Chapter 8
Searching for the "Social Compromise Solution": A Conflict Analysis Procedure for Illuminating Distributional Issues

8.1 Introduction

As discussed in Chap. 1, one of the most interesting research directions in modern public economic policy is the explicit attempt to take political constraints, interest groups and collusion effects into account. The issue of "distributional coalitions" has been considered of key importance in determining growth factors (Olson, 1982). In the framework of sustainability policies, the need to deal with conflicts among various social actors is even more unavoidable.

Ecosystems are used in several ways at the same time by a number of different users. Such situations almost always lead to conflicts of interest and damage to the environment. Any social decision problem is characterized by conflict between competing values and interests and the different groups and communities that represent them. In sustainability policies, biodiversity goals, landscape objectives, the direct functioning of different environments as resources, the historical and cultural meanings that places have for communities, the recreational options environments provide, etc., are a constant source of conflict. Any policy option always implies winners and losers, thus it is imperative to check if a policy option seems preferable just because some dimensions (e.g. the environmental) or some social actors (e.g. the lower income groups) have not been taken into account. This is what was defined in Chap. 2 as the *social incommensurability* issue.

In operational terms, one of the classical evaluation tools is cost–benefit analysis. It is generally considered that cost–benefit analysis focuses on *efficiency* criteria; but, any policy decision affects the welfare of individuals, regions or groups in different ways; consequently, public support for any policy decision very much depends on the *distributional effects* of such a decision. Some revisions of cost–benefit analysis try to include distribution issues directly in the analysis (see e.g. Helmers, 1979). However, all these revisions may sometimes present such theoretical and operational difficulties (see Box 4.2) that it is rather tempting to ignore distributional aspects without further comment. This attitude is rarely defended theoretically, but unfortunately often practiced (Bojö et al., 1990).

A well-known approach for dealing with distributional issues in land-use planning is the so-called *planning balance sheet method* which can be considered an extension

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of conventional cost–benefit analysis (Lichfield, 1964, 1988, 1993). This approach aims to provide a broader framework for the assessment of the gains and losses of a plan by constructing detailed socio-economic accounts of all project effects and by taking into account the different groups in society which are affected in their well-being by the plan. A weakness of this method is that it is primarily meant to present in a systematic way a description of all the distributive impacts, but no elaboration with *normative* purposes is generally made.

This chapter presents a possible way of overcoming this drawback of the planning balance sheet method; introducing concepts coming mainly from fuzzy set theory and social choice. Most of the results presented here proceed from the empirical experience of various real-world applications of the NAIADE conflict analysis procedure (Munda, 1995) over a decade. First a fuzzy coalition formation algorithm will be developed, followed by the introduction of a ranking procedure and a veto index founded on the minority principle.

8.2 Do Similarities Exist Among Social Actors? A Fuzzy Cluster Analysis

As in the planning balance sheet method, the proposed approach requires as a first step the construction of a social impact matrix showing the various policy options and their impact on the social actors. From an empirical point of view, the construction of this matrix requires sophisticated field work based mainly on participative techniques (see e.g. Kasemir, 2003). However, the results obtained with such techniques are qualitative in nature and often presented in an unstructured manner. As a consequence, formal techniques helping the structuring, synthesis and further elaboration of this information are operationally very useful (Funtowicz et al., 1999; Munda, 2004). The following main assumptions are made:

(1) Only a set of well defined policy options has to be taken into account.
(2) The impact of these policy options on different social actors are evaluated by means of "linguistic variables" (good, not very good, etc.).
(3) The semantic distance between any pair of social actors is used as a conflict indicator.
(4) A fuzzy cluster algorithm is used to synthesize similarities/diversities among social actors.

In more formal terms, the problem faced can be described in the following way:

A is a finite set of N feasible policy options; B is the set of different social actors,

$B = \{b_p\}$ $p = 1, 2,\ldots, P$ considered relevant in a policy problem,

$\Lambda = \{\lambda_p\}$, $p = 1, 2,\ldots,P$, with $\sum_{p=1}^{P} \lambda_p = 1$ being the vector of weights attached to the set of the P social actors, indicating their relative importance, i.e. given two non-equal numbers to construct a vector in R^2, then the greatest number must be placed in the

Table 8.1 Example of a social impact matrix

	Policy options			
Social Actors	a_1	a_2	a_3	a_4
b_1	$b_1(a_1)$	$b_1(a_2)$	·	$b_1(a_4)$
b_2	·	·	·	·
b_3	·	·	·	·
b_4	·	·	·	·
b_5	·	·	·	·
b_6	$b_6(a_1)$	$b_6(a_2)$	·	$b_6(a_4)$

position corresponding to the most important social actor (Podinovskii, 1994). In this framework, the policy option a_1 is evaluated to be better than a policy option a_2 (both belonging to the set *A*) according to the *p-th* point of view if $b_p(a_1) > b_p(a_2)$, where the social actor scores $b_p(.)$ are measured on a linguistic variable scale of measurement.

As we have seen in Chap. 4, fuzzy set theory provides a framework for representing "*qualitative information*" by means of the concept of "*linguistic variable*". Human judgements, especially in linguistic form, appear to be plausible and natural representations of cognitive observations. We can explain this phenomenon through *cognitive distance*. A linguistic representation of an observation may require a less complicated transformation than a numerical representation, and therefore less distortion may be introduced by the former than by the latter.

The formal problem we are dealing with can be summarized in a table form, called a *social impact matrix*, as shown in Table 8.1 (where $P = 6$ and $N = 4$).

As discussed in Chap. 7, the semantic distance can be used to compare fuzzy sets in general and linguistic variables in particular. In short if $\mu_1(x)$ and $\mu_2(x)$ are two linguistic variables, one can write:

$$f(x) = k_1\mu_1(x) \; and \; g(y) = k_2\mu_2(x) \tag{8.1}$$

where $f(x)$ and $g(y)$ are two functions obtained by rescaling the ordinates of $\mu_1(x)$ and $\mu_2(x)$ through k_1 and k_2, such that

$$\int_{-\infty}^{+\infty} f(x)dx = \int_{-\infty}^{+\infty} g(y)dy = 1 \tag{8.2}$$

The distance between all points of the membership functions is computed as follows:

$$S_d\big(f(x),\ g(y)\big) = \iint_{x,\,y} |x - y| f(x)g(y)dydx \tag{8.3}$$

In the problem at hand, between any pair of social actors b_i, b_j with $i \neq j$, their relative distance can be computed by considering the set of *N* linguistic evaluations given to the set of policy options (i.e. the rows *i* and *j* in the matrix). In more formal terms, if $\overline{x}$ is the vector of the linguistic evaluations of b_i and $\overline{y}$ is that of b_j, both belonging to R^N, the generalization of the Minkowski metric described in (8.4) can be applied:

$$d(b_{i,}\, b_j) = \left\| \bar{x} - \bar{y} \right\| = \sum_{i=1}^{N} \left[\left(\iint_{x,\,y} |x-y| f_i(x) g_i(y) dy dx \right)^{\beta} \right]^{\frac{1}{\beta}} \tag{8.4}$$

For

$\beta = 1$ an absolute value metric (completely compensatory)
$\beta = 2$ a Euclidean metric (partially compensatory)
$\beta \to \infty$ the Tchebycheff metric (completely non-compensatory) can be obtained.

By using the distance described in (8.4) as a conflict indicator, a similarity matrix (achieved by means of the simple transformation $s_{ij} = \dfrac{1}{1+d_{ij}}$) for all possible pairs of groups can be obtained, so that a clustering procedure is meaningful.

On an axiomatic basis, cluster analysis can be differentiated into deterministic, stochastic and fuzzy. By taking into consideration the "clustering criteria", the following distinction exists (Anderberg, 1973: Hartigan, 1975; Bezdek, 1980):

- Hierarchical methods
- Graph theoretic methods
- Objective functional methods

The hierarchical clustering approach, in particular, allows an evolutionary view of the aggregation process and can easily be dealt with within fuzzy terms. However, in a fuzzy environment a problem exists, i.e. the relation between the concepts of *partition* and *equivalence class*.

In a crisp environment, the choice of treatment of data in terms of partitions or equivalence relations is a matter of convenience, since the two models are fully equivalent (philosophically and mathematically). On the contrary, fuzzy equivalence relations and partitions are philosophically similar, but their mathematical structures are not isomorphic (e.g. the notion of transitivity is unique for crisp relations but may take any of several forms in the fuzzy case).

We begin the discussion of fuzzy cluster analysis with the definition of a crisp equivalence relation. Let $B=\{b_1, b_2, \ldots, b_p\}$ be the finite set of social actors. Then a $P \times P$ matrix $S = [s_{ij}] = [s(b_i, b_j)]$ is a *crisp equivalence relation* for $B \times B$ if

$$s_{ij} = 1 \qquad 1 \le i \le P \qquad \text{(reflexivity)}$$

$$s_{ij} = s_{ji} \qquad 1 \le i \ne j \le P \qquad \text{(symmetry)}$$

$$\begin{cases} s_{ij} = 1 \\ \\ s_{jk} = 1 \end{cases} \Rightarrow s_{ik} = 1 \quad \forall i, j, k \qquad \text{(transitivity)}$$

Let S be a fuzzy binary relation with $\mu_s(b_i, b_j)$ indicating the degree to which two social actors b_i and b_j are similar (similarity matrix). The relation S is obviously reflexive and symmetrical, thus it is called a *resemblance relation*.

A fuzzy relation is a *similitude relation* if it has the following properties:

$$\mu_S(b_i,b_i)=1 \qquad \forall (b_i,b_i)\in B\times B \qquad \text{(reflexivity)}$$

$$\mu_S(b_i,b_j)=\mu_S(b_j,b_i) \qquad \forall (b_i,b_j)\in B\times B \qquad \text{(symmetry)}$$

$$\mu_S(b_i,b_k)\geq \max\min\left[\mu_S(b_i,b_j),\mu_S(b_j,b_k)\right]$$
$$\forall (b_i,b_j),(b_j,b_k),(b_i,b_k)\in B\times B \qquad \text{(max-min transitivity)}$$

Note that compared to the notion of transitivity in conventional analysis, the present concept defines a weaker transitivity of similarity.

If one wants to derive a set of *equivalence classes* (and not simple partitions) it is necessary for the similarity matrix to be at least max–min transitive. As is well-known (Leung, 1988), an intransitive similarity matrix can be transformed into transitive by deriving the *transitive closure* $\widehat{S}$ of *S*. The *max–min transitive closure* of a fuzzy binary relation *S* is

$$\widehat{S}=S\cup S^2\cup S^3\cup\ldots \tag{8.5}$$

where $S^2 = S \circ S$ is the *max–min composition of S* (more technical details can be found in Appendix 8.1).

Knowing that any fuzzy set $\tilde{A}$ can always be decomposed into a series of α-level sets $\tilde{A}_\alpha$, the similitude relation $\widehat{S}$ can be decomposed into

$$\widehat{S}=\bigcup_{\alpha\in[0,1]}\alpha\widehat{S}_\alpha \tag{8.6}$$

Since $\widehat{S}_\alpha$ is reflexive, symmetrical and transitive in the sense of ordinary sets, it is an equivalence class of level α. Within each *α-level equivalence class*, the similarity of any two social actors is no less than α.

Note that the equivalence classes obtained are ordinary disjoint sets. In fact, in order to have non-mutually exclusive equivalence classes, it is necessary to assume the use of a *min-addition transitive similarity matrix* (which is a stronger assumption than max–min transitivity). Consider the social impact matrix described in Table 8.2.

By applying the semantic distance described in (8.4) with β= 2, after the transformation $s_{ij}=\dfrac{1}{1+d_{ij}}$, the similarity matrix for all possible pairs of social actors shown in Table 8.3 is obtained:

This means, for example, that the greatest similarity is found between social actors b_1 and b_2, and between b_4 and b_5. These social actors have a relatively high correspondence of goals, accordingly. The reverse holds true for social actors b_2 and b_4, between which the lowest degree of similarity is found.

By using the notion of max–min composition, the following new fuzzy relations are derived:

S^2

	b_1	b_2	b_3	b_4	b_5	b_6
b_1	1	0.729	0.426	0.426	0.426	0.426
b_2	0.729	1	0.426	0.410	0.410	0.410
b_3	0.426	0.426	1	0.675	0.675	0.672
b_4	0.426	0.410	0.675	1	0.729	0.672
b_5	0.426	0.410	0.675	0.729	1	0.672
b_6	0.426	0.410	0.672	0.672	0.672	1

S^3

	b_1	b_2	b_3	b_4	b_5	b_6
b_1	1	0.729	0.426	0.426	0.426	0.426
b_2	0.729	1	0.426	0.426	0.426	0.426
b_3	0.426	0.426	1	0.675	0.675	0.672
b_4	0.426	0.426	0.675	1	0.729	0.672
b_5	0.426	0.426	0.675	0.729	1	0.672
b_6	0.426	0.426	0.672	0.672	0.672	1

S^4

	b_1	b_2	b_3	b_4	b_5	b_6
b_1	1	0.729	0.426	0.426	0.426	0.426
b_2	0.729	1	0.426	0.426	0.426	0.426
b_3	0.426	0.426	1	0.675	0.675	0.672
b_4	0.426	0.426	0.675	1	0.729	0.672
b_5	0.426	0.426	0.675	0.729	1	0.672
b_6	0.426	0.426	0.672	0.672	0.672	1

Table 8.2 Illustrative example of a social impact matrix

	Policy options						
Social Actors	**a1**	**a2**	**a3**	**a4**	**a5**	**a6**	**a7**
$\mathbf{b_1}$	Very good	good	Moderate	bad	fairly good	fairly bad	very bad
$\mathbf{b_2}$	Very good	good	Moderate	bad	fairly good	very bad	Very bad
$\mathbf{b_3}$	Very bad	fairly bad	Moderate	good	very good	good	moderate
$\mathbf{b_4}$	very bad	fairly bad	fairly bad	good	fairly good	good	very good
$\mathbf{b_5}$	Very bad	bad	fairly bad	moderate	fairly good	good	very good
$\mathbf{b_6}$	Very bad	good	Bad	good	good	good	very good

Table 8.3 Similarity matrix between the social actors of the illustrative example

	b_1	b_2	b_3	b_4	b_5	b_6
b_1	1	0.729	0.426	0.399	0.403	0.403
b_2	0.729	1	0.410	0.386	0.390	0.390
b_3	0.426	0.410	1	0.675	0.584	0.569
b_4	0.399	0.386	0.675	1	0.729	0.672
b_5	0.403	0.390	0.584	0.729	1	0.595
b_6	0.403	0.390	0.569	0.672	0.595	1

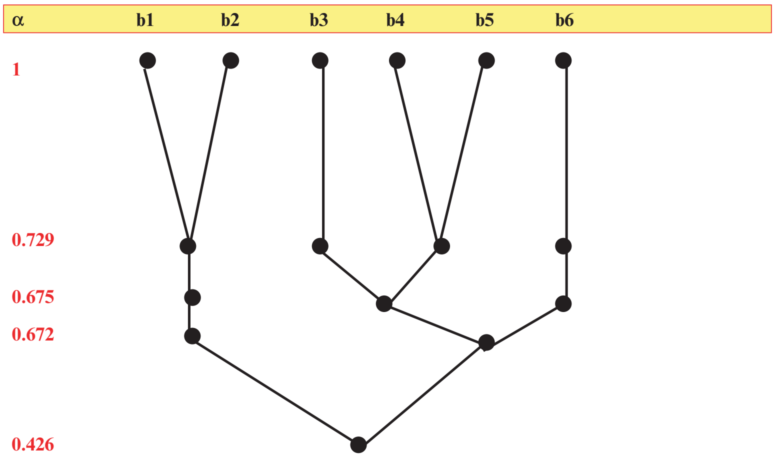

Fig. 8.1 Dendrogram of the cluster formation process

Since in the series of max–min compositions $S^3 = S^4$, the transitive closure is

$$\hat{S} = S \cup S^2 \cup S^3 = S^3 \tag{8.7}$$

Since $\hat{S}$ is a similitude relation, it can be decomposed into equivalence classes with respect to the degree of similarity α.

Thus the application of the clustering procedure leads to the following results (see Fig. 8.1). As long as the similarity degree α required for convergence is higher than 0.729, there will be no cluster formation. Two groups will be formed when α is between 0.729 and 0.675 (b_1 and b_2), and (b_4 and b_5). When the similarity degree is reduced to 0.675 and 0.672, social actors b_3 and b_6 join the last group respectively. The conflict of interest between the remaining groups (b_1, b_2) versus (b_3, b_4, b_5, b_6) is considerable, as can be inferred from the low degree of similarity associated with a grand coalition.

It can be proved that the following four algorithms generate the same partition (Miyamoto, 1990):

- The single linkage method
- The connected components of an undirected fuzzy graph
- The transitive closure of a reflexive and symmetric fuzzy relation
- The maximal spanning tree of a weighted graph

Thus the following conclusions can be drawn:

1. Since the connected components are independent of the numbering of the vertices, the algorithm is independent of the ordering of the inputs, and is therefore *stable*.
2. *No reversal* exists in the dendrogram ("reversal" meaning that the merging levels are not monotonically decreasing, and thus a cut of the dendrogram might produce ambiguous results).
3. One is not obliged to use only the Euclidean metric (e.g. as in the "*centre of gravity*" procedures), any distance measure (even if it does not respect the triangular inequality property) can be used, thus the method is *general*.

In real-world applications, when the actors involved in a policy process look at dendrograms, they can generally make little sense of them. Clearly, further elaboration is then needed. In particular, information on rankings of policy options according to each cluster of social actors seems very desirable.

8.3 Ranking Policy Options

As discussed in Chaps. 6 and 7, the maximum likelihood ranking of policy options is that ranking supported by the maximum number of social actors for each pair-wise comparison, summed over all pairs of policy options. More formally, the C–K–Y–L ranking procedure, adapted to the problem at hand, can be described as follows.

For each α-level equivalence class, let $C_\alpha=\{c_1, c_2,\ldots,c_z\}$ be the finite set of possible groups of social actors, with $|c_1|\cup|c_2|\cup\ldots\cup|c_z| = P$. Then, $\forall c_i \in C_\alpha$, with $i=1, 2,\ldots,Z$, a pair-wise comparison of the N policy options needs to be carried out.

For carrying out such a pair-wise comparison the following axiomatic system is required (adapted from Arrow and Raynaud, 1986, pp. 81–82).

Axiom 1: *Diversity*. Each social actor b_p defines a total order on the finite set A of policy options to be ranked.

Axiom 2: *Symmetry*. The only preference information social actors provide is the ordinal pair-wise preferences.

Axiom 3: *Positive Responsiveness*. The degree of preference between two policy options $\boldsymbol{a}_1$ and $\boldsymbol{a}_2$ is a strictly increasing function of the number $|c_i|$ and weights λ_p, of the social actors who rank $\boldsymbol{a}_1$ before $\boldsymbol{a}_2$.

Clearly all three axioms are fulfilled by giving an ordinal meaning to the linguistic variables contained in the social impact matrix (i.e. no intensity of preference is used). Thanks to these three axioms an $N\times N$ *outranking matrix* E can be built. Any generic element of E: $e_{jk}, j\neq k$ is the result of the pair-wise comparison, according to all the $|c_i|$ social actors, between policy options *j* and *k*. Such a global pair-wise comparison is obtained by means of (8.8).

$$e_{jk} = \sum_{p=1}^{|c_i|} \left(\lambda_p(P_{jk}) + \frac{1}{2}\lambda_p(I_{jk}) \right) \tag{8.8}$$

where $\lambda_p\,(P_{jk})$ and $\lambda_p\,(I_{jk})$ are the weights of the social actors expressing a preference and an indifference relation respectively. All the $N(N-1)$ pair-wise comparisons of policy options *N* compose the matrix *E*.

Let us call T the set of all the *N!* possible complete rankings, of policy options, T = $\{\tau_s\}$, $s = 1, 2, \ldots, N!$. For each τ_s, we compute the corresponding score φ_S as the sum of e_{jk} over all the $\binom{N}{2}$ pairs *jk* of policy options, i.e.

$$\varphi_S = \sum e_{jk} \tag{8.9}$$

where $j \neq k$, $s = 1, 2, \ldots N!$ and $e_{jk} \in \tau_s$

The final ranking (τ_*) is the one[1] which maximises(8.9):

$$\tau_* \Leftrightarrow \varphi_* = \max \sum e_{jk} \qquad \text{where } e_{jk} \in \text{T}. \tag{8.10}$$

As we know from Chap. 6, other properties of the C–K–Y–L ranking procedure are as follows.

- *Neutrality:* it does not depend on the name of any policy option, all policy options are treated equally.
- *Unanimity* (sometimes called *Pareto Optimality*): if all social actors prefer policy option $\boldsymbol{a_1}$ to policy option $\boldsymbol{a_2}$ than $\boldsymbol{a_2}$ should not be chosen.
- *Monotonicity:* if policy option $\boldsymbol{a_1}$ is chosen in any pair-wise comparison and only the social actors' linguistic evaluations of $\boldsymbol{a_1}$ are improved, then $\boldsymbol{a_1}$ should still be the winning policy option.
- *Reinforcement:* if the set *A* of policy options is ranked by two subsets B_1 and B_2 of the social actors set *B*, such that the ranking is the same for both B_1 and B_2, then $B_1 \cup B_2 = B$ should still produce the same ranking.

At this point, we refer to the *normative tradition* in political philosophy, which has also an influence in modern social choice (Moulin, 1981) and public policy (Mueller, 1978). The basic idea is that any coalition controlling more than 50% of the votes may be converted in an actual dictator. As a consequence, the "remedy to the tyranny of the majority is the minority principle, requiring that all coalitions, however small, should be given some fraction of the decision power. One measure of this power is the ability to veto certain subsets of outcomes.…"

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[1] It is important to remember that sometimes the final ranking is not unique. This is a desirable property since it can be considered a measure of the *robustness* of the results provided.

(Moulin, 1988, p. 272). As discussed in Chap. 7, the introduction of a veto power can be further justified in the light of the so-called "*prudence*" axiom (Arrow and Raynaud, 1986, p. 95), whose main idea is that it is not prudent to accept alternatives whose degree of conflictuality is too high (and thus the decision taken might be very *vulnerable*).

Note that allocating veto power across the various groups of social actors has profound ethical implications, since it entails attaching different weights to different groups. Moreover, if too much veto power is allowed, cooperatively stable solutions may disappear; on the other hand, if too little veto power is allowed, stable solutions are too numerous. This problem has a unique *mathematical* solution attributable to Moulin (1981). The philosophy behind Moulin's theorem is that any group with $x\%$ of social actors must be able to veto any subset containing less than $x\%$ of policy options.

Formally, Moulin's theorem can be adapted to our problem as follows. Given P social actors, N policy options and $C_\alpha=\{c_1, c_2,\ldots,c_z\}$ possible groups of social actors, $|c_1|\cup|c_2|\cup\ldots\cup|c_z| = P$, $\forall\ c_i \in C_\alpha$, with $i = 1,2,\ldots,Z$, the corresponding *proportional veto function* is defined in (8.11):

$$V_{P,N}(c_i) = \left(N \bullet \frac{|c_i|}{P}\right) - 1 \tag{8.11}$$

where (x) is the smallest integer bounded below by x, with

$$x = \left(N \bullet \frac{|c_i|}{P}\right).$$

In the case that weights are attached to the social actors, the proportional veto function is presented in (8.12).

$$V_{P,N}(c_i) = \left(N \bullet \lambda_i\right) - 1 \tag{8.12}$$

$$\text{where } \lambda_i = \sum_{p \in c_i} \lambda_p \tag{8.13}$$

Let us continue with the example described in Table 8.2, by applying the ranking method and the veto function just discussed. Let us choose the equivalence class obtained with α=0.672. For $C_{0.672}$, groups c_1 with (b_1, b_2) and c_2 with (b_3, b_4, b_5, b_6) exist. By applying the computations described in Equations from (8.8) to (8.10), with the assumption of equal weighting of social actors, the following rankings are obtained.

For c_1 the permutation with the highest score is unique:

$$a_1 \rightarrow a_2 \rightarrow a_5 \rightarrow a_3 \rightarrow a_6 \rightarrow a_4 \rightarrow a_7$$

For c_2 the ranking is also unique:

$$a_7 \rightarrow a_6 \rightarrow a_5 \rightarrow a_4 \rightarrow a_3 \rightarrow a_2 \rightarrow a_1$$

The application of Moulin's proportional veto function produces the following results:

$V_{6,7}(c_1) = \left(7 \bullet \frac{2}{6}\right) - 1 \cong 1$, only a_7 can be vetoed.

$V_{6,7}(c_2) = \left(7 \bullet \frac{4}{6}\right) - 1 \cong 3$, options a_1, a_2 and a_3 can be vetoed.

From analysing these results it is clear that social compromise solutions could be options a_6 and a_5. Any other choice would imply "*strong value judgements*" such as attaching an enormous weight to group c_1, which would be the only way to defend options a_1 or a_2; while choosing a_7 would imply a complete "dictatorship" of the majority.

It is important to highlight that I do not maintain that a policy-maker should not be free to use these "strong value judgements". What I want to emphasize here is that, when she/he uses them, this fact should be transparent and responsibility of doing so clearly assumed. As discussed in the tradition of public choice (Buchanan and Musgrave, 1999) not necessarily a public policy-maker is always benevolent; this is why I stated that the objective of the proposed approach is to illuminate distributional issues and corresponding ethical (or un-ethical) positions. This call for transparency in modern public economics is widely shared by various contemporary authors (see e.g. Stiglitz, 2002).

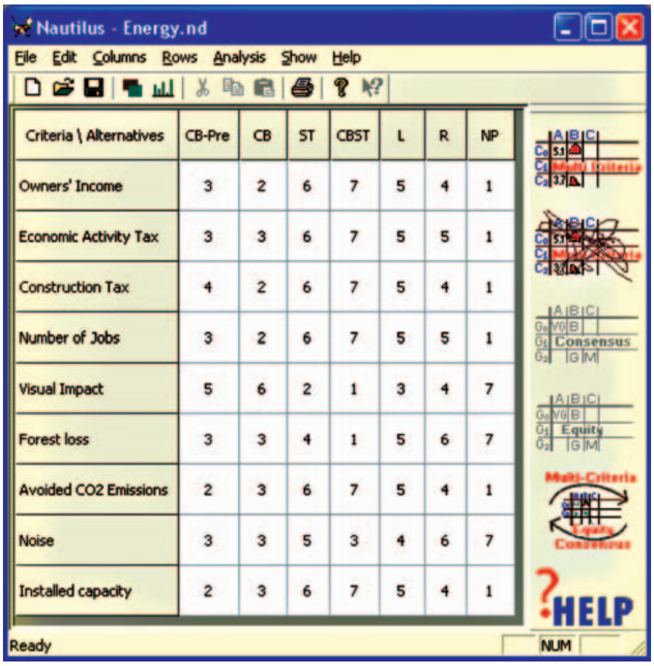
As a final example, let us consider again the Catalan wind park location problem introduced in Chap. 3. The ordinal multi-criteria evaluation matrix for this problem is described in Table 8.4 (the higher the criterion score the better the evaluation). The ordinal criterion scores are obtained by applying a positive indifference threshold q to each quantitative criterion score (for more details see Gamboa and Munda, 2007).

By considering the information contained in the impact matrix shown in Table 8.4, the outranking matrix presented in Table 8.5 is obtained. All criteria are considered under the equal weighting assumption.

By applying the C–K–Y–L ranking procedure, among the 5,040 possible rankings, the following four present the maximum score (see Table 8.6) (where the extreme left alternatives are the top ones and the extreme right alternatives are the bottom ones):

As we know, criteria and criterion scores are not determined directly by social actors. The impact matrix is a result of a technical translation operationalized by the scientific team. Even if the criteria are exactly the ones agreed with the social actors the determination of the criterion scores is independent of their preferences. For example, an interest group can accept the use of a criterion measuring the effects of the various alternatives on the employment, but the determination of the figure cannot

Table 8.4 Ordinal multi-criteria evaluation matrix for the wind park location problem



Criteria \ Alternatives	CB-Pre	CB	ST	CBST	L	R	NP
Owners' Income	3	2	6	7	5	4	1
Economic Activity Tax	3	3	6	7	5	5	1
Construction Tax	4	2	6	7	5	4	1
Number of Jobs	3	2	6	7	5	5	1
Visual Impact	5	6	2	1	3	4	7
Forest loss	3	3	4	1	5	6	7
Avoided CO2 Emissions	2	3	6	7	5	4	1
Noise	3	3	5	3	4	6	7
Installed capacity	2	3	6	7	5	4	1

Table 8.5 Outranking matrix for the wind park location problem

	CB Pre	*CB*	*ST*	*CBST*	*L*	*R*	*NP*
CB Pre	0,00	0,50	0,30	0,40	0,30	0,30	0,70
CB	0,50	0,00	0,10	0,20	0,10	0,10	0,70
ST	0,70	0,90	0,00	0,40	0,70	0,65	0,70
CBST	0,60	0,80	0,60	0,00	0,60	0,60	0,70
L	0,70	0,90	0,30	0,40	0,00	0,65	0,70
R	0,70	0,90	0,35	0,40	0,35	0,00	0,70
NP	0,30	0,30	0,30	0,30	0,30	0,30	0,00

Table 8.6 Multi-criteria maximum likelihood rankings for the wind park location problem

First	Second	Third	Fourth	Fifth	Sixth	Seventh
CBST	ST	L	R	CBPre	CB	NP
CBST	ST	L	R	CB	CBPre	NP
ST	CBST	L	R	CBPre	CB	NP
ST	CBST	L	R	CB	CBPre	NP

Table 8.7 Social impact matrix for the wind park location

Groups \ Alternatives	CB-Pre	CB	ST	CBST	L	R	NP
CAT. GOVERNM (G1)	More or Less Good	More or Less Bad	Very Good	Perfect	Good	Good	Extremely Bad
MUN. VALLBONA (G2)	More or Less Good	More or Less Bad	Very Good	Perfect	Good	Good	Extremely Bad
MUN. OMELLS(G3)	Very Bad	Good	Bad	Good	Bad	Bad	Bad
MUN. ROCALLAURA (G4)	More or Less Good	More or Less Bad	Very Good	Perfect	Good	Good	Extremely Bad
MUN. SENAN (G5)	Very Bad	Very Bad	Very Bad	Extremely Bad	More or Less Bad	Moderate	Perfect
"DEFEND LAND" (G6)	Very Bad	Very Bad	Extremely Bad	Very Bad	Very Bad	Bad	Perfect
PLAT. SENAN (G7)	Very Bad	Very Bad	Extremely Bad	Extremely Bad	More or Less Bad	Moderate	Perfect
ASS. MONTBLANQUET (G8)	Extremely Bad	Extremely Bad	Very Bad	Extremely Bad	Very Bad	More or Less Bad	Perfect
EHN (G9)	Extremely Bad	Extremely Bad	Perfect	Perfect	More or Less Good	Moderate	Extremely Bad
GERSA (G10)	Very Good	Perfect	Extremely Bad	Perfect	Extremely Bad	Extremely Bad	Extremely Bad

be (at least completely) controlled by them. This is one of the main reasons why it is desirable to combine a social impact matrix with the technical impact matrix.

As we have seen in this chapter, the first step is the construction of the *Social Impact Matrix* i.e. the evaluation every social actor gives to each option (see Table 8.7).

By applying the fuzzy clustering procedure introduced in Sect. 8.2 to the social impact matrix presented in Table 8.7 (by using the assumption of equal weighting for the various social actors), the dendrogram presented in Fig. 8.2 is obtained.

- The proximity of aims between the Municipality of Senan (G5) and the Platform per Senan (G7) are reflected in the dendogram. Also the Municipalities of Vallbona de les Monges (G2) and Rocallaura (G4) are working together in looking for their benefits.
- The Association of friends and neighbours of Montblanquet (G8) joints to the first mentioned coalition (G5 + G7) with a medium-high degree of credibility. They meet with other actors in the Coordinating committee to defend the land (G6). Most of them working in independently.
- On the other side, EHN (G9) has been negotiating with the municipalities and with the Catalonian government in order to push their project forward. This coalition (G2 + G4 + G1 + G9) has a medium degree of credibility.
- A coalition between the municipality of Els Omells de Na Gaia (G3) and Gerrsa (G10) shares a medium degree of proximity with the previous coalition. Nowadays this coalition depends more or less in the amount of money that can be received from Gerrsa as benefit tax revenue.

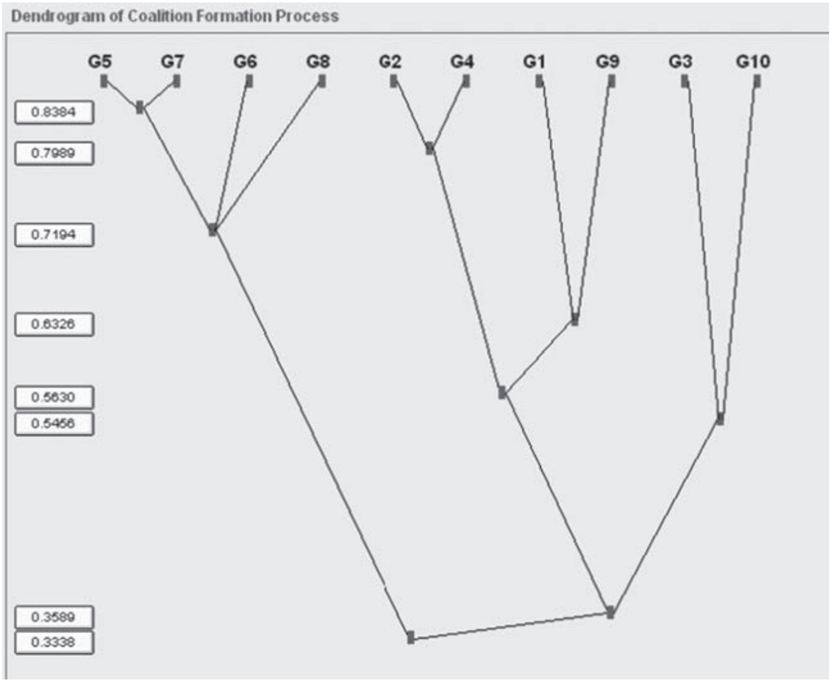


Fig. 8.2 Dendrogram of the coalition formation process for the wind park location problem

Table 8.8 Maximum likelihood rankings for coalition C_1

First	Second	Third	Fourth	Fifth	Sixth	Seventh
NP	R	L	CB Pre	CB	ST	CBST
NP	R	L	CB	CB Pre	ST	CBST
NP	R	L	CB Pre	CB	CBST	ST
NP	R	L	CB Pre	ST	CB	CBST

In real-world applications, when the actors involved in a policy process look at dendrograms generally have a question like: *and so what?* Clearly further elaborations are then needed. In particular, information on rankings of policy options according to each coalition of social actors seems very desirable. This can easily been done by applying again the C–K–Y–L ranking procedure (already used on the multi-criteria impact matrix). The coalitions obtained with the degree of credibility 0.7194 (thus a very high one) are considered.

The coalition C_1, with Municipality of Senan (G5), Platform per Senan (G7), Association of friends and neighbours of Montblanquet (G8) and Coordinating committee to defend the land (G6) present the following rankings as the maximum likelihood ones (see Table 8.8):

Table 8.9 Maximum likelihood rankings for coalition C_2

First	Second	Third	Fourth	Fifth	Sixth	Seventh
CBST	ST	L	R	CB Pre	CB	NP
CBST	ST	R	L	CB Pre	CB	NP
ST	CBST	L	R	CB Pre	CB	NP
ST	CBST	R	L	CB Pre	CB	NP
CBST	ST	L	CB Pre	R	CB	NP
CBST	ST	L	R	CB Pre	NP	CB
CBST	ST	L	R	CB	CB Pre	NP
CBST	ST	R	CB Pre	L	CB	NP
CBST	ST	R	L	CB Pre	NP	CB
CBST	ST	R	L	CB	CB Pre	NP
CBST	L	ST	R	CB Pre	CB	NP
CBST	R	ST	L	CB Pre	CB	NP

For coalition C_2, (including Municipalities of Vallbona (G2) and Rocallaura (G4)) the following rankings receive the maximum score (see Table 8.9):

Moreover by looking at the social impact matrix (Table 8.7), it is clear that for the Catalonian Government, option CBST is the best one. Anyway all the other alternatives are also more o less OK, except for NP that is considered as extremely bad. For the Municipality of Els Omells, the only acceptable alternatives are CB Pre, CB and CBST, all the others are considered bad. For EHN, alternatives ST and CBST are good options. L and R are more or less acceptable but NP is considered as extremely bad. For Gersa, alternatives CB Pre, CB and CBST are at least very good options, all the other possibilities are considered as extremely bad.

By applying Moulin's theorem the only coalition that can veto one option is C_1, which vetoes option CBST. However, it is important to remember that veto power is not a technical decision only. For instance, the alternatives as well as the social actors to be considered are defined in the problem structuring phase, which is mainly a technical, political and social process.

Concluding we can say that technically speaking, the most defensible alternatives are CBST, ST and L. From a social conflict analysis point of view, it seems that alternative CBST is the one which might generate the maximum conflict. Even if CBST seems acceptable for the majority of the social actors involved, coalition C_1 always ranks it in low positions. R has good evaluations, except by GERRSA which would be excluded in this case. L is always ranked in medium positions by all social actors. It might also be a social compromise. NP is not acceptable for most of social actors. In summary, we can state that alternatives L and R seem the only ones defensible from both technical and social points of view. All other options might maximize the social conflict or are not technically acceptable. It is interesting to note that business as usual is definitely not a desirable situation.

8.4 Concluding Remarks

In the area of environmental and resource management and in policies aiming at sustainable development, conflicting issues and interests are the normal state of affairs. Formal approaches like the one proposed here cannot resolve all conflict, but they can help to provide more insight into the nature of the conflict by providing systematic information; and to arrive at political compromises by making a complex situation more transparent to policy-makers and lay people.

In the present chapter, distribution issues have been taken into consideration by means of an eclectic approach using concepts from land-use planning, fuzzy cluster analysis and social choice. Starting with a matrix showing the impact of different courses of action on each social actor, a fuzzy clustering procedure indicating the groups whose interests are closer is used. This is more or less in agreement with the hypotheses underlying the "*minimal range theory*" in coalition formation literature. Rankings for each "credible" group of social actors are obtained by means of the majority principle implemented using a Condorcet voting principle. The issue of cycles has been tackled thoroughly. The minority principle has also been considered by means of Moulin's proportional veto function.

The approach proposed aims to be a *normative* model based on a set of *formal* properties with some *descriptive* meaning. As a consequence, the properties of this approach have to be evaluated at least in the light of these three dimensions (descriptive, normative and formal). By adding Musgrave's distinction between *negligibility assumptions, domain assumptions and heuristic assumptions* the following set of properties is obtained.

Descriptive domain assumptions:

- Evaluation scores are considered in the form of linguistic variables.
- The preference model is a complete pre-order structure.
- The most useful result for policy-making is considered to be a complete ranking of policy options.

Normative domain assumptions:

- Simplicity is desirable and means the use of a few ad hoc parameters as possible.
- Weights are meaningful only as importance coefficients.
- A minority principle must be implemented for ethical and prudential reasons.

Formal domain assumptions:

- α*-level* equivalence classes obtained by using max–min composition operations arriving at a max–min transitive closure.
- Stability of the clustering algorithm.
- Generality of the clustering algorithm.
- No reversal in the dendrogram.
- Monotonicity.
- Diversity.

- Symmetry.
- Positive Responsiveness.
- Unanimity.
- Neutrality.
- Reinforcement.

Heuristic descriptive assumptions:

- Transparency is a desirable feature of policy processes.
- Social actors and policy options can always be identified in a satisfactory way.
- The social impact matrix is a consistent and meaningful representation of the qualitative field work (institutional analysis, interviews, questionnaires, focus groups, and so on).
- A fuzzy cluster algorithm is a good tool for forming an idea of the credibility of similarities/diversities among social actors.

Heuristic formal assumptions:

- Semantic distance as a conflict indicator.
- C–K–Y–L ranking procedure as a proper tool for implementing the majority principle.
- Local stability of the ranking method.
- Cycle-breaking without losing neutrality.
- Proportional veto function as a proper tool for implementing the minority principle.

Negligibility formal assumptions:

- Anonymity.
- Independence of irrelevant alternatives.

Appendix 8.1

Let X and Y be two universes of discourse, a fuzzy binary relation R in the Cartesian product $X \times Y$ is a fuzzy set in $X \times Y$ defined by the membership function

$$\mu_R : X \times Y \rightarrow [0,1]$$
$$(x, y) \rightarrow \mu_R(x, y), \qquad x \in X \text{ and } y \in Y$$

where the grade of membership $\mu_R(x, y)$ indicates the degree of relationship between x and y.

The *max–min composition* is a standard operation for two fuzzy relations: given two relations $R(x, y)$, $Q(y, z)$ defined on $X \times Y$ and $Y \times Z$, respectively, the max–min composition of R and Q, denoted as $R \circ Q$, is defined by

$$\mu_{R \circ Q}(x, z) = \max_{y \in Y} \min\left[\mu_R(x, y), \mu_Q(y, z)\right] \quad x \in X, y \in Y \text{ and } z \in Z.$$

By using the notion of max–min composition, one can derive new fuzzy relations. A transitive closure can be obtained by means of the following theorem (Leung, 1988, p. 125):

Theorem 1

Let R be any fuzzy binary relation. If for some k, the max–min composition $R^{k+1} = R^k$, *then the max–min transitive closure is*

$$\hat{R} = R \cup R^2 \cup R^3 \cup \ldots \cup R^k .$$