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A Combinatorial Assessment Methodology for Complex Transport Policy Analysis

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ABSTRACT

This paper proposes an integrated evaluation methodology which serves to alleviate the limitations of a single evaluation approach by offering a synthesis framework combining different assessment and policy analysis methods. It is demonstrated that, in a multi-criteria context, a so-called combinatorial framework can cope with the serious limitations of the above mentioned approach, in particular the potential redundancy in the information table and the subjectivity of the 'expert' in the weight choice procedure. We illustrate our point by using rough set analysis as a tool for classifying and identifying the most critical decision attributes, while next a multi-criteria approach is deployed in combination with other methods. We apply this new combinatorial assessment methodology to an illustrative case study on transportation planning, where the core assessment methodology is formed by a combined qualitative-quantitative Regime analysis, extended with complementary approaches. The results of the analysis indicate that the combinatorial method indeed has the flexibility and capacity to assess complex multidimensional policy issues.

Keywords: Multi-criteria, rough set analysis, transport policy.

1. THE CONTEXT OF DECISION-MAKING

Decision-making is not a one-shot activity, but part of a choice process in which choice possibilities, relevant criteria and urgency of choices gradually become more clear (a so-called decision trajectory). In the reality of actual policy analysis we observe that decision-making is less often based on information engineering methods and more on compliance with legal procedures or regulatory frameworks. Consequently, in many choice situations – especially in those within the public domain – we observe a tendency to suppress straightforward optimisation behaviour and instead to favour 'satisficing' or compromise modes of planning (see also [1, 2]). In more recent contributions to policy analysis we observe an even lower level of ambition, that is, accountability behaviour or negotiation behaviour. In the latter case the question is whether a decision can be rationally justified or whether it generates sufficient support from various stakeholders with different interests. This also implies that transparency, simplicity and accountability are often necessary ingredients for an effective and scrupulous policy assessment methodology. Consequently, the institutional context of decision-making is of critical importance for a successful implementation of a policy choice emerging from a decision support system. The role of the expert then seems to shift from a professional who knows best to a moderator who scientifically guides a complex choice problem. Complexity in decision-making not only refers to the degree of information uncertainty or choice options related to the strategic behaviour of stakeholders, but also to the varied choice set of assessment methodologies.

When browsing through the literature pertaining to the problem of assessment methods, we find a variety of approaches (see e.g., [3]). We often find approaches which contrast rather than complement each other, for example in conventional cost-benefit analysis versus qualitative multi-criteria methods or Bayesian decision theory versus prospect theory. Although this situation has positively encouraged widespread research on a 'best method' for decision processes, such contrasting characteristics of meta-research on proper assessment methods have, at times, also created opposing and even dogmatic schools of thought.

This paper aims to overcome such contrasting standpoints by proposing a synthesis framework. In the light of recent studies on theoretical aspects of reasoning about data [4, 5], we assume that no single method is exhaustive per se; different assessment methods can be combined to overcome the limitations of the singular methods with the aim to design more flexible evaluation methods. The methodology therefore combines different assessment methods within the same

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framework in relation to a given evaluation problem. We call this assessment procedure a *combinatorial assessment methodology*.

Our attempt in the first part of the paper is to investigate the methodological characteristics of this approach in relation to the more standard means of assessment method selection. In the second part we focus on multi-criteria decision processes. When we wish to utilise a multi-criteria method, we may encounter limitations posed by the subjectivity of the 'expert' when defining alternative weights. In particular, we focus on two main limitations inherent to the subjectivity of the experts. First, in a multi-criteria decision setting, we may encounter a wide variety of different data; this is because the method is designed to handle quantitative as well as qualitative information. But in the case of a large data matrix, there is the risk that part of the same information is often incorporated in more than one attribute. We therefore need a tool that allows us to reduce redundant information.

The second limitation we are considering within multi-criteria methods is the necessity to define various relevant weights for each relevant policy criterion. The procedure of the weight definition is conducted by decision-makers or 'experts.' The subjectivity of this procedure has raised a number of doubts about multi-criteria methods. Our second endeavour in this paper is to address this problem by proposing a framework that allows for accountability.

In the final section we examine an example of transport policy assessment where the newly developed combinatorial methodology is applied to solve the problems emphasised above. Transport policy decisions should not only reflect the functional aspect of a transport system, but also consider economic, social and environmental impacts of transport. This frequent plethora of variables within a multi-faceted evaluation analysis can render the decision assessment very complex. For example, we may have an overwhelming amount of information on a transport problem due to the existence of both quantitative and qualitative data of multiple attributes of a transport system. The complexity of the transport decision problem requires the decision-maker to maintain the consistency of a decision and thus to reduce the subjectivity of the weight decisions. Such a consistency of a decision is an important element if we consider, for instance, European transport policy assessment, where policy decisions must be enforced in different spatial contexts and with different transport modes, as exemplified at present in the Trans-European Network (TEN) plans.

2. COMBINATORIAL ASSESSMENT METHODOLOGY

If the choice of the assessment method which the decision-maker wants to apply is paramount for the entire assessment procedure, this choice must be guided by the problem and the data we are considering. However, often the methodology choice is done prior to the given problem, from the literature we can identify two different selection approaches [6] (see Table 1). The combinatorial assessment methodology that we are here proposing is represented by the third approach. We compare in Table 1 how these three methods – in four successive steps – determine different selection processes in an assessment procedure.

Depending on the evaluation problem, in the first approach (the Procrustus method), the decision-maker chooses which assessment method will be applied to the specific problem. Such a choice can be completely arbitrary and based upon subjective criteria of the decision-maker such as background experience or inert behaviour. At this point it becomes necessary for the analyst to adjust the problem, particularly the data set, to the chosen assessment method. If the chosen assessment method is a cost-benefit analysis, all data must be expressed in monetary terms; if the selected method is a Regime method, the data must have cardinal or ordinal values. The final step is then the evaluation of the problem. This method is often applied in cost-benefit analysis without due attention to the reliability of the database at hand.

In the second approach, the selection method, the decision-maker, given the actual choice problem, first defines the typology of the problem and then selects the evaluation method. In the definition of the type of the evaluation problem, the decision-maker examines the data set and the objective of the evaluation problem and can then easily select the most suitable evaluation method. In this case we avoid the problems of the subjective use of a given method and the consequent manipulation of the data set in approach A. But in the second approach we are faced with a

Table 1. A typology of methods of selection approach.

Methods	First step	Second step	Third step	Fourth step
Procrustus method	Specific project evaluation problem	Selection of evaluation method	Adjustment of problem specification	Evaluation
Selection method	Specific project evaluation problem	Typology of specific evaluation problems	Elimination and selection of evaluation methods	Evaluation
Combinatorial method	Specific project evaluation problem	Typology of specific evaluation problems	Adjustment and selection of evaluation methods	Evaluation

potentially fixed procedure in the selection of the assessment method. By this we mean that, for different problems, the decision-maker may be tempted to use the same heuristic rules for identifying a proper assessment method. This typology of approach is often used in multi-criteria assessment methods.

The procedure we have called *combinatorial assessment methodology* is based upon the combinatorial method that, in contrast to the previous approaches, identifies which combination of various assessment methods can more appropriately solve an evaluation problem. After having analysed the typology of the problem, we need to analyse the difficulties we may encounter during the evaluation process. Such an examination will be able to identify the most suitable combination of methods which have to operate in a complementary way.

In the case of transport policy assessment we have seen that two primary obstacles may arise. There is the variety of available data describing the problem and the necessity for the decision-maker to reach a consistent decision about identical problems over time. Both dilemmas can, in principle, be overcome by analysing the data by means of rough set analysis see [4, 7, 8].

Rough set analysis can classify and then reduce the data available and may also – in some software versions – indicate the degree of dependency among the attributes. Such a feature is relevant if we want to use a Regime method because the different degrees of dependency are here considered in order to evaluate the weights of the attributes and reduce the effect of subjectivity in the weight decisions. A simpler procedure is to apply cost-benefit analysis in which we may encounter some subjectivity effect in the decision of the discount parameter. The discount parameter decision can take into account the results of rough set analysis by treating the data table as a logical tool (see [9] for a detailed discussion).

Additionally, given the results obtained by either a Regime analysis or a cost-benefit analysis, we are able with rough set analysis to re-examine these results obtained and identify the specific ranges of values the representative parameters must have in order to obtain these decisions. With this procedure rough set analysis helps us universalise the decisions. In other words, rough set analysis from the specific results we have obtained is able, through the "inference rule," to identify a general set of decision algorithms/rules which the decision-maker can use in other case studies.

We can summarise the previous arguments by deploying the general Figure 1.

We observe that our combinatorial assessment methodology offers a generic framework which, depending on the evaluation problem at hand, combines existing assessment methods that are well suited – both methodologically and functionally – for solving the evaluation problem. The following schema describes the assessment process discussed throughout our analysis. The assessment procedure is composed of five steps depicted by five diamond shapes, whereas the assessment methodologies are identified by the three rectangles. We emphasise that this schema is illustrative only for the type of synthesis we are striving towards. Instead of rough set analysis, one might e.g., also

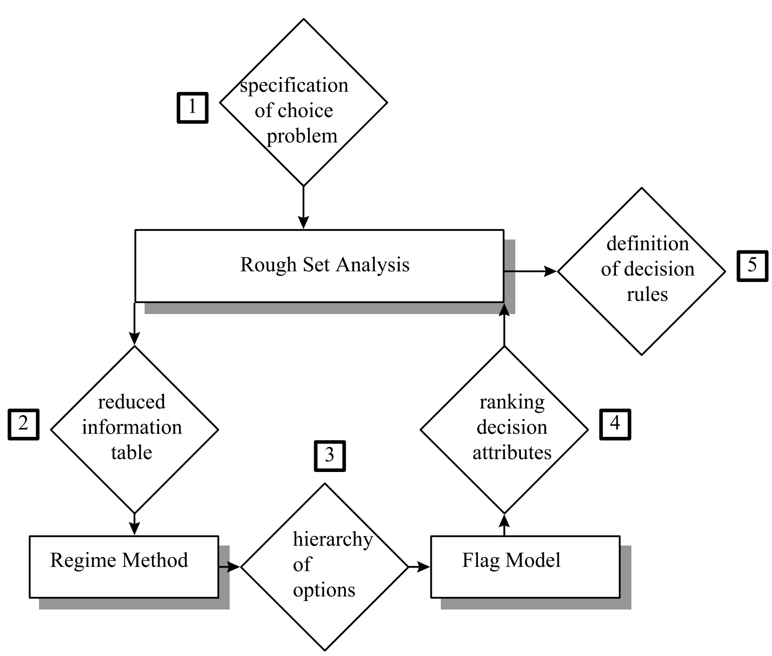

Fig. 1. Assessment process using the combinatorial method.

use fuzzy set analysis, or instead of the Regime method, one might also use a concordance method.

Rather than adjust the data set to the chosen method, in our approach we adjust and select the assessment method in relation to the specific data and objectives. Against this background, the organisation of the paper is as follows. We begin with an introduction of rough set analysis, followed by an illustrative example from transportation planning, in which Regime analysis and the recently developed flag model also play a role as complementary building blocks. We then demonstrate how these methods can be combined to obtain a useful result.

3. DECISION SUPPORT: ROUGH SET ANALYSIS

Rough set analysis is one of the new mathematical tools designed to investigate the meaning of knowledge and the representation of knowledge, i.e., to organise and classify data (see Appendix). It is evident that such a method is very useful in the analysis of assessment problems. The data from which a decision-maker determines an evaluation are often disorganised, or they contain useless details, or are incomplete and vague. This type of data does not represent structured and systematic knowledge.

Knowledge, according to the rough set philosophy, is generated when we are able to define a classification of relevant objects, e.g., states, processes, events. By doing this we divide and cluster objects within the same pattern classes. These classes are the building blocks (granules, atoms) of the knowledge we employ to define the basic concepts used in rough set analysis. But how can we tackle the problem of imprecision which occurs when the granules of knowledge can be expressed only vaguely? "In the rough sets theory each imprecise concept is replaced by a pair of precise concepts called its lower and upper approximation; the lower approximation of a concept consists of all objects which surely belong to the concept whereas the upper approximation of the concept consists of all objects which possibly belong to the concept in question" [7].

By using the lower and upper approximation we address the problem of vague information but in particular, we focus on the problem of dependency and the relationship among attributes. A crucial aspect in the assessment process is the necessity to distinguish between the conditions through which we make a decision and the attributes that describe the various options. The rough set analysis can examine on one hand the dependencies among attributes, but on the other hand can also describe the considered objects in terms of available attributes in order to find essential differences among objects. This latter analysis, which represents the Knowledge Representation Systems or dissimilarity analysis, assumes a relevant role in many decision-making processes wherein it is necessary to indicate the differences among the possible options in order to eliminate superfluous information for a proper decision choice. In the next section we will depict an application of rough set dissimilarity analysis for transport policy assessment.

Another point previously raised was the necessity for the decision-maker to maintain a coherent evaluation process. Also here, rough set analysis can give such a support to the decision-maker. The rough set approach simplifies the original data matrix and decision table in order to define the decision algorithms or decision rules through a minimal set of attributes. The definition of minimal decision algorithms associated with a decision table is one of the standard problems of artificial intelligence, but rough set analysis – compared to other methods [10, 11, 16] – addresses the decision rule generation with fast computer algorithms and has a solid foundation of real-life applications in various fields [8, 9, 12].

Another crucial feature we need to stress is the capacity for rough set analysis to operate mainly with data in tabular form. This characteristic is very important in our context where decision problems are often defined through a matrix table of data. The tabular notation is not only more clear than the logical notation adopted by other methods of analysis, but more importantly, this data structure is easier to revise for computer implementation and logical formulation in, for example, the case of the inference rule [4].

In the next section we will demonstrate how rough set analysis as an analytical tool can play a significant role in solving an assessment problem in order to manipulate and transform data into decisions, while also being able to combine the results with other evaluation methods.

4. ASSESSMENT OF TRANSPORT POLICY: AN ILLUSTRATIVE CASE STUDY

In this section we illustrate an application of our combinatorial assessment methodology for a transport policy decision. Some critics might observe that we are contradicting our original idea of assessment analysis, that is, to decide the assessment method in relation to the given data and problem. Notwithstanding, this example depicts the capacities of the methodology, and thus is based upon a very simple setting in order for the reader to follow the decision process perhaps with paper and pen. Let us suppose that we need to introduce a new transport mode in an existing transport network. We have five different transport mode options and five attributes which describe the modes of transport (Table 2). We observe that the information data is a qualitative matrix. A suitable assessment method in this case is a qualitative multi-criteria method such as the Regime analysis, which is able to handle discrete or ordinal classes [3]. Let us assume here that for the time being we do not know the weight values for the attributes of the transport mode options.

Table 2. Data table of a transport assessment problem.

Options	Attributes				
Transport mode	Cost	Environmental Impact	Size	Max-Speed	Logistic Integration
Mode 1	Medium	Good	Small	High	Excellent
Mode 2	Medium	Poor	Medium	High	Poor
Mode 3	Low	Good	Large	Medium	Good
Mode 4	Medium	Excellent	Medium	Low	Good
Mode 5	High	Good	Large	Low	Good

To solve this type of problem we can examine the information table through a dissimilarity analysis. In the previous section we have seen that rough set analysis is able to operate a dissimilarity analysis; therefore, let us now turn to Table 2. For a simplification of notation, we replace Table 2 first by a coded information table where the values of attributes are coded in the following way:

$V_{cost} = \{$low (+), medium (0), high (−)$\}$;
$V_{env.\ imp.} = \{$poor (−), medium (0), excellent (+)$\}$;
$V_{size} = \{$small (−), medium (0), large (+)$\}$;
$V_{max\text{-}speed} = \{$low (−), medium (0), high (+)$\}$;
$V_{logistic} = \{$poor (−), good (0), excellent (+)$\}$.

Table 2 can now be expressed in the reduced coded form as follows (see Table 3):

Clearly, **a** refers to Cost, **b** to Environmental Impact, **c** to Size, **d** to Max-Speed, and **e** to Logistic Integration.

The first noteworthy characteristic of Table 3 is that each row is different. This means that each transport mode is identified by a unique set of the given features. By analysing this information matrix (Table 3), we can determine which of the features of the five transport modes are dependent on the other mode characteristics and therefore we are able to eliminate unnecessary attributes from the decision analysis. After five computations of the attribute reductions, we obtain the result that the core attributes are framed by the set {a, b}, and that the two sets of reduced attributes, i.e. {a, b, c} and {a, b, e}, are consistent and independent. We can summarise our results in the following logical statements:

$$\{a, b, c\} \Rightarrow \{d, e\} \text{ and } \{a, b, e\} \Rightarrow \{d, c\}$$

These logic dependencies tell us that attributes a (Cost) and b (Environmental Impact) must always be considered when tackling this transport mode evaluation problem. The attributes c (Size) and d (Max-Speed) can be mutually replaced, and attribute e (Logistic Integration) depends on the remaining set of attributes. We can use this information to observe that, attributes a and b, since they must be considered in every evaluation, are more important than attributes c and d, and consequently of attribute e. We can then determine a hierarchical relationship among the attributes.

We are now able to utilise this information about the dependency relations among the attributes when we define the weights of the attributes in the Regime method (see Appendix). For instance, attributes a and b are considered more important than attributes c and d, but have equal weights, i.e. equal importance, when compared to each other. Attribute e is the least important of all the attributes.

For the Regime method we need to re-define Table 3 by considering an ordinal codification that corresponds to the objectives of the decision problem as shown below:

$V_{cost} = \{$low (3), medium (2), high (1)$\}$;
$V_{env.\ imp.} = \{$poor (1), good (2), excellent (3)$\}$;
$V_{size} = \{$small (1), medium (2), large (3)$\}$;
$V_{max\text{-}speed} = \{$low (1), medium (2), high (3)$\}$;
$V_{logistic} = \{$poor (1), good (2), excellent (3)$\}$.

Table 3 can now be reformulated as follows (Table 4):

A Regime method gives a quantitative performance score of each of the alternatives envisaged. When we run the Regime analysis we obtain the following final results:

Table 3. Coded information table.

Options	Attributes				
Transport mode	**a**	**b**	**c**	**d**	**e**
Mode 1	0	0	−	+	+
Mode 2	0	−	0	+	−
Mode 3	+	0	+	0	0
Mode 4	0	+	0	−	0
Mode 5	−	0	+	−	0

Table 4. Ordinal information table.

Options	Attributes				
Transport mode	Cost	Environment Impact	Size	Max-Speed	Logistic Integration
Mode 1	2	2	1	3	3
Mode 2	2	1	2	3	1
Mode 3	3	2	3	2	2
Mode 4	2	3	2	1	2
Mode 5	1	2	3	1	2

Table 5. Results from the Regime analysis.

Rank 1	Mode 3	0.823
Rank 2	Mode 4	0.749
Rank 3	Mode 1	0.501
Rank 4	Mode 5	0.278
Rank 5	Mode 2	0.102

Table 6. Results of the Regime analysis and the flag model.

Rank 1	Mode 3	0.823	accepted
Rank 2	Mode 4	0.749	accepted
Rank 3	Mode 1	0.501	neutral
Rank 4	Mode 5	0.278	neutral
Rank 5	Mode 2	0.102	rejected

The results of the Regime analysis tell us that mode 3 is the most preferable in relation to the attributes and that the worst transport mode is mode 2. The Regime analysis thus ranks the options of the choice from the best to the worst.

Let us now compare this analysis with the flag model analysis [13]. The flag model is a simple assessment method able to indicate the set of most suitable decisions according to the attributes of the options (see Appendix). It uses critical threshold values to eliminate inferior or less acceptable choice possibilities. In this case the flag model gives us the same rank as the Regime method (Table 5), but in addition we can assume to subdivide the rank according to the flag model into *accepted decisions, neutral decisions* and *rejected decisions* (Table 6). These three clusters are defined within the methods by using critical threshold values. These threshold values represent the reference system for judging the different decisions as given by the experts. We estimate a band of values of thresholds ranging from a maximum value (CTV_{max}) to a minimum value (CTV_{min}). We finally obtain the following subdivision of our choice options on the basis of a screening analysis related to our combinatorial framework.

We can universalise the obtained results by defining the decision rules related with decisions ranked by the Regime analysis and flag method. To do so we need to run once more the rough set analysis which will indicate the attributes and their values to reach the obtain decisions. In Table 7 the decision attributes have been calculated by using the results of the Regime method and flag model as follows:

Table 7. Coded information table.

Options	Attributes					Decision attribute
Transport mode	Cost	Environment Impact	Size	Max-Speed	Logistic Integration	
Mode 1	2	2	1	3	3	2
Mode 2	2	1	2	3	1	3
Mode 3	3	2	3	2	2	1
Mode 4	2	3	2	1	2	1
Mode 5	1	2	3	1	2	2

decision attribute = **1** implies that the alternative is **accepted**
decision attribute = **2** implies that the alternative is **neutral**
decision attribute = **3** implies that the alternative is **rejected**

In the event that we obtain a neutral outcome of the decision attribute, we cannot express any judgment about the alternative; in other words, in that case the alternative can be accepted or rejected. In order to avoid this neutral state in this particular case, we need a more precise specification of the alternative and of the attributes.

The following information table can now be examined through rough set analysis

We obtain from the analysis that:

Rule 1	$Attr._{Cost} = 3$	$Attr._{Size} = 3$	$\Rightarrow$	**decision 1**
Rule 2	$Attr._{Env.\ Imp} = 2$	$Attr._{Size} = 3$	$\Rightarrow$	**decision 1**
Rule 3	$Attr._{Cost} = 1$		$\Rightarrow$	**decision 2**
Rule 4	$Attr._{Cost} = 2$	$Attr._{Size} = 1$	$\Rightarrow$	**decision 2**
Rule 5	$Attr._{Env.\ Imp} = 1$		$\Rightarrow$	**decision 3**

The simple algorithms in our result show the minimal set of attributes necessary for reaching the five decision rules, so that we obtain a consistent decision process which we set out to achieve.

In summary, in our case study we have demonstrated how the combination of three assessment methods (in this case a data classification method, i.e., rough set analysis combined with the Regime analysis and the flag model) can operate in a complementary way, how it can consistently reduce the limitations of each method, and how it can reinforce the validity of the assessment procedure by improving the consistency of the process.

5. CONCLUSION

In this paper we have proposed a methodology called *combinatorial assessment methodology*, which is based on the assumption that no single assessment method can be deemed as adequate in a process of decision-making, but that a combination of different methods can achieve more satisfactory results. The combination of methods must be developed within an integrated framework of analysis; that is, the various methods must follow the same methodological idea. This condition is apparently important for obtaining significant and consistent results.

We applied our methodology in the case of multi-criteria methods to choice problems in multidimensional evaluation, such as subjectivity of the experts in the weights definition and the unwieldy data matrix. We examined both problems by using the rough set analysis. Rough set analysis addresses one of the fundamental problems of the decision process: the uncertainty and imprecision of data. Through its application we have confirmed the capacity for this analytical tool to reduce some of the limitations within the multi-criteria analysis.

In the last part of the paper we examined a case study where an assessment is required for a transport planning problem. In this case, since the data are qualitative, we decided to operate with the use of three assessment methodologies: rough set analysis, Regime analysis and the flag model. We have chosen rough set analysis to reduce the redundant attributes in the information table and to define the dependence relationships among the attributes. After this step we defined the rank of decisions through a Regime analysis and compared these results with a similar analysis using the flag model. The results of both analyses appeared to be non-contradictory. Lastly, we identified the minimal set of attributes for each of the decision rules with the use of rough set analysis.

The use of our combinatorial methodology affords a higher level of flexibility for the decision-maker compared to a single assessment methodology. This flexibility and the reduced limitations of the considered assessment methods ultimately points to the combinatorial methodology as a useful strategy for evaluating complex problems in complex public policy assessment.

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APPENDIX: A CONCISE OVERVIEW OF THREE ASSESSMENT METHODS

Rough Set Analysis

The aim of the rough set analysis is to recognise possible cause-effect relationships among the available data and to underline the importance and the strategic role of some data and the irrelevance of other data [4]. The approach focuses on regularities in the data in order to draw aspects and relationships from them which are less evident, but useful in analysis and policy making.

Let us consider a finite universe of objects which we would like to examine and classify. For each object we can define a number n of attributes in order to create a significant basis for the required characterisation of the object. If the attribute is quantitative, it will be easy to define the domain for it. If the attribute is qualitative, we divide its domain into sub-intervals to obtain an accurate description of the object. We have classified our objects with the attributes, and thus for each object we associate a vector of attributes. The table containing all this organised information will be called the *information table*. From the table of information, we can immediately observe which objects share the same types of attributes. Two objects that are not the same object have an indiscernibility relation when they have the same descriptive attributes. Such a binary relation is reflexive, symmetric, and transitive.

Until now we have focused on the classification of uncertain data. Let us examine the case where we want to express a choice among different alternatives; this is most assured when we confront an assessment problem. We have previously described the *information table*, and in this table in the instance of an assessment problem, we can identify two classes from the set of attributes: a class of condition attributes and a class of attributes which are the decision attributes.

The class of condition attributes describe the object following the procedure depicted above. The class of decision attributes is defined by all the attributes the object must have in order to be selected as an acceptable alternative. For instance, a set of objects can be described by values of condition attributes, while classifications of experts are represented by values of decision attributes.

At this point we must define a decision rule as an implication relation between the description of a condition class and the description of a decision class. The decision rule can be exact or deterministic when the class of decisions is contained in the set of conditions, i.e. all the decision attributes belong to the class of the condition attributes. We have an approximate rule when more than one value of the decision attributes corresponds to the same combination of values of the condition attributes. Therefore, an exact rule offers a sufficient condition of belonging to a decision class; an approximate rule admits the possibility of this.

The decision rules and the table of information are the basic elements needed to solve multi-attribute choice and ranking problems. The binary preference relations between the decision rules and the description of the objects by means of the condition attributes determine a set of potentially acceptable actions. In order to rank such alternatives, we need to conduct a final binary comparison among the potential actions. This procedure will define the most acceptable action or alternative.

Regime Analysis

The Regime analysis is a discrete qualitative multi-criteria method [3]. The fundamental framework of multi-criteria methods is based upon two kinds of input data: an evaluation matrix and a set of political weights. The evaluation matrix is composed of elements which measure the effect of each considered alternative in relation to each considered criterion. The set of weights gives us information concerning the relative importance of criteria we want to examine. Regime analysis is an ordinal generalisation of pairwise comparison methods able to examine quantitative as well as qualitative data.

In Regime analysis, as in the concordance analysis, we compare the alternatives in relation to all the criteria in order to define the concordance index. Let us consider for example, the comparison between alternative i and alternative j to all criteria. The concordance index will be the sum of the weights which are related to the criteria for which alternative i is better than alternative j. Let us call this sum, c_{ij}. Then we calculate the concordance index for the same alternatives, but by considering the criteria for which j is better than i, i.e., c_{ji}. After having calculated these two sums, we subtract these two values to obtain the index: $\mu_{ij} = c_{ij} - c_{ji}$. Because we have only ordinal information about the weights, our interest is on the sign of the index μ_{ij}. If the sign is positive, this will indicate that alternative i is more attractive than alternative j; if negative, it will imply vice versa. We will therefore be able to rank our alternatives. We must note that due to the ordinal nature of the information, in the indicator μ no attention is given to the size of the difference between the alternatives; it is only the sign of the difference that is important.

We might nevertheless encounter another complication. We may not be able to determine an unambiguous result, i.e., rank the alternatives. This is because we confront the problem of ambiguity with the sign of the index μ. In order to solve such a problem we introduce a certain probability p_{ij} for the dominance of criteria i with respect to criteria j as follows:

$$p_{ij} = prob \quad (\mu_{ij} > 0)$$

and we define an aggregate probability measure which indicates the success score as follows:

$$p_i = \frac{1}{I-1} \sum_{j \neq i} p_{ij}$$

where I is the number of chosen alternatives.

The problem here is to assess the value of p_{ij} and of p_i. We will assume a specific probability distribution of the set of feasible weights. This assumption is based upon the criterion of Laplace in the case of decision-making under uncertainty. In the case of probability distribution of qualitative information, it is sufficient to mention that in principle, the use of stochastic analysis, which is consistent with an originally ordinal data set, may help overcome the methodological problem we can encounter by conducting a numerical operation on qualitative data.

The Regime method then identifies the feasible area in which values of the feasible weights w_i must fall in order to be compatible with the condition by the probability value. By means of a random generator, numerous values of weights can be calculated. This allows us at the end to calculate the probability score (or success score) p_i for each alternative i. We can then determine an unambiguous solution and rank the alternatives.

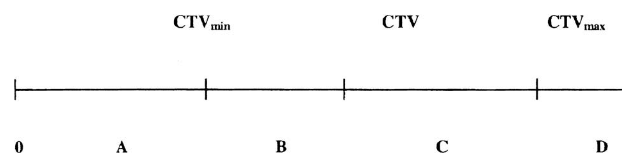
Flag Model

In order to define a normative approach of the concept of sustainability, one requires a framework of analysis and of expert judgment which should be able to test actual and future states of the economy and the environment against a set of reference values. The Flag model has been defined to assess the degree of sustainability of values of policy alternatives [14, 15]. The model develops an operational description and definition of the concept of sustainable development. There are three important components of the model:

1. identifying a set of measurable sustainability indicators;
2. establishing a set of normative reference values;
3. developing a practical methodology for assessing future development.

The input of the program is an impact matrix with a number *n* of variables; the matrix is formed by the values that the variables assume for each considered scenario. Such values are defined by unpartisan experts. The main purpose of the model is to analyse whether one or more scenarios can be classified as sustainable or not; such an evaluation is based upon the indicators. The methodology therefore requires the identification and definition of indicators. Such indicators in the program have two formal attributes: class and type. There are three classes of indicators which correspond to the main dimensions of the sustainability analysis: (1) biophysical, (2) social, and (3) economic. The second attribute, type, relates to the point that some indicators such as water quality, have high scores showing a sustainable situation; while for others such as the pollution indicator, we have low scores which are sustainable as well. This difference is captured in the attribute type of the indicator; the first types are defined as *benefit indicators*, the second types are *cost indicators*.

For each sustainable indicator we have to define the critical threshold values. These values represent the reference system for judging actual states or future outcomes of scenario experiments. Since in certain areas and under certain circumstances experts and decision-makers may have conflicting views on the precise level of the acceptable threshold values, we estimate a band of values of the thresholds ranging from a maximum value (CTV_{max}) to a minimum value (CTV_{min}). This can be represented as follows:



Section A	Green Flag	No reason for specific concern
Section B	Orange Flag	Be very alert
Section C	Red Flag	Reverse trends
Section D	Black Flag	Stop further growth

The third component of the model, the impact assessment, provides a number of instruments for the analysis of the sustainability issue. This analysis can be carried out in two ways. The first is an inspection of a single strategy. The second is the comparison of two scenarios. In the former procedure we decide whether the scenario is sustainable or not. In the latter case by comparing the scenarios, we decide which scenario scores best wherever this question is centred around the sustainability issue. This option may be interpreted as a basic form of multi-criteria analysis.