Management of Attainable Tradeoffs between Conflicting Goals

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***Abstract*— Rational decision-making requires governance of attainable trade-offs between conflicting goals, uncertainties and risks, which in turn demands both novel modeling methods and appropriate modeling technology. The paper deals with recent developments in applied modeling that have been motivated by the requirements for model-based support of solving complex problems. It starts with presenting novel modeling technology and integrated methods of integrated model analysis aimed at supporting decision-makers in diversified ways of analysis of the underlying decision problem. Then, multicriteria analysis is discussed in more detail with a focus on an extension of the reference point optimization, which supports an effective analysis of trade-offs between conflicting criteria aiming at analysis of attainable goals. Next, new approaches to coping with endogenous uncertainty and catastrophic risks are characterized, followed by a summary of issues related to transparency and public understanding.**

***Index Terms*— multicriteria optimization, decision-making support, uncertainty, risk, structured modeling, modeling systems and languages, model management, database management systems.**

I. INTRODUCTION

Everybody deals with conflicting goals, uncertainties, and diverse risks all the time. In most cases we manage even complex problems by successfully making decisions based on experience and intuition. Consider driving a car, for example. Each driver controls a car subconsciously applying quite complex principles of adaptive control, typically without even understanding the dynamics of the car.[1] Moreover, in a congested traffic each driver constantly monitors the behavior of other drivers and every few seconds subconsciously predicts their behavior, assessing the risk related to various combinations of the predicted behavior. Given the complexity of this everyday activity, it is amazing how well (measured e.g., by the frequency of mistakes that lead to accidents) the problem of controlling cars is solved by drivers with very diversified backgrounds and experience. If every driver can do this, then one should ask why formal methods may help solving problems that seem to be simpler.

The simplest answer to this question may result from a more careful consideration of diverse approaches to analysis of relations between decisions and their consequences. It is commonly known that accidents do happen. However, everybody who drives either evaluates a utility of driving higher than a disutility of an unlikely accident, or does not even make such a kind of analysis. Analysis of catastrophic risks (i.e., related to rare events with high consequences) is actually a difficult problem, which is beyond the scope of this paper. Yet, several key problems related to analysis of trade-offs between conflicting goals can be illustrated by even very simple deterministic problems, e.g., a choice from a set of discrete alternatives.

A more complete justification of the need for rational management of conflicting goals, uncertainties and risks comes from diverse applications of science-based support for solving complex problems in policy-making, industry, and management. While it is possible to accumulate enough knowledge and experience to solve diverse problems, often even without understanding all the underlying mechanisms, in many other decision-making situations mathematical models and adequate methods of model-based problem analysis are necessary for finding and/or justifying rational decisions. Such situations are characterized by at least one of the following issues:

- Complex relations between the decisions and the corresponding outcomes (measures of consequences of their implementations).
- Difficult to assess trade-offs between attainable goals (preferred values of outcomes).
- Uncertainties and risks related to the decision-making situation.
- The needs for supporting the transparency of the decision-making process and enhancing public understanding of problems and the considered solutions.

Rational governance of conflicting goals, uncertainties and risks requires concerted handling of all pertinent elements of the decision-making process. A number of methods has been developed for dealing with each of the issues listed above. The craft of decision-making support consists of adopting an appropriate approach to each element of the decision-making process while remembering that the strength of a chain is determined by its weakest link.

The remaining part of the paper is organized as follows. The next Section presents the characteristics of models, and of modeling processes aimed at decision-making support for complex problems. Section III deals with multicriteria analysis of trade-offs between conflicting

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[1]Control engineers could solve differential equations to optimize the way they drive a car, but they do not need to do so.

goals. Novel approaches to coping with endogenous uncertainties and catastrophic risks are discussed in Section IV. Finally, the requirements for transparency and public understanding are summarized in Section V.

II. Decisions and Outcomes

Rational decision-making always involves analysis of relations between alternative decisions and the corresponding consequences. One distinguishes two types of problems:[2]

- There is a given set of (at least two) discrete alternatives. One has to decide which should be selected. In some situations a ranking of alternatives is additionally required. Further on we refer to this type of problem as *Discrete Alternative (DA)* choice problem. Typical examples include: selecting a car, a house, a project.
- A decision is composed of a set of value(s) selected from an infinite[3] set of feasible decisions. Such a set is typically given implicitly, i.e., by a specification of the relations between decisions, optionally also involving other factors that need to be considered when making the decision. A simple (in terms of number of decision variables) example: decide the amount of kerosene to be tanked in an aircraft. A complex problem: decide a portfolio of structural and financial instruments for integrated management of catastrophic flood risks.

Although there are methods and tools specialized for each of these two types of problems, there are also many common methodological issues. Therefore it is worth to consider both of them in terms of the mathematical programming, which provides a powerful analytical framework for analysis of different approaches to decision-making.

A mathematical model describes the modeled problem by means of variables that are abstract representations of those elements of the problem which need to be considered in order to evaluate the consequences of implementing a decision (usually represented by a vector composed of many variables). More precisely, such a model is typically developed using the following concepts:

- Decisions (inputs) $\boldsymbol{x}$, which are controlled by the user;
- External decisions (inputs) $\boldsymbol{z}$, which are not controlled by the user;
- Outcomes (outputs) $\boldsymbol{y}$, used for measuring the consequences of the implementation of inputs;
- Auxiliary variables introduced for various reasons (e.g., to simplify model specification, or to allow for easier computational tasks); and
- Relations between decisions $\boldsymbol{x}$ and $\boldsymbol{z}$, and outcomes $\boldsymbol{y}$; such relations are typically presented in the form:

$$\boldsymbol{y} = \boldsymbol{F}(\boldsymbol{x}, \boldsymbol{z}), \tag{1}$$

where $\boldsymbol{F}(\cdot)$ is a vector of functions.

[2]We discuss here only a single decision-maker support; therefore we refrain from considering issues related to group decision-making.

[3]Or at least large enough to practically exclude analysis of each individual alternative.

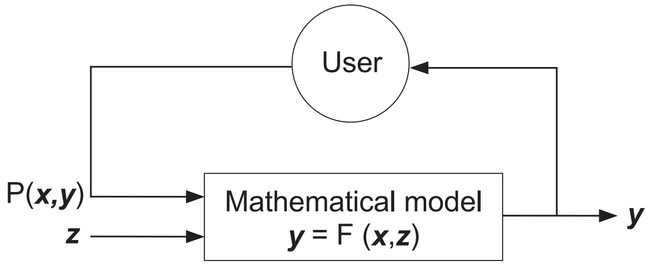


Figure 1. Structure of the use of a mathematical model for decision-making support.

A rational decision-making support aims at finding values of decision variables $\boldsymbol{x}$ which will result in a solution of the problem that best fits preferences of the decision-maker. Such preferences can be represented by a *preferential structure* $P(\boldsymbol{x}, \boldsymbol{y})$, which typically induces partial ordering of solutions obtained for different combinations of values of decisions. Thus, the basic function of decision-making support is to help the decision-maker find values for his/her decision variables $\boldsymbol{x}$ which will result in a solution of the problem that best fits his/her preferences represented by $P(\boldsymbol{x}, \boldsymbol{y})$.

A typical decision problem has an infinite number of solutions therefore the relations (1) need to be represented by a mathematical model. One should note that also the discrete alternative choice problem can be represented as an algebraic model. This is particularly needed if values of criteria for (possibly many) alternatives must be computed from parameterized complex relations, see e.g., [1], and/or for problems with a large number of alternatives.

A structure of the use of a model for decision-making support is illustrated in Figure 1. Such a support is composed of two stages:

- Development and maintenance of a model that adequately represents relations (1);
- Organizing a process of the model analysis in which the user can specify and modify his/her preferences upon combining their own experience and intuition with learning about the problem from the analyses of various solutions.

These two stages are briefly summarized below.

A. Modeling process

Modeling is a network of activities, often referred to as a *modeling process*. Such a process should be supported by a modeling technology that is a craft of a systematic treatment of modeling tasks using a combination of pertinent elements of applied science, experience, intuition, and modeling resources. The latter being composed of knowledge encoded in models, data, and modeling tools. In most publications which deal with modeling, small problems are used as an illustration of the modeling methods and tools presented. Often, these can also be applied to large problems. This is especially true for the DA type of problems for which the model development stage consists of selecting sets of alternatives and attributes, adapting an existing data management utility, and collecting the data. While also for this type of problems it is strongly advisable to follow principles of structured modeling, conforming to these principles is practically a must for model-based support of any complex problem. We stress that the complexity is characterized primarily not by the size, but rather by the structure of the problem and by the requirements for the corresponding modeling process.

Here, we outline the modeling process based on the *Structured Modeling Technology* (SMT) [2]. SMT is based on two successful paradigms: the *Structured Modeling* (SM) paradigm developed by Geoffrion [3], which provides a proven methodological background, and the *Object-Oriented Programming* (OOP) paradigm which, combined with DBMS, XML, and the Web technologies, provides an efficient and robust implementation framework. SMT is used through the Web interface, and all persistent elements of the modeling process are maintained by a DBMS. Thus the Web and a DBMS provide an integrating framework for collaborative work of interdisciplinary teams that use SMT applications for various elements of the modeling process.

A detailed presentation of SMT can be found in [2]. Here we only outline basic features of three SMT components, not including the analysis of trade-offs between conflicting goals, which is discussed in Section III.

1) Model Specification: Model specification is a symbolic definition of the model composed of variables and algebraic relations between them. In order to efficiently handle large and complex models the specification exploits the power of OOP combined with core concepts of SM, such as sets, relations, hierarchy, primitive and compound entities. Primitive entities have attributes and functions common for the derived types, namely parameters, variables, and constraints (representing parametric relations between variables), each possessing additional attributes specific for each of them. Compound entities are derived from the corresponding primitive entities and accompanying indexing structures.

2) Data: Data for large models comes from different sources (also as results from analyses of various models), and larger subsets of data are maintained by teams. SMT exploits the concept of *Data Warehouse* (DW) for supporting persistency and efficiency of data handling. The latter is achieved by defining a base dataset, and supporting incremental modifications of this set (which allows for avoiding duplications of large amounts of data needed in more traditional approaches requiring the storage of complete datasets even when only a small fraction of the data is modified).

The data structures of a DW are generated automatically from the model specification. This not only assures consistency between the declarations of the parameters in the model specification and the data used for their instantiations, but also saves substantial resources that would otherwise have been needed for preparing and maintaining data structures for any complex model.

3) Documentation: SMT exploits the XML capabilities for handling the documentation. In SMT an XML document type is defined for enabling a single-source symbolic model specification that can be used for all relevant tasks of the whole modeling process. The documentation of other elements of the modeling process is done on different levels of detail. The basic information (such as date, user name, options requested for each object to be used) is automatically stored in the DW by each SMT application. Additionally, a user accessing a DB with privileges for data creation or modification is asked to write comments, which are logged.

B. Model analysis

Development of a proper model representation of the relations between decisions and their consequences (outcomes) is obviously a key necessary condition for appropriate support of rational decision-making. However, it has to be stressed that this is not a sufficient condition: one also needs a proper support for model analysis. Both these elements complement each other, and the quality of the weaker one determines the quality of the decision-making support.

Model analysis is probably the least-discussed element of the modeling process. This results from the focus that each modeling paradigm has on a specific type of analysis. However, the essence of model-based decision-making support is precisely the opposite; namely, to support various ways of model analysis, and to provide efficient tools for evaluations of various solutions.

The traditional approach to decision-making support is to represent a decision problem as a mathematical programming problem in the form:

$$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x} \in X_0} \mathcal{P}(\boldsymbol{x}, \boldsymbol{F}(\boldsymbol{x}, \boldsymbol{z})), \tag{2}$$

which provides optimal decisions $\hat{\boldsymbol{x}}$. However, this approach does not work for complex decision-making problems. The main reasons for that are:

- There is no unique representation of preferences $\mathcal{P}(\cdot)$;
- There is no unique definition of the set of admissible solutions X_0 (because X_0 is defined also by the bounds for values of the criteria not included in $\mathcal{P}(\cdot)$);
- Sensitivity analysis recommended for post-optimization problem analysis has very limited applicability to actual complex problems, see e.g., [4]; and
- Large optimization problems usually have an infinite number of very different solutions with almost the same value of the original goal function, see e.g., [4].

Thus, optimization in supporting decision making for solving complex problems has a quite different role from its function in some engineering applications or in very early implementations of Operational Research (OR) for solving well-structured military or production planning problems. This point has already been clearly made e.g., by Ackoff [5], and by Chapman [6], who characterized the traditional way of using OR methods for solving problems as composed of the following five stages: describe the problem; formulate a model of the problem; solve the model; test the solution; and implement the solution. The shortcomings of such an approach are discussed in many other publications, see e.g., [4] and [7] for more details, and have been the main driving force for developing methods of model analysis that better serve the needs of decision makers.

The basic function of a model-based *Decision Support System* (DSS, illustrated in Fig. 1) is to support the user in finding values for his/her decision variables $\boldsymbol{x}$ that will result in a solution of the problem that best fits his/her preferences. A countless number of actual applications shows that to meet such requirements a well-organized model analysis phase of the modeling process is composed of several stages, see e.g., [4], each serving different needs. Thus, not only are different forms of $P(\cdot)$ typically used for the same problem, but also different instances of each of these forms are defined upon analyses of previously obtained solutions.

The analysis of the model instance is composed of a sequence of steps, each of which consists of:

1. Selection of the type of analysis, and the definition of the corresponding preferential structure, which takes different forms for different methods of model analysis, e.g., for:
   - Classical simulation, it is composed of given values of input variables;
   - Soft simulation, it is defined by desired values of decisions and by a measure of the distance between the actual and desired values of decisions;
   - Single criterion optimization, it is defined by a selected goal function and by optional additional constraints for the other (than that selected as the goal function) outcome variables;
   - Multicriteria model analysis, it is defined by an achievement scalarizing function, which represents the trade-offs between the criteria used for the evaluation of solutions.
2. Selection of a suitable solver, and specification of parameters that will be passed to a solver.
3. Generation of a computational task representing a mathematical programming problem, the solution of which best fits the user preferences.
4. Monitoring the progress of the computational task, especially if it requires a substantial amount of computing resources.
5. Translation of the results to a user-friendly form.
6. Documenting and filing the results, and optional comments of the user.

Various specifications of the preferential structure support diversified analyses of decisions problem aimed at:

- Suggesting decisions for reaching specified goals;
- Analyses of trade-offs between conflicting goals; and
- Evaluations of consequences of decisions specified by the user.

The first two types of analyses are goal oriented and are discussed in Section III. Now, we briefly comment on the third one, which focuses on the analysis of alternatives. For large problems it is difficult to specify values of decision variables without a prior knowledge of feasible alternatives, but such alternative solutions are provided by the goal-oriented model analysis, and users typically are interested in examining consequences of various modifications of such alternatives. A frequent problem with using the classical simulation is caused by infeasibility of the modified decisions. The soft simulation methods provide the same functionality without the risk of getting infeasible solutions.

Several generalizations of the soft simulation are useful for a more comprehensive simulation-type analysis. We briefly outline three of them. The first, called *inverse simulation*, provides similar functionality in the space of outcome variables (i.e. the user specifies the desired values of outcome variables instead of the decision variables). The second, called *generalized inverse simulation* consists of a combination of the analysis provided by the soft and inverse simulations. Finally, the *softly constrained inverse simulation* supports the analysis of trade-offs between goals (specified in a more general form as in the inverse simulation) and violations of a selected set of constraints (which are for this purpose treated as soft constraints). However, all these (and other) generalizations of the soft simulation are in fact specific applications of the multicriteria model analysis discussed below. A more detailed discussion of these issues is provided in [4].

III. Trade-offs between Attainable Goals

In reality, almost all actual decision problems have a large (or infinite) number of solutions $\boldsymbol{x}$; the essence of decision-making is to select one of them that optimizes the preferences $P(\boldsymbol{x}, \boldsymbol{y})$. Solving a decision-making problem as a single criterion optimization seems to be very attractive because offering a unique solution based on solid mathematical foundations is appealing, especially if one considers that an abundant choice (even among discrete alternatives) typically creates problems, such as dissatisfaction or regret, see [8]. However, as summarized above, the traditional OR approaches are based on the assumption that the best solution of a decision problem is the one that minimizes a given criterion, e.g., (2). This assumption is applicable only to a specific class of well structured problems; already over 50 years ago Simon [9] demonstrated that such an assumption is wrong for most of actual decision making problems. Recent studies, see e.g., [8], [10] confirm Simon's results.

Most decision problems require an actual[4] analysis of several criteria, which are typically conflicting, e.g., cost, quality, performance, safety. Criteria (denoted by $\boldsymbol{q}$ are defined by selected outcome variables $\boldsymbol{y}$) are typically defined in different measurement units. It is usually possible to compute at least a good approximation of the ranges of values for each criterion.

[4]Based on a proper analysis of trade-offs between criteria, without a prior aggregation of criteria into a single-criterion goal function.

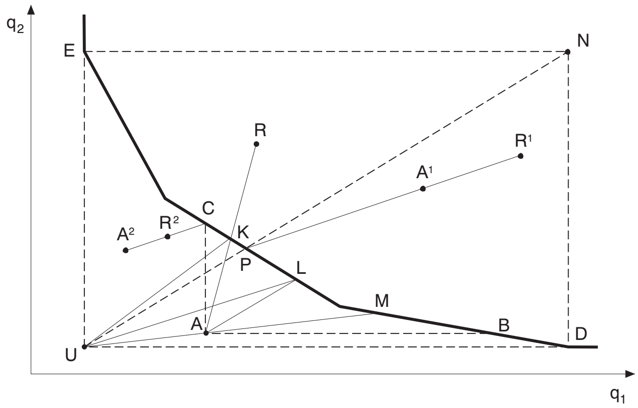


Figure 2. Trade-offs between Pareto solutions.

A rational decision can be selected from a subset of all solutions called the *Pareto set*.[5] A solution is called Pareto-efficient, if there is no other solution for which at least one criterion has a better value while values of remaining criteria are the same or better. In other words, one cannot improve any criterion without worsening at least one other criterion. Solutions that are not Pareto efficient are called dominated.

Pareto-optimal solutions are not comparable in a mathematical programming sense, i.e., one can not formally decide which is better than another one. A choice of a solution depends on preferences of the user that implicitly define properties of the corresponding solution. Thus, in order to find a Pareto-efficient solution that corresponds best to the user's preferences one needs to support the user in analysis of trade-offs between criteria.

The basic concepts related to multicriteria analysis are illustrated in Fig. 2, which shows the Pareto set (segments between the extreme points marked by E and D) for two minimized criteria. Assume that q_1 represents cost, and q_2 pollution emission. Then solution D is expensive but clean, solution E is cheap but dirty, and solutions located on the Pareto frontier between these two extreme solutions match different trade-offs between costs and the corresponding emission; solutions B and M are substantially cheaper than D and for both the corresponding worsening of emission is substantially smaller than for yet cheaper solutions L, K, and C. Analysis of trade-offs, and finding the solution having a preferred trade-off between the criteria values is easy for two-criteria problems. However, when dealing with more criteria it is much more difficult to identify attainable goals[6] that correspond best to the decision-maker preferences typically expressed as trade-offs between the corresponding criteria values. Such preferences can practically be elicited only during an interactive analysis which supports the user in learning about the attainable trade-offs.

[5]Also called: Pareto-efficient solutions, Pareto frontier, non-dominated solutions. For the sake of brevity we don't deal here with more advanced concepts, e.g., properly efficient solutions; these are discussed e.g., in [7].

[6]Values of criteria that can be achieved simultaneously.

Multicriteria analysis is an iterative process supporting the user in the Pareto set exploration that aims at finding subsets of solutions with desired properties (e.g., cheap, or moderately priced, or expensive). For each iteration the user analyzes which criteria he/she wants to improve and which should be compromised, and then sets values of method-specific parameters that support the selection of another Pareto solution that hopefully fits his/her preferences better. At each iteration the multicriteria problem is converted into an auxiliary parametric single-objective problem, the solution of which provides a Pareto solution hopefully having a better trade-off between criteria than the previous solution.

Multicriteria analysis methods differ by the type of parameters/procedures used for specification of the user preferences, and by a conversion to the corresponding single-objective problem, but all commonly known methods can be interpreted in terms of the Achievement Scalarizing Function (ASF),[7] see [11] for details. A necessary condition for acceptability of a method is that it allows for analysis of all Pareto solutions.[8] From the user point of view the most important features of a method are: (1) intuitive interpretation of parameters and procedures used for preference specification, and (2) support of an easy navigation through those parts of the Pareto set that are interesting for the user.

To illustrate these issues we first comment on the weighted sum approach, and then characterize the reference point methods.

A. Linear aggregation of criteria

One of the oldest approaches to multicriteria analysis is known as the weighted sum approach. It uses the ASF in the form:

$$ASF = \sum_{i=1}^{n} w_i q_i, \qquad w_i \geq 0, \qquad \sum_{i=1}^{n} w_i = 1, \quad (3)$$

where n is the number of criteria, and weights w_i are specified (directly or indirectly) by the user. Typically, the original values of criteria are linearly mapped into:

$$q_i \in [0, 1], \qquad i = \{1, \ldots, n\} \quad (4)$$

where $q_i = 0$ and $q_i = 1$ correspond to the worst and best values, respectively; weights w_i are interpreted as compensation ratios between criteria.

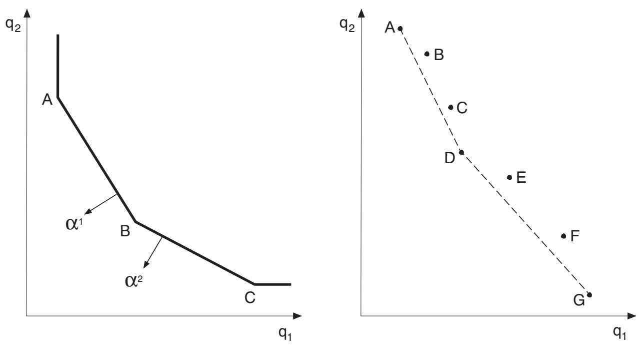
This approach is still popular because it is believed to be simple, intuitive, and reliable. However, in fact it supports poorly analysis of Pareto sets, is often contra-intuitive, and unreliable.

To illustrate the basic problems of using linear criteria aggregation let us consider two-criteria problems, and the ASF (3) in a more convenient (for analysis of the method properties) form:

$$ASF = q_1 + \alpha q_2, \qquad \alpha = w_2/w_1. \quad (5)$$

[7]The concept of ASF was introduced by Wierzbicki see, e.g., [7].

[8]Each method should guarantee that for each Pareto solution there exists a specification of user preferences such that this solution will be selected as fitting best these preferences.



(a) Continuous LP (b) Discrete LP

Figure 3. Limitations of the weighted-sum approach.

The value of α determines the ratio of: (1) improvement (measured in the percentage of the corresponding criterion value) of one criterion, and (2) its compensation by worsening the other criterion. In other words, a stronger preference for q_1 (than for q_2) implies a smaller value of α; therefore to compensate (in terms of keeping the ASF value unchanged) an improvement (worsening) of q_2 by say x%, the value of q_1 has to change by αx%.

The interpretation of values of α appears to be natural, and therefore the linear aggregation is believed to support intuitive and robust analysis. To show that this is not true let us consider two values of α, namely those corresponding to the slopes represented by α^1 and α^2 shown in Fig. 3a. For any $\alpha < \alpha^1$ solution A will be selected, and for $\alpha^1 < \alpha < \alpha^2$ and $\alpha > \alpha^2$ solutions B and C, respectively. For the other two cases ($\alpha = \alpha^1$ and $\alpha = \alpha^2$) there is no unique solution (thus any solution from either segment AB or BC can be selected). Thus the weights used for linear criteria aggregation support poorly examination of the Pareto set. In some situations the same solution is returned even if substantial changes of weights were made; e.g., the cheapest solution A will be selected not only when the cost criterion q_1 is infinitely more important than the emission q_2 but also if q_1 is only slightly more important than q_2. In other situations a tiny change in preferences (represented by α^1 in Fig. 3a) results in a substantially different solution.[9]

The second serious flaw of the weighted sum approach is that many Pareto-efficient solutions are never shown to the user. This is illustrated for two types of problems in Fig. 3. For a continuous LP model (Fig. 3a) a typical LP solver will return a solution corresponding to a vertex, therefore infinite number of solutions located between vertices A, B, C will never be shown. For discrete problems only efficient solutions located on a convex cover defined by the alternatives will be found by this method (e.g., solutions B, C, E, F in Fig. 3b will never be shown to the user). Limiting the user choice to only a subset of Pareto solutions is not only an ethical problem of restricting the user sovereignty. Actually, many of the solutions excluded from the analysis can represent the tradeoffs between criteria that are preferred by the user, see e.g., examples in [12]. To illustrate this point let us consider two maximized criteria and three alternatives: $A = \{0, 1\}$, $B = \{0.49, 0.49\}$, $C = \{1, 0\}$. Assume that a user selects $\alpha = 1$ (i.e., assigns equal weights to both criteria). Solution B corresponds perfectly to these preferences, but the weighted-sum approach never finds it.

The third shortcoming is due to a common belief that using weights is intuitive because there is always a positive correlation between increasing the weight for a criterion and the corresponding improvement of the criterion value. Simple examples (cf e.g., [12], [13]) show that also this is not true.

In addition to the fundamental problems summarized above, the linear aggregation has a number of other drawbacks, including double-counting (of dependent criteria), and a tacit assumption of a fully compensatory character of criteria (with constant substitution rates for the whole ranges of criteria).[10] More details can be found e.g., in [4], [11], [12], and [13].

B. Reference point methods

Most of the successful multicriteria analysis methods are based on the two-step approach:

- define a reference (aspiration, goal) point composed of the desired values of all criteria; further on we denote the reference point as RFP;
- find a Pareto solution that is (in a sense) closest to this point.

The displaced ideal point method [14] uses the Utopia (marked by U in Fig. 2) as the RFP, and the family of methods known as *Goal Programming* (originating from [15]) assumes that the RFP is defined by the user.

Two types of methodological problems had to be solved in order to effectively represent user preferences in this two-stage procedure: first, a sequential specification of RFPs; second, the selection of a measure for the distance between the RFP and the Pareto set. This led to the development of theory, software and application of the aspiration-based decision support-summarized in [16]; their relations to the Goal Programming are summarized in [17]. Another stream of the developments in this field is outlined in [13]. A comprehensive discussion of the theoretical background of the reference point methodology, tools for their implementation as well as a detailed presentation of several applications can be found in [7]. Here we only outline the basic features of this approach.

The Utopia point (composed of best values of all criteria, and marked by the letter U in Fig. 2) is an obvious initial RFP. However, in most practical applications the Utopia point is far away from the Pareto set; the Utopia point is therefore a clearly unrealistic goal. Thus for an effective multicriteria analysis it is essential to represent the user preferences using two mechanisms in a concerted way: first, sequential specifications of RFPs supporting

[9] In many problems the distance between some vertices is large.

[10] If one of the criteria is expressed in monetary units, then this is equivalent to accepting the principles of monetarization (i.e., that all criteria can be converted to monetary units).

their convergence to attainable goals; second, applying a measure for the distance between the RFP and the Pareto set that results in the selection of Pareto solutions fitting best (in terms of tradeoffs between criteria values) the user preferences. In other words, the two mechanisms have the following roles:

- a selected RFP provides a focus on a subset of the Pareto solutions that have trade-offs between criteria similar to those implied by the chosen RFP; the user has full control on selecting any RFP, therefore no Pareto solution is excluded from the analysis;
- the distance measure implies the selection of a Pareto solution that has criteria values with the tradeoffs corresponding to the user preferences.

Let us illustrate the RFP approach by the examples shown in Fig. 2. Obviously, any of the Pareto-optimal solutions between points E and D can be obtained for various definitions of the distance between the aspiration point U and the Pareto set. Thus, for a unique (for a given specification of preferences) selection of a Pareto solution one needs to define either another point (which together with the aspiration point define a direction) or an ASF that provides a unique selection of solutions.

The first approach is exploited by the Aspiration-Reservation Based Decision Support (ARBDS) method, which requires a specification of two points, called aspiration and reservation, composed of the desired and the worst acceptable values of criteria, respectively. A well implemented ARBDS does not impose any restrictions on the feasibility of the aspiration nor of the reservation values. E.g., in Fig. 2 there are three pairs of aspiration and reservation points, denoted by $\{A, R\}$, $\{A^1, R^1\}$, and $\{A^2, R^2\}$, respectively. The corresponding Pareto-solutions are marked by K, P, and C, respectively. A selection of a pair like $\{A, R\}$ (i.e., a not attainable aspiration and a feasible reservation level) is typical for users who have learned the properties of the problem and have a good feeling about the attainable ranges of criteria values. Selection of a non-attainable reservation level (e.g., R^2) is typical for early stages of the model analysis, when unrealistic reservation levels are specified. However, specifications of not attainable aspiration levels (e.g., A^1) are not as rare as one can expect; especially, if some criteria are interdependent. More details on the ARBDS methods are provided in [18].

The second approach has been implemented in the MCMA [18], which exploits an ASF is defined as:

$$ASF = \min_{1 \le i \le n} u_i(q_i, \bar{q}_i, \underline{q}_i) + \frac{\epsilon}{n} \sum_{i=1}^{n} u_i(q_i, \bar{q}_i, \underline{q}_i) \quad (6)$$

where $u_i(\cdot)$ denotes i-th Component Achievement Function (CAF), $q_i, \bar{q}_i, \underline{q}_i$, are the value, aspiration and reservation levels of i-th criterion, respectively; n is the number of criteria, and ϵ is a small positive number.

Two examples of CAFs are illustrated in Fig. 4. The first CAF is defined by four points, with values of the criterion, U, A^1, R, and N, corresponding to the values of utopia, aspiration, reservation, and nadir, respectively.

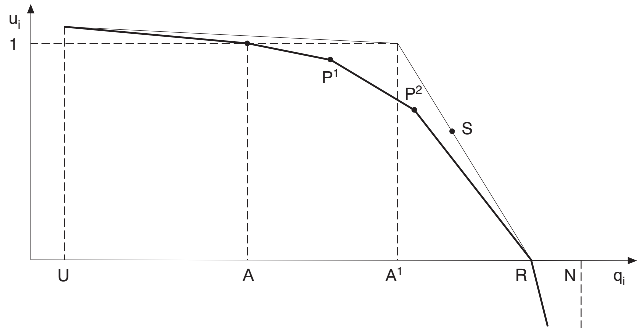


Figure 4. Component achievement scalarizing function.

The second CAF is defined by a modification of the first CAF, where the previously defined aspiration level A^1 was moved to the point A and two more points – P^1 and P^2 – were interactively defined.

Values of CAF have a very easy and intuitive interpretation in terms of the degree of satisfaction from the corresponding value of the criterion. Values of 1 and 0 indicate that the value of the criterion exactly meets the aspiration and reservation values, respectively. Values of CAF between 0 and 1 can be interpreted as the degree of *goodness* of the criterion value, i.e., to what extent this value is close to the aspiration level and far away from the reservation level. These interpretations correspond to the interpretation of the membership function of the Fuzzy Sets, which is discussed in [18].

By using an interactive tool for specification of the CAF illustrated in Fig. 4 such as MCMA [18] a user can analyze various parts of a Pareto set that best correspond to various preferences for trade-offs between criteria. These preferences are typically different for various stages of analysis; they are often modified substantially during the learning process, when both aspiration and reservation levels for criteria values are confronted with the attainable values, which correspond best to the user preferences. In such an interactive learning process, a user gradually comes to recognize attainable goals that correspond best to his/her trade-offs.

C. Discrete Alternatives with Large Number of Criteria

Analysis of more than several discrete alternatives characterized by large number of criteria can hardly be done by commonly used methods; in particular methods based on interactive pairwise comparisons are not applicable. Moreover, in some situations users have no experience in multicriteria analysis. Additionally, some problems are analyzed by many (say, several hundreds) of users. For effectively addressing needs of such types of problems and users new methods for multicriteria analysis, and new types of user interface have been recently developed.

Challenges related to this class of problems, and initial results can be found in [12] and [19] (more publications are under preparation). Information about these developments will be available in 2009 at: `http://www.iiasa.ac.at/~marek`.

D. Opportunities and pitfalls

Multicriteria analysis can be a powerful tool for rational decision-making. However, if not used properly, may provide very misleading results. A main advantage is an efficient support for identifying attainable goals having desired trade-offs between conflicting criteria. Another advantage is active participation of decision-makers in the problem analysis, which through interactive learning about the problem properties builds trust that selected solutions indeed fit his/her preferences. However, to achieve such desired outcomes one should avoid pitfalls associated with multicriteria analysis. We comment here on only two such traps caused by common misunderstandings.

First, the fitness of a solution to the user preferences should always be assessed in the criteria space, i.e., by a pattern of criteria values. Interpretations of the ASF values are typically misleading. This remark can easily be justified by recalling that any Pareto solution can be obtained by rather different specifications of preferences (thus the corresponding values of ASF are different). One should also remember the contra-intuitive features of the linear criteria aggregation, see Section III-A.

Second, ranking alternatives according to the ASF values is likely to be inconsistent with the actual user preferences.[11] As already mentioned, the preferences are iteratively modified based upon analysis of criteria values of a selected Pareto solution, and the iterative analysis stops when the selected Pareto solution has the desired tradeoffs between criteria values. However, the fact that the solution fits the user preferences does not imply[12] that the ASF values are good representations of these preferences. Therefore, when a multicriteria ranking is needed one should make a sequence of analyses of sets of alternatives; the set for a next analysis is equal to the current set without the alternative selected as the best one.

IV. Uncertainties and Risks

The discussion so far clearly shows the challenges of decision-making even without considering the two other elements of decision making, which are the key characteristics of many problems, namely, uncertainty and risk. Appropriate treatment of uncertainties and risks also calls for new approaches. Traditional models in economics, insurance, risk-management, and extreme value theory require evaluations based on corresponding assumptions and large-enough sets of data. For example, standard insurance theory essentially relies on the assumption of independent, frequent, low-consequence (conventional) risks, such as car accidents, and extensive sets of data about accidents/losses, owners, etc. Thus insurance companies use well established models (exploiting rich sets of historical data) for making decisions on premiums, estimating claims and the likelihood of insolvency. Existing extremal value theory also deals primarily with independent events and assumes that these events are quantifiable by a single number [20].

However, there is a class of problems for which established methods cannot provide adequate support. Such problems are characterized by a vast variety of inherent, practically irreducible uncertainties and/or ”unknown” risks, and/or by spatial or temporal or social heterogeneity, see e.g., [21], [22]. The risks often involve events with catastrophic consequences due to either irrecoverable shocks (e.g., insolvency), or a magnitude of impact that may affect at once large territories and communities (e.g., natural or man-made catastrophes).

Traditional approaches are not applicable to problems with irreducible uncertainties because they require adequate sets of data from either real observations or experiments; such data are not available for new[13] problems or for problems involving rare events. Experiments aiming at collecting data, even if possible, may be very expensive and/or dangerous. However, in many situations, especially in policy making and management, experiments are simply impossible.

Moreover, traditional approaches are not applicable to problems involving catastrophes (understood as rare events with large consequences). Catastrophes typically result in abrupt irreversible changes occurring on large spatial, temporal, and social scales. Large-scale potential catastrophic impacts, and in particular magnitudes of uncertainties that surround them, are critically important for the climate-change policy debates and the associated decision-making processes, see e.g., [23], [24]. However, traditional risk analysis (based on the concept of expected cost-benefit analysis) actually ignores catastrophic events. Thus, extreme events are treated as improbable during a human lifetime, and consequently are not rationally considered in decision-making processes. However, a 1000-year disaster (i.e., an extreme event that occurs on average once in 1000 years) may, in fact, occur even today.[14] Moreover, it is impossible to perform a proper evaluation of complex heterogeneous processes on ”average”. Such processes have significantly diversified spatial and temporal patterns and induce heterogeneity of losses and gains which makes it inappropriate to use average (aggregate) characteristics. E.g., on average residents may even benefit from some climate-changes, while some regions may incur dramatic loses.

Novel approaches are therefore needed for scientific support of decision-making on problems characterized by at least one of the above summarized attributes: inherent uncertainty, catastrophic risks, heterogeneity. Rational support should not be based on ”an average” or on a selected scenario.[15] Although even good evaluations

[11] This problem is also known as the *rank reversal*.

[12] Because of the many-to-one relation between preferences and each solution.

[13] *New* also represents old/known types of problems which, however, are not stationary, i.e., whose parameters change over time. This in turn may imply that even large existing sets of data are not adequate for identification of parameters of models representing such problems.

[14] The Chernobyl disaster of 1986 was quantified as a 1,000,000-year event; yet it occurred in 9 years after the power-plant was commissioned.

[15] Note that the probability of occurrence of any given scenario is typically equal to zero.

of particular decisions are impossible, the preference structure among decisions can provide a stable basis for a relative ranking of alternatives. Thus the essence of identifying robust decisions is to perform comparative analyses of feasible decisions and to design robust policies with respect to the uncertainties and risks involved. Such decisions don't attempt to be "optimal" for any given scenario; they reflect trade-offs between being (1) possibly best for most likely situations, and (2) good enough for extreme events.

A more detailed discussion of novel approaches to coping with uncertainties and risks can be found e.g., in [25], [26], [27].

V. Transparency and Public Understanding

By now it is commonly agreed that the provision of information is critical to public acceptance, and that in reality some commonly discussed problems are actually incorrectly understood. Selected issues of modeling for knowledge exchange are discussed in [28]. The relevance of this publication for policy making is illustrated e.g., by Sterman [29], who points out that although the Kyoto Protocol is one of the most widely discussed topics, most people believe that stabilizing emissions at near current rates will stabilize the climate. Recent debates on pension system reforms in several European countries also clearly show a wide misunderstanding of the consequences of population structure dynamics on economies in general and on pension systems in particular. These, and many other problems, can also be explained to the public by adapting relevant models for use in presentations that the public can understand. Unfortunately, various models developed for policy-making problems use different assumptions, and often different sets of data; therefore a comparative analysis of their results can at best be done and understood by a small community of modelers. The need for public access to knowledge pertinent to policy-making will certainly grow, see e.g., [30] for the discussion of access to environmental information; thus the role of models in public life will also grow accordingly.

VI. Conclusions

Development of models for complex problems does, and will, require various elements of science, craftsmanship, and art (see, e.g. [4] for a collection of arguments that supports this statement). Moreover, development and comprehensive analysis of a complex model requires collaboration of interdisciplinary teams, and thus a substantial amount of time and other resources. Therefore new modeling tools are needed for an effective support of collaborative modeling (both model development and exploitation) by interdisciplinary teams working at distant locations. SMT addresses these needs by supporting the development of models with complex structures and huge amounts of data, and diversified analyses of such models; moreover, it provides automatic documentation of the whole modeling process. Thus, SMT promotes modeling quality and transparency, which are critically important for model-based support of decision-making, especially in actual policy-making.

Web-based modeling environments (like the SMT) not only support interdisciplinary modeling, but also provide opportunities for involving a larger audience in model analysis. In particular, a Web-based multicriteria analysis of discrete alternatives (called MCAA) has been recently developed;[16] it is currently being used for several applications, including analysis of future energy technologies (the latter to be done remotely by a large number of stakeholders).

The composition of this paper was also motivated by the requirements of scientific support for decision-making. Each decision problem typically has a *main focus*. However, each non-trivial problem requires an integrated analysis of all relevant aspects, including the decision-making process, the data quality, uncertainties, and risks. Focusing on only one (even main) aspect and/or selecting too early a specific modeling paradigm is dangerous because it may neglect factors that can damage the quality of an incomplete analysis.

Science-based support for policy-making is a process, and quality of the support is determined by its weakest element. This paper focuses mainly on multicriteria analysis of attainable goals. However, it also discusses recent developments in the modeling technology, integrated risk management, and transparency and public understanding. All these topics are relevant to supporting rational decision-making, therefore recent developments might be interesting for researchers and practitioners.

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