3. A SURVEY OF MULTIPLE CRITERIA DECISION METHODS

In this chapter and in the three subsequent chapters, we deal mainly with Multiple Criteria Decision Methods (MCDM). In Chapter 6, this analysis results in a description of a new approach: Interactive Multiple Goal Programming (IMGP). Beforehand - in Chapters 4 and 5 - we describe the methods which constitute the basis for this new approach.

The present chapter is devoted to a survey of multiple criteria decision methods. In Section 3.1 we explain a number of important definitions and some basic concepts of multiple criteria decision making, which is followed in Section 3.2 by the description of a general framework used to show how these kinds of *methods* might help in practical decision *problems*. In order to know which method might be used beneficially in a particular decision problem, the analyst should first determine the most important characteristics of the problem. Therefore, before presenting an overview of methods, we list a number of characteristics of decision problems in Section 3.3. This is followed by a general overview of multiple criteria decision methods in Section 3.4. In Section 3.5 a more detailed discussion of the subclass of methods based on mathematical programming techniques is presented. Our main conclusions are given in Section 3.6.

3.1. Terminology and Basic Concepts

Ultimately, decision making involves choosing between alternative actions (policies, strategies, or simply alternatives). The set of alternative actions can either be described explicitly - by describing its elements one by one - or implicitly. In the latter case, every action is described by a vector $\underline{x}$ of values of the instrumental (policy, or decision) variables $x_1, \ldots, x_n$. The set of alternative actions (set of admissable alternatives or feasible region) is described indirectly by means of constraints (restrictions) on the values of the instrumental variables.

From the set of alternative actions, one (or in some cases more than one) alternative must be found which meets the decision maker's preferences in an optimal (or sometimes if not optimal, at least in a satisfactory) way. The decision maker's preferences depend on certain properties (or attributes) of the alternative actions. These preferences may be considered to be directly related to the attribute values, or alternatively, as a function of certain goal variables, which in their turn depend on the value(s) of one or more attributes. In the case that the set of alternative actions has been described implicitly, it is rather common to consider the values of the instrumental variables in a given solution as attribute values, and thus the goal variables as functions of the instrumental variables. The preferences can then be considered to depend either on the values of the goal variables or on the deviations from certain goal values (aspiration levels, targets) aspired by the decision maker.

The term objective function will be reserved here exclusively for the function in a mathematical model (describing a certain decision situation), which is to be optimized. In general, the objective function serves as a means to optimize the decision maker's preference function. Depending on the problem formulation at hand, the objective function may, but does not need to coincide with the decision maker's preference function.

If some aspired goal value is formulated as a constraint, from which one may deviate through the inclusion of deviational variables (cf. Section 3.3 and Chapter 4), we will term such a constraint a goal constraint (restriction).

An alternative which is described by a set of instrument values can clearly be represented as a vector in the instrument value space. This alternative can of course also be represented by the vector of goal values, attained for this alternative, in the goal value space (often but less desirably called the 'objective function space'). A vector in the goal value space will be referred to as a solution.[1)] Note that an element of the instrument value

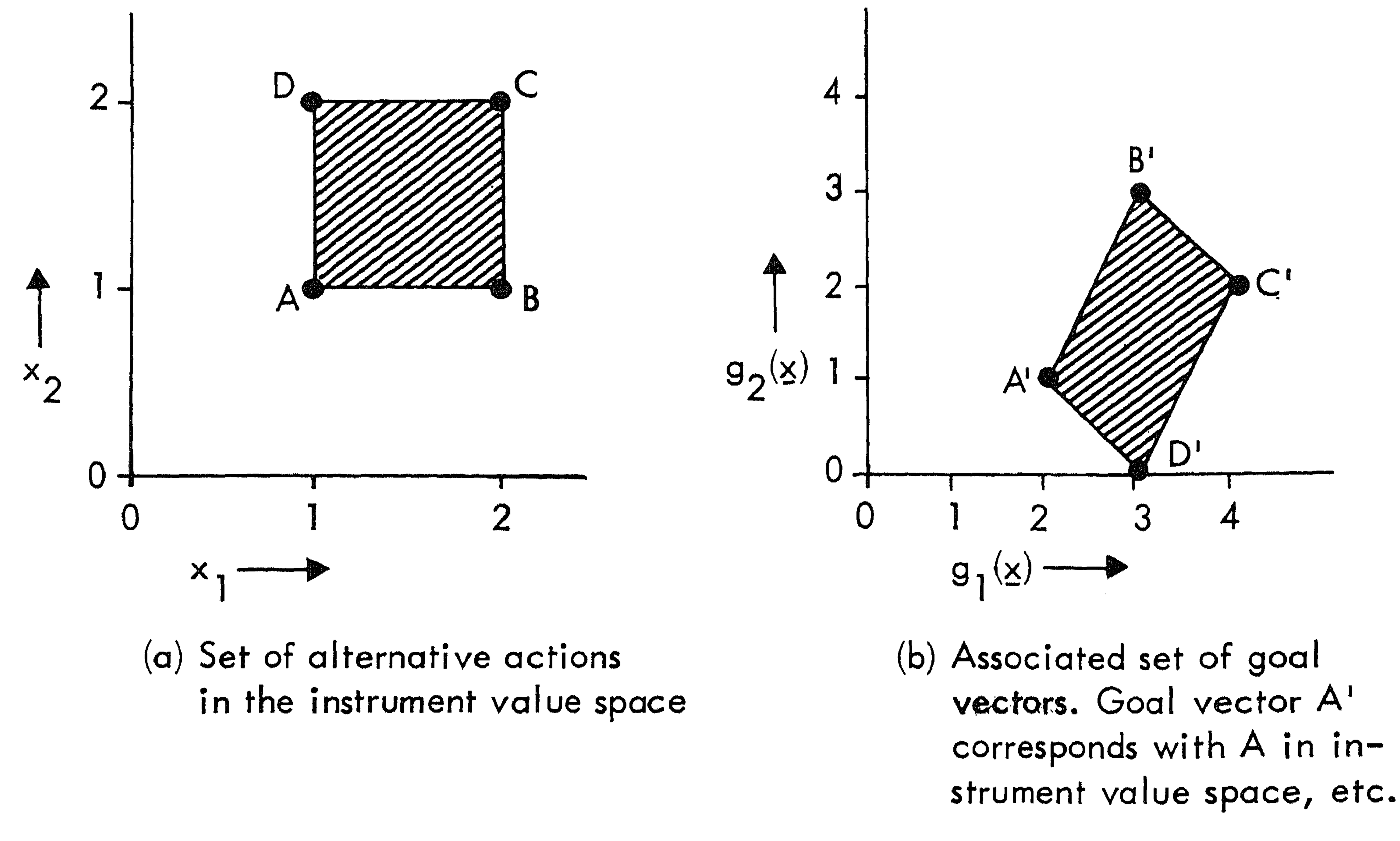

Figure 3.1. A set of alternative actions in the instrument value space and the associated goal vectors in the goal value space

1) The term solution will be reserved exclusively for a vector in the goal value space. Note, however, that many authors in MCDM literature also use this term to indicate an element of the instrument value space. Here, an element of the instrument value space will be referred to as the action, i.e. vector of instruments $\underline{x}$, generating a solution $g(\underline{x}) = (g_1(\underline{x}),\ldots,g_m(\underline{x}))$.
In our opinion it is preferable to use different terms for the elements of these two different spaces.

space can always be mapped uniquely into the goal value space, but that the reverse does not necessarily apply. This is because different actions can result into the same solution. In Figure 3.1 we give an example of a (feasible) set of alternative actions and the associated set of goal vectors in the goal value space. We assume two instrumental variables, x_1 and x_2, and two goal variables, $g_1(\underline{x}) = x_1 + x_2$ and $g_2(\underline{x}) = 2x_1 - x_2$.

A very important concept in multiple criteria decision making is the notion of an efficient (non-inferior, non-dominated, or Pareto-optimal) solution. This is an element of the set of feasible solutions for which no other solution in the same set of feasible solutions can be found to have a better value for one or more of the goal variables without having worse values for one or more of the other goal variables. Returning to Figure 3.1 and assuming that both $g_1(\underline{x})$ and $g_2(\underline{x})$ are to be maximized, it is easily seen that (in the goal value space) both B' and C' and all vectors on the line connecting B' and C' are efficient. Gradually going from C' to B' gives a better value of $g_2(\underline{x})$, but at the price of worsening the value of $g_1(\underline{x})$. However, all feasible solutions below the line B'C' are non-efficient in this case. The problem to find all efficient solutions is generally referred to as the vector-maximum problem.

The concept of efficiency is very useful because it offers a generally powerful tool to reduce the number of alternatives to be evaluated by the decision maker. Nevertheless, one should be very careful with regard to the use of the efficiency concept for the reduction of the set of alternatives. That is, for a given set of alternatives and a given set of goal variables, the set of efficient solutions can, in principle, be calculated. If a new goal variable is added, the set of efficient solutions generally grows considerably. In that case the decision maker will not necessarily choose a solution which was already efficient before adding the new goal variable. Therefore if in a given problem formulation it is not certain that all the decision maker's goal variables have been included, it may be undesirable to limit further analysis to the set of efficient solutions.

Another important notion frequently used in multiple criteria decision making is the concept of the ideal solution (see e.g. Zeleny [1976]). The elements of the ideal solution are the maximum values of the goal variables which are individually attainable within the set of feasible actions. In most multiple criteria decision problems these maxima cannot be attained simultaneously. Then the term utopia solution (cf. Yu [1973]) better denotes the true meaning of this concept. The importance of ideal (utopia) solutions is that they can be used as 'points of reference' for judging alternatives.

In the example underlying Figure 3.1, the ideal solution is defined by $g_1(\underline{x}) = 4$ and $g_2(\underline{x}) = 3$. In this case a unique action corresponds with the ideal solution. This action is found by solving $g_1(\underline{x}) = x_1 + x_2 = 4$ and $g_2(\underline{x}) = 2x_1 - x_2 = 3$, which gives $x_1 = 0.5$ and $x_2 = 3.5$. Clearly, both the ideal solution and the corresponding action are infeasible.

As is the case with the set of efficient solutions, the ideal solution can be found using no information about the decision maker's preferences other than the knowledge on which goal variables are important and whether these should be maximized or minimized.

Because generally not all individual maximum goal values can be attained simultaneously, the decision maker will either have to be content with a compromise solution or will have to enlarge the set of feasible actions (by relaxing constraints or by introducing new actions). In some multiple criteria decision procedures (see Section 3.3 and Chapters 5 and 6), the decision maker is repeatedly confronted with new compromise solutions, on which basis he has to express his (local) preferences, which are then used to calculate a new compromise solution, and so forth. These procedures are aimed at finding a so-called final (best) compromise solution.

3.2. Decision Problems and Methods

Most methods dealt with in this study explicitly aim at helping the decision maker (or the group of decision makers) in the decision making process. As such, these and many other procedures developed in economics, management science, and operations research are normative by construction. '*If you accept our propositions, you are better off to follow our instructions*' could be a general slogan for these approaches. Clearly, the more these propositions correspond to practical decision problems the higher the chance that a certain method will be accepted in practice. This is, however, not the only consideration in evaluating such a method. Many tools developed for assisting decision making are very powerful and worthwhile simply because of a number of basic simplifying assumptions (e.g. the assumption of certainty, transitivity of preferences, etc.). Thus, depending on the decision situation and the type of decision assistance required, a balance between the above factors must be strived for.

To be able to confront the features of these normative methods with the needs in practice, we give, in Figure 3.2, a very simplified scheme of the decision situation of a decision maker who wants to rely on normative methods. The scheme is very simplified indeed. The dynamic aspects of a decision process are not indicated; nor are the organizational (e.g. power structures, hierarchical decision levels, interactions and communication) and human (e.g. capabilities, rationality, preference formation) aspects of decision making. Nevertheless, this scheme helps to describe the character of these normative approaches. As shown in Figure 3.2, we assume the decision maker to be a part of a system (e.g. a firm) which produces (under the influence of the decision maker, other actors participate in the system, the environment, and so forth) a constant stream of actions, which in their turn result in outcomes (e.g. profit, wages, pollution). These outcomes are evaluated by the decision maker and other

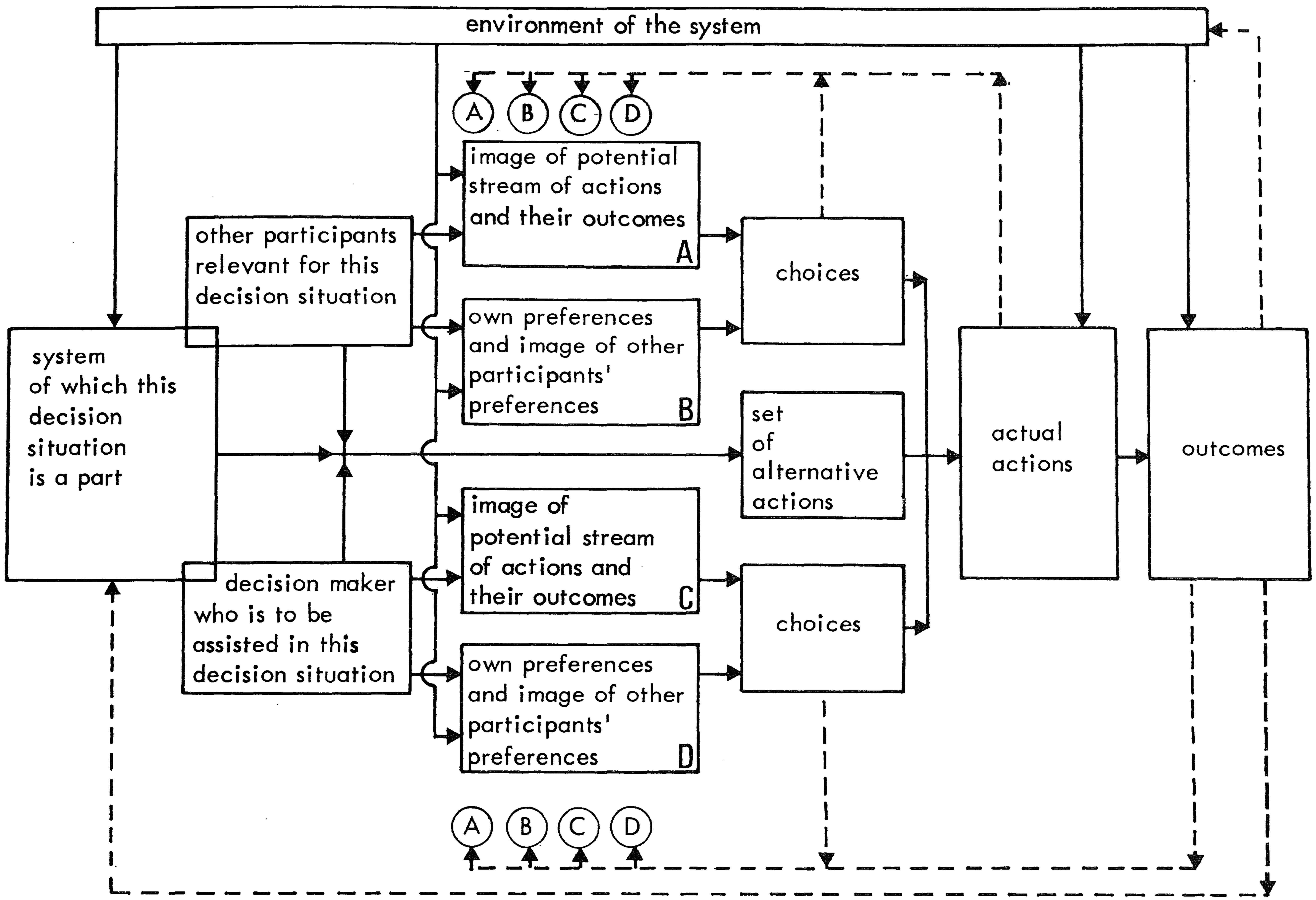

Figure 3.2. A typical decision situation

participants, and may thus give rise to pressures to change the stream of actions in order to improve future outcomes. It then becomes the decision maker's task to influence the stream of actions in a way which will meet the desires of the decision maker(s), other participants and the system's environment as good as possible. The decision maker can influence the stream of actions both directly and indirectly. Directly, by changing his own actions; indirectly, by asking (if not instructing) other participants to change their actions in a certain way. Clearly, as long as the decision maker is not managing a show of puppets, he is not always certain whether the stream of actions will change in the indicated way, and if so, whether they will lead to the desired outcomes. Of course, the decision maker tries to make an appropriate decision. This will be based on his perception of the possible streams of actions (and the outcomes implied), on the desires and pressures of the other participants, and finally on the decision maker's own preferences (see Figure 3.2).

In general, most normative approaches to decision making aim at assisting the decision maker(s) in one or more of the following ways:

(a) Improve the image of the set of alternative streams of actions

Examples are methods which help to find a feasible stream of actions and methods which generate new streams of actions.

(b) Clarify the relationships between actions and outcomes

Many kinds of simulation models and econometric models can be classified under this leading.

(c) Help to choose a (set of) suitable stream(s) of actions

A large part of economics and the main parts of operations research and management science are aimed at providing 'optimal solutions'. Recently, however, it has been stressed that a normative procedure does not necessarily have to indicate a unique, optimal solution (cf. Roy [1976, 1977]).

For instance, these methods may be used to eliminate a number of apparently inferior solutions.
Clearly, there seem to be many perspectives for normative decision methods. Nevertheless, many of the proposed normative methods have been criticized and have encountered a lot of resistance. Why? Several methods have evoked much criticism due to the advanced theoretical nature of these methods which claimed 'to solve all your problems'. On the other hand, methods have been condemned completely because they were erratically used in situations for which they were neither designed nor suited. Indeed, several assumptions which are frequently made are rather strong and thus hard to be met in reality. This has given rise to a lot of principal questions. Is the relationship between means and ends always quantifiable? If so, can it be represented by a rigid mathematical expression? Can all outcomes be translated into a single measure? What about the preferences of participants other than the decision maker: can they be ignored, or should they be represented by restrictions? Is it possible to model 'means' independently of 'ends'? Can preferences be represented by a mathematical function (possibly in one dimension)? Should these methods help to find an optimal solution, or rather help to improve the decision process? Detailed discussions on these and related topics can be found e.g. in Keen [1977], and Lindblom [1959].

Many developments in operations research and management science look very promising. New methods are created and old methods are refined and adapted in order to be suitable for decision situations which were hitherto inaccessible. Also, there are clear tendencies to pay more attention to the dynamic (including the psychological, sociological, and organizational) aspects of decision making. One of the features of these tendencies is the rapid and broad development of multiple criteria decision making theory. Due to their greater correspondence with reality, multiple criteria decision methods seem to be better suited for assisting the decision maker than single criteria decision methods. However, no decision maker can be replaced by any of these methods. No method can prescribe the best solution in a particular situation. At best, a method can assist the decision maker by strengthening the basis on which the decisions are made and by improving the quality of the decision process.

Obviously, for a particular decision problem an appropriate method should be chosen. In order to facilitate this choice we will next list a number of problem characteristics, followed by an overview of available methods.

3.3. Some Characteristics of Decision Problems

Before presenting an overview of multiple criteria decision methods, we list a number of characteristics of decision problems by means of which these methods can be typified. Ideally, a typology of methods should be problem-oriented. The method's description should thus indicate for which decision situation(s) the method might be used. Most multiple criteria decision methods have not yet been described in such a way. The reason is that the field is not only very rapidly growing, but also - and mainly - that there is as yet no detailed and generally accepted overview of the class of decision problems and situations in which multiple criteria decision methods might possibly be used. Studies in this direction have been initiated by Despontin and Spronk [1979] and Moscarola [1979].

From the above it is clear that different decision situations may require different methodologies, although some methods may be useful in several situations. As shown in Figure 3.3, the class of characteristics to be described can roughly be subdivided into three subsets, describing the data, the information processing system and the required output (cf. Despontin and Spronk [1979] and Rietveld [1980]). Without pretending to be exhaustive (which is clearly impossible), we will describe a number of charasteristics for each of these subsets.

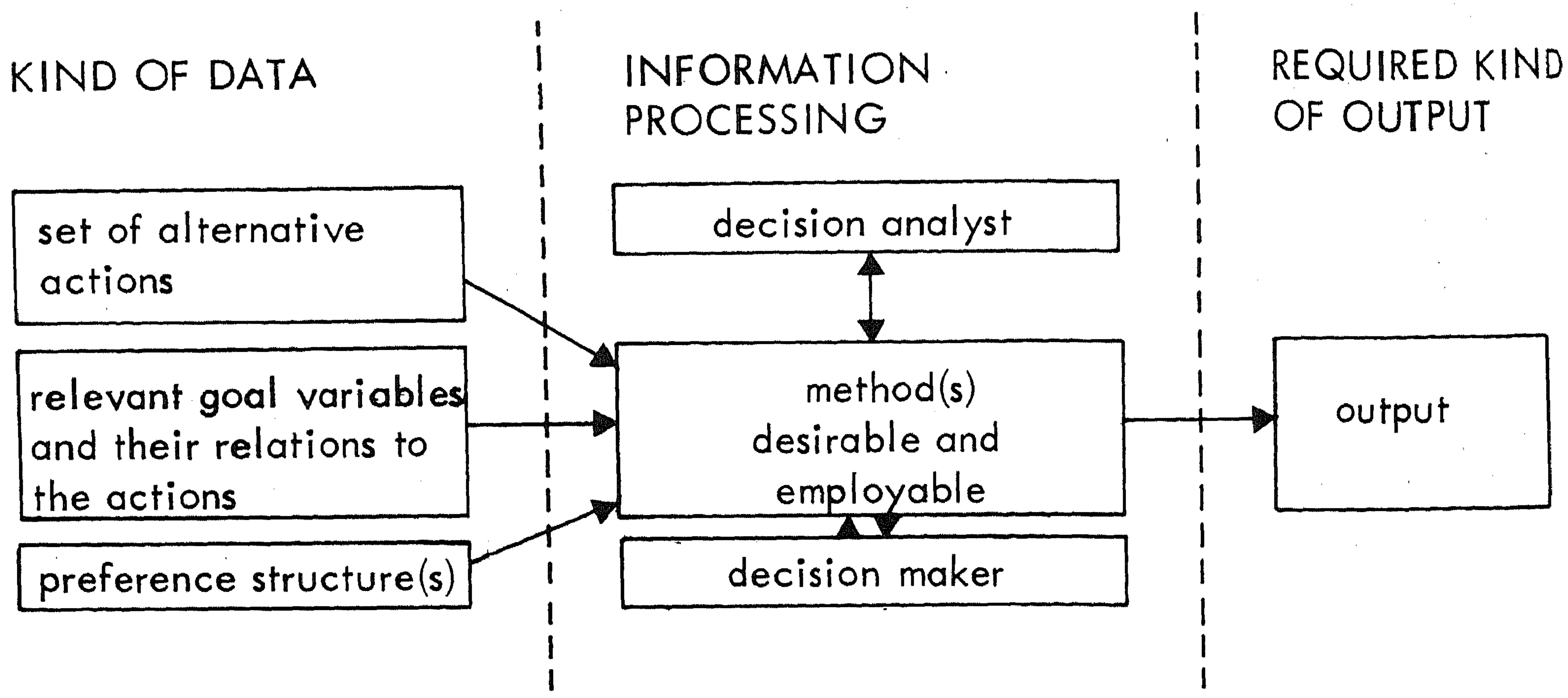

Figure 3.3. Some sets of characteristics of decision problems

The relevant characteristics to typify the kind of data which can be handled by a particular methodology concern the set of alternative actions, the set of goal variables (including their relationships with the set of actions) and the nature of the preference structure(s) of the decision maker(s).

(a) The set of alternative actions

- this set may be fixed or may change in the course of the decision process
- an action may be defined as a single action or as a strategy, i.e. a series of coherent actions
- the actions may be described explicitly (one by one) or implicitly by means of constraints
- the feasibility of the actions may be certain or uncertain
- the actions may be well-defined or may be stated in fuzzy terms

(b) Relevant goal variables and their relationship to the actions

- this set may also be fixed or may change in the course of the decision process
- the goal variables may be well-defined or may be stated in fuzzy terms

- the relations between goal variables and actions may be deterministic or stochastic
- the relations between goal variables and actions may be well-defined or fuzzy

(c) Nature of the preference structure(s)

- how detailed is the preference information required from the decision maker(s)?
- which kind of preference structure(s) can be handled?
- is the preference structure considered to be fixed, or can it change in the course of the decision process?
- are one or more decision makers involved?

To characterize the way in which the input data are transformed into answers and advice to the decision maker i.e. the information processing (see Figure 3.3), the properties of the method, the demands upon both decision maker and analyst as well as their interrelationships are to be described next.

(d) Properties of the method (desirability/feasibility)

- is it a standard method or must it be adapted for each particular decision situation?
- is the method easy to use, or does it for example require that extensive models be built?
- what are the costs to employ the method?
- does the method converge to the desired type of output and if so, how fast?

(e) Demands on the decision maker(s)

- how many decision makers are involved?
- are there one or more hierarchical decision levels involved, and does such a level consist of one or several branches?
- is the method easy or difficult to understand?
- how much time does the method require from the decision maker(s)?

(f) Demands on the analyst(s)

- how many analysts are to be involved?
- how much of their time is needed?

- what kind of training do they need to be able to employ the method?

(g) Interrelationships (see also Section 5.2)

- how many and what kind of questions are to be answered by the decision maker(s)?
- what kind of information is provided to the decision maker(s)?
- what are the decision maker options to control the solution process?
- when and how is the analyst involved?
- does the analyst have the possibility to manipulate the solution process?

Depending on the nature of the decision problem at hand, the kind of output (see Figure 3.3) expected from a normative decision method may vary considerably. For many years, most normative decision methods were built with the aim to provide 'the optimal solution' for a given decision problem. As pointed out by Roy [1977], normative methods may also be aimed at reducing the set of feasible actions (for instance by removing all inferior solutions) or they may help to construct a preference ranking order of the set of alternatives. As a purpose in itself, but usually as a byproduct of serving the other purposes, a normative decision method may help to structure the decision process and to clarify the relationships between actions, goal variables and preferences.

In complete accordance with the possibilities listed under (a) and (b), the action (or set of actions) selected with the help of the decision method may be feasible with certainty or subject to uncertainty, and may be well-defined or formulated in fuzzy terms. The same possibilities hold for the goal values attained through these actions. Consequently, also the output of a decision method may be formulated as a random variable and/or may even be stated in ill-defined terms. For instance, one method may deliver the optimal solution with certainty (given the model of the decision situation), while another method shows a set of actions which will 'very probably' be 'fairly good'.

As mentioned above, this list of characteristics is, and can not be, exhaustive. The closer one looks at particular decision situations, at the way decision makers solve their problems, and at the ways normative methods can be used within the solution process, the clearer it becomes that many situations have their own typical characteristics. The above list is intended to serve only as a general typology. In particular problems, other characteristics may also play a role. For instance, this is the case when we discuss interactive procedures (Chapter 5) and capital budgeting problems (Chapter 8).

3.4. A General Overview of Available Methods

Many overviews of available multiple criteria decision methods have been published (see e.g. Hwang and Masud [1979], MacCrimmon [1973], Nijkamp and Spronk [1979a,1980], Rietveld [1980], Roy [1971,1977], Starr and Zeleny [1977], and Zionts [1979]. With the aid of the list of problem characteristics described in the preceding section, the set of available methods may be subdivided in several ways. The general overview in this section (as well as the more specific overview in the next section) is based on the main operational options (see also Roy [1977]) which can be chosen by the analyst. These options are defined as the main approaches to transform the input data into the desired type of output. In a particular decision situation, the choice of such an option thus depends on the type of input data available and on the type of output desired by the decision maker. We will distinguish between the following options:

(1) Help to clarify and to structure the decision situation.
(2) Reduce the set of alternatives on basis of very obvious *a priori* information.
(3) Collect *a priori* information about the decision maker's preferences. Use this information to reduce and to (partially) order the set of alternatives. Accept the fact that the

decision maker may judge different actions as incomparable and that his preferences might be intransitive.

(4) Collect sufficient *a priori* information about the decision maker's preferences to be able to (completely) order the set of alternatives and to deduct an (optimal) final solution. Do not provide for incomparability and intransitivity.

(5) Confront successively the decision maker with compromise solutions. Collect the decision maker's (local) preferences with respect to such a compromise solution and use this information to calculate a new compromise solution. The decision maker thus progressively articulates part of his preferences while searching for a best compromise solution.

Several combinations of the above options do exist. To mention a few examples, (1) may come prior to any of the other options but it may also be integrated in and result from the other options; (2) and (5) are often integrated; and (5) may be used to reduce the number of alternative actions to be evaluated by means of attitude (4).

Within each operational option, one can, as in Section 3.3, distinguish between deterministic and stochastic methods dealing with explicitly or implicitly given constraints, etc. Below, we give a general description of each option, together with an indication of the kind of methods which are typical for these options.

(1) Clarification of the decision situation

In general, the proclaimed purpose of multiple criteria decision methods is to assist the decision maker in choosing a suitable action or set of actions. Nevertheless, these methods may also help the decision maker to clarify his perception of the decision situation. In close co-operation with the decision maker, the analyst tries to learn which alternative actions do exist, how the decision maker's preferences look, and how these preferences relate to the actions. All these questions improve the decision maker's understanding of the decision problem. In this respect, multiple criteria decision methods are not principally different from other normative methods. However, the fact that multiple criteria decision methods explicitly take account of multiple and mutually conflicting goal variables, defined by one and sometimes more decision makers, raises some additional problems. Decision makers do not necessarily know exactly what they want, and even if so, they may not always be willing to express their desires. If more decision makers and/or other participants are involved, it may be very difficult to estimate the interpersonal relationships which might influence the decision situation (cf. Patton [1978, Chs. 6 and 7]). Thus far, the theory of multiple criteria decision making has paid relatively little attention to these problems. Although a wide body of literature on the psychological and organizational aspects of decision making does exist, many of the reported results from these fields have never, or seldom been used in normative multiple criteria decision methods. This may be one reason why some of these - and other normative methods - have never been, and probably never will be used in practice. Fortunately, more and more attention is being paid to the psychological and organizational side of normative decision making (cf. Moscarola [1979] and Roy [1977]).

Very few methods and procedures especially intended to help clarify the decision maker's image of the decision situation exist apart from the more general 'clarification methods' already mentioned in Section 3.2. For example, one procedure is to give a spatial representation of the alternative actions which may be useful e.g. in location problems with multiple goals. This procedure was used in a highway location problem. Alternative routes were proposed, respectively characterized by minimum costs for construction, maximum scenic attractiveness, minimum disruptiveness, and so forth. These and the subsequent compromise locations were shown on transparencies (see Manheim [1966]).

(2) Reduction of the set of alternatives.

In many decision situations at least some elementary *a priori* information is available. Even if this information is very simple, it can often be used beneficially in multiple criteria decision situations. With the help of an everyday example, we will show how simple information can be used to reduce the number of alternatives to be evaluated by the decision maker. Let us assume a decision maker, who has to select a new truck. One example of very simple information may be that the decision maker wants a truck of about the correct size, i.e. (in his words) that its length should be 20 - 25 feet and 7 - 9 feet in width. Obviously, the set of available alternatives can be reduced drastically by formulating constraints on the size of the truck to be bought. In fact, formulating constraints is one of the oldest and most straightforward ways to reduce the number of alternatives to be evaluated by the decision maker. Constraints may be of different types, i.e. they may be conjunctive, which means that the alternatives have to satisfy all constraints, as for example in linear programming, or they may be disjunctive, which means that every alternative has to meet at least one of a series of constraints: 'We generally accept a proposal for an expansion investment if it has excellent sales expectations or if it removes important bottlenecks in the production process'. Continuing our earlier example, the decision maker might have given the additional information, that his truck must be as cheap and as powerful as possible. With the help of this information, the efficiency-concept (cf. Section 3.1) may help to reduce the number of alternatives to be evaluated in more detail. Given a set of trucks which only differ with respect to price and power, all trucks which are non-efficient, and thus dominated by other trucks, do not have to be evaluated further by our decision maker. The efficiency-concept has proved to be extremely useful, especially in relation to multiple objective programming methods (see for instance Gal [1977], and Yu and Zeleny [1975]).

(3) Partial ordering of the set of alternatives

In this option, which has been developed and promoted by a.o. Roy (see e.g. Roy [1977]), the analyst only models 'those preferences he is capable of establishing objectively and with sufficient reliability' (ibid, p. 200). In doing so, incomparability of alternatives and intransitivities of preference relations are not excluded. Roy starts with the 'fundamental partial comparability axiom', which states that the preferences for every two potential actions α and α' can be modelled by exactly one of the following relations: (a) indifference, which is reflexive and symmetric, (b) strict preference, which is irreflexive and antisymmetric, (c) large preference, which is also irreflexive and antisymmetric, and (d) incomparability, which is irreflexive and symmetric. Thus, in contrast to utility theory (see option (4)), this approach explicitly includes incomparability and large preference. The latter is defined as the case in which one of two actions is not strictly preferred to the other, although it is impossible to say whether this other action is strictly preferable or whether indifference holds. Given these concepts, Roy introduced the notion of outranking relation. A potential action α' outranks the potential action α if the analyst has enough reasons' ... to admit that in the eyes of the decision maker α' is at least as good as α...'. Action α' does not outrank α if'... the arguments in favor of the outranking proposition are judged insufficient' (in this case α is either incomparable with or preferred to α'). To include the case in which the analyst hesitates to either accept or reject an outranking relation, the latter notion can be extended to that of a fuzzy outranking relation (see Roy [1977]), in which the degree of credibility of a certain outranking relation can be expressed by means of a number $d(\alpha,\alpha')$, $0 \leq d \leq 1$. Several techniques to establish the outranking relations are discussed by the same author, who also shows how the relations can be used (a) to help to choose a best action, (b) to subdivide the set of actions in a subset of 'good' actions, a set of 'bad' actions, and a set of actions which are to be examined in more detail and (c) to help rank the actions in decreasing order of preference. All of the procedures are operational (known by the names ELECTRE I, II, III) and have found various applications, especially in the French-speaking world (see Roy [Ibid] for more references).

(4) Complete ordering of the set of alternatives

This option underlies most of the existing normative decision methods. The usual way to proceed is (in very simply-fied terms) to model the decision alternatives and the decision maker's preferences first, and next to calculate the 'optimal' solution. This 'classical' option has also been chosen in several approaches to multiple criteria decision making. Given the *a priori* information (or 'model') of the decision maker's preferences, several ways to calculate the final solution exist. One may calculate an index value of each alternative action, one may maximize a preference function relating to the attributes or goal variables, one may minimize a distance function (i.e. a dispreference function) to an ideal point, or one may use other procedures. A more fundamental difference between the approaches of this class lies in the ways the decision maker's preferences are modelled.

One approach to this modelling problem is to infer the decision maker's preferences from past decisions. Provided that the decision problem is sufficiently repetitive, data concerning past decisions and the corresponding attribute values can be used as inputs for an extrapolation procedure as for instance linear regression and related techniques (see e.g. Dawes [1971] and Slovic and Lichtenstein [1971]). Surprisingly, even very simple models of the decision maker's preferences often give very good predictions of the decision maker's choices in new situations.

Another way to model the decision maker's preferences is based on direct questioning. For the case in which there is a number of explicitly given alternatives, the outcomes of which are random variables, the utility theory developed by von Neumann and Morgenstern [1953] has been extended explicitly to a 'multiple attribute utility theory'. Surveys and theoretical details are given a.o. by Farquhar [1977], Fishburn [1978], and Keeney and Raiffa [1976]. Once the probability distributions and the utility function have been assessed, the most preferred action can be calculated using the customary techniques. Consequently, most attention has been paid to the techniques of obtaining information about probabilities and utilities from the decision maker. The multiple attribute utility approach has a firm theoretical basis and is therefore very attractive. An important axiom underlying multiple attribute utility theory is that the decision maker's preferences with respect to any pair of potential actions α and α' can be modelled by means of the indifference or the strict preference relation mentioned under (3) above, which moreover are assumed to be transitivity relations. As argued by Roy [1977] a.o., these assumptions are rather strong. Since this approach is moreover very demanding for the decision maker, it can at best be used only in very important decisions, with a limited number of mutually comparable and well-defined decision alternatives playing a role.

(5) Sequential articulation of preferences

Instead of requiring all preference information from the decision maker prior to calculating the desired solution (or set of solutions), many procedures gather this information in a stepwise and iterative manner. As suggested by an overview of 'sequential elimination methods' (cf. MacCrimmon [1973]), decision makers in practice do often decide in a stepwise and iterative way. This phenomenon has been formalized within the so-called interactive procedures, which operate in an iterative fashion from one solution (or set of solutions) to another, guided by the local (i.e. given the current solution) preferences of the decision maker. Compared with approaches (3) and (4), the interactive procedures need much less *a priori* information on the decision maker's preferences. Moreover, the decision maker becomes more closely involved in the solution process which may induce important learning effects. Interactive procedures have been developed both for problems with explicitly and implicitly given alternatives. Chapter 5 will be completely devoted to a general discussion and overview of interactive procedures.

3.5. An Overview of Multiple Objective Programming Methods

In this section we present an overview of the class of multiple criteria decision methods dealing with implicitly given alternatives (see Section 3.3). These methods are generally based on mathematical programming methods and are therefore often called multiple objective programming methods. In the present study we limit ourselves to this class of methods and to their applications in capital budgeting and financial planning. Note that in case alternative capital investment projects, budgets or financial plans have been described explicitly, they can quite easily be adopted in a programming framework. Nevertheless, if only a limited number of explicitly given alternatives is relevant, the role of programming methods may become less important.

Multiple objective programming methods can be classified along the same lines as followed in the preceding section for the more general classification of multiple criteria decision methods: i.e.

by means of the operational options chosen by the analyst, although one of them (the partial ordering approach) is not found in multiple objective programming. The other operational options exist in multiple objective programming and will be discussed next.

(1) Clarification of trade-offs

In single objective programming, the calculation of the optimal solution is generally not considered to be the only answer to be submitted by the analyst. A presumably more important question to be answered is what happens if the values of the instrumental variables differ slightly from their 'optimal' values, or what happens if the availability of resources changes. These questions are generally tackled by means of sensitivity analysis, for which many methods offer a well-developed analytical apparatus. As observed by several authors, this apparatus can be very helpful in clarifying multiple criteria decision situations. One straightforward way is to optimize only one goal variable, subject to constraints on the values of the goal variables which are not optimized. A subsequent sensitivity analysis can then be used to clarify the trade-offs between the various goal variables. For the linear case, this line of thought has been elaborated by Gal [1979] and Gal and Nemoda [1972].

(2) Reduction of the set of alternatives on the basis of elementary *a priori* information

Obviously, if threshold values of certain goal variables are stated *a priori*, these can be formalized quite easily by means of 'hard' constraints in multiple objective programming models. Because these constraints co-determine the feasible region, one should verify whether the decision maker is certain about the goal values which are formulated as 'hard' constraints. That is, goal values which are formulated as 'hard' constraints, have absolute priority over all the other goal variables. Therefore, it is often preferable to formulate desired goal values as goal constraints (see Section 3.1).

As mentioned in the preceding section, the efficiency concept has proved to be very useful in multiple objective programming methods. The body of literature relating to the properties of the efficient set under different assumptions about the feasible region and the nature of the goal variables is rapidly growing. Moreover, for different problems, procedures have been developed to find all elements of the efficient set or to find a well-defined subset of this efficient set.

(3) Reduction of the set of alternatives by means of (partial) orderings

Thus far, this operational option has not been pursued in multiple objective programming methods, although some starting points might be found in the 'fuzzy multiple objective programming techniques' discussed by Zimmerman [1978], in which goal variables and constraints are characterized by their membership functions.

(4) Collection of sufficient *a priori* information to reach an optimal solution

Many multiple objective programming methods assume the availability of sufficient *a priori* preference information to reach an optimal solution, given the set of feasible actions. They do not deal as such with the collection of this information, but rather with using it to calculate the optimal solution given the preference information. The calculation of the optimal solution can be accomplished along one of the following lines:

(a) *Maximization of a preference function.*

In this case it is assumed that the whole vector of relevant goal variables can be translated into an unambiguous scalar-valued preference function by means of a weighing procedure. The most straightforward weighing procedure is the linear one, i.e. the preference function is a linear combination of the (possibly standardized) goal variables.

(b) *Minimization of deviations from targets.*
Here it is assumed that the decision maker has specified certain aspiration or target values of the goal variables. Discrepancies between the actual goal values and the target values are penalized by a dispreference or penalty function which is also to be specified by the decision maker. Well-known examples are the quadratic penalty function approach (see among others Theil [1968]) and goal programming. Both approaches are attractive because of the use of aspiration levels which are not uncommon in practice (cf. Chapter 2). Among these two methods, goal programming is most attractive because it is more flexible than the other approach with respect to the nature of the preference functions that can be incorporated, and moreover is much easier to use. We return to these approaches in greater detail in Chapter 4.

(c) *Minimization of deviations from ideal solution(s).*
In this third approach, an ideal point (as defined in Section 3.1) is calculated after which a dispreference function (again to be specified by the decision maker) is minimized. This approach is often imbedded in interactive approaches. We will return to them later.

(5) <u>Sequential articulation of preferences</u>

This option can also be adopted within a multiple objective programming framework. Especially, many interactive procedures have been developed. Chapter 5 will be devoted to these interactive multiple objective programming methods because, in our view, they constitute very promising tools for solving multiple objective programming problems. In Chapter 6 we present our own interactive multiple objective programming method.

3.6. Conclusion

Normative decision methods are not only useful in helping the decision maker to choose a suitable action but may also improve his way of viewing the decision situation. Normative decision methods may be better accepted by the decision maker if the underlying assumptions do not go too far beyond the decision maker's reality. For this reason we seek methods that are able to include multiple, conflicting goal variables. Many multiple criteria decision methods have been developed for many kinds of decision situations. With the set of characteristics described in Section 3.3 one might check for which decision situation(s) a particular method is suited. In our opinion, five different (although not mutually exclusive) operational options for the multiple criteria decision problem can be distinguished. These options are described in Section 3.4.

In the remainder of this study we restrict ourselves to those decision problems which can be translated as multiple objective programming methods. Within this class we attempt to combine the advantages of goal programming (see Chapter 4), with the advantages of interactive procedures (see Chapter 5). Goal programming closely corresponds with decision making in practice, but requires a fair amount of *a priori* information about the decision maker's preferences. By means of interactive procedures, the decision maker becomes more closely involved in the solution process while demanding relatively little *a priori* information.

The new method, Interactive Multiple Goal Programming, is described in Chapter 6 and illustrated in Chapter 7. Its merits for capital budgeting and financial planning with multiple goals are discussed and illustrated in Chapters 8 and 9.

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