A non-interactive methodology to assess farmers' utility functions: An application to large farms in Andalusia, Spain

FRANCISCO AMADOR
Business School, ETEA, Córdoba, Spain

JOSE MARIA SUMPSI and CARLOS ROMERO
Technical University of Madrid, Spain

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Summary

This paper proposes a methodological approach for eliciting farmers' utility functions. The methodology is non-interactive, in that the parameters defining the utility function are obtained by observing the actual behaviour adopted by farmers without resorting to the use of questions on random lotteries. The methodology recognises that the farmer attempts to achieve several objectives, most of which are in conflict. The methodological approach is applied to a large farmer in the county of Vega de Córdoba, Spain. The primary empirical finding of this research was a satisfactory explanation of farmers' behaviour through a multi-attribute utility function with three attributes: working capital, risk and level of relative profitability.

Keywords: farmers' goals, utility function, multi-criteria analysis, goal programming.

1. Introduction

Nowadays, it is well accepted that multiple objectives are the rule rather than the exception in the agricultural field when decisions are taken at the farm or regional level (see Gasson, 1973; Cary and Holmes, 1982; Romero

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and Rehman, 1989; Dent and Jones, 1993, and a large body of other literature). Once the multiplicity of objectives in agriculture is accepted, there are two main approaches to building decision-making models.

The first and most rigorous direction consists in defining a utility function comprising all relevant objectives for a given decision problem. This kind of methodology, known as Multi-Attribute Utility Theory (MAUT), was chiefly developed by Keeney and Raiffa (1976). MAUT is a theoretically sound approach based on the assumption of rationality underlying the classic paradigm of expected utility created by Von Neumann and Morgenstern (1944). However, its applicability poses many difficulties, as is explained below. Thus, very few applications of MAUT in the agricultural field can be reported (e.g., Herath, 1981; Delforce and Hardaker, 1985; Foltz et al., 1995).

The second direction consists in looking for multi-criteria approaches without the theoretical soundness of MAUT, but which can accommodate in a realistic manner the multiplicity of criteria inherent to most agricultural planning problems. Among the possible surrogates of MAUT, the most widely used in the agricultural field are: goal programming, multi-objective programming and compromise programming. Rehman and Romero (1993) analyse the pros and cons of these surrogates in agriculture.

A major problem associated with the formulation of MAUT models lies in the high degree of interaction with the decision maker required by this methodology. This issue is particularly important in agriculture where the cultural background of the decision maker is often not the most suitable for undertaking such an interactive process. Thus, within the context of a peasant economy, to question the person in charge of a family farm thoroughly about his/her preferences concerning different random lotteries in order to test independence conditions or assess individual utility functions can be a very indecisive process.

This paper presents a pragmatic methodology capable of assessing a farmer's utility function. The proposed approach does not require any kind of interaction with the decision maker, but rather an awareness of the actual behaviour followed by the farmer. In other words, it attempts to obtain a utility function consistent with preferences revealed by farmers themselves. A drawback of the method is that revealed preference can be distorted by factors not under control of the farmer (see end of Section 3).

The next section examines the main problems associated with the implementation of the MAUT approach, especially in agricultural applications. The paper then uses our non-interactive approach to assess the utility function of a big farmer in the county of Vega de Córdoba in Andalusia, Spain.

2. The classic implementation of a MAUT model: Some criticisms in the agricultural field

The classic assessment of a MAUT model requires the implementation of five basic steps, which can be summarised as follows (Zeleny, 1982: 419–431):

1. To train the decision maker in the terminology, concepts and techniques to be used.
2. To test the corresponding independence conditions in order to justify the appropriate functional form of the multi-attribute utility function (additive, multiplicative, etc.).
3. To assess the individual utility functions for each objective relevant to the corresponding decision problem.
4. To estimate the weights and scaling constants associated with each utility function. Once the values of these parameters and their corresponding functional form (step 2) are known, then the individual utility functions can be amalgamated into an aggregate multi-attribute utility function.
5. To test the consistency of the results obtained.

The last four steps require notable interaction with the decision maker as several artificial random lotteries requesting values of outcome which secure certain indifference statements are presented to him/her. These kinds of questions are not easy to answer. Moreover, as some researchers have pointed out, the MAUT methodology assumes *a priori* that decision makers evaluate lotteries as if they are maximising expected utility. Consequently, there is a certain circularity within the MAUT approach.

Indeed, some of the procedural steps demand from the decision maker not only answers to difficult questions but a large number of answers. Thus, to estimate the values of the scaling constants in a multiplicative functional form, where the additive independence condition does not hold, requires answers to 2^q-1 questions, where q is the number of objectives under consideration, i.e. for 5 objectives – not an uncommon situation in agriculture – elicitation of the scaling constants requires formulating and obtaining answers to 31 statements based upon random lotteries!

For these reasons, the pragmatic value of the MAUT approach is limited to problems with few objectives (at most two or three) and with an important economic relevance, such as the location of an airport or a nuclear power plant. Within this context, the capacity and responsibility of the decision maker makes it possible to implement such a complex interactive process.

It is obvious that the application possibilities of the traditional MAUT approach are scarce in the agriculture field. To establish such an exhaustive interaction with a subsistence farmer or even a commercial farmer in order to elicit their utility function does not seem advisable. The next section demonstrates how it is possible to elicit this kind of utility function without the need to interact with the decision maker. In this way, by preserving the basic theoretical underpinning of the classic utility optimisation, a multi-attribute utility function consistent with the actual preferences shown by farmers will be obtained. In short, the information necessary to assess the utility function will be obtained by observing actual behaviour rather than by posing complex questions to farmers.

It should be emphasised that this paper does not claim the superiority of the proposed method with respect to MAUT. The latter remains the theoretically correct method to follow when a strong interaction with the farmer is possible.

3. Methodology

The first step in the methodology corresponds to a previous study (Sumpsi et al., 1993, 1997) where weights indicating the relative importance to be attached to the objectives followed by a farmer are elicited. The 'best' weights are those compatible with the preferences revealed by the farmer being analysed. For this task and the new methodological proposal, the following notation is used:

$\mathbf{x}$ = vector of decision variables (i.e., area covered by each crop)
$\mathbf{F}$ = feasible set (i.e., the set of constraints imposed on the model)
$f_i(\mathbf{x})$ = mathematical expression of the i-th objective
w_i = weight measuring relative importance attached to the i-th objective
f^*_i = ideal or anchor value achieved by the i-th objective
f_{i*} = anti-ideal or nadir value achieved by the i-th objective
f_i = observed value achieved by the i-th objective
f_{ij} = value achieved by the i-th objective when the j-th objective is optimised
n_i = negative deviation, i.e. the measurement of the under-achievement of the i-th objective with respect to a given target.
p_i = positive deviation, i.e. the measurement of the over-achievement of the i-th objective with respect to a given target.

The first step consists of defining a tentative set of objectives $f_1(\mathbf{x})$, ... $f_i(\mathbf{x})$, ... $f_q(\mathbf{x})$ which seeks to represent the actual objectives followed by the farmer. The second step consists of determining the pay-off matrix for the above objectives. The elements of this matrix are obtained by optimising each objective separately over the feasible set and then computing the value of each objective at each of the optimal solutions [see Sumpsi et al. (1997) for technical details about the design and construction of the pay-off matrix].

Once the pay-off matrix is obtained, the following system of q equations is formed:

$$\begin{aligned} &\sum_{j=1}^{q} w_j f_{ij} = f_i \qquad i=1, 2, \ldots, q \\ &\sum_{j=1}^{q} w_j = 1 \end{aligned} \tag{1}$$

The last condition of (1) is not essential and is introduced only to normalise the weights w_j. If this system of equations has a non-negative solution, this will represent the set of weights to be attached to each objective, and thus the actual behaviour $(f_1, f_2, \ldots, f_q)$ followed by the farmer is reproduced. In most cases, an exact solution does not exist. In other words, there is no set of weights $w_1, w_2, \ldots, w_q$ capable of reproducing the actual preferences revealed by the farmer. Consequently, the best solution of (1) is sought. This problem can be considered equivalent to a regression analysis case where f_i are the endogenous variables and f_{ij} the exogenous one. Among the possible criteria for minimising the corresponding deviations, and given our preferential context, the following are proposed:

The L_1 criterion. With this approach, the sum of positive and negative deviational variables is minimised. This criterion underlies the use of metric 1. As is well known since Charnes et al. (1955), this kind of regression analysis problem can be formulated in terms of goal programming (GP), as follows (see also, Ignizio, 1976; Romero, 1991):

$$\text{Min} \sum_{i=1}^{q} \left(\frac{n_i + p_i}{f_i} \right)$$

subject to:

$$\begin{aligned} &\sum_{j=1}^{q} w_j f_{ij} + n_i - p_i = f_i \qquad i = 1, 2, \ldots, q \\ &\sum_{j=1}^{q} w_j = 1 \end{aligned} \tag{2}$$

It should be remarked that GP is not used here as a 'satisficing' decision-making approach, and, as such, the right-hand-side values do not represent proper targets. In this paper, GP is simply used as a mathematical device to approximate a solution for an unfeasible system of equations such as (1) where the right-hand sides are the values achieved by the objectives under consideration.

From a preferential point of view, the L_1 *criterion* is consistent with a separable and additive utility function (see, e.g., Dyer, 1977). That is, weights obtained from (2) lead to the following utility function:

$$u = \sum_{i=1}^{q} \frac{W_i}{k_i} f_i(x) \tag{3}$$

where k_i is a normalising factor (e.g., ideal minus anti-ideal values; i.e. $k_i = f_i^* - f_{i*}$).

The L_∞ criterion. With this approach, the largest deviation D is minimised. This criterion underlies the use of metric ∞ and the corresponding regression analysis problem can be formulated in terms of linear programming (LP) as follows (see Appa and Smith, 1993):

$$
\begin{aligned}
&\text{Min } D, \text{ subject to:}\\
&\sum_{j=1}^{q} w_j f_{ij} + f_i D \geqslant f_i\\
&-\sum_{j=1}^{q} w_j f_{ij} + f_i D \geqslant -f_i \qquad i=1, 2, \ldots, q \qquad (4)\\
&\sum_{j=1}^{q} w_j = 1
\end{aligned}
$$

It has been proved elsewhere (Ballestero and Romero, 1991) that model (4) implies the following chain of equalities:

$$\frac{1}{f_1}\left[\sum_{j=1}^{q} w_j f_{1i} - f\right] = \frac{1}{f_2}\left[\sum_{j=1}^{q} w_j f_{2i} - f_2\right] = \ldots \ldots = \frac{1}{f_q}\left[\sum_{j=1}^{q} w_j f_{qi} - f_q\right] \qquad (5)$$

That is, from a preferential point of view, the L_∞ criterion implies a perfectly balanced allocation between the differences given by the prediction

$$\sum_{j=1}^{q} w_j f_{ij}$$

and the value observed for f_i in the q objectives considered. The corresponding utility contours are represented in Figure 1 for a bi-criterion case. This

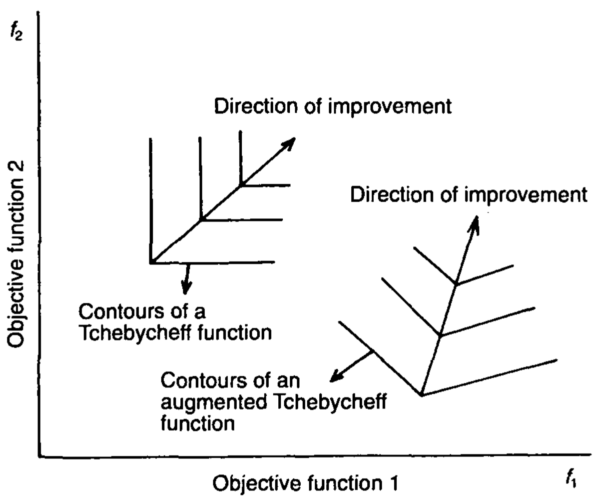

Figure 1. *Utility contours for a Tchebycheff and an Augmented Tchebycheff function (bi-criteria case)*

kind of utility function, in the operational research literature, is called a Tchebycheff or maximin function for which the largest deviation is minimised (see Steuer, 1989).[1] This structure of preferences leads to the following utility function:

$$u = -\left[\underset{i}{\text{Max}} \frac{w_i}{k_i} [f_i^* - f_i(\mathbf{x})] \right] \tag{6}$$

The above utility function does not imply separability among objectives but a perfect complementary relationship between them (see again Figure 1). On the other hand, function (6) is not smooth and hence its maximisation is performed by solving the following equivalent problem (e.g., Nakayama, 1992):

$$\begin{aligned} &\text{Min } D \text{ subject to:} \\ &\frac{w_i}{k_i} [f_i^* - f_i(\mathbf{x})] \leqslant D \qquad i = 1, 2, \dots q \end{aligned} \tag{7}$$

A compromise between L_1 and L_∞. With this approach, a compromise between minimising the sum of deviational variables and minimising the largest deviation is sought. This aggregate criterion attempts to take advantage of both approaches (Lewis and Taha, 1995). The corresponding problem is formulated in terms of LP as follows:

$$\text{Min } D + \lambda \sum_{i=1}^{q} \left(\frac{n_i + p_i}{f_i} \right)$$

subject to:

$$\begin{aligned} &\sum_{j=1}^{q} w_j f_{ij} + n_i - p_i = f_i \\ &\sum_{j=1}^{q} w_j f_{ij} + f_i D \geqslant f_i \qquad i = 1, 2, \dots, q \\ &-\sum_{j=1}^{q} w_j f_{ij} + f_i D \geqslant -f_i \\ &\sum_{j=1}^{q} w_j = 1 \end{aligned} \tag{8}$$

Weights obtained from (8) lead to the following utility function:

$$u = -\left[\underset{i}{\text{Max}} \left\{ \frac{w_i}{k_i} [f_i^* - f_i(\mathbf{x})] \right\} - \lambda \sum_{j=1}^{q} \frac{w_i}{k_i} f_i(\mathbf{x}) \right] \tag{9}$$

If λ is very large, u becomes an additive and separable utility function [see expression (3)], whereas for $\lambda = 0$, u becomes a Tchebycheff function [see expression (6)]. For small values of λ, u can be considered an augmented

Tchebycheff function. That is, the second term of (9) gives the utility contours a 'certain slope'. Thus, if parameter λ takes a small value, then (9) will lead to a well-balanced solution (an augmented Tchebycheff function) (see Figure 1). However if the parameter λ takes a large value, then (9) will lead to a solution close to the solution corresponding to the separable function given by (3).[2] Thus, depending on the value of parameter λ, different utility functions are generated. Again, the above utility function is not smooth. Consequently, its maximisation is performed by solving the following auxiliary problem:

$$\text{Min } D-\lambda \sum_{i=1}^{q} \frac{w_i}{k_i} f_i(x)$$

subject to:

$$\frac{w_i}{k_i}[f_i^* - f_i(\mathbf{x})] \leqslant D \qquad i=1, 2, \ldots, q \tag{10}$$

The next step in our methodology involves determining the functional form of the multi-attribute utility function which best approximates the actual situation. For this purpose, we only need to maximise alternatively expressions (3), (6) or (9) subject to the relevant constraint set and to compare the results with the actual values achieved by the q objectives. For instance, for utility function (3) the following mathematical programming problem is formulated:

$$\text{Max} \sum_{i=1}^{q} \frac{w_i}{k_i} f_i(\mathbf{x})$$

subject to:

$$\begin{aligned} & f_i(\mathbf{x}) + n_i - p_i = f_i \qquad i=1, 2, \ldots, q \\ & \mathbf{x} \in \mathbf{F} \end{aligned} \tag{11}$$

Similar mathematical programming problems are formulated for the other utility functions. The preference structure which provides the solution closest to the actual situation will be considered the utility function consistent with the preferences revealed by the farmer. If none of the utility functional forms examined leads to consistent results, then other forms of utility function should be tried until the behaviour of the farmer is predicted with enough accuracy. By consistent results, we mean that there is a marked similarity between the predictions provided by the utility function chosen and the observed values for each of the objectives. The similarity can be checked using a variety of statistics (see note 3).

It should be noted that the methodology proposed uses just one year's data. Therefore, it is crucial that the year chosen reflects a typical year for which stochastic variables are close to their expected values, otherwise biased results may be obtained.

4. Application

In this section, the methodology previously described is used to elicit the utility function of a farmer belonging to a homogeneous group of large-scale farmers in the county of Vega of Córdoba, Andalusia (Spain). The characteristics of this group of farmers (farm size, cropping patterns, soil quality, etc), are similar (see Sumpsi et al., 1993) so one might hypothesise that the behaviour of the different farmers in the group will follow a similar pattern; that is, the utility function elicited for the farmer being analysed can also be used to reproduce accurately the behaviour of the other farmers in the group. This hypothesis will be checked.

To begin, we need to identify a set of tentative objectives. After preliminary interviews with farmers belonging to the group of farms studied, the following list of objectives tentatively reflect the economic goals of the corresponding farmers:

	Direction of improvement
1. Gross margin	Max.
2. Working capital	Min.
3. Employment	Min.
4. Management difficulty	Min.
5. Risk (MOTAD)	Min.
6. The ratio $\frac{\text{Gross margin}}{\text{Working capital}}$	Max.

Gross margin is an indicator of absolute profitability and is measured in million ptas. Working capital is measured in thousand ptas. Employment refers to the amount of labour required by the different crops each year and is measured in hours. Management difficulty is a qualitative index, defined by the authors, and is measured on a scale from 1 to 10 for each crop. Risk is incorporated according to the MOTAD method (Hazell, 1971). The ratio gross margin/working capital is a measure of relative profitability.

The next step was to determine the pay-off matrix for the farmer analysed. In order to do so, a mathematical model representing the farmer's decision-making environment was built. The model includes, along with the six objectives, a feasible region F which takes into account different constraints, including different types of land and availability for each type, standard agronomic practices adopted by farmers, cash-flow limits, capital investment limits and labour use in different time periods. For our data, the pay-off matrix in Table 1 was obtained.

The last column of Table 1 is not actually a part of the pay-off matrix. It has only been added to show the observed value of each objective for the

Table 1. *Pay-off matrix for the six objectives considered*

	Gross margin	Working capital	Use of labour	Management difficulty	Risk	Gross margin/ working capital	Observed values for each of the objectives
Gross margin (mill.ptas.)	57.1	6.1	7.5	13.8	48.6	39.0	28.1
Working capital (thou.ptas.)	42,689	7979	9113	14,354	34,347	20,753	19,521
Employment (hours)	71,682	3999	3382	7899	50,202	25,699	16,012
Management difficulty (index)	1754	711.1	836.5	519.2	1646.8	1559	1103
Risk (MOTAD)	39,170	18,646	37,334	7009	0	6068	8882
Gross margin/ working capital	1.338	0.768	0.825	0.963	1.415	1.880	1.441

farm considered. Once the pay-off matrix has been obtained, the following system of equations is formulated:

$$
\begin{array}{rrrrrrr}
57.1\,w_1 + & 6.1\,w_2 + & .\,7.5\,w_3 + & 13.8\,w_4 + & 48.6\,w_5 + & 39.0\,w_6 = & 28.1 \\
42{,}689\,w_1 + & 7{,}979\,w_2 + & 9{,}113\,w_3 + & 14{,}354\,w_4 + & 34{,}347\,w_5 + & 20{,}753\,w_6 = & 19{,}521 \\
71{,}682\,w_1 + & 3{,}999\,w_2 + & 3{,}382\,w_3 + & 7{,}899\,w_4 + & 50{,}202\,w_5 + & 25{,}699\,w_6 = & 16{,}012 \\
1{,}754\,w_1 + & 711.1\,w_2 + & 836.5\,w_3 + & 519.2\,w_4 + & 1{,}646.8\,w_5 + & 1{,}558\,w_6 = & 1{,}103 \\
39{,}170\,w_1 + & 18{,}646\,w_2 + & 37{,}334\,w_3 + & 7{,}009\,w_4 & + & 6{,}068\,w_6 = & 8{,}882 \\
1.338\,w_1 + & 0.768\,w_2 + & 0.825\,w_3 + & 0.963\,w_4 + & 1.415\,w_5 + & 1.880\,w_6 = & 1.441 \\
w_1 + & w_2 + & w_3 + & w_4 + & w_5 + & w_6 = & 1
\end{array}
\tag{12}
$$

The above system of equations does not have a non-negative solution, i.e., there is no set of weights actually capable of reproducing the observed values for each of the objectives. Therefore, an approximate solution is sought by resorting to (2), (4) and to the family of functions given by (8). The results obtained are shown in Table 2.

For a value of the parameter λ less than 0.02, the compromise criterion provides the same set of weights as the L_∞ criterion and for a value of the λ parameter larger than 1.5, the compromise criterion provides the same set of weights as the L_1 criterion. It is interesting to note that for the farmer analysed, what matters is not gross margin *per se* but gross margin generated per money unit of working capital (i.e., $w_1 = 0$ and $w_6 > 0$). This clash between absolute and relative profitability has been observed in other agricultural scenarios (e.g., Mendez-Barrios, 1995).

The next step in our procedure consists of inserting these weights in the corresponding utility functions (3), (6) and (9). To facilitate calculation of the different utility functions, only weight values larger than 0.05 were

Table 2. *Set of weights generated by different minimisation criteria*

	Criterion					
			Compromise			
	L_1	L_∞	$0.02 \le \gamma < 0.25$	$0.25 \le \lambda \le 0.50$	$0.75 \le \lambda \le 1.5$	$\lambda > 1.5$
Gross margin (W_1)	0	0	0	0	0	0
Working capital (W_2)	0.31	0.19	0.24	0.34	0.26	0.31
Employment (W_3)	0	0.09	0.08	0	0	0
Management difficulty (W_4)	0	0.05	0.05	0	0.11	0
Risk (W_5)	0.19	0.05	0.08	0.09	0.10	0.19
Gross margin/ working capital (W_6)	0.50	0.62	0.55	0.57	0.53	0.50

considered. In fact, the inclusion in the computation process of weights less than or equal 0.05 had a negligible effect on the numerical predictions provided by the model. When a weight is omitted, its value is allocated proportionally to the values of the other weights. For instance, for the L_∞ criterion, the weights used to build the different utility functions are: $w_1=w_4=w_5=0$, $w_2=0.21$, $w_3=0.10$ and $w_6=0.69$.

The different utility functions were obtained by arithmetic calculation. These utility functions were optimised subject to the constraint set in order to check their capacity to reproduce the observed reality [see (11) for the separable and additive case]. The three utility functions which provide results more consistent with the actual observed values are the following:

(a) *Separable and additive utility functions (u_1)*

$$u_1=\{-0.89f_2(\mathrm{x})-0.49f_5(\mathrm{x})+44964f_6(\mathrm{x})\}$$

(b) *Tchebycheff utility functions (u_2)*

$$u_2=-[\mathrm{Max}\{0.61(f_2(\mathrm{x})-7979),\ 0.15(f_3(\mathrm{x})-3382),\ 62050(1.88-f_6(\mathrm{x}))\}]$$

(c) *Augmented Tchebycheff utility functions ($\lambda=1.6$) (u_3)*

$$u_3=-\begin{bmatrix}\mathrm{Max}\{0.89(f_2(\mathrm{x})-7979),0.49(f_5(\mathrm{x})-0),44964(1.88-f_6(\mathrm{x}))\}\\ +1.42f_2(\mathrm{x})+0.78f_5(\mathrm{x})-71942f_6(\mathrm{x})\end{bmatrix}$$

Table 3 shows the actual observed values for the six objectives considered, as well as the predictions generated by the three utility functions selected.

The rationale of Table 3 is to check that the objectives and weights estimated in equation (12) are compatible with observed values. A similar comparison could be carried out directly in equation (12) by analysing the values of the deviation variables. In short, the results in Table 3 allow us to conclude that the parameters of the utility function have been correctly estimated.

The three 'best' utility functions chosen (i.e., u_1, u_2 and u_3) basically show the same capacity to reproduce the reality observed.[3] Finding several utility functions with the same basic predictive power, rather than a single 'best' utility function, is not surprising. In fact, Köksalan and Sagala (1995: 200–201) have rightly remarked that different utility functional forms in many cases yield exactly the same optimum. For example, in Figure 2, the Tchebycheff and linear utility functions yield exactly the same optimum.[4]

To validate the applicability of the results to other farmers in the group, we checked that the utility functions elicited were also able to reproduce these farmers' behaviour with a good degree of accuracy.[5] In fact, the consistency index for all the cases in the group of farmers analysed was never higher than 10 per cent (see note 3). This verification confirms the conjecture stated at the beginning of this section and reinforces the pragmatic

Table 3. *Comparison between observed and predicted values*

Objectives	Actual observed values	Prediction provided by u_1	Prediction provided by u_2	Prediction provided by u_3	Prediction provided by max gross margin
Gross margin (million ptas.)	28.1	28.1	32.8	30.8	57.1
Working capital (thousand ptas.)	19,521	22,552	19,521	19,521	42,689
Employment (hours)	16,012	16,012	16,012	16,012	71,682
Management difficulty (index)	1103	1103	1103	1103	1754
Risk (MOTAD)	8882	8882	8882	8882	39,170
Gross margin/working capital (ratio)	1.441	1.250	1.680	1.580	1.338

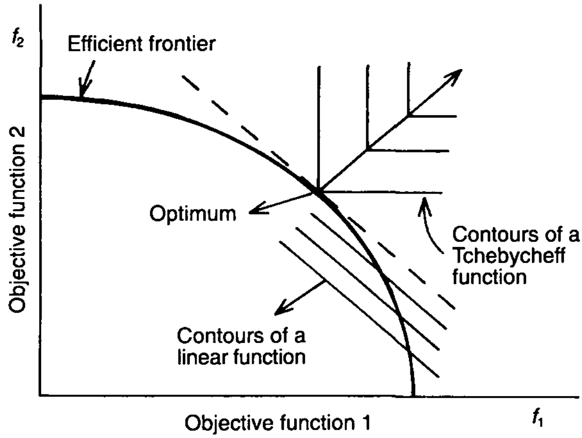

Figure 2. *A Thebycheff and a linear function leading to the same optimum (adapted from Köksalan and Sagala, 1995: 201)*

value of our analytical effort within an *ex-ante* policy analysis perspective.

The last column in Table 3 shows the values achieved by each objective when the traditional objective function that maximises the gross margin is used. It is obvious that there is no resemblance between the observed values for each of the objectives and gross margin maximisation behaviour. In fact, for gross margin criterion the calculated consistency index was more than 160 per cent! This result has important practical implications. Suppose that a mathematical programming model is built to evaluate the effects of different agricultural policies for our homogeneous group of farmers. A conventional choice of the objective function (i.e., gross margin) would lead to erroneous results. However, the choice of utility functions u_1, u_2 or u_3 as objective function would predict realistic behavioural responses to the policy changes for the homogeneous group of farmers analysed.

5. Concluding remarks

From a *methodological* point of view, it is important to point out that, whereas in the MAUT approach it is crucial to test whether the elicited utility function is consistent with the answers provided by the decision maker, within our non-interactive context, an equivalent crucial point is to check whether the elicited utility function is or not compatible with the behaviour of the farmer observed. It is obvious that an 'as if' methodology underlies this approach. This kind of philosophical underpinning is quite licit in economics, especially when the task is to build mathematical programming models for the evaluation of the effects of different agricultural policies.

Within an agricultural planning context, the proposed non-interactive methodology seems more operational than the classic MAUT approach. However, when this kind of comparison is considered, certain doubts can arise. In fact, the implementation of our approach requires the definition of a constraint set representing the farmers' decision-making environment. Indeed, as the first step in the proposed methodology shows, we need to define the constraint set, which is obviously not an easy task. However, a specific constraint set is also necessary with a MAUT approach if we want to use the elicited MAUT function for *ex-ante* policy analysis, since we need to optimise this function over the feasible set.

From an *empirical* point of view, we want to emphasise that the results obtained clearly show how the farmer analysed has a behaviour compatible with a series of objectives which differ considerably from the traditional objective maximising the gross margin of the farm. The latter is the objective function commonly used in most mathematical programming models, which can give rise to misleading results, especially if the model is used for *ex-ante* analysis of agricultural policies.[6]

It should be noted that the methodology focuses on an individual farmer. However, for a homogeneous group of farmers, inferences about the group can be made in the following two cases: (a) the utility functions elicited are able to reproduce with a good degree of accuracy the behaviour of most of the farmers of the group or (b) the individual farmer analysed represents the *average* farmer of the group.

Our analytical effort should not be considered a purely theoretical exercise, as it is precisely in the evaluation of the effects of agricultural policy measures that this research can reach its maximum point of interest. Indeed, one of the basic problems in the accuracy of *ex-ante* policy analysis from research based on mathematical programming models is the correct specification of the objective function. However, to do this, it is necessary first to identify farmers' utility functions that are consistent with the observed reality.

It is important to notice that although we have worked with a variety of utility functions, if none of these had provided consistent results, others should have been tried. In short, the approach proposed can be viewed as a powerful generator of empirically testable behavioural hypotheses. In fact, each of the utility functions used can be considered a behavioural hypothesis. The 'best' empirically corroborated hypothesis will correspond to the utility function whose predictions are closest with respect to the observed values for each objective (i.e., expressions u_1, u_2 and u_3 in our case study).

Finally, we want to point out that this paper does not claim that our method is better than MAUT given that these approaches are to some extent non-comparable. MAUT is based on a philosophy of interaction with the decision maker, while the method proposed here is non-interactive and is based upon observations of the farmers' actual behaviour. In conclusion, if the analyst is capable of establishing an effective interaction process with farmers, then MAUT is the right approach. On the contrary, if this type of interaction is not possible, then MAUT should give way to approaches such as the one proposed in this paper.

Notes

1. Within a welfare economics context, some authors refer to this function as Rawlsian (e.g. Johansson, 1992: 32–39) given the connections between it and the principles of justice introduced by Rawls (1973: 75–80). However, as the translation of Rawls' ideas from ethics to economics is a controversial topic (see e.g. Roemer 1996: Chap. 5), we have decided to denominate these functions as Tchebycheff as is usual in the mathematical and operational research literature.
2. We note that a similar function has been proposed by Steuer and Choo (1983) for interactive multi-criteria analysis and by Wierzbicki (1982) as a basis for the reference point methodologies.
3. From a technical point of view, it is possible to measure the degree of closeness between the predictions provided by functions u_1, u_2 and u_3 and the actual observed values. This task can be undertaken by resorting to any statistical procedure for measuring the similarity between two sets of data. In our case, we calculate a consistency index based upon metric 1 by adding the ratios: 100*|(observed value–predicted value)|/(observed value) for the six objectives considered and then dividing the corresponding sum by six. In this way, the index can be interpreted as the average percentage deviation between the observed and the predicted values. Other consistency indices based on other metrics can also be used. In any case, the degree of accuracy must be specified beforehand. In our application, the consistency index defined above was used with a maximum allowed error of 10 per cent. The predictions provided by u_1, u_2 and u_3 embody errors of 2.9, 3.33 and 1.96 per cent, respectively. The results are robust with respect to the metric chosen. Thus, if metric 2 is used, the same ranking is obtained.
4. Stewart (1995), using a Monte Carlo simulation experiment, found that different multi-attribute utility functions yield similar results when the same set of weights is used. This suggests that the essential element of the procedure here involves the elicitation of preferential weights rather than identifying the most appropriate functional form.
5. In fact, the predictions provided by the estimated utility functions u_1, u_2 and u_3 were compared with the observed values for all the farmers of the homogeneous group. With this purpose, the consistency index defined in note 3 was calculated, obtaining that, in all the cases, the value of the index was lower than 10 per cent. Hence, this supports the applicability of the results to other farmers of the group.
6. Some specialists may be surprised by the assumption that the group of farmers analysed behave 'as if' all had the same objectives. Yet, paradoxically, most of the mathematical programming applications in agriculture reported in the literature assume in one way or in another that all the farmers are gross margin maximisers, which does not seem to produce much surprise among some specialists!

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Carlos Romero
ETS Ingenieros de Montes
Unidad de Economia
Avenida Complutense s/n
28040 Madrid
Spain