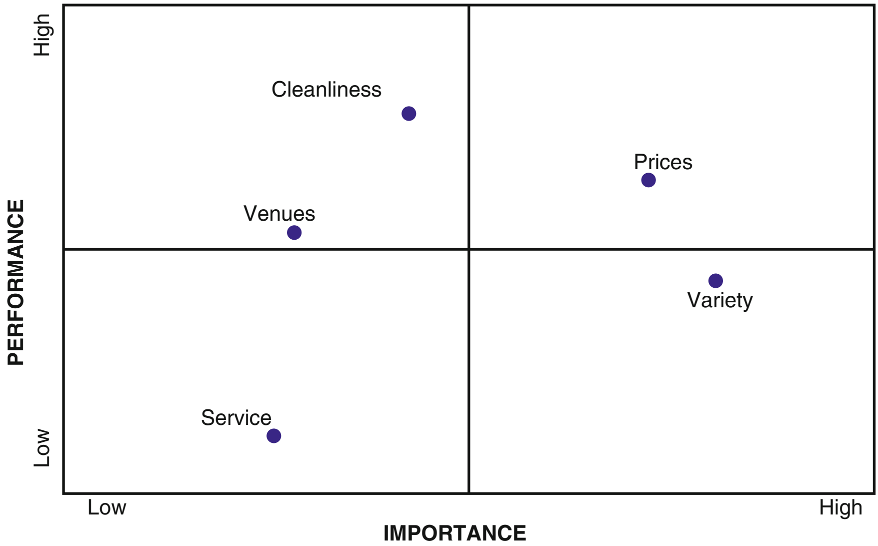

Fig. 10 Action Diagram for the "Entertainement" criterion. The placement of sub-criteria in the plot correspond to their relative order

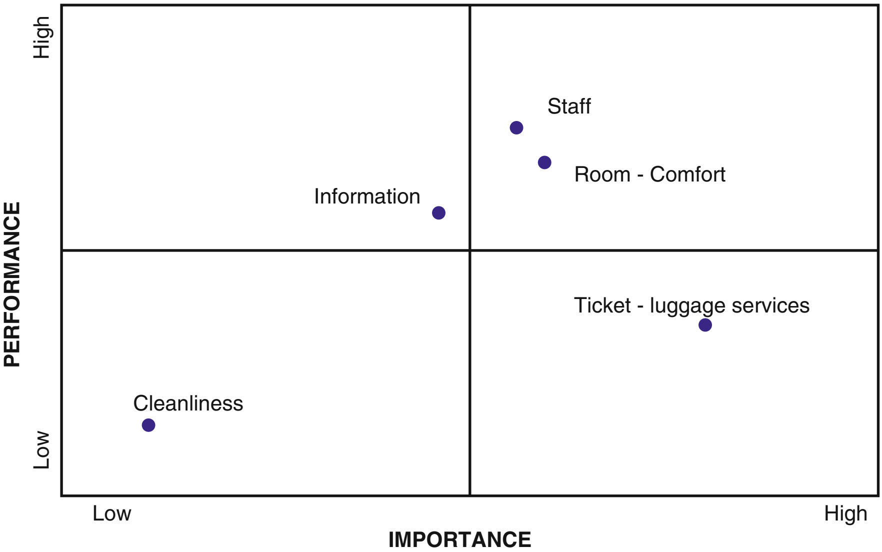

Fig. 11 Action Diagram for the "Airports" criterion. The placement of sub-criteria in the plot correspond to their relative order

that have been in Crete for vacations at least once during the past. To measure a relevant metric, we asked tourists directly. The overall percentage of returning visitors is a bit greater than one third of the population (37%). However, this

Table 9 Satisfaction analysis for the "Entertainment" criterion

Sub-criterion	Satisfaction Index	Weight
Variety	81.56%	29.00%
Venues	82.73%	13.63%
Cleanliness	85.70%	17.81%
Service	77.71%	12.93%
Prices	84.05%	26.61%

Table 10 Satisfaction analysis for the "Airports" criterion

Sub-criterion	Satisfaction Index	Weight
Room—Comfort	78.61%	20.71%
Staff	81.04%	20.44%
Information	75.04%	19.69%
Cleanliness	59.93%	16.89%
Ticket—luggage services	67.05%	22.26%

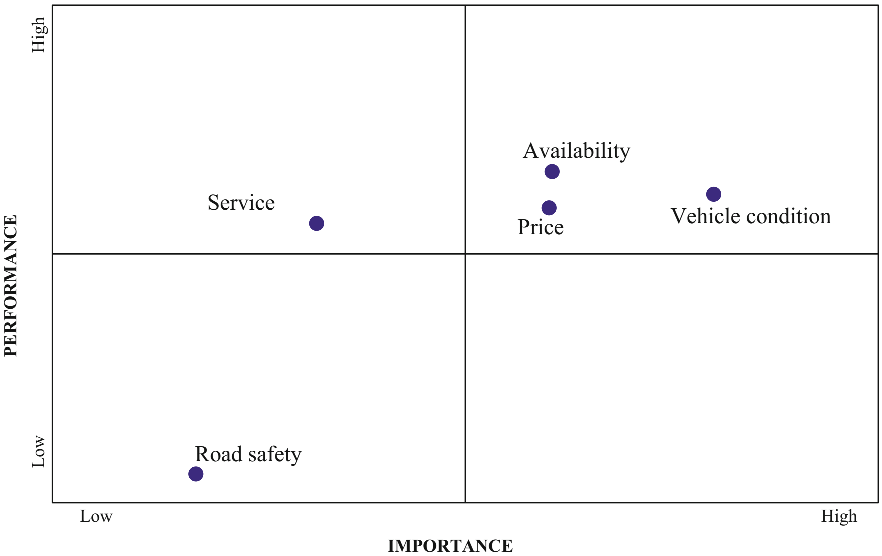

Fig. 12 Action Diagram for the "Local transportation" criterion. The placement of sub-criteria in the plot correspond to their relative order

Table 11 Satisfaction analysis for the "Local transportation" criterion

Sub-criterion	Satisfaction Index	Weight
Availability	90.27%	21.53%
Service	84.52%	17.35%
Vehicle condition	87.80%	24.40%
Price	86.19%	21.49%
Road safety	56.32%	15.22%

percentage is significantly improved according to the following factors: Geographic location (tourists of the prefecture of Chania are far more loyal since more than 50% of them are returning visitors); Aged tourists (more than 61 years old) appear expectedly larger figures; single travelers as well as wealthy travelers have also greater percentages; tourists that prefer to stay in all-inclusive hotels have lower percentages. Last, there are some nationalities that include more returning visitors than the average. In particular Germany, United Kingdom, and the Scandinavian countries have the greatest percentages while Italy and Russia hold the smallest ones. Yet, we have to recognize that Russia is a relatively new market for the touristic product of Crete. It is also interesting to note that among returning visitors, more than one over four (approximately 10% of the total population), has visited Crete for vacations more than three times.

The third approach we applied to measure loyalty was the degree of expectations' confirmation. We asked tourists to rate their vacations experience when compared with their pertinent expectations. Every tourist could choose an option of a five-level ordinal scale corresponding to the whole spectrum from exceeding expectations to disconforming expectations. We present the relevant results factored by nationality in Fig. 14. Results suggest that approximately one third of the population responds with the neutral level option (expectations met—"More or less as expected"). However, the positive levels (expectations exceeded—"Somehow better" and "Better") correspond to a percentage of 59.03%, while the cummulative percentage of the negative levels ("Somehow worse" and "Worse") have just 5.51%. These results are in accordance with the satisfaction analysis, where we regarded a similar percentage for the low levels of the satisfaction scale. Regarding the factors that affect expectations' confirmation, we regarded that income and nationality are the important ones. In particular, the higher the income, the lower the level of the expectations' confirmation. The role of nationalities is illustrated in Fig. 14.

Second, we analyze loyalty by asking the following pair of questions: "How likely is it that you will visit Crete again on holidays in the near future?" and "How likely is it that you will recommend to friends/relatives to visit Crete on holidays?". We used a five-level ordinal scale (ranging from "Not at all likely" to "Definitely"), and results (illustrated in Fig. 13) suggest that the touristic destination of Crete reaches satisfactory levels of loyalty. It is noteworthy that the factors identified when using the previous approach (returning visitors), have the same effects, namely aged tourists, and single travelers appear more loyal, and tourists that stay in all-inclusive hotels appear less loyal. However, geographic locations do not make any difference to these loyalty metrics.

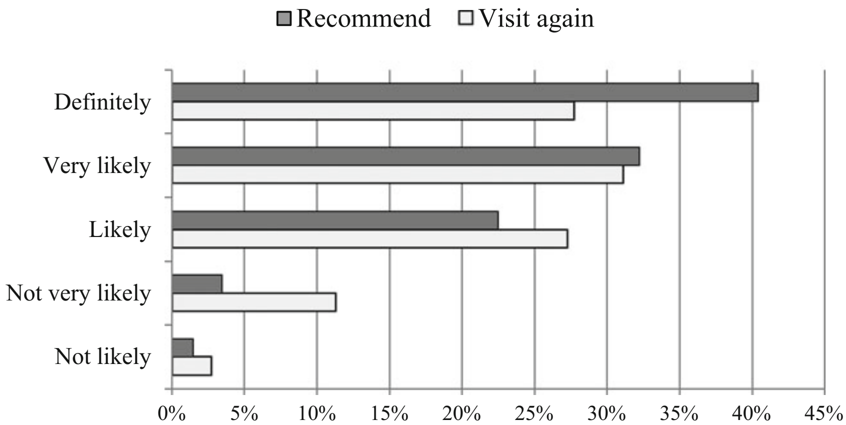

Fig. 13 Measuring loyalty by asking direct questions if tourists will visit again, and if they would recommend the destination to other persons

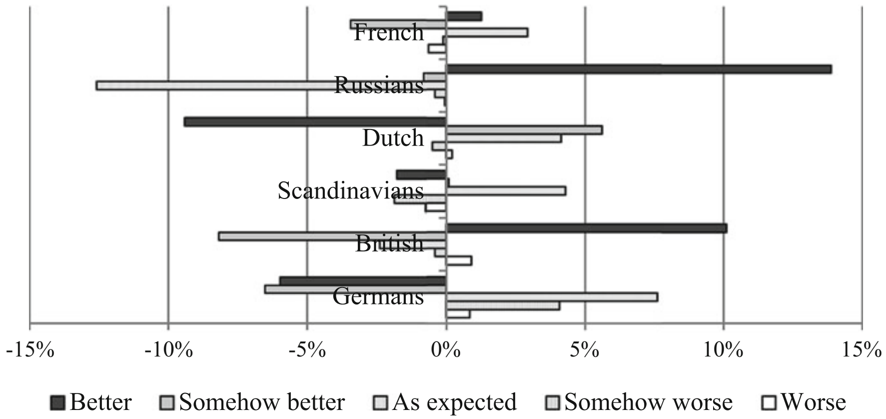

Fig. 14 Expectations' confirmation per nationality. The center of the horizontal axis is the overall average

4 Strategic Plan

To deliberate the numerous (diverse) dimensions of tourist satisfaction, and to provide effective recommendations to exploit the potential of the opportunities and strengths, as well as to minimize the effect of weaknesses and threats, in the following, we group the elements that affect satisfaction in four groups:

- *Strengths* are the elements that guide high-level satisfaction (tourists demand high performance and the tourism destination of Crete delivers). Such elements are ultimately the reasons why tourists select this particular destination, and can be considered as the competitive advantages. This is why maintaining a

Table 12 SWOT Analysis for tourists' satisfaction

Strengths	Weaknesses	Opportunities	Threats
Environment—People (Climate, Natural environment) Feeling safe Accommodation (Room, environment) Catering (Food quality, Ambience)	Airports (Control services)	In general service/staff related elements	Airports' cleanliness/sanitation Road safety Service in recreational places Roads and sidewalks Beach cleanliness, noise Value for money for accommodation and eating

high-level satisfaction to those elements is vital (if these characteristics begin to deteriorate, the overall satisfaction will be significantly reduced). Strengths are contained in the upper right quadrant of the action diagrams.

- A *weakness* is identified when the destination does not fulfill tourists' expectations. In such cases, it is necessitated to take immediate actions of improvement, considering that their existence contributes to dissatisfaction. We can detect weaknesses by looking at the lower right quadrant of the action diagrams.
- An *opportunity* emerges when the destination performs well in a less-important dimension. There is a twofold interpretation for an opportunity: It is an indication either to transfer resources towards a more important element, or to try to exploit this element as an advantage against competition (inflate its importance through marketing). Opportunities are located in the upper left quadrant of action diagrams.
- Last, a *threat* is an element that exhibits low performance, yet it is not that important. We can identify threats by looking at the lower left quadrant of action diagrams. The threat can be generated when the element's importance grows.

The particular SWOT Analysis for the target destination is outlined in Table 12. The tourism destination of Crete, even if it does not fully satisfies tourists to all dimensions, it achieves to make them overall satisfied. This happens because it achieves very good performances to the most important dimensions (environment-people, accommodation, and eating), while simultaneously it holds down the poor performances to the less important dimensions (airports, and infrastructures).

5 Conclusions

Customer satisfaction is a reliable feedback, considering it reflects customers' preferences and expectations directly, expressively, and objectively. It acts effectively as a baseline for performance, and as a standard of excellence (Gerson 1993). Therefore, satisfaction is not only a metric to-be improved, but a drive for strategy formulation. Because of the multivariate nature of tourist satisfaction, the multiple criteria paradigm looks prominent to support the analysis. In this work, we used an established multiple criteria method of the aggregation-disaggregation methods' family to analyze the satisfaction of tourists of a specific touristic destination.

Although the sample population was impressively large, there are some inherent limitations when the goal is a global strategy: We were able to sample just tourists arriving with charter flights, ignoring the part of people arriving via ferries (mostly domestic tourists). Moreover, the current study could yield far more interesting results if it was compared to studies of other competitive destinations (unfortunately no such data are available yet).

Considering the results, our work plainly suggests the weaknesses and the threats of the destination, and it indicates clearly actions for improvement. However, it seems that the essential profile of the destination is based on its nature/climate conditions, and there is very narrow space to modify it.

Acknowledgement This work was supported by the regional development fund of Crete, the prefectures of Chania, Rethymnon, Heraklion, and Lasithi, the commercial chambers of Heraklion, Rethymnon, and Chania, the hoteliers union of Heraklion, the associations of hoteliers of Chania, Rethymnon, Lasithi, and by the Cretan society of hotel managers.

Appendix: The MUSA Method

The MUSA method infers an additive collective value function Y^* and a set of partial satisfaction functions X_i^*. The main objective of the method is to achieve the maximum consistency between the value function Y^* and the customers' judgements Y. Based on the modelling approach presented in the relevant section and introducing a double-error variable (see Fig. 15), the ordinal regression equation becomes as follows:

$$\tilde{Y}^* = \sum_{i=1}^{n} b_i X_i^* - \sigma^+ + \sigma^-$$

where $\tilde{Y}^*$ is the estimation of the global value function Y^*, and σ^+ and σ^- are the overestimation and the underestimation errors, respectively.

The global and partial satisfaction Y^* and X_i^* are monotone functions normalised in the interval [0,100]. Thus, in order to reduce the size of the mathematical program, removing the monotonicity constraints for Y^* and X_i^*, the following transformation equations are used:

$$\begin{cases} z_m = y^{*m+1} - y^{*m} & \text{for} \quad m = 1, 2, \ldots, \alpha - 1 \\ w_{ik} = b_i x_i^{*k+1} - b_i x_i^{*k} & \text{for} \quad k = 1, 2, \ldots, \alpha_i - 1 \ \text{ and } \ i = 1, 2, \ldots, n \end{cases}$$

where y^{*m} is the value of the y^m satisfaction level, x_i^{*k} is the value of the x_i^k satisfaction level, and α and a_i are the number global and partial satisfaction levels.

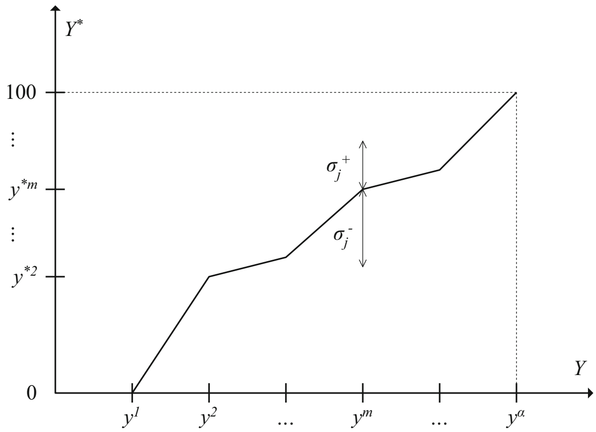

Fig. A.1 Error variables for the j-th customer

According to the aforementioned definitions and assumptions, the basic estimation model can be written in a linear program formulation, as follows:

$$\begin{cases} [\min]\ F = \sum_{j=1}^{M} \sigma_j^+ + \sigma_j^- \\ \text{subject to} \\ \sum_{i=1}^{n} \sum_{k=1}^{x_i^j - 1} w_{ik} - \sum_{m=1}^{y^j - 1} z_m - \sigma_j^+ + \sigma_j^- = 0 \quad \text{for} \quad j = 1, 2, \ldots, M \\ \sum_{m=1}^{\alpha - 1} z_m = 100 \\ \sum_{i=1}^{n} \sum_{k=1}^{\alpha_i - 1} w_{ik} = 100 \\ z_m, w_{ik}, \sigma_j^+, \sigma_j^- \quad \forall m, i, j, k \end{cases}$$

where M is the size of the customer sample, and x_i^j, y^j are the j^{th} level on which variables X_i and Y are estimated.

The preference disaggregation methodology includes also a post optimality analysis stage in order to overcome the problem of model stability. The final solution is obtained by exploring the polyhedron of multiple or near optimal solutions, which is generated by the constraints of the previous linear program. This solution is calculated by n linear programs (equal to the number of criteria) of the following form:

$$\begin{cases} [\max]\ F' = \sum_{k=1}^{\alpha_i - 1} w_{ik} \quad \text{for} \quad i = 1, 2, \ldots, n \\ \text{under the constraints} \\ F \leq F^* + \varepsilon \\ \text{all the constraints of the previous LP} \end{cases}$$

where ε is a small percentage of F^*. The average of the solutions given by the n *post-optimality* LPs may be taken as the final solution. In case of non-stability, this average solution is less representative.

The assessment of a performance norm may be very useful in customer satisfaction analysis. The average global and partial satisfaction indices are used for this purpose and are assessed through the following equations:

$$\begin{cases} S = \frac{1}{100} \sum_{m=1}^{\alpha} p^m y^{*m} \\ S_i = \frac{1}{100} \sum_{k=1}^{\alpha_i} p_i^k x_i^{*k} \quad \text{for } i = 1, 2, \ldots, n \end{cases}$$

where S and S_i are the average global and partial satisfaction indices, and p^m and p_i^k are the frequencies of customers belonging to the y^m and x_i^k satisfaction levels, respectively.

Combining weights and average satisfaction indices, a series of action diagrams can be developed (Fig. 16). These diagrams indicate the strong and the weak points of customer satisfaction, and define the required improvement efforts. Each of these maps is divided into quadrants, according to performance (high/low) and importance (high/low) that may be used to classify actions:

- *Status quo* (low performance and low importance): Generally, no action is required.
- *Leverage opportunity* (high performance/high importance): These areas can be used as advantage against competition.
- *Transfer resources* (high performance/low importance): Company's resources may be better used elsewhere.
- *Action opportunity* (low performance/high importance): These are the criteria that need attention.

In several cases, it is useful to assess the relative action diagrams, which use the relative variables b_i' and S_i' in order to overcome the assessment problem of the cut-off level for the importance and the performance axis. The normalised variables b_i'

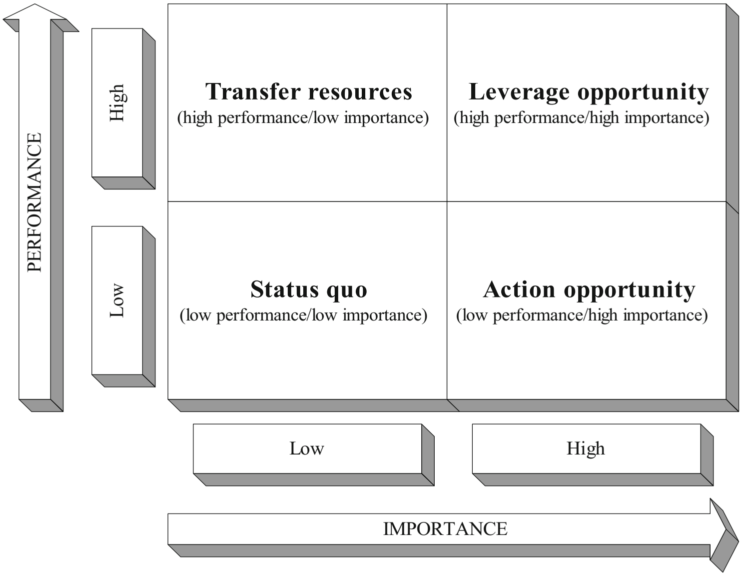

Fig. A.2 Action diagram advised by (Customers Satisfaction Council 1995)

and S_i' are assessed as follows:

$$\begin{cases} b_i' = \dfrac{b_i - \overline{b}}{\sqrt{\sum_i \left(b_i - \overline{b}\right)^2}} \\ S_i' = \dfrac{S_i - \overline{S}}{\sqrt{\sum_i \left(S_i - \overline{S}\right)^2}} \end{cases} \quad \text{for} \quad i = 1, 2, \ldots, n$$

where $\overline{b}$ and $\overline{S}$ are the mean values of the criteria weights and the average satisfaction indices, respectively. This way, the cut-off level for axes is recalculated as the centroid of all points in the diagram.

This type of diagram is very useful, if points are concentrated in a small area because of the low-variation that appears for the average satisfaction indices (e.g., case of a high competitive market). These diagrams are also mentioned as decision, strategic, perceptual, and performance-importance maps, or gap analysis, and they are similar to SWOT analysis (Hill and Alexander 2006).

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Analyzing Perceived Quality of Health Care Services: A Multicriteria Decision Analysis Approach Based on the Theory of Attractive Quality

Evangelia Krassadaki and Evangelos Grigoroudis

Abstract Health services play an extremely important role in the quality of citizens' life. People demand increasingly good health care services as a result of their inherent need for high quality health services, the prevailing high living and cultural standards of modern life and the technological and medical advancements. This paper examines the satisfaction of citizens from a public hospital in terms of the perceived quality of its characteristics. In effect, an effort is made to answer the question 'what is it that citizens expect from the hospital in their town.' In order to analyze satisfaction the multicriteria MUSA method has been used, while the classification of the examined characteristics has been based on the Kano's theory of attractive quality. Analysis highlighted certain characteristics of the hospital as of expected, desired or attractive quality. With respect to the criteria studied, personnel and services were highlighted as of expected quality or must-be characteristics. Hygiene, hospital's location and additional services were specified as of desired quality (one-dimensional characteristics), while facilities-infrastructure was described as of attractive quality.

1 Introduction

The significant cost of health services and the increased needs of patients have resulted in laying more emphasis on measuring the quality of health services and patient satisfaction (Fitzpatrick 1991; Bond and Thomas 1992). In many countries, mainly in the US and Great Britain, both quality measurement of health services and participation of patients in improving the quality of health care are regulated

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by law. Today, the major hospital supervision and assessment body in the US, the 'Joint Commission on Accreditation of Health Care Organizations', acknowledges the importance of patient satisfaction measurements as an index of the result of health services rendered (Holzemer 1990). In Great Britain, considerable attention is paid to patient satisfaction, as reflected in the white paper 'Working for Patients', whose targets include the planning and provision of services aiming to satisfy the desires of patients (Bond and Thomas 1992).

Despite the extensive bibliography (see for example Sitzia and Wood (1997) for a review of more than 100 published papers), patient satisfaction surveys can be divided in the following categories, according to their purpose:

a) Patient satisfaction surveys aiming at health service reorganization (Stimson and Webb 1975; Bragadottir 1999; Barkell et al. 2002; Tokunaga and Imanaka 2002; Olusina et al. 2002).
b) In-patient satisfaction surveys as a primary means to allocate limited resources of health organizations (Ryan et al. 1998, 2001).
c) Patient satisfaction surveys aiming to evaluate either the medical and nursing personnel or the entire health organization (Merkouris 1996; Barr et al. 2000; Stamouli and Mantas 2001) using standardized questionnaires in several cases (e.g., VSQ-9, SF-12, CSQ-18B).
d) Satisfaction surveys on the physician-patient relationship aiming to explore the patient behavior models and evaluate patients' response to treatments (Abdellah and Levine 1957; Pascoe 1983; Cleary and McNeil 1988; Fitzpatrick 1991; Valindra 2009).

Although patient satisfaction from health services is a concept easily understood, no generally accepted conceptual definition can be found (Bond and Thomas 1992). The concepts of patient satisfaction and their understanding of quality are often used alternatively, while according to Oberst (1984) there is a difference between the two concepts. Petersen (1988) claimed that satisfaction is the patient's general perception of the way care is provided, without the patient taking account of the results or appropriateness of care. According to Smith (1992), patient satisfaction is a combination of perceived needs, expectations and experience from health care.

In this paper we examine what affects satisfaction of citizens from their town's hospital. For this purpose, the satisfaction results derived by the MUSA method, a multicriteria approach for measuring and analyzing customer satisfaction, are further analyzed based on the Kano's theory of attractive quality. In this way, we classify satisfaction dimensions as, of must-be, desired or attractive requirements, respectively. Our effort is twofold: firstly to examine the dimensions which mostly affect dissatisfaction or does not affect citizens' satisfaction for the public hospital of their town, and secondly to propose an original methodology which incorporates the results of the MUSA method for the benefits of the Kano's quality levels.

The MUSA (MUlticriteria Satisfaction Analysis) method is a preference disaggregation model for measuring and analyzing customer satisfaction (Grigoroudis and Siskos 2002, 2010). It follows the principles of ordinal regression analysis and aims at evaluating the satisfaction level of a set of individuals (customers, employees, etc.) based on their values and expressed preferences. In this study the MUSA method was mainly used to process survey data, while the satisfaction or non-satisfaction expressed by citizens was used to classify the quality characteristics according to the Kano's model. The principles and the mathematical development of the MUSA method may be found in Siskos et al. (1998) and Grigoroudis and Siskos (2002, 2010), while several applications of the method in different domains are given in Siskos et al. (1998), Grigoroudis et al. (1999a, b), Michelis et al. (2001) and Siskos et al. (2001a, b).

A brief presentation of the Kano's theory of attractive quality is given in Sect. 2. The proposed methodological framework is presented in Sect. 3, which includes the derived importance assessment through the MUSA method and the Dual-Importance diagram. The application of the proposed approach is presented in Sect. 4. Finally, Sect. 5 summarizes some concluding remarks, as well as the main limitations and extensions of the proposed methodology.

2 Kano's Model

Customer satisfaction in most cases is related to the perceived quality. The higher the quality, the higher the customer satisfaction and vice versa. However, fulfilling the individual product/service requirements to a great extent does not necessarily imply a high level of customer satisfaction. For example, when a pen writes, the user is not highly satisfied, but when it doesn't the user is completely dissatisfied (Vavra 1997). On the other hand, when somebody usually waits in a bank queue for 10 min if on any given day he/she is served earlier, this unexpected event becomes a satisfaction situation. Kano's model proposes three types of product/service requirements (Fig. 1), which, when met, affect customer satisfaction in different ways. Based on this model, customer satisfaction is not a one-dimensional issue.

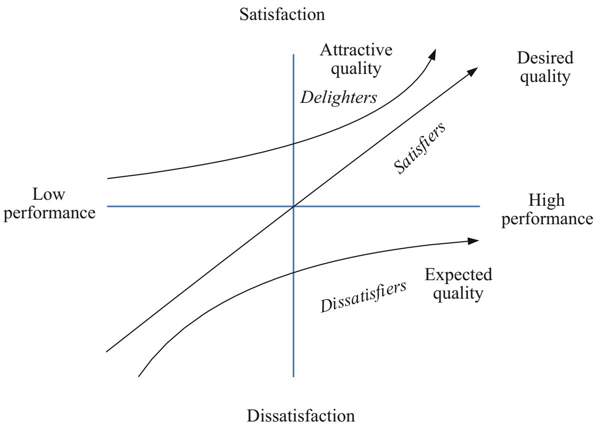


Fig. 1 The three quality levels of Kano's model

The three types of product/service requirements in Kano's model are (Kano 1984):

1) *Must-be requirements*. The must-be requirements are basic attributes/characteristics of a product/service. If these requirements are not fulfilled, the customer is completely dissatisfied while on the contrary if they are fulfilled they do not affect satisfaction. The customer regards these characteristics of a product/service as prerequisites and does not ask for them. When a customer buys a pen, it is implied that it can write; when a customer buys a car everyone expects it has brakes. Usually, these requirements are obvious, not-expressed, implied or self-evident. The must-be, as they are called, attributes constitute the 'expected quality' of a product/service. Thus, as these attributes constitute basic expectations, they do not make customers happy; their absence, however, does make customers unhappy (dissatisfiers).
2) *One-dimensional requirements*. The one-dimensional requirements, when fulfilled, affect satisfaction in an analogous way. The higher the level of fulfilment the higher the satisfaction level and vice versa. Usually, these attributes of a product/service are explicitly demanded by the customer and constitute what is called 'desired quality'. Thus, if for example a new car has heated seats, this attribute adds additional satisfaction (satisfier) to those of us who live in colder climates.
3) *Attractive requirements*. The attractive requirements have the greatest influence on satisfaction. They are neither explicitly expressed nor expected by the customer. Fulfilling these requirements leads to increased satisfaction, as in the case of the unexpectedly fast service in the bank. On the contrary, if these requirements are not met, they do not imply dissatisfaction. The characteristics of a product/service which cause delight to customers (delighters) represent the 'attractive quality'.

It should be noted that the specific classification of customer requirements in one of the above categories is dynamic, and is affected by the competitiveness of the market. An attractive attribute of a product/service may, in a short time, become a one-dimensional or even expected attribute. An indicative example is the built-in air conditions in cars. The unexpected introduction of this attribute had pleased many customers due to its innovation and function. Given that many manufacturers successively adopted this attribute, customers started to expect it. This attribute became one-dimensional because the higher the level of fulfilment of the specific attribute in the product, the higher the customer satisfaction level. Today, for most car buyers, air condition has become a basic attribute which no longer causes satisfaction when available, it brings dissatisfaction when not present, and to cause delight, a significantly improved system should be provided. It has thus become a must-be attribute.

Must-be, one-dimensional and attractive requirements differ, as a rule, in the utility expectations of different customer segments (Grigoroudis and Spyridaki 2003). For example, in the car market, a specific attribute may, at the same point of time since introduced in the market, be an attractive attribute in one category of vehicles yet a must-be attribute in another more expensive category of vehicles.

The advantages of classifying customer requirements using Kano's model are the following (Matzler et al. 1996; Matzler and Hinterhuber 1998):

- It enables better understanding of customer desires/demands. In addition, it helps identify the attributes of the product/service which mostly affect customer satisfaction. Through the classification of the characteristics in basics, one-dimensional and attractive ones, it is possible to set the priorities for the development of a product/service. For example, it is not advisable to improve basic characteristics, which are already satisfactory. On the contrary, it is better to improve one-dimensional or attractive attributes, as they have a greater influence on the perceived quality of the product/service and consequently on the customer satisfaction level.
- The identification and development of attractive attributes is also very important as it creates a large field of alternatives for the diversification of the products/services. A product which satisfies basic and one-dimensional attributes is regarded as common and therefore interchangeable (Hinterhuber et al. 1994).
- Kano's model can be used to determine the significance of the different characteristics of the product/service on customer satisfaction, and it can therefore significantly support the development of customer-oriented products/services.
- As a rule, the basic, one-dimensional and attractive attributes are different in each group of customers. Starting from there, it is possible to develop different custom-made solutions for specific problems and therefore ensure the high level of satisfaction in each category of customers.

In order to classify quality attributes, Kano et al. (1984) use a specific questionnaire that contains pairs of customer requirement questions, that is, for each customer requirement two questions are asked:

a) How do you feel if a given feature is present in the product (functional form of the question)?
b) How do you feel if that given feature is not present in the product (dysfunctional form of the question)?

Using a predefined preference scale and the evaluation table of Fig. 2, each customer requirement may be classified into the predefined dimensions of the Kano's model (Löfgren and Witell 2008). The dimension designated as questionable contains sceptical answers and is used for responses in which it is unclear whether the responder has understood the question. Finally, in order to decide on the classification of a quality attribute, the proportion of respondents (statistical mode) who classify a given attribute in a certain category is used (i.e., the attribute is assigned into the category with the highest frequency according to customer answers). Several variations of this classification procedure have been proposed, referring mostly to alternative quality dimensions and evaluation scales. Löfgren and Witell (2008) present a thoroughly review of these alternative approaches.

Customer Requirements		*Dysfunctional*				
		Like	Expect	Neutral	Accept	Dislike
Functional	Like	Q	(A) Q	A	A	O
	Expect	(R) Q	(I) Q	I	I	M
	Neutral	R	I	I	I	M
	Accept	R	I	I	I	M
	Dislike	R	R	R	R	Q

A: Attractive quality
O: One-dimensional quality
M: Must-be quality
I: Indifferent quality
R: Reverse quality
Q: Questionable result

Fig. 2 Kano evaluation table (Lee and Newcomb 1997)

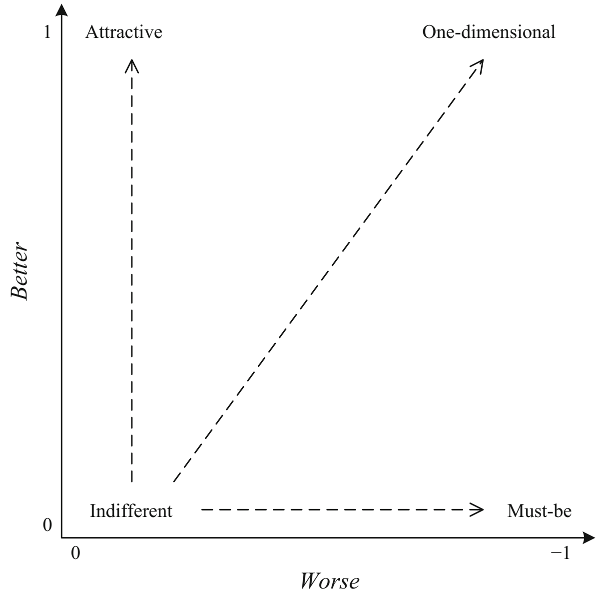
However, as Grigoroudis and Siskos (2010) argue, the previous procedure does not take into account that quality attributes are in fact random variables and customer responses form a probability distribution function on the main categories of the Kano's model. Thus, the statistical mode is not always a good indicator of central tendency. Furthermore, different market segments usually have different needs and expectations, so sometimes it is not clear whether a certain attribute can be assigned to a specific category. For this reason, several indices have been proposed to aid the classification process of quality attributes (Löfgren and Witell 2008). A simple approach is to calculate the average impact on satisfaction and dissatisfaction for each quality attribute. Berger et al. (1993) introduced the Better and Worse averages, which indicate how strongly an attribute may influence satisfaction or, in case of its non-fulfilment, customer dissatisfaction:

$$\begin{cases} Better = \frac{A+O}{A+O+M+I} \\ Worse = \frac{O+M}{A+O+M+I} \end{cases}$$

where A, O, M, and I are the attractive, one-dimensional, must-be, and indifferent responses, respectively (i.e., percentage of customers assigning a given attribute to a certain category).

The pairs of *Better* and *Worse* averages can be plotted in a two-dimensional diagram representing the impact of quality attributes on satisfaction or dissatisfaction (Fig. 3), and thus a clearer view for the classification of quality attributes may be obtained.

Fig. 3 Two-dimensional representation of Kano quality categories (Berger et al. 1993)



In the MUSA approach, the required information is collected via a simple questionnaire in which the customers evaluate the provided product/service, i.e., they are asked to express their satisfaction judgments, namely their global satisfaction and their satisfaction with regard to a set of assessed criteria. A predefined ordinal satisfaction scale is used for these customers' judgments, as the one used in the present public hospital application (see next section). Thus, the respondents answer in questions clearly stated, expressing their satisfaction level in the predefined ordinal scale, avoiding in this way any misunderstanding. Moreover, the MUSA method provides a set of useful results, like the global and partial satisfaction functions (monotonic, non-decreasing, discrete piecewise linear functions) indicating three different demanding levels of customers (neutral, demanding and non-demanding); and assesses, per criterion, weights and a set of average indices like, satisfaction, demanding and improvement. Derived importance is estimated by a regression-type quantitative technique using customer judgments for the performance of the set of criteria. Combining weights and average satisfaction indices, a series of action diagrams can be developed, which indicate the strong and the weak points of customer satisfaction, and define the required improvement efforts. Moreover, combining the average improvement and demanding indices, a series of improvement diagrams can be developed, which determine the output or the extent of improvement efforts. The methodology adopted in this study utilizes, from the whole set of MUSA results, the derived weights (importance coefficients) of each criterion.

3 Methodological Framework

3.1 Derived Importance Using the MUSA Method

The methodological framework used in this study is based on the comparative examination of the relationship between derived importance of the two target groups, those of satisfied and of non-satisfied customers.

In the first stage, the necessary data are collected via a specialized questionnaire aiming at satisfaction measurement. Through simple questions, customers are asked about their satisfaction level from each criterion. Usually, these questions have the following form: *'How satisfied are you from the criterion ....?'*, while customers express their judgments using a predefined ordinal scale (e.g., very satisfied, satisfied, dissatisfied).

At the second stage, the derived importance is estimated separately for each target group using the MUSA method. The two different importance estimations for each characteristic/criterion are the inputs for the dual importance diagram. Finally, at the last stage the characteristics are classified as 'must-be', 'one-dimensional' or 'attractive'. The whole framework is presented in Fig. 4.

In particular, the methodology used to measure the importance by satisfied and non-satisfied citizens from the local public hospital is analyzed into the following steps:

a) The necessary data are collected through a customer satisfaction survey, where citizens are asked to express their satisfaction level on a set of health care quality attributes.
b) For each criterion, the questionnaires of completely satisfied and very satisfied citizens are separated, and thus n different datasets of satisfied citizens are created, equal to the number of satisfaction criteria. Then, using the MUSA method, the weights b_i^s of the satisfied citizens for attribute i are estimated.
c) Similarly, for each criterion, the questionnaires of not at all satisfied, slightly satisfied and moderately satisfied citizens are separated and n different datasets of satisfied citizens are created, equal as before to the number n of satisfaction criteria. The MUSA method is then used to estimate the weights b_i^d of the dissatisfied citizens for attribute i.
d) The aforementioned weights (b_i^s or b_i^d) are normalized in order to avoid comparability problems. The normalized relative weights b_i' compare the importance of each satisfaction criterion to the importance of the other criteria and they are calculated using the following formula:

$$b_i' = \frac{b_i - \overline{b}}{\sqrt{\sum_i \left(b_i - \overline{b}\right)^2}}$$

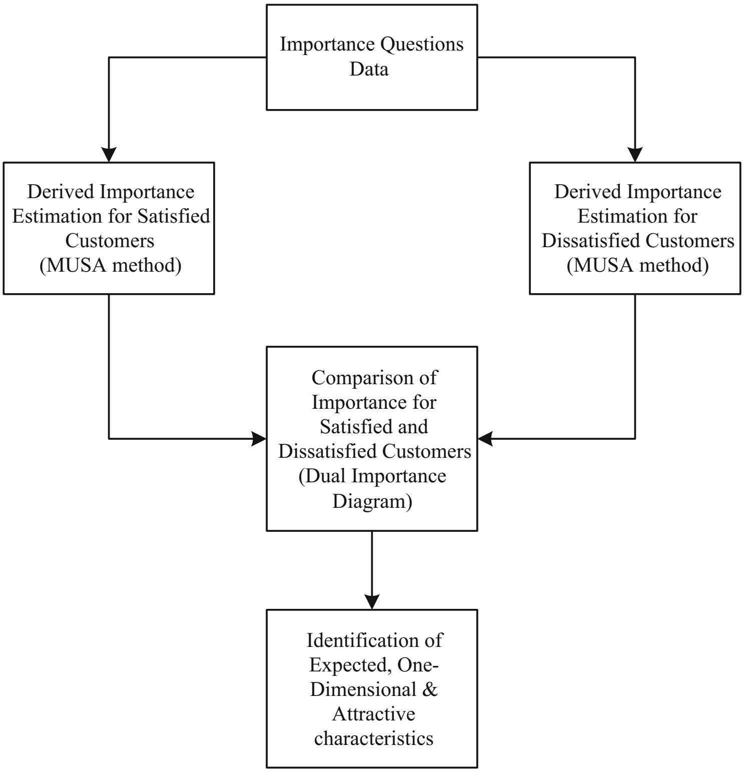


Fig. 4 Proposed methodological framework

where b'_i is the relative weight of criterion i (i.e., b'^s_i or b'^d_i), b_i is the weight of criterion i (i.e., b^s_i or b^d_i), and $\overline{b}$ is the average of b_i.

Based on the previous formula, it can be easily observed that relative weights depend on the number of criteria (or subcriteria) examined. In particular, a criterion is considered important if $b_i > 1/n$, taking into account that if all criteria are of equal importance, then the weight for each one of them will be equal to $1/n$. Also, because of the previous normalization formula, the relative weights have some useful properties: $\sum b'_i = 0$ and $\sum b'^2_i = 1$.

A similar process is also applied in the case of satisfaction subcriteria. Therefore, for each subcriterion, satisfied and dissatisfied customers are separated and $2m$ different datasets are created, where m is the number of satisfaction subcriteria. The MUSA method is then used to estimate the weights of subcriterion j of the i-th criterion b^s_{ij} and b^d_{ij} of the satisfied and dissatisfied customers, respectively.

It should be noted that in the previous steps a 5-level ordinal scale of the following form is assumed: not at all satisfied, slightly satisfied, moderately satisfied, very satisfied, completely satisfied. Although alternative separation patterns may be applied, the aforementioned approach assumes that the first three levels of the scale correspond to dissatisfied citizens, while the last two levels refer to satisfied citizens. In case of satisfaction scales with different lengths, a similar approach may be applied.

3.2 Dual Importance Diagram

Based on the estimated relative weights, the Better-Worse diagram may be developed (Fig. 5), which is actually a Dual Importance diagram. This diagram depicts the relative weights for satisfied and dissatisfied citizens and allows the identification of the characteristics, which are of the same or different importance for both customer groups.

Quadrants I and III include the characteristics which are of the same importance for either satisfied or dissatisfied customers, or citizens herein. Quadrant I includes the dimensions which are of high importance, while quadrant III those which are of low importance for both sets, respectively. Usually, the influence of each quality attribute over customer satisfaction is associated with the importance given by the customer to the attribute. Thus, the coincidence of views between satisfied and dissatisfied customers highlights attributes for which customers do not attach high importance when satisfied, while on the contrary they consider them to be important when not satisfied. According to the Kano's model, desired quality is related to the

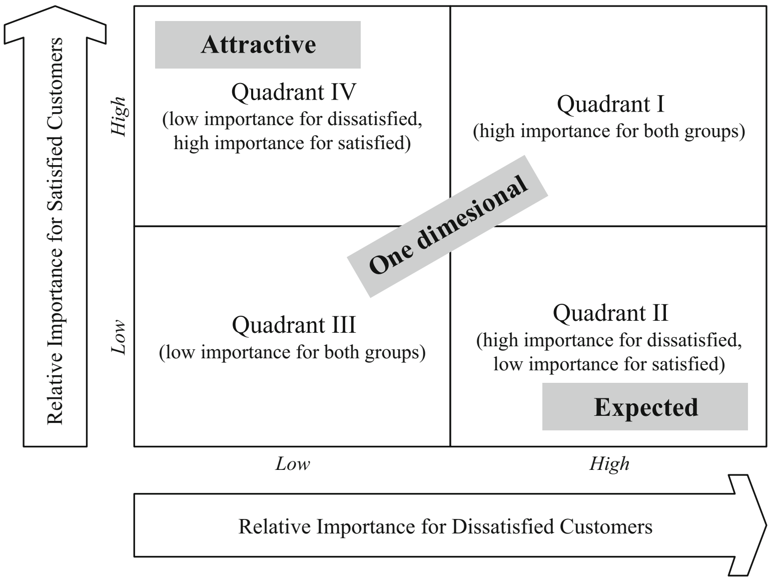


Fig. 5 Better-Worse diagram

characteristics of a product/service whose low performance creates dissatisfaction while high performance creates satisfaction, therefore we could say that quadrants I and III include the one-dimensional characteristics. An improvement in the quality of these characteristics will apparently result in the proportional increase of satisfaction in both groups of satisfied and dissatisfied customers, taking into consideration that satisfaction is associated with importance.

In quadrants II and IV the derived importance between satisfied and dissatisfied customers is diversified. In particular, quadrant II contains the characteristics for which dissatisfied customers attach higher importance compared to satisfied customers (or citizens herein). In this case, these characteristics seem to influence dissatisfied customers to a higher degree. Therefore, dissatisfaction is related to the low performance of these characteristics and thus they constitute what Kano proposed as must-be requirements or expected quality. In quadrant IV we have the exact opposite situation. Dissatisfied customers attach lower importance to these characteristics and it appears that their dissatisfaction is not due to their possibly low performance. It is true that if a characteristic is of a given low performance and this does not affect satisfaction, then any sudden improvement in its performance would cause unexpected satisfaction. In this sense, the characteristics of quadrant IV are those of attractive quality.

4 Application

4.1 Survey and Satisfaction Criteria

In the presented case study, we carried out a survey to measure the citizens' satisfaction from health care at the local public hospital of the city of Chania, Greece. Located in Mournies, an area approximately 8 km away from the city, the hospital started its operation in September 2000, much to the relief of citizens who, for many years, had to use the services of an outdated old hospital located in the city center. The hospital has a capacity of 468 beds, 400 out of which are used, and its staff includes 781 professionals of all specialties.

Within the framework of the present satisfaction investigation, two different surveys were carried out. The first survey aimed at measuring the satisfaction of in-patients (year 2002 and 2008) and the second at measuring the satisfaction of citizens (year 2003). This paper uses the data of the second survey, citizens' satisfaction, in order to classify the hospital characteristics according to the three levels of quality proposed by the Kano's model (Kano 1984). A special questionnaire was drawn up for the two surveys, and a consistent family of criteria, according to the principles of multicriteria decision analysis modeling (Jacquet-Lagrèze and Siskos 2001), was determined, via the cooperation of the persons in charge of the survey with the hospital management and the medical and nursing personnel.

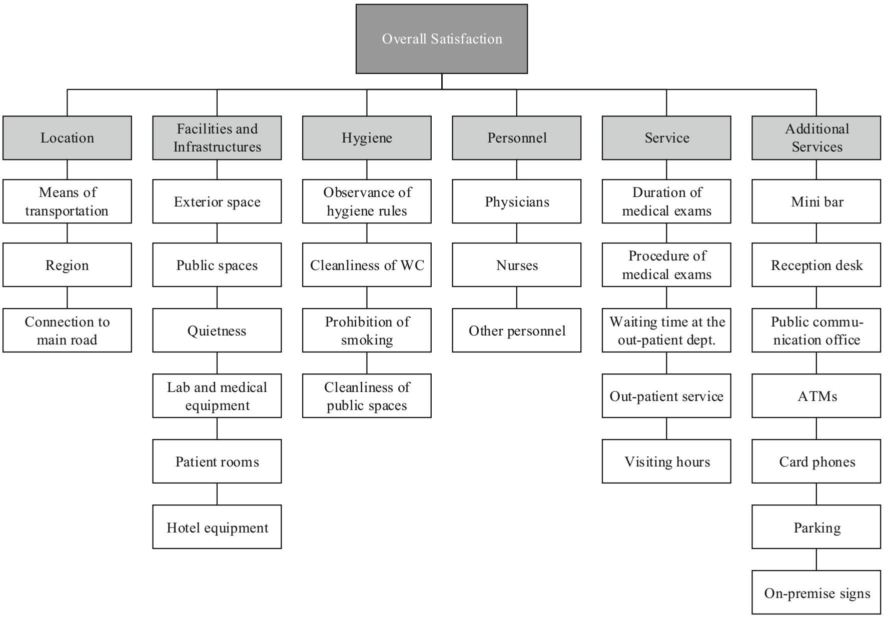


Fig. 6 Criteria and subcriteria

The citizens' satisfaction survey was carried out with the aim to explore the opinion that the citizens of Chania had formed after the first 3 years of the hospital's operation (survey: May–June 2003). The survey questionnaire included questions targeting the personal opinion of participants as in-patients and/or out-patients and/or visitors/persons accompanying patients. In particular, the survey was carried out with a simple yet properly structured questionnaire, which included six criteria: hospital location, facilities and infrastructure, hygiene, personnel, service and additional services. Each dimension of the satisfaction survey was analyzed into a set of subcriteria. The hierarchical form of the criteria and subcriteria is shown in Fig. 6.

The hospital location was analyzed into three subcriteria: connection to public transport (buses in this case), region where the new hospital was built, and connection of the hospital to the main road networks. Although the location criterion and subcriteria are not directly linked to the hospital provisions, they are characteristics commonly included in surveys concerning banks, public services, etc., and concern access, one of the eight satisfaction dimensions proposed by Ware and Snyder (1975) after an extensive literature review.

The natural surroundings of a hospital (Greeneich et al. 1992; Parasuraman et al. 1985; Ware and Snyder 1975), quietness (Abramowitz et al. 1987), as well as living conditions (Meterko et al. 1990; Carey and Seibert 1993) have been suggested as components of satisfaction in several surveys. They were thus also considered herein as elements of the criterion of hospital facilities and infrastructure, which was finally analyzed into six subcriteria: exterior space, public spaces inside the building, keeping quiet in the premises, laboratory and other equipment, condition of rooms and hotel equipment.

The criterion of hygiene was analyzed into four subcriteria: observance of hygiene rules, WC cleanliness, prohibition of smoking, and cleanliness of public spaces.

The personnel criterion included three dimensions: medical and nursing personnel and other personnel of remaining specialties. International bibliography extensively refers to the correlation of patient satisfaction, particularly in regard of hospital physicians and nurses.

The criterion of service was analyzed into five subcriteria, four out of which refer to the hospital's out-patient department as a service with free access for all citizens, while the fifth criterion refers to satisfaction from patient visiting hours.

Finally, the criterion of additional services was analyzed as follows: mini bar, reception desk for general information, public communication office (for specific information, e.g., appointments for the out-patient department, physicians' availability), bank ATMs, card phones, parking and on premise signs.

A 5-level ordinal satisfaction scale was used for both criteria and subcriteria, having the following form: not at all satisfied, slightly satisfied, moderately satisfied, very satisfied, and completely satisfied.

A total of 177 questionnaires were collected and it follows from the demographical characteristics of the sample that 59% of the respondents were men and 41% women. 99% had formed an opinion on the new hospital either as in-patients or as out-patients, or as visitors/persons accompanying patients. Finally, the age distribution of the sample was: 27% up to 25 years old, 20% from 26 to 35, 20% from 36 to 45, 12% from 46 to 55 and 21% over 55 years old.

4.2 MUSA Results and Classification of Criteria and Subcriteria

The MUSA method was used to process the survey data, while the satisfaction or non-satisfaction expressed by citizens was used to classify the criteria and subcriteria according to the Kano's model.

In our case, where satisfaction was analyzed into 6 criteria and 28 subcriteria, 68 $((6{+}28){\times}2)$ different datasets were created. Therefore, the MUSA method was applied 68 times for estimating the derived importance of the satisfaction criteria/subcriteria.

The results of the importance of the survey criteria in the six satisfaction dimensions investigated in relation to the different opinion expressed by satisfied and dissatisfied citizens are summarized in Table 1. In particular, columns 2 and 3 contain the weights as given by the MUSA method, and columns 4 and 5 present the relative weights of satisfied and dissatisfied citizens, respectively.

It follows from the above remarks and the weights of Table 1 that satisfied citizens consider the criterion of hospital facilities and infrastructure as important (0.252), while dissatisfied citizens consider the criteria of personnel (0.48) and service (0.32) as important. Therefore, the importance attached to the survey criteria is diversified depending on the satisfaction or dissatisfaction expressed by citizens. Hygiene is an exception, as both satisfied and dissatisfied citizens attach almost the same importance.

Combining the relative weights for satisfied and dissatisfied citizens for each criterion, a Better-Worse diagram is created. As shown in Fig. 7, satisfied and dissatisfied citizens share the view that the criteria of hygiene, additional services and hospital location concern characteristics of low importance. Therefore, and

Table 1 Criteria weights and relative weights for satisfied and dissatisfied citizens

	Weight of satisfied (b_i^s)	Weight of dissatisfied (b_i^d)	Relative weight of satisfied (b'^s_i)	Relative weight of dissatisfied $\left(b'^d_i\right)$
Location	0.147	0.073	−0.235	−0.446
Facilities and infrastructure	0.252	0.160	0.896	−0.186
Hygiene	0.151	0.156	−0.192	−0.198
Personnel	0.147	0.480	−0.235	0.768
Service	0.148	0.320	−0.224	0.291
Additional services	0.168	0.146	−0.009	−0.228

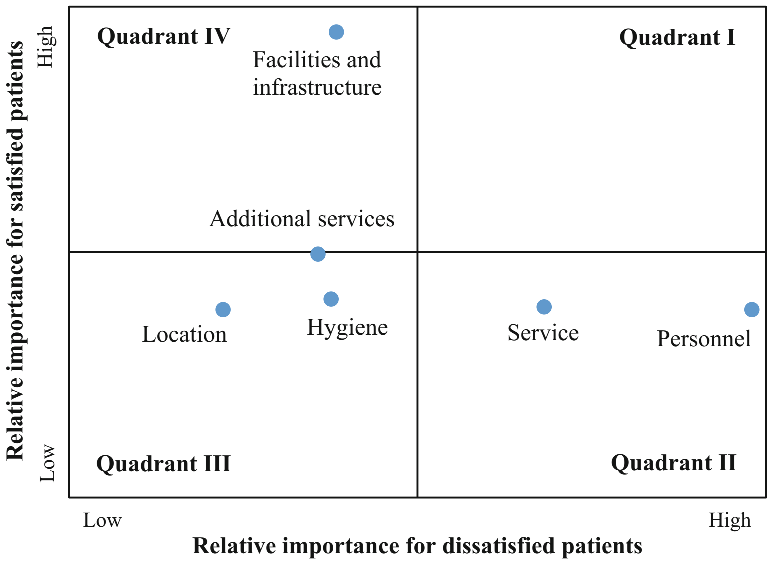


Fig. 7 Better-Worse diagram for satisfaction criteria

according to the analysis above, they constitute the one-dimensional characteristics and represent the desired quality. Low performance in the aforementioned criteria causes dissatisfaction while high performance leads to satisfaction (satisfiers). This result seems to be a logical desired requirement from citizens. Actually, citizens associate their satisfaction with the high performance of the hygiene conditions in the hospital, the hospital location and the additional services rendered, as they consider that, beyond any medical and nurse services, a hospital should also provide a satisfactory level of additional services. Given that additional services are very close to quadrant IV, we can assume that an unexpected improvement in their performance could easily affect satisfaction, therefore they could be included in the attractive characteristics of the hospital.

On the contrary, the criteria of service and personnel are of high importance for dissatisfied citizens and of low importance for satisfied citizens. Therefore, it appears that the two criteria affect dissatisfied citizens to a high degree and their dissatisfaction is justified to a certain extent. Consequently, these are classified as must-be characteristics or the expected quality dimensions of the hospital. Their low performance leads to dissatisfaction (dissatisfiers). These are quality dimensions that concern the operational condition of the public hospital, which are not expressed as they are considered as obvious or implied for the citizens. On the other hand, the infrastructure of the hospital is of a given performance. If it could somehow be improved, this would affect satisfaction of already satisfied citizens to a high degree, as an unexpected delightful situation. Therefore, the infrastructure of the hospital belongs to the attractive requirement and quality, respectively.

As far as the subcriteria are concerned, Table 2 summarizes their classification (the set of subcriteria weights, initial and relative, for both groups of citizens are detailed in Appendix 2). It follows that the connection of the hospital to the main road network explains the classification of the location criterion as a characteristic of desired quality. Therefore, low performance in this sub-dimension leads to dissatisfaction while high performance to satisfaction, for both groups of citizens. Means of transport, buses in this case, is a must-be requirement and an expected quality characteristic, since the new hospital, as opposed to the old one, is located 8 km away from the city. We must stress that the fact that dissatisfied citizens expressed a view of high performance of the means of transport to and from the hospital does not imply their high satisfaction while, on the contrary, their view of low performance of the means of transport creates great dissatisfaction. he location, on the other hand, is classified as an attractive characteristic. We believe that this is explained by the comparison between the former location of the hospital and the current one. The old hospital was located in the city and it was fast and easily accessible by foot or car. The distance of the new hospital from the city explains to a certain extent why a different location, would particularly please the already satisfied citizens.

With respect to the dimensions of the infrastructure criterion, the subcriterion of public spaces in the hospital is classified in the attractive quality characteristics, along with the criterion of facilities & infrastructure. Citizens' perception of public spaces in the hospital explains in general their view of the criterion of facilities &

Table 2 Classification of criteria and subcriteria

	Attractive Quality (attractive requirements)	**Expected Quality (must-be requirements)**	**Desired Quality (one-dimensional requirements)**
LOCATION			
Means of transport			
Region			
Connection to main road			
INFRASTRUCTURE			
Exterior space of the hospital			
Public spaces			
Quietness			
Laboratory & medical equipment			
Patient rooms			
Hotel equipment			
HYGIENE			
Observance of hygiene rules			
Cleanliness of WC			
Prohibition of smoking			
Cleanliness of public spaces			
PERSONNEL			
Physicians			
Nurses			
Other personnel			
SERVICE			
Duration of medical examinations			
Procedure of medical examinations			
Waiting time at the out-patient department			
Out-patient service			
Visiting hours			
ADDITIONAL SERVICES			
Mini bar			
Reception desk			
Public communication office			
ATMs			
Card phones			
Parking			
On-premise signs			

infrastructure. The classification of this specific characteristic of the hospital as an attractive quality dimension implies that the low performance of the characteristic does not create dissatisfaction, but of course, any unexpected improvement would cause great satisfaction to the already satisfied citizens. This is possibly due to the fact that, at the time of the survey (the considered data set dates back to 2003), citizens had low expectations with respect to the infrastructure and facilities of the hospitals operating in Greece. The quiet hospital environment is a must-be characteristic, which means that it increases the dissatisfaction of the already dissatisfied citizens, if not fulfilled, while when respected, it does not lead to high satisfaction. The hospital exterior space, laboratory & medical equipment and patient rooms are included in the desired quality characteristics. Their high performance leads to satisfaction, while their low performance to dissatisfaction for either satisfied or dissatisfied citizens. Hotel equipment cannot be classified in any of the three levels of the Kano's model. It follows from the data of Appendix 2 that dissatisfied citizens do not attach high importance to it (0.153), we could thus assume that they are satisfied, while satisfied citizens express a level of importance similar to the average importance of the individual dimensions of the infrastructure (0.159).

With regard to the criterion of hygiene, its classification as of desired quality is explained by the subcriteria: observance of hygiene rules, WC cleanliness and public space cleanliness. We should stress that the low performance of the specific characteristics creates dissatisfaction, while their high performance increases satisfaction in both groups of citizens, respectively. In this particular case and according to the data of Appendix 2, all citizens, both dissatisfied and satisfied, agree that attention must be paid to the observance of hygiene rules and therefore higher importance is attached to this characteristic compared to all other subcriteria. Prohibition of smoking belongs to the attractive quality characteristics. Of course, smoking is prohibited inside hospitals, however due to the significant number of smokers in Greece the exterior space of hospitals is always used by smokers. We believe that the possible complete prohibition of smoking even outside the hospital would be an unexpected event that could positively affect the satisfaction of the already satisfied citizens.

As far as the hospital personnel is concerned, its classification in the must-be requirements is interpreted in connection with the nursing personnel.[1] This is explained, to a certain extent, by the opinion that citizens have of the low number of nurses in Greek hospitals and hence the inadequate care provided to patients. Usually, a patient must be assisted by a third person during hospitalization. Therefore, we must point out that the nursing personnel is a key factor of the hospital that is expected to be available, and at the same time it defines certain levels of acceptance by citizens. Due to the fact that the nursing personnel is a basic characteristic, the high performance of the hospital in connection with the nursing personnel does not imply high satisfaction of dissatisfied citizens while, on the contrary, low performance creates great dissatisfaction. As expected, the remaining personnel belongs to the one-dimensional characteristics of the desired quality for both groups of citizens, while the medical personnel belongs to the attractive quality of the hospital. If for some reason, other than demand, the already satisfied citizens form a better idea of the medical personnel, this could dramatically affect their satisfaction. This practically means that the citizens' moderate opinion of the medical personnel neither creates dissatisfaction nor affects satisfaction. If, however, the citizens' idea of the medical personnel improves, this will lead to unexpected delight and satisfaction (delighters). We believe that satisfied citizens would actually express high satisfaction, if the number of the medical personnel

[1] In many surveys, patient satisfaction from nurse care has been identified as the most important factor that forms the overall satisfaction of patients (Abramowitz et al. 1987; Carey and Posavac 1981; Fleming 1979; Oberst 1984). In fact, the role of nurses covers the whole range of hospital services and, due to their constant presence next to the patients, they play a decisive part in the formation of satisfaction (Scardina 1994).

increases thus eliminating the current shortages of physicians that result in the non- or improper function of certain hospital units.

As far as general service provided at the hospital is concerned, performance seems to be dominated by the performance of the out-patient department, as a large number of citizens visit physicians on a daily basis at this department. Service therein appears to be a basic characteristic whose high performance does not affect the satisfaction of dissatisfied citizens, while low performance creates great dissatisfaction. Consequently, the opinion of dissatisfied citizens on the low-quality service at the out-patient department justifies the classification of the specific criterion in the must-be requirements. True is indeed that almost all out-patient hospital departments face on daily basis long queues of patients waiting to be examined, delays in the appointment booking process from few days to several weeks, etc. The opinion therefore of citizens in the case of the local hospital is not surprising. All other dimensions concerning the criterion of service belong to the one-dimensional quality characteristics, which constitute the main desires and needs expressed by both groups of citizens. In this case, their low performance creates dissatisfaction while high performance creates satisfaction. The duration of medical examinations belongs to the, high importance for all, quadrant I, while the rest of the subcriteria belong to quadrant III of low importance for either satisfied or dissatisfied citizens (see data on Appendix 2).

Finally, the citizens' opinion on the criterion of additional services is explained by their view of the public communication office, ATMs in the hospital, parking and on-premise signs, which are characteristics of desired quality. These characteristics correspond to the main desires and needs of both groups of citizens (satisfied/dissatisfied), thus satisfaction increases proportionally according to their performance. The hospital management should be aware that the low performance of these specific characteristics creates dissatisfaction, while high performance creates satisfaction to all citizens in general. In particular, attention should be paid to the fact that high importance is attached to ATMs by both groups of citizens (quadrant I), while expressing their dissatisfaction. Card phones are considered a must-be characteristic of expected quality. Attention must be paid to the specific characteristic because its low performance creates dissatisfaction, while its high performance does not imply high satisfaction for the already dissatisfied citizens. Finally, the hospital's mini bar and reception desk belong to the attractive characteristics. This means that the high performance of these specific characteristics implies high satisfaction while, on the contrary, their low performance does not create dissatisfaction. It appears that the moderate performance of these two particular characteristics is considered as expected and does not affect the opinion of the already satisfied citizens. Certainly, if for any reason the already satisfied citizens are 'surprised' by the high performance of these two characteristics, they will express an even higher satisfaction.

5 Concluding Remarks

The study presented herein has utilized the answers of an earlier citizen satisfaction survey in order to classify the criteria-subcriteria in the three levels of the Kano's model. Following the limitations of the initial survey, i.e., sample size and formation method of citizens' opinion in relation to the measurement of satisfaction from the new hospital in the city of Chania, we have presented a procedure that can use comparative data and associate them with the demands of customers on a case-by-case basis (here, citizens).

Conclusively, we could claim that according to the classification of both criteria and subcriteria of the survey in the Kano's three levels of quality and in relation to the perceived needs, expectations or experiences, as expressed by citizens who participated in the survey, the following are revealed:

- Characteristics of low/moderate performance, which do not cause dissatisfaction while their unexpected improvement will create high satisfaction include location, infrastructure as a criterion and public spaces as a subcriterion, prohibition of smoking, physicians, mini bar, and reception desk. Therefore, non-satisfaction of the above characteristics (criteria or subcriteria) does not necessarily lead to dissatisfaction, yet it simply does not bring satisfaction.
- Basic characteristics whose low performance creates great dissatisfaction while high performance does not imply high satisfaction include the means of transport, keeping quiet, personnel as a criterion and nurses as a subcriterion, service as a criterion and out-patient service as a subcriterion, as well as card phones. Therefore, satisfaction of the above characteristics when leading to dissatisfaction may not bring satisfaction, yet simply eliminate dissatisfaction.
- Characteristics whose low performance creates dissatisfaction while high performance causes satisfaction include location as a criterion and connection of the hospital to main road network as a subcriterion, exterior space of the hospital, laboratory and medical equipment, patient rooms, hygiene as a criterion and all but the prohibition of smoking subcriteria of hygiene, other personnel, duration and procedure of medical examinations, waiting time at the out-patient department, visiting hours, additional services as a criterion and the subcriteria of public communication office, ATMs, parking and on-premise signs.

Future research of the presented methodology includes the implementation in a larger sample in order to confirm the classification of the hospital's characteristics and eventually to investigate the demands of different groups of population. In addition, the methodology could be used with patients hospitalized for a certain period of time at the hospital, who have participated in a satisfaction survey. Finally, it should be noted that to evaluate its effectiveness and give answers to what it is indeed that mostly affects dissatisfied customers, the methodology should be applied to various data.

Acknowledgements The authors would like to thank Professor Nikolaos F. Matsatsinis who supervised the initial satisfaction research, Dr Christina Diakaki for her valuable editing, comments, and corrections, as well as E. Katemis and K. Kokkinos, students of the Technical University of Crete who conducted the survey.

Appendix 1: The MUSA Method

The MUSA method infers an additive collective value function Y^* and a set of partial satisfaction functions X_i^*. The main objective of the method is to achieve the maximum consistency between the value function Y^* and the customers' judgements Y. Introducing a double-error variable (see Fig. 8), the ordinal regression equation becomes as follows:

$$\tilde{Y}^* = \sum_{i=1}^{n} b_i X_i^* - \sigma^+ + \sigma^- \tag{1}$$

where $\tilde{Y}^*$ is the estimation of the global value function Y^*, n is the number of criteria, b_i is the weight of the i-th criterion, and σ^+ and σ^- are the overestimation and the underestimation errors, respectively.

The global and partial satisfaction Y^* and X_i^* are monotone functions normalized in the interval [0,100]. Thus, in order to reduce the size of the mathematical program, removing the monotonicity constraints for Y^* and X_i^*, the following transformation equations are used:

$$\begin{cases} z_m = y^{*m+1} - y^{*m} & \text{for } m = 1, 2, \ldots, \alpha - 1 \\ w_{ik} = b_i x_i^{*k+1} - b_i x_i^{*k} & \text{for } k = 1, 2, \ldots, \alpha_i - 1 \text{ and } i = 1, 2, \ldots, n \end{cases} \tag{2}$$

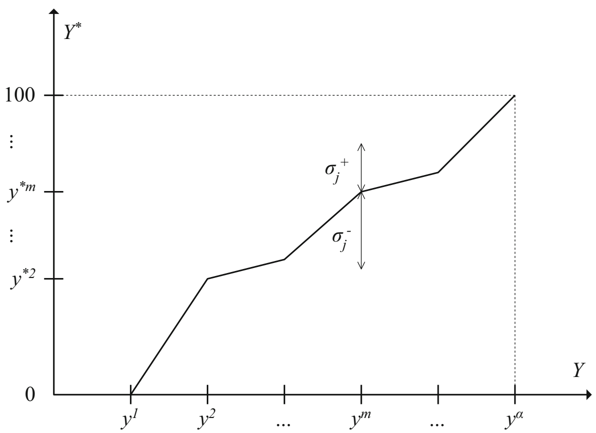


Fig. 8 Error variables for the j-th customer

where y^{*m} is the value of the y^m satisfaction level, x_i^{*k} is the value of the x_i^k satisfaction level, and α and α_i are the number of the global and partial satisfaction levels.

According to the aforementioned definitions and assumptions, the basic estimation model can be written in a linear program formulation, as follows:

$$\left\{\begin{array}{l} [\min]\, F = \sum\limits_{j=1}^{M} \sigma_j^+ + \sigma_j^- \\ \text{subject to} \\ \sum\limits_{i=1}^{n} \sum\limits_{k=1}^{x_i^j-1} w_{ik} - \sum\limits_{m=1}^{y^j-1} z_m - \sigma_j^+ + \sigma_j^- = 0 \quad \text{for} \quad j = 1, 2, \ldots, M \\ \sum\limits_{m=1}^{\alpha-1} z_m = 100 \\ \sum\limits_{i=1}^{n} \sum\limits_{k=1}^{\alpha_i-1} w_{ik} = 100 \\ z_m, w_{ik}, \sigma_j^+, \sigma_j^- \quad \forall m, i, j, k \end{array}\right. \tag{3}$$

where M is the size of the customer sample, and x_i^j, y^j are the j-th level on which variables X_i and Y are estimated.

The preference disaggregation methodology includes also a post optimality analysis stage in order to overcome the problem of model stability. The final solution is obtained by exploring the polyhedron of multiple or near optimal solutions, which is generated by the constraints of the previous linear program. This solution is calculated by n linear programs (equal to the number of criteria) of the following form:

$$\left\{\begin{array}{l} [\max]\, F' = \sum\limits_{k=1}^{\alpha_i-1} w_{ik} \quad \text{for} \quad i = 1, 2, \ldots, n \\ \text{under the constraints} \\ F \leq F^* + \varepsilon \\ \text{all the constraints of LP (3)} \end{array}\right. \tag{4}$$

where ε is a small percentage of F^*. The average of the solutions given by the n LPs (4) may be taken as the final solution. In case of non-stability, this average solution is less representative.

Appendix 2: Estimated Subcriteria Weights for Satisfied and Dissatisfied Citizens

	Weight of satisfied (b^s)	Weight of dissatisfied (b^d)	Relative weight of satisfied (b'^s)	Relative weight of dis-satisfied(b'^d)
Means of transport	0.333	0.557	−0.399	0.816
Region	0.523	0.333	0.816	−0.408
Connection to main road	0.330	0.333	−0.418	−0.408
Exterior space	0.154	0.069	−0.194	−0.272
Public spaces	0.182	0.063	0.894	−0.285
Quietness	0.153	0.609	−0.233	0.897
Laboratory and medical equipment	0.153	0.151	−0.233	−0.094
Patient rooms	0.153	0.123	−0.233	−0.155
Hotel equipment	0.159	0.153	0	−0.090
Observance of hygiene rules	0.236	0.761	0.797	0.865
WC cleanliness	0.213	0.220	−0.425	−0.300
Prohibition of smoking	0.222	0.215	0.053	−0.311
Cleanliness of public spaces	0.213	0.241	−0.425	−0.255
Physicians	0.559	0.285	0.786	−0.408
Nurses	0.348	0.577	−0.201	0.816
Other personnel	0.266	0.285	−0.585	−0.408
Duration of medical examinations	0.336	0.294	0.878	0.806
Procedure of medical examinations	0.204	0.197	−0.070	−0.245
Waiting time at the out-patient dept.	0.169	0.170	−0.322	−0.538
Out-patient service	0.174	0.220	−0.286	0.004
Visiting hours	0.186	0.217	−0.200	−0.028
Mini bar	0.560	0.126	0.686	−0.226
Reception desk	0.435	0.049	0.388	−0.358
Public communication Office	0.135	0.126	−0.327	−0.226
ATMs	0.321	0.591	0.116	0.574
Card phones	0.130	0.611	−0.339	0.609
Parking	0.184	0.157	−0.210	−0.172
On-premise signs	0.140	0.140	−0.315	−0.201

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