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DECISION SUPPORT SYSTEMS FOR SEMI-STRUCTURED BUYING DECISIONS

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SYSTEMES INTERACTIFS D'AIDE A LA DECISION D'ACHAT

RESUME

En utilisant des recherches récentes sur la conception de systèmes évolutifs et sur les processus d'apprentissage en décision multicritère, on propose un Système Interactif d'Aide à la Décision (SIAD) pour des décisions d'achat semi-structurées. Le modèle du processus de décision met en oeuvre les quatre phases suivantes ainsi que des rétroactions entre elles :

- 1. Choix des critères et d'un ensemble de produits candidats.
- 2. Recherche de cohérence entre la préférence globale intuitive du décideur et un modèle analytique de cette dernière.
 - 3. Etablissement d'un modèle de préférence compromis.
 - 4. Evaluation de l'ensemble des produits à l'aide du modèle.

On donne un exemple illustratif (achat d'une voiture).

En conclusion, la mise en oeuvre du SIAD sur micro-ordinateur est évoquée et on commente brièvement l'extension au cas de décideurs multiples.

DECISION SUPPORT SYSTEMS FOR SEMI-STRUCTURED BUYING DECISIONS

ABSTRACT

Using recent research on evolutionary systems design and on the process of learning preferences in multicriteria decision making, a Decision Support System (DSS) is proposed for semi-structured buying decisions. The general decision process model involves 4 phases and feedbacks among them:

- 1. Selecting criteria and an admissible set of alternatives products.
- 2. Searching for consistency between the decision maker's whollistic preference and an analytical model of it.
 - 3. Assessing a compromise preference model.
- 4. Evaluating the alternative products using the compromise preference model.

An illustrative example (purchasing a car) is presented.

We conclude with some brief remarks on implementation of the DSS on microcomputers and extension to the case of several decision makers.

INTRODUCTION

The decision to purchase a product may often be difficult for an individual or an organization. Even if (1) considerable data on the available alternatives and their characteristics exist, (2) information is known of the behavior of previous decision-makers (the criteria used, the biases and pitfalls encountered), and (3) there are experts who know a lot about the product, the buying decision can remain difficult. It seems that society as a whole knows a lot about this type of decision, but a given decision-maker may know relatively little or not enough about the particular problem before him. Thus the decision problem can be almost perfectly structured from the point of view of society as a whole and relatively unstructured from the point of view of the decision-maker. In this paper, this is what we refer to as a semi-structured buying decision problem. Typical examples of such decision problems for the individual or family consumer would be:

- buying a car;
- buying or renting a dwelling (house, apartment);
- buying a long distance travel ticket or vacation package;
- buying heating equipment for a house (e.g. solar heating);
- buying a microcomputer;
- etc.

Some examples for organizations include:

- choosing a type of car for a given use;
- buying a new production machine tool;
- buying or leasing a new computer;
- buying a new copying machine;
- etc.

We may list the features of the semi-structured buying decision problem as follows:

- i. There usually exists a large number of alternative products; the decision maker (DM) knows a few of them.
- ii. Considerable data exist on the characteristics and performance warranties of these alternatives, but only some of this information is of interest to a particular decision-maker.
- iii. There is certainty regarding the characteristics, alghough there might well be some uncertainty on the needs of the decision-maker.
- iv. Despite the large amount of information on each alternative, some information subjective in nature may be missing. The decision-maker must be able to introduce such subjective criteria as taste, liking or disliking the shape of a car, etc.
- v. The criteria are conflicting. Thus, the D.M. has to learn about his own preferences, considering his values, tastes and needs on one hand, and the available alternatives and their characteristics on the other hand.

Research on consumer behavior (see for instance Engell, Kollat, Blackwell [4], Assael [1], Chan and al. [3]) shows that the decision-making process for purchasing a new product in which there is a high stake can be described as an individual and sometimes a multiparticipant conflict resolution process. Shakun [12, 13] has developed a general methodology - called evolutionary systems design (ESD) - for such processes. These same studies and others such as that of Janis and Mann [6] suggest that because of time pressure, limited cognitive capacities, and the existence of conflicting criteria, the buying decision process could be much more efficient if it was supported by some decision support system (DSS). Keen and Scott Morton [10], Sprague and Carlson [15], Bonczek, Holsapple and Whinston [2] suggest that semi-structured decision problems are fruitful area for DSS.

We shall design a DSS for the semi-structured buying decision which will enable the decision-maker to learn in an efficient way what his preferences and goals are in relation to what is available on the market, and thus to make a buying decision.

To achieve this, we shall use an up-dated data base on the existing alternatives and their characteristics. We shall build into the DSS a set of goals (criteria) which have been commonly used by previous decision-makers and those suggested by experts in the field. Thus, we include society's collective memory (knowledge) on the subject. There is of course not a unique answer to the buying decision - different decision-makers will choose different products. Thus, we must be able to assess the preference function of the particular decision-maker involved. The DSS should be user-oriented in the sense that the decision-maker is cognitively comfortable in using the system.

In section 2 we present the main theoretical framework which is used in the DSS. Section 3 is a detailed presentation of the DSS. Section 4 is an illustrative example of the decision to purchase a car. Section 5 presents concluding remarks.

2. DECISION MAKING AS CONFLICT RESOLUTION

2.1 The general framework: Evolutionary systems design

We may view decision making as a process of evolutionary systems design (ESD) involving conflict resolution in which decision makers (players) define and attain goals as operational expressions of underlying values. In the methodology developed by Shakun [12, 13], N players are viewed as playing a dynamical (difference) game in which a coalition C of the set of N players can form provided it can deliver to itself (and hence to its members) a set of agreed-upon goals. Formally this means that for each time period the intersection of the coalition goal target $Y^{C}(t)$ and its technologically feasible performance $y^{C}(t)$ is non-empty [12, 13]. Thus, the geometry of conflict and conflict resolution is shown in Figures 1 and 2.

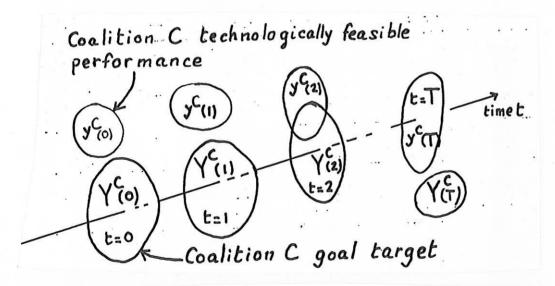


Fig. 1 : The geometry of conflict

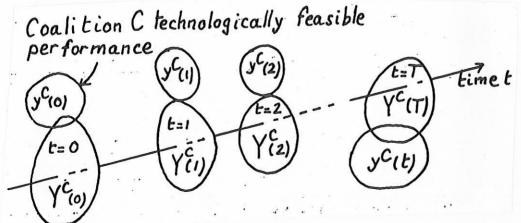


Fig. 2 : Conflict resolution

For a given operational goal space, if the intersection of $Y^C(t)$ and $y^C(t)$ in Figure 1 is empty, then one or both of these sets may expand to give a non-empty intersection to resolve conflict as shown in Figure 2. By expansion we mean that new points are added to the sets $Y^C(t)$ and $Y^C(t)$; this process of expansion does not preclude the dropping of some other points of these sets. However, the dimensions of the operational goal space itself may be redefined using a goal/values referral process [12, 13]. Within the new goal space - either originally or after goal target and/or technological feasible performance expansion - the target-performance intersection may be nonempty.

If the target-technological performance intersection has one point, then the point is the solution in output goal space. If the intersection contains more than one point, then $Y^C(t)$ and/or $y^C(t)$ may contract (negative expansion) to give a unique solution. It is also possible that the dimensions of the operational goal space could be redefined. The controls (inputs) which give this unique solution point in output goal space represent the decision to be taken.

The above methodology - called evolutionary systems design - is developed in [12, 13] and dicussed for hierarchical systems in [14]. It constitutes an approach to problem definition and solution in complex contexts involving multiparticipant, multicriteria, ill-structured dynamic problems and provides a basis for decision support systems (DSS).

2.2 Evolutionary system design in semi-structured buying decisions

For DSS for semi-structured buying decisions a simpler version of the general evolutionary systems design methodology may be employed. Frequently, in these buying decisions we may consider only one decision maker - the buyer (we shall comment on the case of more than one decision maker in the concluding remarks). He has multiple criteria and his problem is semi-structured in the sense discussed above. For many buying decisions the general dynamical framework can be reduced to the present time period for purposes of analysis. For example, purchase costs or

other costs (e.g. maintenance costs) paid in the future may be discounted to the present time. With these simplifications the evolutionary systems design methodology suggests the following framework for DSS for a semistructured buying decisions.

Consider that we have a set A of products (purchase choices, controls or inputs) e.g., all the different types of cars we may buy. Let g be a function from A into R^p (the goal space, the p-dimensional real vector space); then y = g(a) for $a \in A$ is the vector of R^p representing the outputs of a particular purchase choice and y = g(A)represents technologically feasible performance, i.e. a set of possible outputs (characteristics) which may be obtained from the inputs (purchase choices) A. These outputs are generally constrained a priori by preliminary goal target Y_0 information. For example these constraints could be $Y_0 = \{y \in \mathbb{R}^p : y_i \ge b_i, i = 1, ..., p\}$. The intersection of Y_0 and g(A) is called $g(A_0)$, a set of a priori admissible outputs; $A_0 = \{a \in A : g(a) \in Y_0\}$ is the corresponding set of a priori admissible inputs. Typically in buying (e.g. buying cars) the set $g(A_0)$ has many points. By learning how the operationally contract Y_0 (see section 2.3) the decision maker reaches a point where the intersection of the evolved goal target Y and $g(A_0)$ is a single output point whose input in A_0 is the buying decision. In this learning process the output goal space itself may be redefined (e.g. a new criterion added). Figure 3 illustrates the output goal (criterion) space.

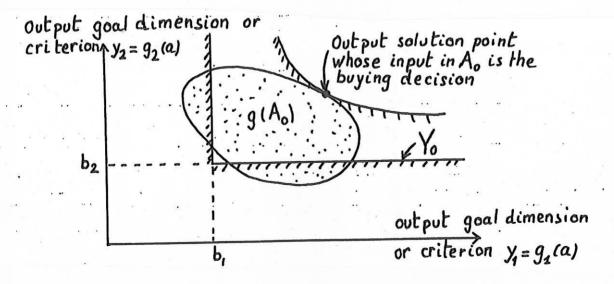


Figure 3: Output Goal or Criterion Space

2.3 Evolution of the goal target as a preference learning process

As discussed in section 2.2, from an operational point of view, we need a methodology which enables the decision maker to assess and contract goal target Y in order to obtain a solution leading to a buying decision. This can be achieved by using some recent research on multicriteria decision making. Once an initial goal space g_1, \ldots, g_p and an initial target set Y_0 have been defined as in section 2.2, we can use a utility function u(y) in order to contract Y_0 . If we define u^* as a particular level of utility, evolving goal target Y is defined by:

$$Y = \{y \mid u(y) \ge u^*\}.$$

In the evolution of Y, for a given goal space g_1, \ldots, g_p , the aspiration level u^* will change (increase) and the utility function u(y) may also change. In addition, the goals g_1, \ldots, g_p themselves may change. The finally evolved Y (see figure 3) corresponds to a maximum level of utility

$$U_{\text{max}} = \underset{a \in A_{0}}{\text{Max}} u(g(a)).$$

In this section we discuss general elements of the learning process by which the DM define u(g(a)). We then detail these general concepts as they are used in the DSS in section 3.

Usually, assuming a nonlinear additive utility function $u(y) = \sum_{i=1}^{p} u_i(y_i)$ is a quite reasonable assumption which we make here (the non-additive case is duscussed later - see step 1.7 in figure 6 and then the Appendix). To assess the parameters of the utility function, it is generally understood (see Fishburn [5]) that one can use either a direct or an indirect procedure :

- A <u>direct</u> procedure consists in asking the DM to make judgements on each criterion in order to estimate separately each marginal utility $v_i(y_i)$ and then asking for judgements on weights and/or trade-offs in

order to assess the relative weights w_i of $v_i(y_i)$ such that $u(y) = \sum_{i=1}^{\infty} v_i(y_i) = \sum_{i=1}^{\infty} u_i(y_i)$. When u is normalized, the weight w_i equals the utility $u_i(y_i)$ at the most preferred value of y_i .

- An <u>indirect</u> procedure consists in asking for whollistic judgements based on several criteria at a time in order to estimate the weights using multiple linear regression or even nonlinear marginal utilities using an ordinal regression method such as UTA (see [9]).

If we consider the process of assessing preference as a learning-process (see Jacquet-Lagrèze [7, 8]) then a more general methodology consists of using both procedures interactively. A highly analytical-oriented decision maker is more likely to use the direct procedure (aggregation of the criteria) and a highly intuitive-oriented decision maker is more likely to use the indirect procedure (disaggregation of a whollistic preference). But many decision makers will feel cognitively comfortable in using both procedures involving aggregation phases and <a href="disaggregation-disaggregati

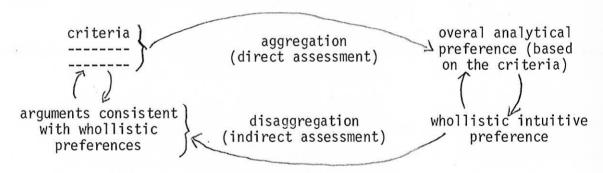


Figure 4: Aggregation-disaggregation of preferences

Furthermore, using such a procedure interactively enables the decision maker to find some hidden criteria (see [8]). Thus a whollistic preference order may be inconsistent with a given set of criteria. Revealing such inconsistencies might help the decision maker to find hidden criteria or operational goals y_i which better express underlying values, tastes or needs of the decision maker. Thus, aggregation-disaggregation procedure is well-suited as a learning process in which the DM defines u(y). We shall incorporate it in the DSS in section 3.

In the practical use of the aggregation-disaggregation procedure, (see [8]) the DM will express whollistic preference on a subset ${\rm A_1}$ of ${\rm A_0}$, the set of a priori admissible outputs as defined in section 2.2. ${\rm A_1}$ generally consists of some alternative products the consumer already knows. The whollistic preference needed as an input to UTA which is used in the DSS (section 3) consists of a rank-order ${\rm R}({\rm A_1})$ of the alternatives in ${\rm A_1}$. ${\rm A_1}$ should represent a broad sample of ${\rm A_0}$ since we want to assess u(y) over the whole set ${\rm g}({\rm A_0})$. Therefore, if necessary the DSS should suggest to the decision maker that he add some alternatives to the set ${\rm A_1}$ so that ${\rm g}({\rm A_1})$ "covers" ${\rm g}({\rm A_0})$. For a buying decision problem, ${\rm A_1}$ might contain 5 to 15 alternatives and ${\rm A_0}$ might contain 10 to 100 or even more alternatives. When ${\rm A_0}$ is small (say 5), then ${\rm A_1}$ could be identical with ${\rm A_0}$.

THE DECISION SUPPORT SYSTEM

The DSS has been designed considering on one hand the main features of a semi-structured decision problem as outlined in section 1 and on the other hand the methodological framework presented in section 2. The DSS uses a data base containing the set A of all available products, their objective characteristics (size, country of manufacture, etc.), and objective-criteria including expert judgements considered "objective" by the users (price, gasoline consumption, seating comfort (an expert judgement)). Preferences on the objective criteria are either nondecreasing or nonincreasing. In addition, subjective criteria are used as explained below. The general decision process model (Fig. 5) shows how to use the DSS.

The decision process is not a linear one; the DSS is designed to allow the DM to come back to earlier phases in the course of the learning process. Phase 1 is concerned with the definition of a set of criteria, constraints levels (a priori goal target information) defined on these criteria and the selection of the a priori admissible set of products A_0 . Usually $A_0 \subseteq A$ where A is the initial set included in the data base. This is because each particular decision-maker is obviously not interested in the whole set. Phase 2 enables those decision makers who wish to use their intuitive whollistic preference to do so, i.e. people who are intuitive can give an initial rank order preference to the alternatives in $A_1 \subseteq A_0$. They can then look for consistency of their whollistic preference with an analytical model of their preference as computed by UTA. The highly analytical DM may not want to use this whollistic preference and may wish to go directly to phase 3 in order to make a direct assessment of his preferences. Therefore the DSS includes as a particular case the usual methodological approach used in decision analysis to assess value functions in the certain case [11]. Most decision makers will probably use a combined intuitive-analytical, i.e., disaggregation-aggregation, approach and get into phase 3 after a phase 2. The utility function computed in phase 3 by UTA and proposed as a compromise will considerably help direct assessment. The DM should enter phase 4 only when the rank

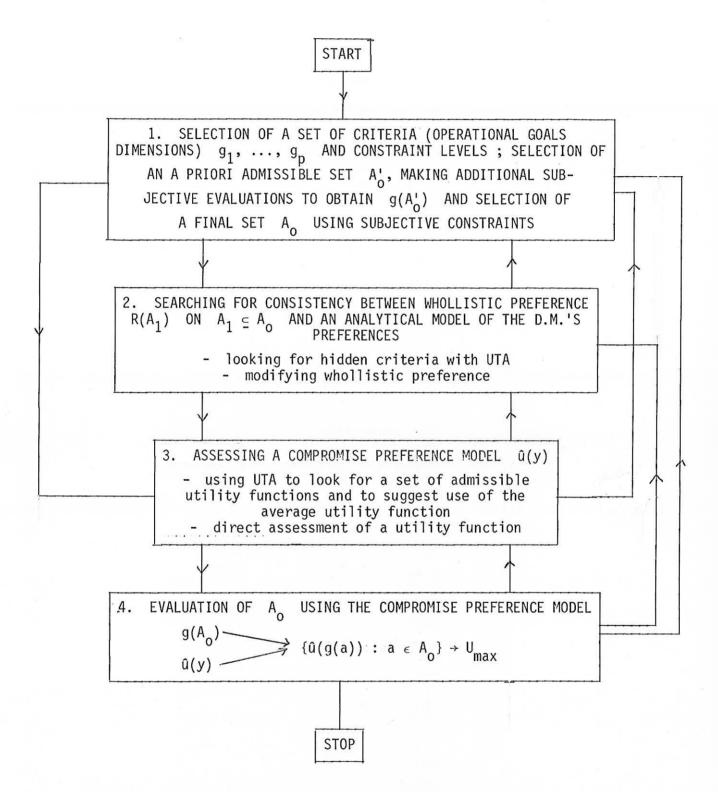


Figure 5: The general decision process model with phases 1, 2, 3 and 4

order of the alternatives in A_1 as computed from the compromise utility function u(y) is consistent with his whollistic ranking $R(A_1)$. In phase 4, the DM will use u(y) to compute the utility of every alternative product in the admissible set A_0 . We note that the ranking and/or utilities computed on A_0 might suggest feedback towards earlier phases.

We now present the four phases in detail.

Phase 1: Selection of an admissible set A of alternative products

 $(\overline{1.1})$ DSS shows the list of objective criteria and other objective characteristics available in the data base.

DSS indicates the criteria, objective and subjective usually considered as important.

 $(\overline{1.2})$ DM selects the objective criteria to be used.

 $\underline{\mathsf{DM}}$ states a set of constraints :

- defines if he wishes a constraint level $\, {\bf b}_{\, \dot{i}} \,$ for each objective criterion :
- . $y_i \ge b_i$ when preference is a nondecreasing function of y_i (e.g. a constraint level on a performance criterion),
- . $y_i \le b_i$ when preference is a nonincreasing function of y_i (e.g. a constraint level on price);
- defines if he wishes constraints on objective characteristics (e. g. 2 door cars are to be eliminated).

 $\overline{\text{DSS}}$ applies the set of constraints to A and $\overline{\text{DM}}$ gets a list A_0 .

- $(\overline{1.3})$ If A_0' is not considered too small by \overline{DM} , then go to $(\overline{1.5})$.
- $(\overline{1.4})$ DSS suggests some constraints to relax.

 $\underline{\mathsf{DM}}$ chooses constraints to be relaxed. Go to $(\overline{1.2})$.

 $(\overline{1.5})$ DM defines subjective criteria which use objective characteristics (e.g., classifying the country of manufacture on a scale such as : preferred, acceptable).

 $\underline{\rm DM}$ defines subjective criteria which will require of him a personal evaluation of all alternatives in A_0^{\prime} . He might use a predefined scale including a constraint level when the criterion is commonly used (e.g. the shape of a car could be evaluated on a scale as : unacceptable (constraint), ordinary, attractive, outstanding).

 $\underline{\rm DSS}$ applies these new constraints to $\rm A_0^\prime$ giving $\rm A_0$, the set of a priori admissible product alternatives.

- $(\overline{1.6})$ If the admissible set A_O is considered too small by $\overline{\rm DM}$, then go to 1.4.
- $(\overline{1.7})$ DSS computes $y_i^* = \max g_i(a)$ and $y_{i*} = \min g_i(a)$.
- If $y_{i*} = y_i^*$ such a non discriminant criterian is deleted (in practice more than 10 remaining criteria will be hard to work with).
 - If only one criterion is remaining, go to $(\overline{4.1})$.

 $\underline{\text{DSS}}$ uses a nonlinear additive utility function with marginal utilities defined by 1 to 3 linear pieces (piecewise linear) (1).

- $(\overline{1.8})$ DM may define, if he prefers, another number of linear pieces (1 to 5).
- $(\overline{1.9})$ The assessment of u(y) starts at this stage. DSS will ask the DM to start by giving a whollistic preference (a ranking of some alternatives he knows). If DM prefers to give a direct assessment of u(y), then go to $(\overline{3.3})$.

⁽¹⁾ See Appendix.

Phase 2: Searching for consistency

 $(\overline{2.1})$ \underline{DM} selects a subset $A_1 \subseteq A_0$ which he is willing to rank order according to his intuitive whollistic preference.

 $\underline{\rm DSS}$ suggests adding some alternatives to $\rm A_1$ if necessary (there must exist at least one alternative of $\rm A_1$ in each of the piecewise-linear intervals computed in step 1).

 $(\underline{2.2})$ \underline{DM} gives a rank-order $R(A_1)$ on A_1 based on his intuitive preference and noting the values $g(A_1)$.

 $(\overline{2.3})$ DSS uses UTA (see [9]) to check consistency between R(A₁), and R*(A₁), the rank-order computed by UTA (optimilaty step in [9]).

 $\underline{\text{DSS}}$ plots the alternatives A_1 in the ranking diagram where consistency is indicated by a straight line (see fig. 6).

If there is consistency, then go to $(\overline{3.1})$.

If there is inconsistency, then:

- for an alternative such as "a", DSS searches for a missing criterion on which "a" has a high value and suggest the DM consider adding this criterion;
- for an alternative such as "b", DSS searches for a missing criterion on which "b" has a low value and suggest the DM consider adding this criterion.

These suggestions are one way to move "a" up and "b" down so that $R^*(A_1)$ becomes more equal to $R(A_1)$.

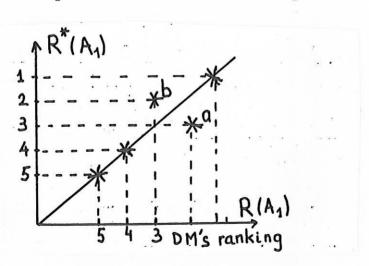


Figure 6

$(\overline{2.4})$ DS has several options :

- \underline{DM} is willing to change $R(A_1)$ into $R^*(A_1)$ "a" moves left and "b" moves right in diagram of $(\underline{2.3})$ Go to $(\underline{3.1})$;
- DM is willing to change $R(A_1)$ into a new one different from $R^*(A_1)$, go to $(\overline{2.2})$;
- DM is not willing to change $R(A_1)$, then he should lool for missing criteria, adding perhaps one suggested in $(\overline{2.3})$ and then go to $(\overline{1.2})$, or additing a subjective one and go to $(\overline{1.5})$.

If $\underline{\mathsf{DM}}$ is not willing to make any of the above decisions, he might increase the number of linear pieces on some of the marginal utility functions for better preference modeling and go to $(\overline{1.8})$. Otherwise it means that the numbers of linear pieces will remain insufficient or that the assumption of an additive utility function in DSS is not suitable (in this case, see appendix).

Phase 3 : Assessing a compromise preference model

 $(\overline{3.1})$ DSS uses UTA with $R(A_1) = R^*(A_1)$ in order to show the DM the range of admissible utility functions (shape of $u_i(y_i)$ maximum weights w_{imax} , minimum weights w_{imin} , and the average utility function $\bar{u}(g)$ (post-optimality analysis in [9]).

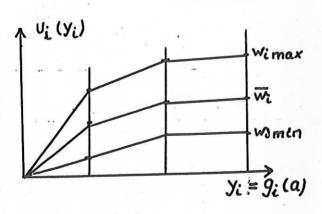


Figure 7

DSS suggests an average utility function as a compromise utility function $\bar{u}(y) = \sum_i \bar{u}_i(y_i)$.

 $(\overline{3.2})$ If DM thinks that the average utility function u(y) reflects his preferences, then go to $(\overline{3.6})$.

 $(\overline{3.3})$ Direct assessment of $u'(y) = \sum_{i} u'_{i}(y_{i})$

If \underline{DM} comes from $(\overline{3.2})$, he reacts to $\overline{u}(y)$. He can modify the weights $\overline{w_i} \rightarrow w_i'$ (such that $\sum\limits_i w_i' = 1$) and/or modify the shape of the marginal utilities $u_i(y_i)$.

If he wishes \underline{DM} can ask DSS to compute the values of the trade-off between any pair of criteria for $\bar{u}(y)$ and/or u'(y).

If \underline{DM} comes from $(\overline{1.9})$ or $(\overline{3.5})$, he must specify the weights $w_i^!$ and the shapes of the marginal utilities $u_i^!(y_i)$ (answering questions on trade-offs, indifference points, ...).

(3.4) DSS computes the ranking R'(A₁) using u'(y). If the DM agrees with R'(A₁) and/or the utility values u'(g(a)): a \in A₁, then go to (3.6).

(3.5) DM might choose between

- modify u'(g) in a direct assessment way : go to $(\overline{3.3})$;
- modify the set of criteria $~{\bf g_1},~\dots,~{\bf g_p}~$ and/or constraints : go to $(\overline{1.2})$ or $(\overline{1.5})$;
 - modify some personal evaluations : go to $(\overline{1.5})$;
 - modify the ranking $R(A_1)$: go to (2.2);
 - modify the number of linear pieces : go to $(\overline{1.8})$.

 $(\overline{3.6})$ Let $\hat{u}(y)$ be the compromise utility function which is either $\bar{u}(y)$ or u'(y).

Phase 4: Evaluations of Ao using the compromise preference model

- $(\overline{4.1})$ Using $g(A_0)$ (from 1) and $\hat{u}(y)$ (from 3), \underline{DSS} computes the utilities $\hat{u}(g(a))$: a A_0 and the rank-order $\hat{R}(A_0)$.
- $(\overline{4.2})$ If \underline{DM} agrees with $\widehat{R}(A_0)$ and/or $\widehat{u}(g(a))$: $a \in A_0$, then go to $(\overline{4.5})$.

- $(\overline{4.3})$ If \underline{DM} nonetheless has enough information to make a decision, then go to $(\overline{4.5})$.
- $(\overline{4.4})$ DM might choose between :
 - modify $\hat{u}(g)$ in a direct way : go to $(\overline{3.3})$;
- add some alternatives of A_0 - A_1 into A_1 and use the indirect assessment procedure with UTA : go to $(\overline{2.1})$;
- modify the set of criteria $~{\bf g_1},~\dots,~{\bf g_p}~$ and/or constraints : go to $(\overline{1.2})$ or $(\overline{1.5})$;
 - modify some personal evaluations : go to $(\overline{1.5})$.
- $(\overline{4.5})$ DM makes his decision : buy or go and try the best or some of the best products.

STOP.

4. AN ILLUSTRATIVE EXAMPLE : THE DECISION TO PURCHASE A CAR

We shall present as an illustrative example of the above methodology the decision to purchase a car. We shall use a small data base involving a set A of 10 alternative cars. We shall follow step by step the decision process model given in section 3.

Step (1.1) and (1.2) The first two steps have been simplified for this We here assume that the DM has chosen the following three criteria:

 g_1 : consumption at 120 km/h expressed in liters/100 km;

 g_2 : space measured in square meters (length x width);

 \mathbf{g}_3 : price expressed in French Francs.

The \underline{DM} does not specify any constraints, so $A_0' = A$. Of course in a real application A would contain a few hundred alternative cars and DM would no doubt want to specify some constraints.

- No : A_0^{\prime} is a reasonable size (10 cars). $(\overline{1.3})$
- DM does not use any subjective criteria for this simplified illustration, so $A_0 = A_0'$.
- $(\overline{1.6})$ Yes: A₀ is a reasonable size (10 cars).
- (1.7)Maximum and minimum values are the following:

 \mathbf{g}_1 : 11.95 and 6.75 [1/100 km] ; \mathbf{g}_2 : 8.47 and 5.11 [m²] ;

 g_3 : 75 700 and 24 800 [FF].

 $(\overline{1.8})$ <u>DSS</u> will use 3 linear pieces for g_1 and g_2 but <u>DM</u> prefers to use 4 linear pieces for g_3 since price is important to him and its range is quite large.

Step $(\overline{1.9})$ DM is willing to assess indirectly his utility function by giving a whollistic preference.

 $(\underline{2.1})$ \underline{DM} chooses the following subset A_1 = [DYANE, M230, P505, P104], because he is familiar with these cars. \underline{DSS} suggests adding BMW or VOLVO in order to have in A_1 a car with a high consumption. \underline{DM} chooses BMW. Therefore A_1 = [DYANE, M230, P505, P104, BMW].

 $(\overline{2.2})$ Considering the criteria values for the car in $\,{\rm A}_1,\,{\rm DM}$ gives the rank order $\,{\rm R}({\rm A}_1)$ - see Table 1.

A ₁	R(A ₁)	C ₁₂₀ 1/100 km	SPACE M ²	PRICE FF	MAX.SP km/h (added in step 2.4)
P505	1st	10.01	7.88	49 500	173
P104	2nd	8.42	5.11	35 200	161
DYANE	3rd	6.75	5.81	24 800	117
BMW	4th	12.26	7.81	68 593	182
M230	5th	10.40	8.47	75 700	180

 $\underline{\text{Table 1}}$: Whollistic ranking and criteria values for cars in set A_1

Step $(\overline{2.3})$ UTA gives the following results shown in figure 8 R*(A₁) \neq R(A₂): the rank orders are not consistent.

We note it is not possible to have a utility function with u(g(P104) > u(g(DYANE)) since actually, DYANE dominates P104 on the 3 criteria (see table 1 above). Therefore, the best UTA could do is to calculate a utility function where these 2 cars are tied.

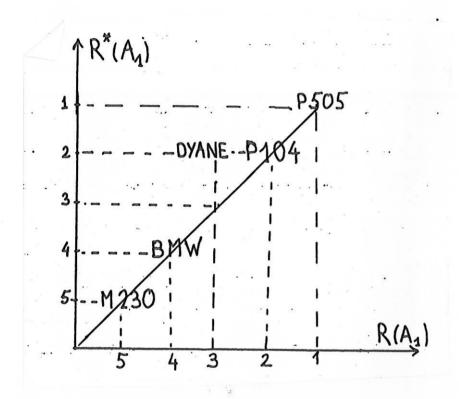


Fig. 8: Inconsistency between $R(A_1)$ and $R^*(A_1)$

DSS suggests adding one of the following criteria for which P104 is better than DYANE: Maximum speed, horse power.

 $(\overline{2.4})$ DM selects the third option. He strictly prefers P104 to DYANE and agrees to add a criterion g_4 : Maximum speed expressed in km/h and goes to 1.2.

Step $(\overline{1.2})$ DM is going to work with the 4 criteria and does not give a constraint level on the new criterion (see table 1).

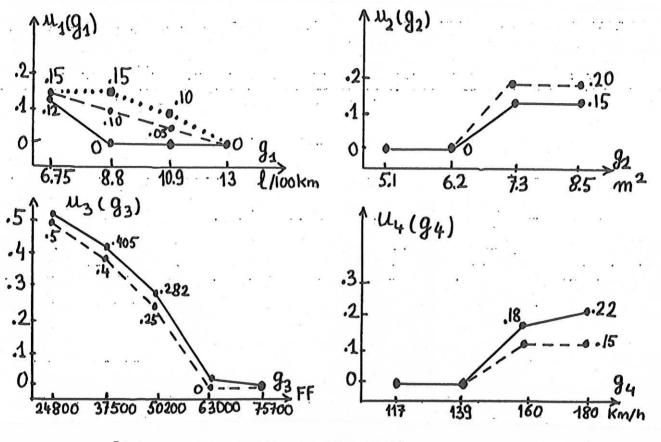
 $(\overline{1.7})$ $g_4^* = 182$ km/h and $g_{4*} = 117$ km/h.

 $(\overline{1.9})$ DM is willing to assess indirectly his utility function.

 $(\overline{2.1})$ and $(\overline{2.2})$ DM does not want to modify A_1 or $R(A_1)$.

 $(\underline{2.3})$ and $(\underline{2.4})$ UTA yields $R^*(A_1) = R(A_1)$ i.e. there is consistency.

 $(\overline{3.1})$ The 4 marginal average utility functions $u_i(g_i)$ suggested as a compromise after the post optimality analysis are shown by the solid lines on figure 9 (ignore the other lines for the time being).



 $\bar{u}(g)$: average utility function (UTA) u'(g) : modified utility function by direct assessment

 $\hat{u}(\hat{g})$: final compromise utility function

Fig. 9: Evolving additive utility functions

Step

 \underline{DM} does not like the shape of $u_1(y_1)$. $(\overline{3.2})$

 \underline{DM} modifies the shape of $u_1(y_1)$ and changes slightly the weights $(w_1 = .15, w_2' = .2, w_3' = .5, w_4' = .15)$ giving more importance to the space criterion g_2 to obtain the modified utility functions u'(y) shown by the dashed lines in Figure 9.

 $(\overline{3.4})$ R'(A) and u'(g(a)) : a \in A₁ are shown in table 2.

	Average		Average Modified			Final Compromise		
A ₁	R(A ₁)	ū(g(a))	R'(A ₁)	u'(g(a))	$\hat{R}(A_1)$	û(g(a))		
P505	1	.650	1	1.680	1	.730		
P104	2	.637	2 NO	.678	2	.718		
DYANE	3	.627	3	.650	3	.650		
BMW	4	.382	57 YES	7.367	5	.383		
M230	5	.371	4 1 2	√.412	4	.462		

Table 2: Average, modified and final rank-orders and utilities

 $\underline{\rm DM}$ agrees with the modified ranking R'(A₁) where the ranking of M230 and BMW are reversed, but does not agree with the computed utilities for P505 and P104 which are almost numerically the same.

- $(\overline{3.5})$ and $(\overline{3.3})$ Looking at Table 1 and figure 10, \underline{DM} realizes that the impact of changing the shape of utility function $u_1(y_1)$ to $u_1'(g_1)$ has been to penalize relatively the overall utility u' of BMW which has a high gas consumption, and to narrow the overall utility gap between the P505 and the P104. As he does not like this narrow gap, \underline{DM} decides to change the shape of $u_1'(y_1)$ even further as shown by the dotted line in figure 9 in order to avoid excessively penalizing the P505 on the consumption criterion.
- $(\overline{3.4})$ This widens the overall computed utility gap between the two cars as shown by the final compromise utilities \hat{u} (see Table 2), with which \underline{DM} agrees.
- $(\overline{3.6})$ <u>DM</u> adopts the newly modified utility function as the final compromise $\hat{u}(y)$ the one with dashed lines for g_2 , g_3 , g_4 , and the dotted line for g_1 in figure 9.

$(\overline{4.1})$	<u>DSS</u> computes	the ranking	$R(A_o)$	and utilities	û(g(a))	:	a	ϵ	A_{o}
(see T	able 3).								10.000

a	Ř(Α _o)	û(g(a))	c ₁₂₀	SPACE	PRICE	MAX. SPEED
OPEL	1	.752	10.48	7.96	46 700	176
P505	2	.730	10.01	7.88	49 500	173
P104	3	.718	8.42	5.11	35 200	161
DYANE	4	.650	6.75	5.81	24 800	117
VISA	5	.616	7.30	5.65	32 100	142
GOLF	6	.576	9.61	6.15	39 110	148
M230	7	.462	10.4	8.47	75 700	180
CX	8	.442	11.05	8.06	64 700	178
VOLVO	9	.401	12.95	8.38	55 000	145
BMW	10	. 383	12.26	7.81	68 593	182

 $\underline{\text{Table 3}}$: Computed ranking, overall utility and criteria values for cars in set A_0

 $(\overline{4.2})$ Noting the overall utilities and values, $\underline{\rm DM}$ agrees with R(A $_{\rm o}$). He is especially interested in finding out that the OPEL, which he did not know before, ranks 1st ahead of P505.

 $(\overline{4.5})$ DM would go and try the OPEL.

STOP

Suppose in step $(\overline{4.2})$ <u>DM</u> has not agreed with R(A_O) because there is no nearby service for OPEL. Then from step $(\overline{4.3})$ he might have gone directly to $(\overline{4.5})$ and bought the second-ranked P505, a car he already knew. Alternatively, if there had been several unknown cars ranked ahead of the P505, <u>DM</u> might have gone to $(\overline{4.4})$ formally introducing the new "service availability" criterion and going to $(\overline{1.5})$. Later in the procedure, he would probably add OPEL and possibly some other cars to set A₁.

5. CONCLUDING REMARKS

Some remarks on implementation are in order. We plan to put the DSS on a microcomputer. So far phases 1 to 4 have been programmed in BASIC for microcomputers using an enhanced version of UTA (*). Our initial product will be automobiles, perhaps followed by microcomputers themselves as a product-buying decision.

We plan at least initially to supplement the computerized support system with a consultant to aid the decision maker in using the system. Later, as we gain more knowledge of user behavior and as users become more familiar with microcomputers, the DSS can become even more conversational and perhaps the consultant's role could be eliminated. In any case, we would need ongoing expertise for designing and updating the data base.

In specializing the general evolutionary systems design (EDS) methodology for use in DSS for semi-structured buying decisions, we have treated in this paper a situation involving only one decision maker (buyer). In a subsequent paper we plan to discuss the case of two or more decision makers within the ESD framework. In this case, for example, each decision maker can use the above DSS to assess his own preferences. Then, depending on the results, decision makers could decide to bargain and/or attempt to integrate their preference structures by exchanging information on their preferences and judgements. Alternatively, decision makers could use the DSS together from the start for joint learning and assessment of a coalition preference structure.

Finally, we note that the ESD framework provides a general methodology for designing specific DSS. The latter, in turn, as operational systems clarify the meaning of the general methodology and can provide suggestions for its evolution.

^(*) A microcomputer program, called PrefCalc, is available and running on IBM-PC (with the graphic card) and Zenith 100. For more information, contact EURO-DECISION, B.P. 57, F-78530 BUC - Tel. (33-3) 956 37 05.

APPENDIX

RELAXING THE ADDITIVITY AND/OR PIECEWISE LINEARITY ASSUMPTIONS

Whenever a marginal utility function $v_i(y_i)$ (normalized such that $v_i(y_i^*) = 0$ and $v_i(y_i^*) = 1$) is known or assessed through any direct procedure (see Keeney and Raiffa [11]) we could still use the UTA procedure and estimate indirectly the weights w_i by replacing $g_i(a)$ by $g_i^*(a) = v_i(g_i(a))$ using 1 linear piece for g_i . Thus after step 1.9 the user could go to 2.1. However behaviorally speaking, most users would find it easier proceed with piecewise linear utilities as suggested in 1.7.

This procedure permits us also to use a non-additive utility function. For example if $u(y) = \sum\limits_{i} w_{i} v_{i}(y_{i}) + \sum\limits_{i} w_{ij} v_{i}(y_{j}) v_{j}(y_{j})$ the weights w_{i} and w_{ij} could be indirectly estimated using 1 linear piece for the new criteria $g_{i}^{l}, \ldots, g_{ij}^{l}(a)$ defined by $g_{i}^{l}(a) = v_{i}(g_{i}(a))$ and $g_{ij}^{l}(a) = v_{i}(g_{i}(a)) v_{j}(g_{j}(a))$.

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