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Interactive Learning Models for Integrated Planning

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RECENT TRENDS IN POLICY ANALYSIS

THE USE of programming models has a long history in the area of planning and policy analysis. Operations research methods especially have been widely applied in economic, environmental and energy policy problems, even on a global scale. The use of such models and techniques, however, also has been severely criticized due to the stringent assumptions underlying such advanced mathematical tools. The usual assumptions regarding mathematical models for policy analysis are:

(a) the existence of a clearly identifiable and unambiguous decision-maker or policy-maker;

(b) in a multi-person decision framework, the role of the successive decision-makers involved can be assessed precisely, either by defining an aggregate decision system or by estimating the relative power influence of the individuals or sub-groups (Blair, 1979; Saaty, 1977; and Shapley and Shubik, 1954);

(c) the objective(s) relevant for the planning problem concerned are exactly known (including their mutual trade-offs);

(d) spatial and social impacts of decisions to be made may be either neglected or assessed accurately via a spatial or social distributional systems model;

(e) equity and distribution problems (between either groups or regions) can be taken into account by means of the policy objectives and the structure of the special model in hand;

(f) the complex relationships between policy measures and policy objectives are precisely known via an operational economic model describing the various relevant impacts;

(g) the technical, institutional, social and economic side-conditions of the system concerned are also precisely known and can be specified in an operational way;

(h) the time trajectory of all variables of the system can be computed precisely;

(i) when the state of a system is characterized by uncertainty (for instance, due to stochastic variables), the probability distribution of the stochastic elements is known.

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In the practice of decision-making, however, such conditions are hardly ever fulfilled, so that the optimal state of the system in hand is often an unrealistic concept. Consequently, traditional programming models tend to receive a fairly modest position in modern policy analysis. It turns out that the attention of policy makers has shifted from optimality analyses to impact analyses, effectiveness analyses and strategic-decision analyses. In such analyses, much more emphasis is placed on effects of policy measures, on shifts in social objectives and on conflict management and compromise principles.

Consequently, modern policy analyses have to be multidimensional in nature (Nijkamp, 1979; Nijkamp and Spronk, 1981; Rietveld, 1980) as they have to take into account the existence of a wide variety of social interests, decision groups and policy structures. This broader view on policy analysis requires an integrative framework for judging alternative policy options. Instead of designing optimizing systems, more emphasis has to be put on rationalizing systems by providing relevant information; revealing conflicts among objectives or groups; assessing trade-offs among different choice possibilities; gauging the distributive impacts of policy measures; identifying efficient (non-dominated) solutions; designing suitable and relevant methods for policy evaluation; and so forth. The current interest in interactive, multidimentional programming models for policy analysis clearly demonstrates the new trends in designing and employing formal tools for decision-making. This will be further discussed in the following sections.

POLICY ANALYSIS: CONTENTS

Given these recent trends in policy analysis, the following stages may be distinguished in setting up a policy analysis:

— the identification of policy objectives and of related judgement criteria for policy measures;
— the identification of all alternative choice possibilities which are considered to be relevant for the policy problem in question;
— the assessment of all foreseeable and expected effects of policy measures (or policy choices) upon the above mentioned objectives and criteria (for instance, by means of a formal structural model or an impact system);
— the identification of interest groups, and/or decision groups associated with the policy problem in question, as well as the assessment of conflicts among diverging priorities;
— the assessment of policy priorities and weights attached by policy-makers to the effects of measures taken by them;
— the development of appropriate evaluation methods and procedures (based on learning principles, for example);
— the treatment of information during the implementation stage of a

policy plan so as to get insight into the sensitivities of the policy impact analyses;

— an *ex post* evaluation of the actual policy decisions and of the role of the policy analysis in making these decisions.

Following on these remarks about policy analysis, criteria may be specified for a meaningful policy analysis:

— it should be able to assess the impacts of decisions or measures to be taken on policy objectives and/or criteria;

— it should provide a complete picture of relevant policy objectives, so that direct and indirect, intended and unintended impacts are included;

— it should reflect the variety and multidimensionality of the system concerned;

— it should be flexible, so that the policy analysis can easily be adjusted to new circumstances;

— it should be comprehensible to the decision-makers;

— it should be able to employ (available) data in an efficient way;

— beside efficiency criteria, it should take into account equity and/or other relevant social criteria;

— it should pay attention to conflicts among (interest) groups or other subsystems of the entire system;

— it should be able to assess trade-offs among different policy objectives;

— it should leave possibilities for a learning strategy in an (interactive) planning approach;

— it should be able to provide an integrated picture of all interactions and effects within the system in hand;

— it should open ways for compromise policies in case of policy conflicts;

— it should take into account the institutional structure of the existing policy framework;

— it should leave open a meaningful decision space for achieving a satisfactory state, based on either optimizer or satisficer principles.

MODELS IN POLICY ANALYSIS

A model provides a stylized picture of part of a complex reality. Clearly, models in a policy analysis should be able to indicate the boundaries within which policy decisions can be made, the trade-offs inherent in choosing alternative solutions, the impacts of policy measures on a (normally large) set of policy objectives and the possibilities for an interplay between experts and policy-makers.

Usually such a model is composed of a set of mathematical equations (Tinbergen, 1956) but this is not always necessary. Even impact systems and

graph-theoretic representations might provide useful information (Blommestein and Nijkamp, 1981), while soft information can also be meaningfully taken into account (Nijkamp and Rietveld, 1981). Let us take the following formal model, containing a vector of decision variables z (instruments e.g.), of policy objectives $\underline{w}$ (with elements w_i, $i = 1, \ldots, I$), of endogenous variables $\underline{x}$ and of exogenous data $\underline{v}$:

$$\underline{f}(\underline{z}, \underline{w}, \underline{x}, \underline{v}) = \underline{0} \tag{1}$$

Then the following reduced form for the objectives may be assumed:

$$\underline{w} = \underline{g}(\underline{z}, \underline{v}) \tag{2}$$

Furthermore, a set of constraints (technical, social, political, economic, etc.) on the whole system may be defined:

$$\underline{z} \in K \tag{3}$$

where K represents a feasible area. Then, an efficient (non-dominated or Pareto-optimal) solution may be defined as follows: $\underline{z} \in K$ is efficient, if no $\underline{z}^* \in K$ does exist, such that:

$$\underline{w}^* = \underline{g}(\underline{z}^*, \underline{v}) \geq \underline{w} \tag{4}$$

and

$$w_i^* = g_i(\underline{z}^*, \underline{v}) > w_i \qquad\qquad i \in \left\{ 1, \ldots, I \right\} \tag{5}$$

Thus, an efficient solution supposes that no other feasible policy exists, which is for all policy criteria at least equally good and for at least one criterion better (Despontin, 1980). Normally, one may expect that any good policy should be an efficient solution, although sometimes—due to political reasons or uncertainties—non-efficient solutions are also being selected (Leibenstein, 1976).

Therefore, a meaningful policy analysis should focus attention in particular on the efficiency frontier (i.e. the set of efficient solutions) in order to identify a policy that will not be dominated by other policies. This is especially important in the framework of interactive policy models which usually aim at finding a compromise solution located on the efficiency frontier.

OBJECTIVES IN POLICY ANALYSIS

The previous discussion was based on the assumption that policy objectives can easily be indentified and are given prior to the actual use of the model. In reality, however, neither the analysts nor the decision-makers have a perfect insight into the various objectives to be considered in a policy analysis. Clearly, official reports and documents of decision-makers may give some indications concerning objectives but these are often defined in a fuzzy way and left open to many interpretations when general objectives have to be translated into operational policy criteria. Moreover, during the process of policy analysis itself, new insights are obtained which may lead to a re-orientation and re-specification of policy criteria. Of course, it might be possible to include policy objectives as 'hard' constraints but this runs the risk of excluding policy flexibility from the model. Consequently, it is recommended to include objectives, wherever possible, in the form of objective functions instead of contraints.

The choice of objective functions should evidently be based on the priorities of decision-makers but should also be co-determined by the interests of other groups, including conflicts among objectives: conflict analysis is an essential ingredient of policy analysis. Furthermore, whenever possible, the policy objectives taken into consideration should not only refer to traditional welfare indicators (such as income or employment), but should also pay attention to 'soft' social or environmental indicators, so that the policy analysis in hand is based on a broad and balanced spectrum of policy considerations. In this respect, a policy analysis may also contribute substantially to gaining more insight into the political feasibility of compromise solutions, especially in the framework of an interactive policy approach with multiple objectives.

INTERACTIVE POLICY MODELS

Many problems in a policy analysis do not require an unambiguous solution that represents once and for all the optimal state of the system concerned. In light of the process character of many decision problems, an

interactive policy analysis is, however, a reasonable approach. This approach is usually composed of a series of steps based on a systematic exchange of information between decision-makers and analysts. These interactive approaches normally have two common steps:

(a) the analysts propose meaningful and feasible trial solutions on the basis of a well-defined compromise procedure;

(b) the decision-makers respond to each trial solution by indicating in which respect (i.e. in regard to which effects) the proposed compromise is still unsatisfactory.

These steps can be successively repeated until, after a series of steps, a final satisfactory compromise solution has been identified. Recently, a large number of interactive models has been developed (Rietveld, 1980; Spronk, 1981).

Such interactive policy models, which have already demonstrated their usefulness on several occasions, have many significant advantages compared to traditional optimization methods:

— they are in agreement with the process character of many planning problems;

— they are built on learning principles for decision-makers;

— they provide necessary and meaningful information in a systematic stepwise way;

— they take into account the limited capability of the human mind to judge complex decision problems, with many choice options, in one step;

— they emphasize the active role of decision-makers in specifying and solving choice problems *inter alia* by making policy objectives more explicit;

— they are able to take account of the variety and conflicting nature of policy options or decision criteria;

— they allow an assessment of (implicit or explicit) trade-off in many choice situations, without necessarily requiring the specification of weights;

— they provide an integrative framework for choosing consistent compromise solutions;

— they may be used to successively eliminate less relevant alternative choice options;

— they may fit into an institutional structure based on multiple decision-makers or various decision levels.

In conclusion, interactive policy models may provide a coherent, operational and systematic contribution to a scientific rationalization of complex policy problems in reality. More explicit attention will now be devoted to one of the recently developed, interactive policy models, namely interactive multiple goal programming.

INTERACTIVE MULTIPLE GOAL PROGRAMMING (IMGP)

Consider the following multiple goal programming problem:

$$\max g_i (\underline{x}) \qquad \forall i$$
$$\text{subject to } A\underline{x} \geq \underline{b} \qquad (6)$$

where $\underline{x}$ is a vector of instrumental variables (see also equation 2). One of the methods for dealing with multiple goal functions is interactive multiple goal programming (IMGP) (Nijkamp and Spronk, 1980; Spronk, 1981).

In IMGP, the decision-maker provides information about his preferences on the basis of a provisional solution and a potency matrix presented to him. The potency matrix consists of two vectors, representing respectively the pessimistic and the ideal solution. For each of the goal variables separately, the pessimistic solution represents a minimum value (usually proposed by the decision-maker), whereas the ideal solution represents the individual maximum values, given the pessimistic solution. The decision-maker has to indicate whether or not a solution is satisfatory and, if not, which of the minimum goal values should be increased in value. Then a new solution is presented to him, together with a new potency matrix. The decision-maker has to indicate whether the shifts in the proposed solution are outweighted by the corresponding shifts in the potency matrix. If not, a new solution is calculated and so forth.

For ease of presentation, the method is described here by assuming that in each iteration, one and only one element of the solution will alter. However, a generalization to more elements is straightforward.

Step 1

Maximize each goal variable g_i (x) separately, and denote the maxima by g^*_i and the I resulting values of the instrumental variables by $x^{i}{}^*$, $i = 1, \ldots$, I. It is not possible to find a feasible value of $g_i (\underline{x})$ that exceeds $g_i{}^*$. Generally, it is not necessary to accept a value of $g_i (\underline{x})$ which is lower than g_i^{min}, defined as:

$$g_i^{min} = \min_{} \left| g_i (\underline{x}^{j*}) \right| \qquad , j = 1, \ldots, I \qquad (7)$$

This is the lowest value of $g_i (\underline{x})$ resulting from the successive maximization of the goal variables. Then, the final solution S* must be found between the 'ideal' (but normally unfeasible) solution I, and the 'pessimistic' solution Q, which are defined respectively as:

$$I = [g_1{}^*, g_2{}^*, \ldots, g_I{}^* \,] \text{ and}$$

$$(8)$$

$$Q = [g_1{}^{min}, g_2{}^{min}, \ldots, g^{min}{}_I]$$

To facilitate the notation, we have included the ideal solution I and the pessimistic solution Q in the $(2 \times I)$ 'potency matrix' P.

Step 2

$$\text{Define for all } j = 1, \ldots, I$$
$$\delta_j = g^*{}_j - g_j{}^{min}$$

$$(9)$$

Step 3

Define the initial solution as:

$$S_1 = [g_1{}^{min}, g_2{}^{min}, \ldots, g_I{}^{min} \,]$$

$$(10)$$

which is thus equal to the pessimistic solution defined in (8). Present this solution together with the potency matrix P_1 to the decision-maker.

Step 4

If the proposed solution satisfies the decision-maker, one may terminate; if not define R_i as the subset of R defined by the goal levels in S_i, and proceed to step 5.

Step 5

The decision-maker has to answer the question: 'Given the provisional solution S_i, which goal variable should first be improved?'.

Step 6

Assume that the decision-maker wants to augment the j-th goal variable. Then construct a new trial solution $\hat{S}_{i+1}$, which differs from S_i only in the value of the j-th goal variable (denoted by $g_j(\underline{x})\hat{S}_{i+1}$ and $g_j(\underline{x})S_i$ respectively). Define next:

$$g_j(x)\hat{S}_{i+1} = g_j(x) S_i + \tfrac{1}{2} \delta_j$$

$$(11)$$

and introduce the restriction:

$$g_j(x) > g_j(x) \hat{S}_{i+1}$$

$$(12)$$

Step 7

Combine the restriction formulated in step 6 or in step 9 with the set of

restrictions describing the feasible region R_i. Calculate a new potency matrix, like in step 2, but subject to the new set of restrictions. Denote this potency matrix by $\hat{P}_{i+1}$.
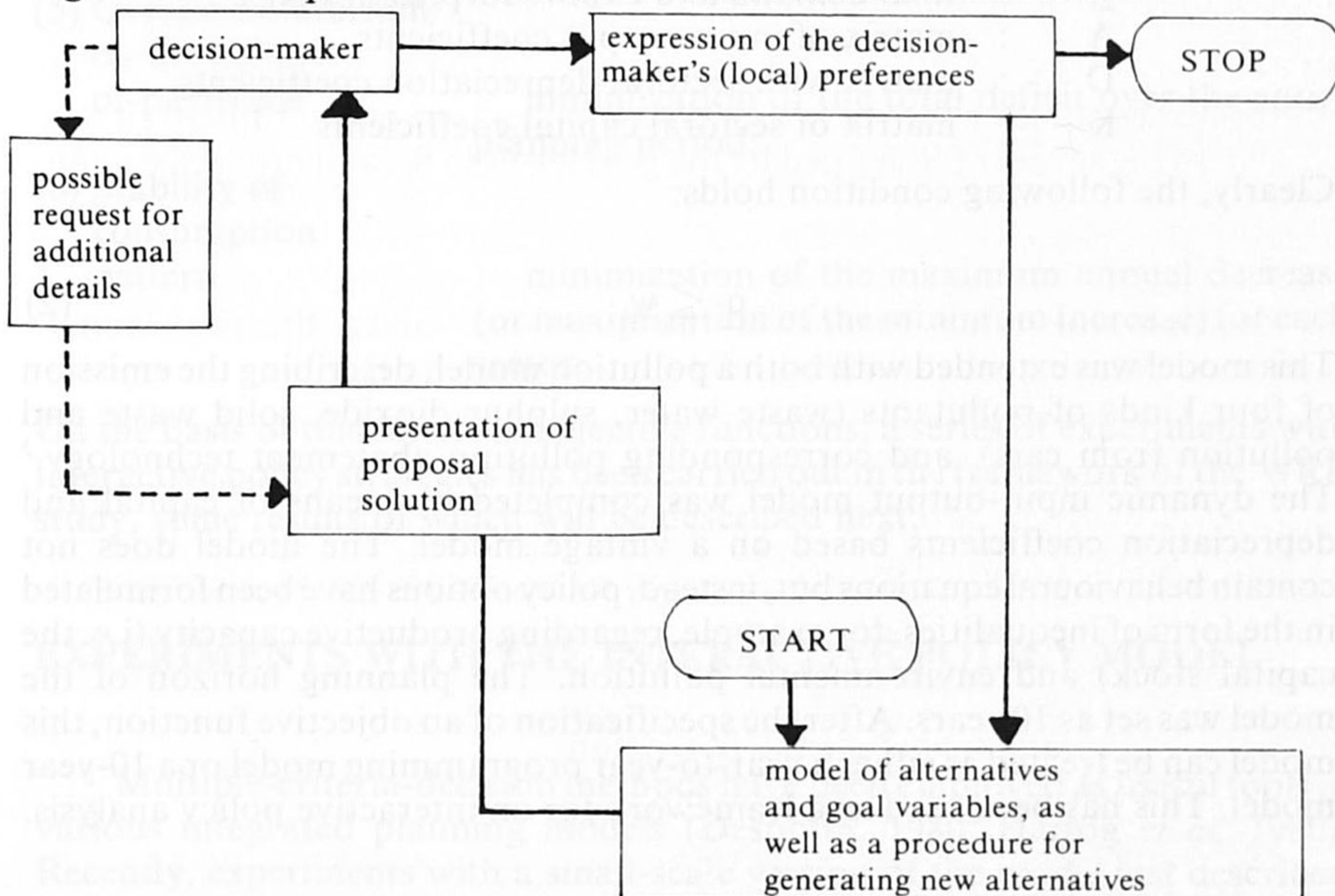
Step 8

Confront the decision-maker with S_i and $\hat{S}_{i+1}$ on the one hand, and with P_i and $\hat{P}_{i+1}$ on the other hand. The shifts in the potency matrix can be viewed as a 'sacrifice' trade-off for reaching the proposed solution. If the decision-maker judges this sacrifice to be reasonable, accept the proposed solution by putting $S_{i+1} = \hat{S}_{i+1}$ and $\hat{P}_{i+1} = \hat{P}_{i+1}$ and put $\delta_j = \frac{1}{2}\delta_j$. Continue with step 4. If the decision-maker regards the sacrifice as unjustified, the proposed value of $g_j(x)$ is obviously too high. In that case, one may drop the constraint added in step 7.

Step 9

We know that $g_j(x)S_i$ is too low and that $g_j(x)\hat{S}_{i+1}$ is too high in the decision-maker's view. Set δ_j equal to the difference between these two values. Then a new proposal value $\hat{S}_{i+1}$ is calculated according to (11). Like in step 6, we add the restriction that $g_j(x)$ must equal or exceed the new proposal value and go to step 7.

A flowchart of the IMG procedure is given in figure 1. The method is entirely operational and has been used in various real-world problems.[1] For further details on IMGP (inclusion of aspiration levels, etc.), we refer the reader to Nijkamp and Spronk (1980) and Spronk (1981).

Figure 1. Simplified flowchart of the interactive framework

ILLUSTRATION: A MODEL FOR WESTERN EUROPE

The model used in this empirical illustration was designed for a major industrial heartland in Western Europe, composed of the areas: Netherlands, Belgium, Nordrhein-Westfalen and France Nord, by van Driel *et al.* (1980). This part of Western Europe contains approximately 45 million inhabitants in an area of 115,000 square kilometres. In this industrialized and densely populated area, various conflicting options regarding economic growth, environmental conditions and energy availability are most likely to emerge.

Van Driel *et al.* (1980) have developed a dynamic economic sectoral model based on an input-output framework. The number of sectors in this model was 17. The structure of this input-output model, formulated as an inequality condition, is:

$$q_t \geq {}_M (A+D) \, q_t + K \, (w_{t+1} - w_t) + v_t \qquad (1)$$

with:

q_t : vector of sectoral production levels in year t
w_t : productive capacity in year t
v_t : final demand and export surplus in year t
A : matrix of input-output coefficients
D : matrix with sectoral depreciation coefficients
K : matrix of sectoral capital coefficients

Clearly, the following condition holds:

$$q_t \leq w_t \qquad (2)$$

This model was extended with both a pollution model, describing the emission of four kinds of pollutants (waste water, sulphur dioxide, solid waste and pollution from cars), and corresponding pollution abatement technology.[2] The dynamic input-output model was completed by means of capital and depreciation coefficients based on a vintage model. The model does not contain behavioural equations but, instead, policy options have been formulated in the form of inequalities, for example, regarding productive capacity (i.e. the capital stock) and environmental pollution. The planning horizon of the model was set as 10 years. After the specification of an objective function, this model can be treated as either a year-to-year programming model or a 10-year model. This has been used as a framework for an interactive policy analysis.

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[2]In fact, the pollution coefficients for a sector were expressed as the abatement costs per unit of production value of the sector concerned.

The experiments with this interactive model were induced by the Dutch Scientific Council for Public Policy, abbreviated as WRR (WRR, 1980). Consequently, the Interactive Multiple Goal Programming approach was chosen as a tool to obtain more insight into the conflicting nature of different policy objectives, the feasibility of certain economic policy scenarios and the (in)stability of the results of the model for alternative policy variants.

After a discussion, six goal variables were ultimately selected for an interactive policy analysis. These were:

(1) Employment : maximization of the total wage sum over the planning horizon;

(2) Growth : minimization of the difference between the actual growth rate of production and a three per cent target growth rate of production;

(3) Environmental
Quality : minimization of pollution by introducing a desired negative growth path for each pollutant (varying from five to ten per cent);

(4) Balance-of-
payments : minimization of the maximum change in export surplus compared to a base year for each sector separately;

(5) Overall equilibrium
on the balance-
of-payments : minimization of the total deficit over the entire planning period;

(6) Stability of
consumption
pattern : minimization of the maximum annual decrease (or maximization of the minimum increase) for each sector.

On the basis of this set of six objective functions, a series of experiments with interactive policy strategies has been carried out in the framework of the WRR study, some results of which will be described next.

EXPERIMENTS WITH THE INTERACTIVE POLICY MODEL

Multiple-criteria-decision methods have been employed as useful tools in various integrated planning models (Despotin, 1980; Hartog *et al.* 1980). Recently, experiments with a small-scale version of the model just described were carried out. A fully operational version of this interactive policy model was demonstrated to various experts and decision-makers in government and

industry. Two main conclusions can be drawn from these demonstrations: first, both the experts and the decision-makers regarded the interactive framework as a useful decision aid, mainly because of the induced learning effects; secondly, since the input-output model as proposed by van Driel *et al.* (1980) does not include any behavioural relationship, the results depend on the technical relations only and on the decision-maker's evaluations. These technical relationships are rather 'hard', so that one may conclude that, if a certain combination of the objectives is not feasible within the model, then this combination is certainly not feasible in the real world.

On the other hand, if a certain combination of objectives turns out to be feasible within the model, it is not certain—because of the omitted behavioural relationships—that this combination can be realized in practice. In summary, the results obtained by means of this interactive policy model are rather hard (although stated in negative ('falsification') terms). Further details of this small version of the model are given by Hartog *et al* (1980).

On the basis of these experiments, the Dutch Scientific Council for Public Policy (WRR) decided to implement the IMGP procedure in combination with the complete version of the Western Europe model, previously described. Because this project had to be carried out within a limited time period and because the experiences with the interactive procedure were not yet related to large-scale models, the results of the experiments were not as satisfactory as they could have been (Hartog and Spronk, 1980; WRR, 1980). Nevertheless, the results were judged to be satisfactory. Several conclusions were also drawn which turned out to be helpful in new experiments with interactive modelling (for instance, a new study of the WRR uses an adapted version of this methodology).

In table 1, the respective sets of limit goal values ('pessimistic' solutions), subject to which each goal variable had to be optimized separately at each iteration, are given. All figures are in billions of Dutch guilders (1965), except those relating to the third goal variable which are expressed in percentages. The first iteration consists of the computation of the unconditional optimal solutions. Thus, in the first iteration, each goal variable is optimized separately—without any constraint on the values of the (other) goal variables. From the second iteration onwards, the decision-maker can add minimally (or maximally) required (pessimistic) goal values. Analysis of the optimal solutions of the first iteration may be helpful for finding suitable pessimistic values for the second iteration. Until the fifth iteration, no pessimistic goal value is given for goal variable 6 because, until this very iteration, it was provisionally (but incorrectly) assumed that the balance-of-payment deficit could be decreased implicitly by means of the other goal variables. In fact, the realization of this mistake can be considered to be one of the learning effects obtained by using the interactive policy model.

More interesting than the pessimistic goal values are the optimal values which can be obtained while taking account of the pessimistic goal values.

Table 1: Sets of limits on the Goal Variables

Goal Variable		1	2	3	4	5	6	7	8	9	10
Employment	1	-	300	350	350	350	350	350	350	350	350
Deviation from growth target	2	-	19	10	10	10	10	10	10	10	10
Deviation from pollution decrease target	3	-	50	25	25	25	15	5	5	5	5
Maximum change in sectoral export-surplus	4	-	16	5	1	1	1	1	1	1	1
Maximum decrease of sectoral consumption	5	-	10	5	5	5	5	5	0.1	5	0.1
Total balance-of-payments deficit	6	-	-	-	-	10	10	10	10	5	5

Three examples are given in table 2. The set of goal values A is obtained when the first goal variable is maximized in the 10th iteration subject to the corresponding set of limits given in table 1. The set of goal values B is obtained when the 6th goal variable is minimized in iteration 7 and set C is obtained when the 3rd goal variable is minimized in the 7th iteration.

Table 2: Some illustrative outcomes

Goal Variable	A	B	C
1	513	439	350
2	10	10	10
3	5	5	4.6
4	1	1	1
5	5	10	0
6	0.1	0.33	0.23

For a much more detailed report of these results we refer the reader to WRR (1980). It should be stressed here that, within the pessimistic goal values in iteration 10 still many alternatives are feasible. These remaining alternatives were not studied in detail. This was partly due to the limited time available for the study. However, a much more important reason was that the obtained results had given new insights to both experts and decision-makers. It was felt that new restrictions should be added to the model and that some of the goal variables should be re-formulated. For example, the outcomes suggested that different formulations of goal variables, which are defined in terms of growth paths, may give rise to very different results. Furthermore, within a 10-year-period policy model incorporating many sectors, the number of goal variables tends to become unmanageable. Therefore, some of the goal variables were formulated in a minimax sense, i.e. as the maximum deviation (to be minimized) from a target growth path. In principle, all these deviations may be scaled in different dimensions. Thus, many different ways exist to handle the problem of large numbers of goal variables, not yet studied in full detail.

CONCLUSIONS

From the experiments described, several important lessons can be drawn. The main conclusion is that interactive policy models can be an important decision aid. It should be stressed that the primary purpose of these models is not to provide 'good', or even 'optimal', solutions (although formally speaking, this kind of solution can be provided by these models). The main use of these models is that they can be an important learning tool, both for decision-makers and experts. This is especially true since, in practice, exact goal definitions very often do not exist. Interactive policy models can help to define the decision-makers' goals. Furthermore, it is not always easy to identify the decision-maker(s). In this case, interactive policy models can serve as a flexible means of communication.

References

Blair, P.D. (1979). *Multiple Regional Energy Planning.* Kluwer Nijhoff, Boston.

Blommestein, H.J. and Nijkamp P., (1981). *Soft Spatial Econometric Causality Models.* Research Memorandum, Dept. of Economics, Free University, Amsterdam.

Despontin, M. (1980). *Kwantitatieve Economische Politiek vanuit een Besluitvormings-optiek.* Ph.D., Free University, Brussels.

Driel, G.J. van., Hartog J.A., and Ravenzwaaij, C. van. (1980). *Limits to the Welfare State.* Martinus Nijhoff, Boston/The Hague.

Hartog, J.A. and Spronk J. (1980). *Een Modelstudie naar de Relatie Milieu-economie.* Werkdocument WRR, Staatsuitgeverij, Den Haag.

Hartog, J.A., Nijkamp P., and Spronk J. (1980). *Operational Multiple Goal Models for Large Economic Environmental Systems.* Proceedings for the IX-th IFIP Conference on Optimization Techniques, Vol. II, K, Iracki *et al.*

Leibenstein, H. (1976). *Beyond Economic Man.* Harvard University Press, Cambridge.

Nijkamp, P. (1979). *Multidimensional Spatial Data and Decision Analysis,* John Wiley and Sons, Inc., New York/Chichester.

Nijkamp, P. and Rietveld, P. (1981). *Ordinal Multivariate Analysis.* Professional Paper 81-2, IIASA, Laxenburge.

Nijkamp, P. and Spronk J. (1980). Interactive Multiple Goal Programming : An Evaluation and Results. In *Multiple Criteria Decision Making: Theory and Application.* G. Fandel and T. Gal (Eds.) Springer, Berlin, pp. 278-293.

Nijkamp, P. and Spronk J. (1981). *Multicriteria Analysis: Operational Methods.* Gower, Farnborough.

Rietveld, P. (1980). *Multiple Objective Decision Methods and Regional Planning.* North-Holland Publ. Co., Amsterdam.

Saaty, T.L. (1977). *Scaling for Priorities in Hierarchical Structures.* Journal of Mathematical Psychology, Vol. 15, No. 3, pp. 234-281.

Shapley, L.S. and Shubik, M. (1954). *A Method for Evaluating the Distribution of Power in a Committee System,* American Political Science Review, Vol. 48, pp. 787-793.

Spronk, J., (1981). *Interactive Multiple Goal Programme Applications to Financial Planning.* Kluwer Nijhoff, Boston.

Tinbergen, J. (1956). *Economic Policy: Principles and Design.* North-Holland Publishing Co., Amsterdam.

WRR (1980). *Plaats en Toekomst van de Nederlandse Industrie.* Staatsuitgeverij, Den Haag.