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Blommestein, H.J.; Nijkamp, P.

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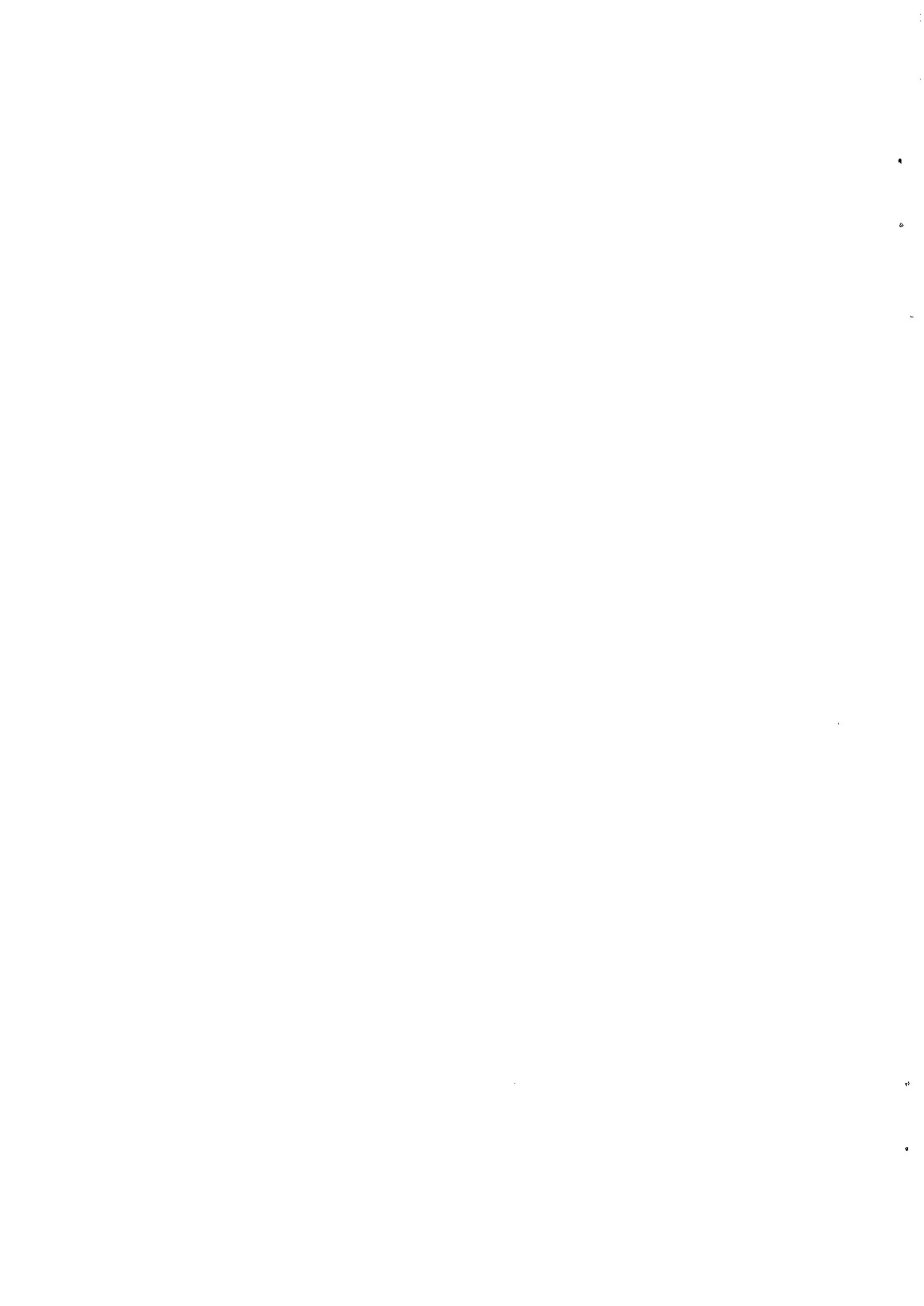
## Serie Research Memoranda

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H.J. Blommestein  
P. Nijkamp

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A COMPARISON OF SOME ANALYTICAL PROCEDURES

for

NONMETRIC INFORMATION IN CONFLICT ANALYSIS

H.J. Blommestein\*  
O.E.C.D.  
Economics & Statistics Dept.  
2, rue André Pascal  
75775 Paris Cedex 16  
France

P. Nijkamp  
Free University  
Dept. of Economics  
De Boelelaan 1105  
1081 HV Amsterdam  
The Netherlands

\* A first draft was finalised when the first author was affiliated with the Ministry of Finance in The Hague, The Netherlands. However, the views expressed are strictly personal and therefore do not necessarily reflect or implicate the position of the Netherlands Ministry of Finance, of the O.E.C.D. or of the governments of its member countries.

Hans Blommestein is Senior Researcher at OECD in Paris.  
Peter Nijkamp is Professor of Regional Economics in Amsterdam.



## ABSTRACT

Private and public decision methods for conflict resolution are often characterized inter alia by the presence of a multiplicity of interdependent and possibly conflicting criteria measured on non-metric scales. In the paper various reasons are given why these two general features of decision problems have become increasingly important. Four procedures for the analysis of (non-metric) information are proposed in the context of selecting mutually conflicting urban development scenarios. The strengths and weaknesses of these four multiple attribute decision making techniques are demonstrated by a comparative study of (a) the main characteristics of these procedures, and (b) their actual performance when applied to a particular data set. Despite the fact that each of the procedures has been designed to handle non metric information, and despite the high degree of mathematical and computational sophistication involved, in three cases no completely decisive conclusion for the public decision problem at hand could be reached, because only a partial ordering of urban development scenarios could be obtained. Only one method for conflict resolution, i.e., regime analysis, appeared to generate unambiguous, metric solutions.



## 1. Introduction

Technological innovations, rapid economic changes, changes in the political environment of private and social decision making processes are all trends which increased the complexity of decision problems. Consequently, both private and public decision makers (DM's) are confronted with a multiplicity of interdependent (and often conflicting) criteria in solving decision problems. For example, in a regional planning context, water resource development plans (or scenarios) should be evaluated in terms of financial consequences, safety and water quality aspects, demands for political participation, probability of water shortage, spill-over effects, the consequences for recreation possibilities and effects on land and forest use.

The multiplicity of interdependent criteria requires in turn that the action (or policy) spaces of DM's (e.g. a planning framework) are of an interwoven and multidimensional nature. Conventional modes of planning such as facet planning, blueprint planning, top-down planning and the like, fail to take into account the fact that public (and private) planning is an **interdependent** process of criteria and actors (cf. Van Delft and Nijkamp, 1977). Therefore, new planning concepts such as process planning, concerted planning, interactive planning modes, multiple-aspect planning and bottom-up types of planning have emerged (Blommestein and Van Veenendaal, 1981).

A second general feature of decision problems is the (increasing) occurrence of so-called **soft information** (cf. Blommestein and Van Deth, 1981, Blommestein and Nijkamp, 1983, Nijkamp et al., 1985). Soft information is a generic term to indicate data on variables (impacts, objects, stimuli, items, individuals, regions, etc.), which are measured on a so-called non-metric scale (nominal or ordinal levels of measurement). Soft information in decision analysis may emerge when a DM takes into account the complex interrelationships of human behaviour (preferences, perceptions, attitudes, categorical responses, and the like). Other reasons for the presence of soft information are difficulties in the quantification of intangibles and problems in assessing long-run impacts on metric scales.

In this article the following decision problem is analyzed: how to select an optimal - or acceptable - alternative (plan, project, scenario), given the presence of a multiplicity of interdependent and possible conflicting criteria, in the case of soft information. In answering this question four models for the analysis of soft information will be discussed, viz., an ordinal version of concordance analysis (CA),



multidimensional unfolding analysis (MDU), homogeneous scaling analysis (HOMALS) and the regime method (RM). In contrast to many publications, ample attention is also given to **limitations** of these four models. These limitations will be studied in two ways: (a) by presenting an overview of the main characteristics of these models, and (b) by comparing the actual performance of the models when applied to a particular data set.

As a case study, we selected the decision problem faced by the city council of a medium sized town in the Netherlands. For the further development of this community eight alternative scenarios were designed. These alternatives ranged from ('no) action' to the execution of a large scale economic growth programme. Each of these scenarios is evaluated in terms of 29 different criteria. Whereby each criterium is ranked on a 8-point scale. Thus, in operational terms the decision problem to be solved, is the selection of a scenario that has the most acceptable ('optimal') profile of scores with respect to the complete set of 29 criteria.

The organization of this article is as follows. The background of the case study is discussed in section 2. Section 3 reports the main findings of a comparative study of four models for the analysis of soft information. Empirical results are presented in section 4, while conclusions are given in section 5.

## 2. Urban Development Scenarios

The four soft (or qualitative) information models have been applied to the following case study. The city council of a medium sized town in the county of Twente (in the eastern part of the Netherlands) wishes to select an optimal development scenario from the following eight urban development scenarios (see for more details Remmerswaal, 1981):

**Scenario A:** The so-called 'zero' alternative, i.e. do nothing;

**Scenario B:** A stationary growth scenario, viz. providing employment, housing and public facilities proportional to the natural growth rate of the present population in this town.

**Scenario C:** A large-scale housing programme in order to meet the housing demand of (i) the present population (proportional to the natural growth rate), (ii) the part of the (inflow) commuters who live relatively far from the town, and (iii) immigrants originating from nearby (rural) villages.

- Scenario D:** The execution of an economic growth programme characterized by the acquisition of new industries with an emphasis on diversification and by measures to reduce the probable future pressure on the housing market by reducing existing commuting inflows.
- Scenario E:** An expansion of the present administrative territory of the town in order to build even more houses than in scenario C.
- Scenario F:** The execution of an economic growth programme, alongside with a small-scale housing programme and an expansion of the present administrative area.
- Scenario G:** A combination of scenarios C and D, with approximately equal interests assigned to the goals of economic growth and housing.
- Scenario H:** The execution of a balanced programme for the realization of an increase in employment (economic growth) and housing facilities, together with an expansion of the present administrative territory.

The successful realization of these scenarios depends mainly on the regulation of the in- and outflows of commuters. The town under consideration has to trade off physical space for housing against space for new (or expansion of existing) industries. For this reason a survey was conducted to reveal the size of existing in- and outflows of commuters, as well as the main determinants of commuting behaviour. All these numerical assessments were collected in a so-called **impact matrix P**. Each element  $p_{ij}$  of this matrix denotes the technical/physical quantification of the impact of criterion  $i$  on scenario  $j$ . However, for a number of criteria it is very difficult or impossible to assign a meaningful quantification. In these cases, only ordinal information can be obtained, so that the ultimate impact matrix **P** consists of a mixture of scores measured on different levels. For this reason, an ordinal **impact matrix R** is constructed with elements  $r_{ij}$  referring to the ordinal evaluation of scenario  $j$  with respect to criterion  $i$ . Actually, a 8-point scale is applied ranging from  $r_{ij}=1$  (most favourable) to  $r_{ij}=8$  (least favourable). This matrix is shown in Table 1. In case of tied scores we have used the mean value.

Table 1: Ordinal Scenario Impact Matrix R

i \ j		SCENARIOS								
		A	B	C	D	E	F	G	H	
CRITERIA	1	1.5	3.5	5	3.5	8	6.5	1.5	6.5	
	2	2.5	4	1	5	7	7	2.5	7	
	3	2.5	5	2.5	2.5	7	7	2.5	7	
	4	8	7	4.5	6	3	1.5	4.5	1.5	
	5	1	5	5	5	5	5	5	5	
	6	1	4	4	4	4	7.5	4	7.5	
	7	1	2	4	4	6	7.5	4	7.5	
	8	1	3.5	3.5	7	3.5	7	3.5	7	
	9	8	4	4	4	4	4	4	4	
	10	6	8	2.5	6	2.5	2.5	6	2.5	
	11	6	6	6	6	2	2	6	2	
	12		4.5	4.5	4.5	4.5	4.5	4.5	4.5	
	13		7	8	5	6	1.5	3	4	1.5
	14		8	5.5	2	5.5	2	5.5	5.5	2
	15		4	4	1.5	4	6	7.5	1.5	7.5
	16		2	2	4.5	2	7	7	4.5	7
	17		3	3	1	6	6	8	3	6
	18		3	3	3	3	7.5	6	3	7.5
	19		4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5
	20		8	6.5	4.5	6.5	1.5	3	4.5	1.5
	21		3	4.5	1.5	4.5	6.5	8	1.5	6.5
	22		4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5
	23		4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5
	24		8	4	1.5	3	5.5	7	1.5	5.5
	25		6	6	2.5	2.5	2.5	6	2.5	8
	26		6	6	8	3.5	3.5	1.5	6	1.5
	27		2	4	1	4	6	7.5	4	7.5
	28		1	5.5	2	3.5	5.5	7.5	3.5	7.5
	29		8	5.5	5.5	5.5	2	2	5.5	2

The 8 columns of matrix  $R$  ( $r_{.j}$ ) coincide with the eight scenarios discussed above. The 29 rows ( $r_{i.}$ ) coincide with the 29 criteria, which equal the major dimensions of the urban development problem under study. A systematic valuation can be facilitated by a subdivision of the 29 criteria into 7 sub-profiles viz., housing (I), employment (II), infrastructure (III), public facilities (IV), environment (V), commuting (VI), and juridicial structure (VII). In order to give an impression of both the complexity of this case study and of the difficulties encountered in the valuation of the 29 criteria, a brief discussion of each criterion will be given.

### **Subprofile I**

This subprofile encompasses four indicators for the assessment of housing development programmes. Naturally, the element of space plays an important role. Available physical space, defined by present administrative boundaries, must be allocated according to different objectives. Criterion 1 is an indicator for the allocation of physical space needed for the realization of the housing component of the eight urban development scenarios. Criteria 2 and 3 are ordinal measures for the impact of carrying out a particular development scenario  $j$  on the push and pull factors of residential choice behaviour, respectively. The estimated monetary costs of new dwellings is denoted by criterion 4.

### **Subprofile II**

The employment subprofile consists of criteria with respect to new economic activities. The allocation of physical space needed for the realization of new industrial and other commercial activities is reflected in criterion 5. Criterion 6 is an indication for the impact of urban development scenarios on the diversification of economic activities, and thus on the diversification of jobs. The estimated growth of the employment rate is denoted by criterion 7. Criterion 8 is an indicator for the impact on the determinants of locational choice behaviour of entrepreneurs, while criterion 9 stands for estimated financial costs.

### **Subprofile III**

The third subprofile denotes the transportation aspects of these scenarios. Criteria 10, 11 and 12 refer to improvements in three types of public transportation, viz., by road, rail, and air. Improvements in the infrastructure for private transportation are captured in the ordinal

criterion 13, while criterion 14 stands for the estimated financial consequences of both improvements in public and private transportation.

#### **Subprofile IV**

This subprofile encompasses six indicators for the valuation of public and private facilities. Criterion 15 is an indicator of the necessary physical space. The ordinal impact on the diversification of facilities is measured by criterion 16, while criteria 17, 18 and 19 are indicators of the impact on the availability of shops, capacity of cultural facilities and the size of recreation areas, respectively. An estimate of the necessary costs of this component of the different scenarios is denoted by criterion 20.

#### **Subprofile V**

This subprofile stands for an ordinal valuation of the environmental consequences, viz. criterion 21 (density of dwellings), criterion 22 (air and noise pollution), criterion 23 (impact on the size of natural areas) and criterion 24 (the (estimated) additional costs for securing the supply of clean (purified) drinking water).

#### **Subprofile VI**

One of the objectives of the city council was to reduce in- and outgoing commuting flows. This means, inter alia, that new jobs have to be created, whereby the discrepancy with the job profile of the commuters must be minimized, and sufficient housing - and other facilities - must be made available. Criteria 25 and 26 record the impacts of the different urban development scenarios on the volume and composition (with respect to the job profile) of ingoing commuting flows, while criteria 27 and 28 denote the same type of impacts on outgoing commuting flows.

#### **Subprofile VII**

This subprofile encompasses only one criterion, viz., the juridicial actions necessary for a successful implementation of the different scenarios. The juridicial problems concern changes in the legal boundaries of the city (for obtaining additional physical space) and to obtain formal approval for building houses or factories near protected natural areas.

In the introduction various reasons for the presence of soft information in private and public decision making processes were briefly mentioned. At this stage these reasons can be further substantiated. First there is the occurrence of so-called intangibles. Intangibles (cf. Prest

and Turvey, 1965) are impacts which are difficult to quantify (e.g. the impact of the beauty on the landscape due to the construction of highways or electricity transmission lines) and which cannot or very difficult be valued in any market sense (e.g. a reduction in human life or an increase of the noise level). The impossibility of the valuation of impacts at market prices has led to adjusted concepts like shadow prices, hedonic prices and contingent valuation within the framework of monetary evaluation techniques, and to the development of non-monetary evaluation techniques. However, both approaches require the quantification of impacts, which may be a very difficult and/or costly matter. On the other hand it is often relatively easy to indicate the impacts on an ordinal scale. For example, two criteria of our matrix R express the impacts on the natural environment of the town under study (i.e., criteria 22 and 23).

Secondly, the long-run impacts are very often difficult to assess on a metric scale (due to an increase in uncertainty). Also the costs of gathering information may increase quite substantially. However, it is often relatively easy to indicate long run **tendencies** such as a higher GNP, an increase in pollution, a decrease in employment, etc. by means of a ranking of impacts. Examples from our case study are the impacts on the development of employment (criterion 7) and commuting flows (criteria 25 and 27).

Thirdly, it is necessary to take into account the preferences of both private individuals and public decision makers. Those preferences are most often available in ranked form, and thus measured on an ordinal scale. Examples from the case study discussed here are criteria 2, 3 and 8.

### 3. Four Multiple Attribute Decision Making Techniques

#### 3.1 Prologue

The rich variety of techniques for the evaluation and selection of plans may be classified into two groups: (a) monetary evaluation techniques such as cost benefit analysis, cost effectiveness analysis, or planning balance sheet methods, and (b) multiple criteria evaluation (or multiple attribute decision making: MADM) techniques such as trade-off analysis, goals achievement method, correspondence analysis, concordance analysis or scaling analysis. If monetary evaluation techniques are used, the matrix P has to be transformed in a monetary plan impact matrix, whereas this is not required for the application of MADM techniques.

The choice of monetary or non-monetary evaluation techniques is dependent upon the fulfilment of a set of assumptions underlying these two distinct approaches. An appropriate use of a monetary evaluation technique such as cost benefit analysis (notably its Paretian interpretation) requires the fulfilment of a set of rather stringent conditions, such as the availability of market or accounting prices to translate costs and benefits in financial terms, and the absence of intangible criteria (see Blommestein and Mol 1984). MADM techniques, on the other hand, can be used to deal with a wider range of problems than monetary evaluation techniques. For example, conflicts among criteria, the existence of incommensurable units of measurement, the explicit incorporation of preferences, or the scoring of attributes, objectives and the like on different levels of measurement can be considered simultaneously by means of MADM techniques. Monetary evaluation techniques cannot handle soft information, since these models require some kind of quantification of the impacts  $p_{ij}$ . In order to avoid these complications, and to preserve our information in its available form, we have chosen MADM techniques to analyze the ordinal plan impact matrix  $R$  of the eight scenarios and the 29 criteria.

Four variants of MADM techniques will be applied here: an ordinal version of concordance analysis (CA), multidimensional unfolding analysis (MDU), homogeneous scaling analysis (HOMALS), and regime analysis (RA). These techniques have in common that they start with the same impact matrix and result in some positioning of the scenarios relative to each other by using only the non-metric properties of the data. There are, however, important differences between the models and the algorithms underlying these techniques. CA is selected here because it is a rather straightforward and widely used MADM technique. Its main limitation is that, by definition, CA yields a rank order of the scenarios. This one-dimensional representation of the data might violate the actual relationships between the plans. The use of MDU provides the opportunity to position the scenarios in a higher dimensional space; the question of whether or not there exists a simple ordering of the scenarios in a multi-dimensional space can be subjected to empirical tests. Thirdly, the more complicated HOMALS technique is selected. Its attractiveness is the fact that, in addition to the positioning of the scenarios in some higher dimensional metric space, information can be obtained about the degree of discrimination of each of the 29 criteria. Finally, we will use the recently developed regime method, which tries to reconcile mathematical soundness with accessible and user-friendly software. A brief and

simplified account of CA, MDU, HOMALS and RA will illustrate the differences and advantages of these four techniques.

### 3.2 Concordance analysis

**Concordance analysis** (A) can be considered as an elaboration of the so-called Electre method (cf. Benzécri, 1973; Guigou, 1974). An ordinal version of CA consists of the following steps:

**Step 1:** Construction of a plan impact matrix  $R$  of order  $(I \times J)$  with elements  $r_{ij}$  measured on the ordinal scale. Thus  $r_{ij}$  is the rank order consistent with the plan impact value  $p_{ij}$ .

**Step 2:** Determination of  $J(J-1)$  concordance sets  $C_{jj', (>)}$  with criteria defined for each pair of plans  $j$  and  $j'$  as  $C_{jj', (>)} = \{i | r_{ij} < r_{ij'}\}$ ,  $j \neq j' \in \{1, \dots, J\}$ ,  $i \in \{1, \dots, I\}$  (where  $>$  represents a strong preference relationship,  $<$  not preferred to, and  $\epsilon$  membership of a set). Between concordance and discordance sets the following relationship exists (see Rietveld, 1980):  $C_{jj', (>)} = D_{jj', (<)}$ .

**Step 3:** Calculation of the concordance indices  $CV_{jj', (>)}$  defined as  $CV_{jj', (>)} = \frac{1}{i \in C_{jj', (>)}} \psi_{jj', (>)}(i)$ ; where  $\psi_{jj', (>)}(i)$  is a concordance function for which different forms are proposed (cf. Nijkamp and Van Delft, 1977; Rietveld 1980). We use two different definitions:  $CV_{jj', (>)} = \frac{1}{i \in C_{jj', (>)}} 1$ , and  $CV_{jj', (>)} = \frac{1}{i \in C_{jj', (>)}} (r_{ij} - r_{ij'})$ .

**Step 4:** Computation of the vector  $d$  with the net concordance dominance values  $d(j)$  as elements, defined as  $d = (CV - CV')f$ ; where  $CV$  is a matrix with typical values  $CV_{jj', (>)}$ , and  $f$  a unity column vector. The optimal alternative  $j^*$  is that scenario with the maximum net concordance dominance value:  $d(j^*) = \max |d(j), j \in \{1, \dots, J\}|$ .

### 3.3 Multidimensional unfolding

The application of **multidimensional unfolding** (MDU) results in a common or joint space for both the scenarios and the criteria (see Kruskal et al, 1973). The procedure includes a series of steps, including an iterative optimization routine.



**Step 1:** Construction of a (dis)similarity matrix  $S$  by computing some measure of distance or correlation for each pair of vectors of the impact matrix  $P$  (or the ordinal matrix  $R$ ).

**Step 2:** Representation of the (dis)similarities in a space of selected dimensionality. Suppose that  $S_{jk}^i$  means that for criterion  $i$  scenario  $j$  has a higher score than scenario  $k$ . This value  $S_{jk}^i$  will be represented by a distance  $Z_{ij}$  between the points  $i$  and  $j$  in some solution space. The distances can be defined in several ways (cf. Young, 1972), but usually the Euclidean (or Minkowsky-2) metric is used.

**Step 3:** Transformation of the obtained distances in a set of intermediate variables (so-called disparities). These values are used in a stress function (a loss function), so as to minimize the discrepancies between the rank order of the entries of the (dis)similarity matrix  $S$  and those of the distance matrix  $Z$ .

**Step 4:** Repeat steps 3 and 4, until some convergence criterion is satisfied. In the final configuration, the order of the distances  $Z_{ij}$  has to be as close as possible to the order of the scores of the criterion for each scenario, i.e.:  $Z_{ij} \leq Z_{ik} \leftrightarrow S_{jk}^i$ .

### 3.4 Homogeneous scaling

As a third technique we use **homogeneous scaling** or, more precisely, HOMogeneity analysis by Alternative Least Squares (HOMALS) (Gifi, 1980). This can be considered as an extension of correspondance analysis as well as a member of the multidimensional scaling family. The HOMALS procedure is summarized below.

The aim is to find one single criterion for the selection of scenarios, that could replace the total set of 29 different scaling vectors. If such a 'stand-in' criterion exists, the set of 29 vectors can be called homogeneous. As a measure for the degree of homogeneity a loss function of the following type can be defined (see for more details Gifi, 1980; p.56):

$$\sigma(\underline{z}) \triangleq \frac{1}{m} \sum_{j=1}^m V(\underline{z} - \underline{h}_j)$$

where  $\underline{h}_1 \dots \underline{h}_m$  are the distinct criteria,  $\underline{z}$  the vector that replaces the set of criteria and  $V$  the variance to be computed.

However, there is nothing inherent in the actual problem that forces us to use only the figures from 1 to 8 for the scoring of the scenarios; only an ordinal level is required. There might be a monotone transformation of the scores that provides a higher degree of homogeneity than obtained now. A general transformation in these cases is a non-linear one of the type:

$$\underline{Y}_j = \phi_j(h_j)$$

yielding a loss-function of the form:

$$\sigma(\underline{z}) \triangleq \frac{1}{m} \sum_{j=1}^m V(\underline{z} - \underline{Y}_j)$$

The most interesting candidate for the  $\phi_j$  seems to be the first principal component of the correlation matrix. In that case the loss function is minimized and the computation is partly redefined as an eigenvalue problem. This implies that the scores on the criteria will be transformed in such a way that the largest eigenvalue of the correlation matrix of the transformed criteria will be as large as possible.

HOMALS, which originated in psychometrics (Gifi, 1980), is based on an optimal weighting algorithm to an indicator matrix  $G$  of dimension  $(I \times \sum k_j)$ , with as elements binary matrices  $G_j$  of order  $(I \times k_j)$ . The binary matrices  $G_j$  contain the information obtained by a binary coding of the original data matrix. This means that the data matrices used in HOMALS indicate for each of the  $I$  objects (individuals, scenarios, regions, etc.) in which category  $k_j$  of the  $J$  variables (criteria) they have scored. This feature is very useful when a prior quantification of the categories is not available or too complex (e.g., when relations between variables cannot properly be described by means of linear relations).

The loss function used in the HOMALS algorithm can be written as

$$\sigma(X;Y) = \frac{1}{J} \sum_{j=1}^J \text{SSQ}(X - G_j Y_j)$$

where  $X$  is a  $(I \times S)$  matrix with objects scores, and  $Y$  a matrix with quantifications of all  $\sum k_j$  categories;  $S$  denotes the dimensionality chosen by the user, with boundaries 1 and  $\sum(k_j - 1)$ , and SSQ the sum of squares. This loss function is minimized (thus homogeneity is maximized) by employing the principle of **alternating least squares** in the following (basic) algorithmic steps of HOMALS:

**Step 1:**  $\text{Min}_Y \phi(X; Y)$ ,  $X$  fixed,

yields  $Y_j^\ell = (G_j^T G_j)^{-1} G_j^T X^\ell$ ; where the superscript  $\ell$  indicates iteration step  $\ell$ . Clearly, the algorithm requires an initial choice for  $X$ . The initialization starts with an arbitrary choice of  $X$  subjects to the normalization restriction  $X^T X = I_s$ , in which  $I_s$  is a  $(S \times S)$  diagonal matrix with elements 1 on the main diagonal. Thus for step  $\ell=0$  we have  $Y_j^0 = (G_j^T G_j)^{-1} G_j^T X^0$ , where  $X^0$  is an orthogonalized configuration of arbitrarily chosen numbers (random configuration) between 0 and 1; and  $Y_j^0$  the category quantifications for variable  $j$  with  $k_j$  categories in an  $S$ -dimensional space.

**Step 2:**  $\text{Min}_X \phi(X; Y)$ ,  $Y$  fixed,

yields  $X^\ell = \frac{1}{J} G Y^{\ell-1}$ . In both steps some sort of normalization is required to avoid degenerate solutions of the loss functions to be minimized. The HOMALS programme takes as a normalization condition  $X^T X = I_s$ . The matrix  $X$  is normalized by a so-called Gram-Schmidt orthogonalization procedure.

The HOMALS algorithm proceeds in alternating steps, where in step 1  $\sigma(X; Y)$  is minimized with respect to  $Y$  for fixed  $X$ , and in step 2  $\sigma(X; Y)$  is minimized with respect to  $X$  for fixed  $Y$ . This alternating procedure stops when  $|\sigma_\ell - \sigma_{\ell-1}| < \delta$ , where  $\sigma_\ell$  is the value of the loss function in iteration step  $\ell$ , and  $\delta$  is an accuracy or convergence criterion selected by the user.

### 3.5 Regime analysis

Finally, we will discuss concisely the regime method. Consider two choice options  $j$  and  $j'$ . If for criterion  $i$  a certain alternative  $j$  is better than option  $j'$  (that is,  $s_{jj'i} = e_{ji} - e_{j'i} > 0$ ), then it should be noted that in the case of ordinal information, the order of magnitude of  $s_{jj'i}$  is not relevant, but only its sign. Consequently, if  $r_{jj'i} = \text{sign } s_{jj'i} = +$ , then alternative  $j$  is better than alternative  $j'$  for criterion  $i$ . Otherwise,  $r_{jj'i} = -$ , or (in the case of ties)  $r_{jj'i} = 0$ . By making such a pairwise comparison for any two alternatives  $j$  and  $j'$  for all criteria  $i$  ( $i = 1, \dots, I$ ), we may construct a  $I \times I$  regime vector  $r_{jj'}$ , defined as

$$r_{jj'} = (r_{jj'1}, \dots, r_{jj'I})^T, \quad j, j', j' \neq J$$

Thus, the regime vector contains only + and - signs (or, in the case of ties, 0 signs as well), and reflects a certain degree of (pairwise) dominance of choice option  $j$  with respect to option  $j'$  for the unweighted effects for all  $I$  judgement criteria. Clearly, we have  $J(J-1)$  pairwise comparisons altogether, and hence also  $J(J-1)$  regime vectors. These regime vectors can be included in an  $J \times I(I-1)$  regime matrix  $R$ :

$$R = \left[ \begin{array}{cccc} r_{12}, r_{13}, \dots, r_{1J}, & \dots, & r_{J1}, \dots, & r_{J(J-1)} \\ \underbrace{\hspace{10em}}_{J-1} & & \underbrace{\hspace{10em}}_{J-1} & \end{array} \right]$$

It is evident that if a certain regime vector  $r_{jj'}$  would contain only + signs, alternative  $j$  would dominate alternative  $j'$  absolutely. Usually, however, a regime vector contains both + and - signs, so that additional information in the form of a weights vector  $w = (w_1, \dots, w_I)^T$  is required.

In order to treat ordinal information on weights, the assumption is now made that the ordinal weights  $w_i$  ( $i = 1, \dots, I$ ) are a rank order representation of an (unknown) underlying cardinal stochastic weight vector  $w^*$ , viz.  $w^* = (w_1^*, \dots, w_I^*)^T$ , with  $\max_i \{w_i^*\} = 1$ ,  $w_i^* \geq 0, \forall i$ .

The ordinal ranking of the weights is then supposed to be consistent with the quantitative information incorporated in an unknown cardinal vector,  $w^*$ ; in other words,  $w_i > w_{i'} \rightarrow w_i^* > w_{i'}^*$ . Next, we assume that the weighted dominance of choice option  $j$  with regard to option  $j'$  can be represented by means of the following stochastic expression based on a weighted summation of cardinal entities (implying essentially an additive linear utility structure):

$$v_{jj'} = \sum_{i=1}^I r_{jj'} w_i^*$$

If  $v_{jj'}$  is positive, choice option  $j$  is clearly preferred to option  $j'$ . However, in our case we do not have information on the cardinal value of  $w_i^*$ , but only on the ordinal value of  $w_i$  (which is assumed to be consistent with  $w_i^*$ ). Therefore, we introduce a certain probability,  $p_{jj'}$ , for the dominance of option  $j$  with respect to option  $j'$ , i.e.

$$P_{jj'} = \text{prob}(v_{jj'} > 0),$$

and define as an aggregate probability measure:

$$P_j = \frac{1}{J-1} \sum_{j' \neq j} P_{jj'}$$

Then it can easily be seen that  $p_j$  is the probability that alternative  $j$  is on average higher valued than any other alternative. Consequently, the eventual rank order of choice options is determined by the rank order (or the order of magnitude) of the  $p_j$ .

However, the crucial problem here is to assess  $p_{jj'}$  and  $p_j$ . This implies that we have to make an assumption about the probability distribution function both of the  $w_i^*$  and of the  $s_{jj'}$ . In view of the ordinal nature of the  $w_i$ , it is plausible to assume for the whole relevant area a uniform density function for the  $w_i^*$ . The motive is that if the ordinal weights vector,  $w$ , is interpreted as originating from a stochastic weight vector,  $w^*$ , there is, without any prior information, no reason to assume that a certain numerical value of  $w^*$  has a higher probability than any other value. In other words, the weights vector,  $w^*$ , can adopt with equal probability each value that is in agreement with the ordinal information implied by  $w$ . This argument is essentially based on the 'principle of insufficient reason', which also constitutes the foundation stone for the so-called Laplace criterion in the case of decision making under uncertainty (Taha, 1976). However, if prior information in a specific case suggests it is plausible to assume a different probability distribution function (a normal distribution, for example), there is no reason to exclude this new information. Of course, this may influence the values of  $p_{jj'}$  and hence the ranking of alternatives. The precise way in which rank order results can be derived from a probability distribution when there is qualitative information will not be discussed further here, as this topic has been extensively described elsewhere (Hinloopen and Nijkamp, 1988). But it may suffice to mention that, in principle, the use of stochastic analysis in combination with computer simulations, which is consistent with an originally ordinal data set, may help to overcome the methodological problem emanating from impermissible numerical operations on qualitative data. The regime method is also able to handle ties in the effect matrix and in the weight vector. The regime method is available on a diskette for an IBM-compatible PC, so that it can easily be used by planners in the field.

#### 4. Results of Methods for the Development Scenarios

##### 4.1 Concordance analysis

Application of the ordinal CA to the case study described above yielded - for both forms of  $\psi$  - the following solution configuration:

$$F > H > B > E > D > A > G > C$$

The following remarks can be made with respect to the ordinal version of CA:

- In steps 3 and 4 the calculations were made under the assumption that the length between two successive rank orders is equivalent. This means that an ordinal CA requires more information than provided by the ordinal impact matrix R.

- By definition CA yields solution configurations in a one-dimensional space. This may be an incorrect description of the actual situation. Suppose, for instance, that the solution configuration of four alternatives A, B, C and D can be represented on a complete higher ordered metric scale, and that the  $4(4-1)/2$  interpoint distances have the rankorder  $AB < CD < BC < AC < AD$ . This can be reconciled only in a two - or higher - order dimensional space.

It can be concluded that in steps 3 and 4 of the 'ordinal' CA, untenable assumptions are included with respect to dimensionality of solution spaces and measurement levels of data. For this reason multidimensional scaling models will be used in the next section. These models are capable to deal more adequately with ordinal data matrices and higher-dimensional ( $\geq 2$ ) solution spaces.

##### 4.2 Multidimensional unfolding

Multidimensional (unfolding) scaling models provide configurations for either the stimuli or the subjects (i.e., scenarios and criteria, respectively). The application of multidimensional unfolding models, however, results in a common or joint space for both the scenarios and the criteria. A multidimensional unfolding analysis of the 29 criteria and the eight scenarios have been undertaken in our study. Stress measures have been obtained with the multipurpose programme KYST (Kruskal, Young, Seery, 1973). For the set of criteria two different approaches to handle ties in the data are explored ('primary' and 'secondary' approaches) for both two-

and one-dimensional solution spaces. In order to assess the stability of the solutions, two distinct ways to estimate the initial configurations for the nonmetric analyses have been used, viz. 'torsca' and 'random'. Besides, a so-called metric analysis has been carried out by fitting polynomials of degree 1 to 4 as functions for the relation between data and distances (see Kruskal, Young, Seery, 1973 for further details and references). The results of these analyses are summarized in Table 2.

Table 2: Results of the MDU analysis of 8 scenarios and 29 criteria.

STRESS: TIES: DIMENSIONS:		SFORM1				SFORM2			
		PRIMARY		SECONDARY		PRIMARY		SECONDARY	
		1	2	1	2	1	2	1	2
TYPE	START								
NON-METRIC }	TORSCA	.009	.015	.010	.017	.008	.059	.558	.292
	RANDOM	.004	.009	.010	.009	.006	.008	.479	.247
METRIC	POL= 1	.009	.012	.009	.012	.757	.316	.757	.316
	POL= 2	.008	.015	.008	.015	.498	.324	.498	.324
	POL= 3	.008	.011	.008	.011	.533	.306	.533	.306
	POL= 4	.008	.013	.008	.013	.523	.304	.523	.304

The one-dimensional solutions have stress measures which are lower than the two-dimensional results. Since lowering the dimensionality of the space places additional restrictions on the data, the stress should increase when the dimensionality decreases. Inspection of the one-dimensional plots shows so-called degenerate solutions. The stress is minimized by placing all criteria and all scenarios in two distinct, very small regions. However, some of the two-dimensional solutions are 'good' in terms of stress. But again we have to conclude that the results are useless for our purpose of selecting an optimal scenario. The two-dimensional solutions with acceptable levels for the 'badness-of-fit' measure appear to be partly degenerate, since the scenarios are all located in one very small region. The criteria are placed at about equal distances to this region and thus the plots are useless to evaluate the criteria separately. The same applies to the metric model using the SFORM1 definition for the 'badness-of-fit'. For the SFORM2, the values for this measure are too high to spend time interpreting the configuration plots.

The results of these MDU analyses are apparently rather disappointing. Hardly any meaningful information could be obtained for selecting a

scenario, although many variants of this model were explored and a widely used computer programme was available. The relatively large number of ties in the data is mainly responsible for the great many degenerate solutions.

#### 4.3 Homogeneous scaling

As a third technique we used the HOMALS approach. The use of the HOMALS programme for our scenarios and criteria provides us first of all with some information about the 29 criteria. It becomes clear which criteria are able to discriminate between the scenarios and which are more or less unable to do so. As a measure for discrimination, the square of the total-item correlation of the transformed variables can be used (see Gifi, 1980, p.69 for further details). For criteria 12, 19, 22 and 23 the discrimination measure is zero. They should have a zero for this measure since it is clear from the data matrix that they each have the same score for the eight scenarios. The criteria 5, 9, 14 and 25 have relatively poor figures for the measure of discrimination (i.e. below .500). This too could be predicted from the data since these criteria have equal scores for various scenarios. There are 21 criteria left that have good measures of discrimination. The model will mainly use these criteria to order the scenarios. Figure 1 shows the two-dimensional plot of the obtained scores for the scenarios after transformation of the criteria to maximum homogeneity.

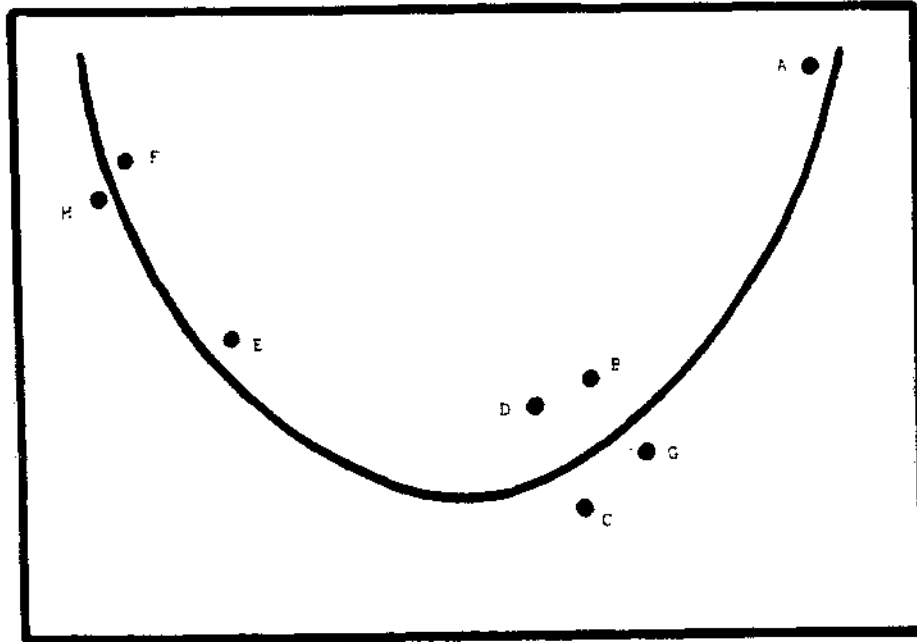


Figure 1. HOMALS Solution of Object Scores for the 8 Scenarios in Two-Dimensional Space



Although a two-dimensional plot is obtained, a one-dimensional interpretation seems to be most appropriate, since the points are located on a line usually called a 'horse shoe'. That implies that the second scale is a cubic regression of the second dimension on the first, and thus a one-dimensional ordering of the scenarios along the shoe can be considered. This leads to the following ordering of scenarios: F-H>E>C~D~B-G>A. Since HOMALS provides metric information, it can be seen that H and F are about equal preferable while E follows at some distance. Scenario A appears clearly to be the least desirable one. This configuration differs partly from the results obtained with the CA ranking of the scenarios. In addition to the rank order resulting from that analysis, we are now able to evaluate the 29 criteria in terms of discrimination power and to infer conclusions about higher-dimensional metric solutions. Before we accept the HOMALS-solution we have to check whether the requirement of monotone transformations of the scores has not been violated. Unfortunately, the results of the HOMALS analyses appear to be very misleading after a closer look at the required transformations. In order to obtain the above mentioned ranking of the scenarios, the scores have been transformed in such a way that homogeneity is optimized. In this case, homogeneity could be reached only by applying a nominal transformation instead of a monotone one. In other words, if we accept the ranking obtained for the scenarios, we are able to test the assumption that the criteria provide information on an ordinal level. According to the HOMALS analyses, however, this hypothesis has to be rejected. Therefore, we cannot accept a ranking of the scenarios as indicated above. That presents the same dilemma as encountered in the CA analysis: we have to make more or less heroic or arbitrary assumptions on the level of measurement of the data in order to obtain a ranking at all! In case the homogeneous scaling model is applied to our data, the required transformation also leads to unacceptable results, despite the sophistication of ideas that have been incorporated in this model.

#### 4.4 Regime analysis

The results of the RA solution algorithm appeared to lead to more useful results. They are presented here as aggregate probability measures  $p_j$  (see Table 3) in descending order for the eight scenarios.

	$P_j$
F	.987
H	.845
E	.643
B	.598
D	.405
A	.353
G	.159
C	.009

Table 3. Results from (unweighted) regime method

Table 3 indicates that these results are consistent with results from the previous soft modeling approaches: F and H appear to score very high; clearly, F has the highest success score. This implies that the RA is not only capable to generate a rank order of alternatives, but also a unique cardinal representation of the importance of each choice option. In this respect, the regime method is apparently superior to the previous methods.

#### 4.5 Retrospect

It must be ascertained that it was not possible for any of the first three soft modelling procedures to generate a complete metric ordering of the urban development scenarios without violating the basic assumptions of the models. Only a partial non-metric ordering could be obtained with these three procedures: the scenarios F and H dominate all other scenarios. In this context it can be noted that the application of another soft modelling procedure, viz. the permutation method of Jacquet-Lagrèze (1969), appeared to lead to exactly the same outcome as the CA analysis.

However, the RA method yielded plausible and numerically testable results. Not only did we obtain an unambiguous ranking but even an unambiguous cardinal representation of the importance of each alternative was derived.

## 5. Conclusions

In this article four multiple attribute decision making techniques for conflict resolution were applied in a case study on urban development scenarios. The case-study itself was presented as an example of a public decision problem (i.e., the selection of an optimal urban development scenario), with main characteristics the presence of a multiplicity of interdependent and possibly conflicting criteria measured on a non-metric scale.

It has become clear, first, that the results (final configuration data) from MDU and HOMALS can be used as a check on the results (dimensionality and level of measurement of the 'final' configuration) of CA. Similarly, HOMALS can be used as a check on the MDU results. Secondly, if CA, MDU and HOMALS (or any combination) would yield different results, a decision-maker should rely on the performance of the most powerful model, i.e. that soft modelling procedure which imposes the least stringent restrictions on the level of measurement of the data of the urban development scenarios (e.g. HOMALS). These results are only valid of course, if they are judged to be satisfactory according to such diagnostic criteria as stress, transformation scores, plots of object and subject scores, etc.

For our case study it must be concluded that the data analyzed were - given our objectives - too imprecise for three of our models, and for these cases it was not possible to obtain a perfect solution for the public decision problem described above. In other words, it was not possible to obtain a complete metric ordering of the urban development scenarios for CA, MDU and HOMALS. Only a partial non-metric ordering was generated by these first three soft modelling procedures; the scenarios F and H dominate all other scenarios. In contrast to the disappointing results of CA, MDU and HOMALS, the RA method appeared to be much more powerful and to lead to quantitative inferences on the importance of alternatives.

## References

- Benzécri, J.P. (1973), L'Analyse des Données, Tome 1 and 2, Dunod, Paris.
- Blommestein, H.J. and Van Deth, J.W. (1981), The Analysis of Soft Information for Urban Planning Processes, Proceedings of the 8th European Urban Data Management Symposium, June 2-5, Oslo, Norway.
- Blommestein, H.J. and Nijkamp, P. (1983), Causality Analysis in Soft Spatial Econometric Models, Papers of the Regional Science Association, 51, pp. 64-77.
- Blommestein, H.J. and Van Veenendaal, W.M. (1981), Urban Welfare and Urban Facilities, in Locational Developments and Urban Planning, W.F.J. van Lierop and P. Nijkamp (eds.), Sijthoff and Noordhoff, Alphen aan den Rijn.
- Blommestein, H.J. and Mol, N.P. (1984), Kosten-batenanalyse en Decisie-Analyse, in Blommestein et al., (eds.), Handboek Beleidsevaluatie, Samson Publ. Cy., Alphen aan den Rijn.
- Delft, A. van and Nijkamp (1977), Multi-Criteria Analysis and Regional Decision-Making, Stenfert Kroese, Leiden.
- Faludi, A. (1973), Planning Theory, Pergamon Press, New York.
- Gifi, A. (1980), Niet-lineaire Multivariate Analyse, Leiden, University of Leiden, Department of Data Theory, the Netherlands.
- Guigou, J.L. (1974), Analyse des Données et Choix à Critères Multiples, Dunod, Paris.
- Hinloopen, E., and Nijkamp, P. (1988), Qualitative Multiple Criteria Choice Analysis: the Dominant Regime Method, Quality and Quantity (forthcoming).
- Jacquet-Lagrèze, E. (1969), L'agrégation des Opinions Individuelles, Informatiques en Sciences Humaines, 4.
- Kruskal, J.B., Young, F.W. and Seery, J.B. (1973), How to Use KYST, a very Flexible Program to do Multidimensional Scaling and Unfolding, Bell Laboratories, Murray Hill, N.J.
- Nijkamp, P., Leitner, H. and Wrigley, N. (eds.), Measuring the Unmeasurable, Kluwer Nijhoff, Dordrecht, 1985.
- Prest, A.R. and Turvey, R. (1965), Cost-Benefit Analysis: A Survey, Economic Journal, 75, pp. 287-315.
- Remmerswaal, H. (1981), Pendelonderzoek Oldenzaal, Uitgave Industriestichting Oldenzaal (mimeographed).
- Rietveld, P. (1980), Multiple Objective Decision Methods and Regional Planning, North-Holland Publishing Company, Amsterdam.
- Taha, H.A., 1976, Operations Research (Macmillan, New York)
- Young, F.W. (1972), A Model for Polynomial Conjoint Analysis Algorithms, in: Multidimensional Scaling, Theory and Applications in the Behavioural Sciences, R.N. Shepard et al. (Eds.), Seminar Press, New York etc.

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