A COMBINATORIAL ASSESSMENT METHODOLOGY FOR COMPLEX 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 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 use rough set analysis as a tool for classifying and identifying the most critical decision attributes, while next a multi-criteria analysis 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.

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. In the reality of actual policy analysis we observe that decision-making is based less on information engineering 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 Simon, 1960; Mintzberg, 1979). In more recent contributions to policy analysis we observe an even lower level of ambition, viz. 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. This also implies that transparency, simplicity and accountability are often necessary ingredients for a policy assessment methodology. Consequently, the institutional context of decision-making is of critical importance for a successful implementation of a policy choice. The role of the expert seems then 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 information uncertainty or the strategic behaviour of stakeholders, but also to the choice of assessment methodology.

 When browsing through the literature pertaining to the problem of assessment methods, we often find approaches which contrast rather than complement each other, for example, cost-benefit analysis versus 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 nevertheless sometimes created opposing and even dogmatic schools of thought.

This paper aims to overcome such contrasting standpoints. It proposes a methodology that combines different assessment methods within the same framework in relation to a given evaluation problem. In the light of recent studies on theoretical aspects of reasoning about data (Pawlak, 1991; Barwise and Moss, 1996), 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. We call this assessment procedure a *combinatorial assessment methodology*. For example, in the case of cost-benefit analysis, the existence of a multiple dimension phenomenon reveals one of the main restrictions in the application of this method. However, when we wish to utilise a multi-criteria method, we may encounter limitations posed by the subjectivity of the 'expert' when defining alternative weights. 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 of the paper we focus on multi-criteria decision processes. There are two main limitations inherent in the standard multi-criteria decision methodology. First, we may be faced with 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 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. 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 should 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, since policy decisions must be enforced in different spatial contexts and with different transport modes, a situation observed in current Trans-European Network (TEN) plans.

2.   COMBINATORIAL ASSESSMENT METHODOLOGY

The choice of assessment method which the decision-maker wants to apply is important for the entire assessment procedure. This choice affects the specific angle from which the decision-maker will examine and evaluate real-world phenomenon, as well as the perception of the problem. From the literature we can identify two different selection approaches (van Pelt et al., 1990) (see Table 1). The combinatorial assessment methodology 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 is necessary 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.

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

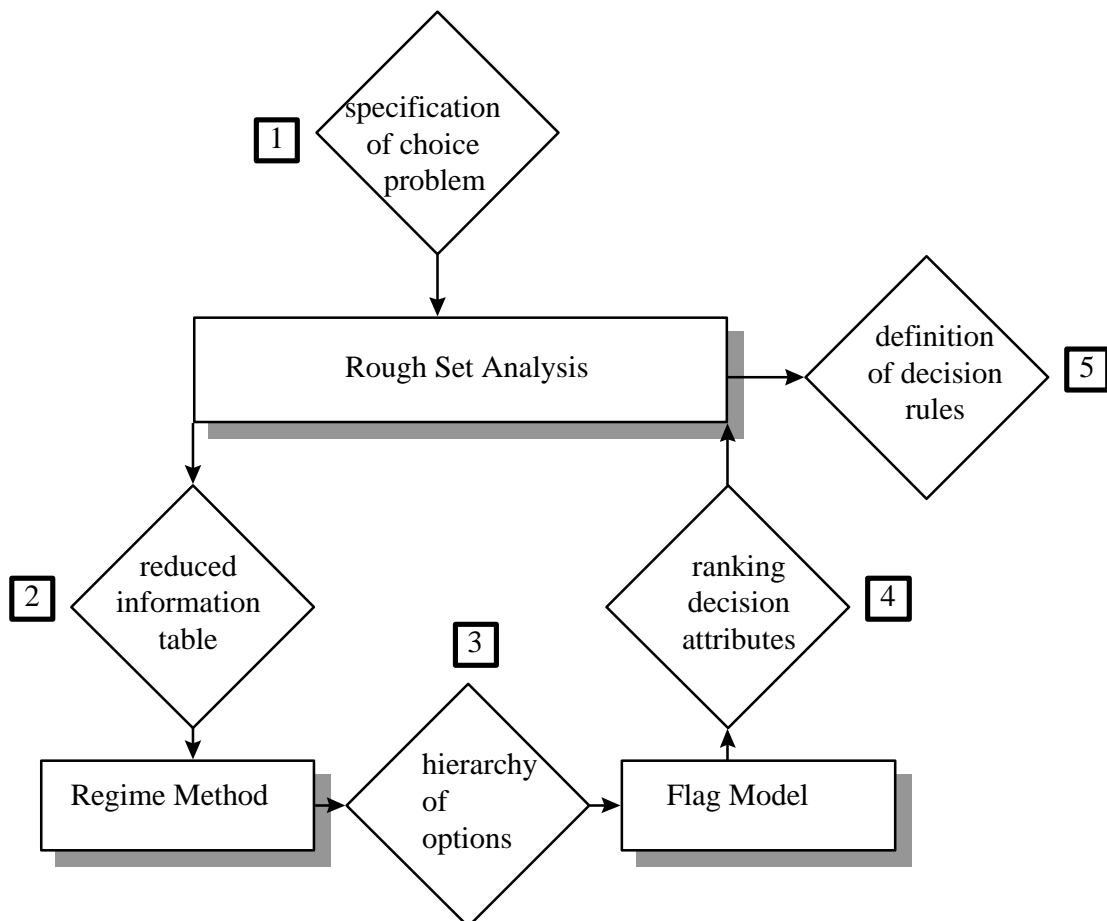Table 1.　　A typology of methods of selection approach

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 selection of the assessment method and the consequent manipulation of the data set in approach A. But here we are faced with a potentially fixed procedure in the selection of the assessment method. By this we mean that, for different problems, the decision-maker selects the same assessment methods every time. 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. We will clarify the characteristics of this method in the next section. Rough set analysis can classify and then reduce the data available and can also indicate the degree of dependency of the attributes. Such a feature is relevant if we want to use a regime method for an assessment problem. The different degrees of dependency are considered in order to value 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. Such a decision can take into account the results of

rough set analysis by treating the data table as a logical tool (Orlowska, 1998). In either case, i.e. by applying a regime analysis or a cost-benefit analysis, we are able to re-examine the results obtained with rough set analysis in order to define the values of the representative parameters that determine the various decisions. These decision rules form, through the "inference rule", a general set of decision algorithms which the decision-maker can use in other case studies. We may therefore obtain a so-called universalisation of decisions.

We can summarise the previous arguments (see Schema 1) by observing that our combinatorial assessment methodology is a method which, depending on the evaluation problem at hand, combines specific assessment methods that are better-suited both methodologically and functionally to solve the evaluation problem. The following schema describes the assessment process that will be discussed throughout our analysis. The assessment procedure is composed of five steps which are depicted by four diamond shapes, whereas the assessment methodologies are identified by the three rectangles.

```
         ┌─┐      ◇ specification
         │1│        of choice
         └─┘          problem

    ┌──────────────────────────┐          ◇ definition    ┌─┐
    │    Rough Set Analysis     │─────────→  of decision   │5│
    └──────────────────────────┘              rules        └─┘

 ┌─┐    ◇ reduced                    ◇ ranking      ┌─┐
 │2│      information      ┌─┐         decision      │4│
 └─┘        table          │3│         attributes    └─┘

    ┌────────────────┐   ◇ hierarchy   ┌────────────┐
    │ Regime Method  │─→   of          │ Flag Model │
    └────────────────┘     options     └────────────┘
```

Schema 1.   Assessment process using the combinatorial 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. 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" (Pawlak, 1992).

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 dissimilarity analysis examines then the dependencies among attributes, but also describes some objects in terms of available attributes in order to find essential differences between objects of interest. The information data table can be reduced by discarding the redundant attributes and identifying the relationships among the attributes in, for example, hierarchical preferences. With rough set analysis we conduct all the computations related with the dissimilarity analysis. 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 (Quilan, 1979, Cendrowska, 1987) -- addresses the decision rule generation with fast computer algorithms and has a solid foundation of real-life applications in various fields (Krysinski, 1990, Slowinski, 1992, Orlowska, 1998). 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 (Pawlak, 1991). 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. Let us suppose that we need to introduce a new transport mode in an existing network. We have five different transport mode options and five attributes which describe the modes of transport (Table 2 below). We observe that the information data is a qualitative matrix. A suitable assessment method in this case is certainly a multi-criteria method such as the regime analysis (Nijkamp et al., 1990). Let us assume here that for the time being we do not know the weight values for the attributes of the transport mode options.

OPTIONS	ATTRIBUTES				
Transport Mode	Price	Mileage	Size	Max-Speed	Acceleration
Mode 1	low	medium	full	low	good
Mode 2	medium	medium	compact	high	poor
Mode 3	high	medium	full	low	good
Mode 4	medium	medium	full	high	excellent
Mode 5	low	high	full	low	good

Table 2.   Data table of a transport assessment problem
(Source: Pawlak, 1991)

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 table where the values of attributes are codes in the following way:

$V_{price}=$ { low (-), medium (0), high (+) };
$V_{mileage}=$ { low (-), medium (0), high (+) };
$V_{size}=$ { low (-), medium (0), high (+) };
$V_{max-speed}=$ { low (-), medium (0), high (+) };
$V_{acceleration}=$ { poor (-), good (0), excellent (+) }.

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

OPTIONS	ATTRIBUTES				
Transport Mode	**a**	**b**	**c**	**d**	**e**
Mode 1	-	0	+	-	0
Mode 2	0	0	-	+	-
Mode 3	+	0	+	-	0
Mode 4	0	0	+	+	+
Mode 5	-	+	+	-	0

Table 3.   Coded information table

where **a** refers to Price, **b** to Mileage, **c** to Size, **d** to Max-Speed, and **e** to Acceleration.

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 and that the corresponding rules are true and relevant. By analysing the information matrix (Table 3), we can determine which of the features of the five transport modes are dependent on the other mode characteristics. In so doing we can determine a hierarchical relationship among the attributes. 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} and {a, b, e } $\Rightarrow$ {d, c}

These logic dependencies tell us that attributes a (Price) and b (Mileage) 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 (Acceleration) depends on the remaining set of attributes. Now we are ready to utilise these dependency relations in a regime analysis when we define the weights of the attributes (see Appendix). 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_{price} = { low (3), medium (2), high (1) };
$V_{mileage}$ = { low (1), medium (2), high (3) };
V_{size} = { compact (1), medium (2), full (3) };
$V_{max-speed}$ = { low (1), medium (2), high (3) };
$V_{acceleration}$ = {poor (1), good (2), excellent (3) }.

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

OPTIONS	ATTRIBUTES				
Transport Mode	Price	Mileage	Size	Max-Speed	Acceleration
Mode 1	3	2	1	3	2
Mode 2	2	2	1	3	1
Mode 3	3	2	3	1	2
Mode 4	2	2	3	3	3
Mode 5	1	3	3	1	2

Table 4.   Ordinal information table

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:

Rank 1	mode **3**	0.935
Rank 2	mode **4**	0.694
Rank 1	mode **1**	0.440
Rank 5	mode **5**	0.363
Rank 2	mode **2**	0.069

Table 5.   Results from the regime analysis

The results of the regime analysis tell us that mode 3 is the most preferable in relation to the attributes. Let us now compare this analysis with the flag model analysis (Nijkamp et al., 1998). 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.* These three clusters are defined within the methods by using critical threshold values. These values represent the reference system for judging the different decisions. We estimate a band of values of thresholds ranging from a maximum value (CTV_{max}) to a minimum value (CTV_{min}). We obtain the following subdivision:

Rank 1	mode **3**	0.935	*Accepted*
Rank 2	mode **4**	0.694	*Accepted*
Rank 1	mode **1**	0.440	*Neutral*
Rank 5	mode **5**	0.363	*Neutral*
Rank 2	mode **2**	0.069	*Rejected*

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

We can observe from the results of these examples that we are now able to define the decision rules related to our assessment and choice problem. Finally, we will once more run the rough set analysis of the following information table:

OPTIONS	ATTRIBUTES					
Transport Mode	Price	Mileage	Size	Max-Speed	Acceleration	Decision Attribute
Mode 1	3	2	1	3	2	2
Mode 2	2	2	1	3	1	3
Mode 3	3	2	3	1	2	1
Mode 4	2	2	3	3	3	1
Mode 5	1	3	3	1	2	2

Table 7.   Coded information table

In Table 7 the decision attributes have been calculated, as we have seen previously, with the regime method and flag model as follows:

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.

We can next analyse Table 6 by means of rough set analysis in order to define the minimal set of attributes for the decision rules. This set allows us to generalise the decision process of this case study. We obtain from the analysis that :

Rule 1	$Attr._{Price} = 3$	$Attr._{Size} = 3$	$\Rightarrow$	**decision 1**
Rule 2	$Attr._{Mileage} = 2$	$Attr._{Size} = 3$	$\Rightarrow$	**decision 1**
Rule 3	$Attr._{Price} = 1$		$\Rightarrow$	**decision 2**
Rule 4	$Attr._{Price} = 3$	$Attr._{Size} = 1$	$\Rightarrow$	**decision 2**
Rule 5	$Attr._{Acceleration} = 1$		$\Rightarrow$	**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 (regime analysis, rough set 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 reduction in 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.

APPENDIX

ROUGH SET ANALYSIS

The aim of the rough set analysis is to recognise possible cause-effect relationships between the available data and to underline the importance and the strategic role of some data and the irrelevance of other data (Pawlak, 1986, 1991). The approach focuses on regularities in the data in order to draw aspects and relationships from them which are less evident but which can be useful in analyses and policy making.

Let us consider a finite universe of objects 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 so as 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 distinguish 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 are those which describe the object following the procedure that we have 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 decision 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 (Nijkamp et al. 1990). 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 in order to obtain the index: $\mu_{ij} = c_{ij} - c_{ji}$. Because we have only ordinal information about the weights, our interest is focused 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:

$$p_{ij} = prob \quad (\textbf{\textit{m}}_{ij} > 0 \;)$$

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 trying 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 allow 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 ecology against a set of reference values. The Flag model has been defined to assess the degree of sustainability of values of policy alternatives (Nijkamp, 1995; Nijkamp and Ouwersloot, 1997). 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 that 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:

$$CTV_{min} \qquad CTV \qquad CTV_{max}$$

0	A	B
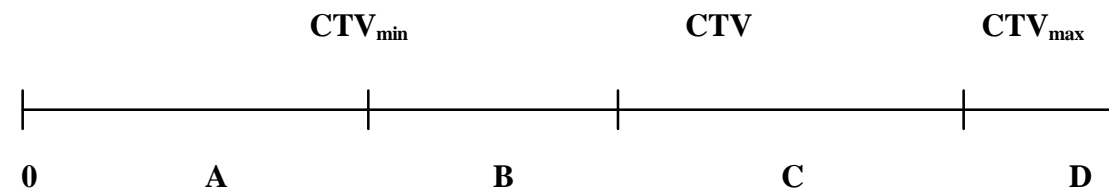
Section **A**	**Green Flag**	no reason for specific concern
Section **B**	**Orange Flag**	be very alert
Section **C**	**Red Flag**	reverse trends
Section **D**	**Black Flag**	stop further growth

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.

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