Improving the Elicitation Process for Intra-criterion Evaluation in the FITradeoff Method

Paolla Polla Pontes do Espírito Santo[1,2](✉), Eduarda Asfora Frej[1,2], and Adiel Teixeira de Almeida[1,2]

[1] Departamento de Engenharia de Produção, Universidade Federal de Pernambuco, Av. Da Arquitetura-Cidade Universitária, Recife, PE, Brazil
paolla.polla@ufpe.br, {eafrej,almeida}@cdsid.org.br

[2] Center of Decision Systems and Information Development-CDSID, Universidade Federal de Pernambuco, Av. Da Arquitetura-Cidade Universirtária, Recife, PE, Brazil

Abstract. With the advance coming from studies in the area of decision making, different models have emerged to assist in the interpretation of multicriteria decision problems. One of the most recent improvements in the MCDM/A mathematical models deals with the use of partial information about the preferences of the decision makers at the elicitation process. The FITradeoff method is a MAVT (Multi-attribute Value Theory) method that requires only strict preferences and uses partial information in judgments, reducing the amount of information required. Therefore, this study aims to improve the intra-criteria evaluation step of the FITradeoff method, by proposing a new approach for elicitation of marginal value functions based on partial information. The proposed approach is based on the traditional bisection method, but requires preference statements only. The results obtain show that the approach using the bisection method associated with the use of partial information appears to have a good performance, enabling the improvement of the process in terms of reducing the effort and time required.

Keywords: Bisection method · Intra-criteria evaluation · Partial information · FITradeoff method

1 Introduction

Decision making is an essential cognitive process of human beings (Zuheros et al. 2020). With the advance coming from studies in this area, different models have emerged to assist in the interpretation of multicriteria decision problems. Analyzing the widest possible range of alternatives and solving them according to multiple criteria of interest, generally conflicting, with one or more decision-makers.

Thus, there is a variety of elicitation procedures that use different tools to obtain the expectations and necessities of its users. de Almeida, Geiger and Morais (2018) show that one of the most recent improvements in the MCDM/A mathematical models deals

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with the use of partial information about the preferences of the decision makers (DM) at the moment of elicitation.

Regarding the additive multicriteria methods, after the problem has been well structured, the first step to start eliciting preferences is the intra-criterion evaluation (de Almeida et al. 2021). They can be performed in different ways, for example, with the construction of qualitative scales, through indirect evaluations-Bisection Method and Differences Method, or by direct evaluation (Belton and Stewart 2002).

However, in an attempt to simplify the elicitation procedure, several additive MCDM methods reduce this assessment considering only the linear form of the value function for the criteria, obtained based on a normalization process. This simplification introduces modeling errors but reduces elicitation errors (de Almeida et al. 2021). Toubia et al. (2013), highlight that these simplifications can limit the performance of the analyzes realized.

Several decision support methods have been developed to aid the DM in solving multicriteria problems, offering them structured approaches. One of these is the Flexible and Interactive Tradeoff elicitation- FITradeoff (de Almeida et al. 2016; Frej et al. 2019). The FITradeoff is a MAVT method that requires only strict preferences statements and uses partial information in judgments, reducing the amount of information required (Pergher et al. 2020). Consequently, demanding less cognitive effort from the decision maker, leading to fewer inconsistencies during the elicitation process.

Therefore, the present study aims to improve the intra-criteria evaluation step of the FITradeoff method, with a flexible elicitation procedure that uses the bisection method with partial information to construct non-linear value functions.

This article is structured as follows. Section 2 presents the FITradeoff method, commenting on some studies with real applications that used it. Section 3 shows the intra-criterion evaluation in additive models, presenting it in the context of partial information and with the bisection method. Section 4 describes a new approach for intra-criterion evaluation with partial information, followed by a numerical application, in Sect. 5. Finally, Sect. 6 presents the final comments and highlights future research.

2 Flexible and Interactive Tradeoff

The Flexible and Interactive Tradeoff method (de Almeida et al. 2016) is based on the classic tradeoff procedure (Keeney and Raiffa 1976), being a MAVT method with considers that decision makers have compensatory rationality, i.e., they admit that low performance in one criterion can be compensated by high one in another, and presents an additive aggregation model (Pergher et al. 2020). The FITradeoff solves MCDM/A problems with partial information from the DMs (de Almeida et al. 2016). Assuming an MCDM/A problem with m alternatives and n criteria, the MAVT procedure is illustrated in Eq. (1), where a_j is an alternative to the set of m alternatives, k_i is the scale constant of criterion i, and $v_i(x_{ij})$ is the value of consequence of alternative j in criterion i, normalized in an interval 0–1 scale, defined according to a marginal value function. Thus, the best alternative of the set is the one with the highest global value $V(a_j)$ (Roselli and de Almeida 2021).

$$V(a_j) = \sum_{i=1}^{n} k_i v_i(x_{ij}) \tag{1}$$

The main difference in relation to previous studies is related to the elicitation process. de Almeida et al. (2016) present the concept of flexible elicitation, a constructive context of multicriteria value models which allows the consequences between alternatives to be compared, exploring strict preferences statements instead of indifference.

In this way, possibilities are considered such as that of the decision maker not being familiar with certain methods or cannot provide information and visualize more satisfactory and real results when less cognitively demanded. Frej, Ekel and de Almeida (2021) argue that the development of an approach to deal with partial information is a constructive way to apply traditional MCDAs with elicitation techniques that significantly reduce the time and efforts required.

The use of partial information is based on preference relations to find a solution, which in most cases can be achieved by incomplete information declared from the decision maker. And these are used to solve a linear programming problem (LPP) (de Almeida et al. 2016). The problems can be classified as of choice (de Almeida et al. 2016), ranking (Frej et al. 2019) or sorting (Kang et al. 2020).

Frej et al. (2019) explain that the LPP referring to the choice problems aims to use the concept of potential optimality, finding at the ending of the procedure an optimal solution or set of potentially optimal alternatives. The ranking problematic uses the concept of pairwise dominance relations to find a complete or partial (pre)order ranking of alternatives. While for the sorting problems, Kang et al. (2020) present the use of border values that limit the consecutive classes of problems.

The FITradeoff method has been used to solve several multicriteria problems in different areas of expertise. For example, an application for supplier selection (Frej et al. 2017), in the selection of programming rules (Pergher et al. 2020), applications in the textile sector (Rodrigues et al. 2020), real cases in the energy sector (Fossile et al. 2020), system design studies using neuroscience experiments (Roselli et al. 2019a,b) and prioritizing Brazilian Federal Police operations (Cunha et al. 2020).

The method is embedded in a Decision Support System (DSS), which is available at www.cdsid.org.br/fitradeoff. The DSS uses the concept of flexible elicitation. The flexibility in this consists in systematically assessing the possibility of finding a solution to the problem during the elicitation process. The procedure can be interrupted as soon as a solution is found or until the moment when the DM wants to provide information (de Almeida et al. 2016). During the elicitation process, partial results can be viewed using tables and graphs. Displaying the information processed in different ways, helping the decision maker to understand the performance of the alternatives about each evaluated criterion (Roselli et al. 2019a,b).

Regarding the intra-criterion evaluation stage, the FITradeoff method was originally conceived to allow the incorporation of non-linear value functions, since the whole structure of the classical tradeoff procedure is preserved. The current version of the FITradeoff DSS, however, consider the incorporation of non-linearity in the value function throughout a direct specification of the form of the function by the DM, which can be of four different types: linear, exponential, logarithmic, and logistic. When non-linear functions are declared, the decision maker is asked to assign values of parameters. However, these values may not be precisely known, or the DM may not be willing to provide them. Therefore, there is an opportunity to improve the intra-criteria evaluation process of FITradeoff, by allowing the DM to elicit marginal value functions, instead of direct specifying them. However, this elicitation process should be carried out considering partial information, as well as the intercriteria evaluation does, in order to keep the basic premises of the method of saving time and effort from DMs.

Based on this motivation, the study proposes a new approach to improve the intra-criterion evaluation in FITradeoff, based on the well-known bisection method (Belton and Stewart 2002), but considering partial information from the DMs. Hence, the proposed approach works with preference statements obtained from the DM, instead of indifferences points required by the classical bisection method. It is intended that, from the beginning of elicitation, the values and forms of the functions of each criterion more faithful reflecting the relations between the decision maker preferences and the final model of his problem. Furthermore, making use of partial information reduces the amount of direct information required from the DM, consequently reducing the cognitive effort required during the procedure.

3 Intra-criterion Evaluation in Additive Models

The intra-criterion evaluation of additive model for aggregation of criteria consists of establishing the value function of each criterion, including cases where this function is non-linear. The value function methods synthesize the evaluation of the performance of the alternative against individual criteria, together with inter-criterion information, providing an overall evaluation of each alternative indicated of the decision makers' preferences. Once the scale reference points are determined, it should be considered how the other scores will be assessed. It can be done in three ways: (a) definition of a partial value function, (b) construction of a qualitative value scale, or (c) direct evaluation of alternatives (Belton and Stewart 2002).

The first step to defining a value function is identifying a measurable attribute scale that is closely related to the decision maker values. The partial value function reflects the preferences of decision makers at different levels of aspiration on the measurable scale. It can be evaluated directly or through indirect evaluation. Direct assessment usually uses a visual representation. About indirect evaluation, the bisection method is one of the widely used methods (Belton and Stewart 2002).

In the bisection method, the decision maker is asked to define a point on the attribute scale that is halfway in terms of value between the two endpoints, obtaining two linear partial value functions. This process can be repeated several times until the decision maker is indifferent between the partitions (Groothuis-Oudshoorn et al. 2017). Belton and Stewart (2002) also state that usually with five points it is possible to provide enough information to the analyst to find the value functions.

This is generally used in elicitation procedures that enable linearized and non-linear functions and permit the search for behaviors that more accurately reflect the preferences of the decision maker. Thus, using this method to identify the behavior of the partial value function of criteria, in the intra-criteria evaluation stage of multicriteria problems, may prove to be especially suitable.

However, its main disadvantage is the requirement of indifference points when comparing the performances between alternatives, generating inconsistencies during the elicitation process, because it requires major cognitive effort on the decision maker when requiring complete information (de Almeida et al. 2016; Roselli et al. 2019a,b). Thus, the development of an intra-criteria elicitation procedure that reconciles the application of the bisection method to the use of partial information can be relevant, as it would allow the decision maker to declare their aspirations and behaviors from the intra-criterion evaluation stage.

3.1 Partial Information in the Intra-criterion Evaluation Stage

In the intra-criteria evaluation, some methods consider a simplified approach when assuming linear value functions, as in the SMARTS and SMARTER methods (Edwards and Barron 1994). Another group of methods builds the value function based on pairwise comparisons between preference statements, such as the analytical hierarchy process AHP and MACBETH (Vasconcelos and Mota 2019). Outranking problems or multiobjective mathematical programming, seek to identify upper, lower, and/or veto thresholds that reflect the interests of a decision maker, for these attribute values.

In the literature, it is possible to identify the increasing use of partial information, due to the use of strict preference statements during an interactive process between the decision maker and analyst. Making the procedure less stressful and less susceptible to inconsistencies. The use of partial information in the inter-criterion evaluation stage is widespread in the literature when determining the ordering of a problem's criteria and their respective values. When contextualized in the intra-criterion evaluation stage, it is noted that studies have been exploring this potential better.

Jaszkiewicz and Slowinski (1997) presented an interactive procedure, the LBS-Discrete, for the analysis of a multicriteria agricultural problem. The procedure is an extension of multiobjective linear programming (PLMO) Light Beam Search, being non-linear for the discrete case. To ensure an easily assessment for the decision maker, the authors considered preference statements at the steps intra and inter-criterion information for the set of points analyzed in the sample, updating the space of solution for each question asked. In the rounds, the decision maker determined the upper and lower bounds of the permissible solution space. The procedure could be interrupted if the DM wished.

Eum et al. (2001) provided an extended outranking model to establish the potential optimization of alternatives in the analysis of the multicriteria decision. Assuming that in problems with partial information, not only are the weights of attributes are imprecise known, but also their marginal values. In this way, the resulting model became a non-linear programming problem being transformed to an equivalent LPP. To demonstrate the method, the authors solved problems found in the literature.

Lahdelma et al. (2003) describe the SMAA-O method. Designed for problems where weights are not precisely known and criteria information is partially or integrally ordinal, making the DM to list alternatives in terms of ratings for some or all criteria. To modeling the value function of these criteria, numerical mappings were created that generated stochastic cardinal values corresponding to the ordinal values. In the end, a problem of the selection of a solid waste management system was applied.

Narula et al. (2004) developed an interactive learning-oriented method for solving MCDA problems with many alternatives and few criteria. Where it is possible for the DM to successively evaluate small sets of alternatives, systematically, specifying only the information that wishes or changes considered acceptable for the values and direction of the criteria involved. With the aid of software, at each iteration the decision maker compared neighboring groups of alternatives, ordering them, solving a scalarization of the problem.

Thus, it is considered relevant that the context of partial information is also explored in the stage of intra-criteria assessment of MAVT problems, making the elicitation stage more realistically for the preferences of the decision makers. By demanding them less cognitively, so exploring gradually the space of action of their problems, becoming a learning process.

3.2 Bisection Method in Interactive Procedures

In recent decades, research has shown the desire to understand in a more real way how decision makers behave in the face of not fully understanding aspects of their multicriteria problems, making use of partial information and flexible elicitation procedures, in different decision methods and methodologies.

Approaches based on problems with dynamic systems and Utility Theory have also been exploring solutions that consider issues that are normally dealt with a deterministic vision in a more realistic way. Some of the resources explored to structure these problems include the use of analytical and/or statistical tools, the bisection method - traditional or improved - and inferences without parametric equations.

Toubia et al. (2013) propose a dynamic methodology to relate time and risk parameters in decision making. The use of pre-computed tables of possible preference questions to a decision maker is implemented, as the latter provides answers. Designing such choices to optimize the information provided, while taking advantage of the distribution of parameters, capturing the deviations between responses.

Chapman et al. (2018) present the DOSE-Dynamically Optimized Sequential Experiment- estimating the preference parameters accurately and quickly when selecting a personalized sequence of simple questions for each participant. The method used a parametric structure and Bayesian computation, to dynamically select a sequence from a set of statements. The process is interactive, updating the problem's constraints space until a predetermined number of questions or when the parameters are found.

Recently, Bertani et al. (2020) identified values and behavior of the weighting function, parameterizing it through a family of linear splines that can return smooth nonlinear shapes. Thus, the permissible limits were obtained as the solution to problems of restricted linear optimization. The judgments of decision makers were captured using the bisection method with partial information, to identify the space of actions of the problem. Some questions of preference were defined a priori.

Oliveira and Dias (2020) found consumer preferences for alternative fuel vehicles through a MAUT-based approach. The authors use the bisection method to obtain utility and tradeoff functions for calculating the scale constants of the attributes. Belton and Stewart (2002) considered that one of the possible areas of research in the MCDA area would be the identification of general weaknesses in decision support models. Groothuis-Oudshoorn et al. (2017) point out that a structural source of problems, in the performance evaluation stage, in the form of the value function, as it is normally assumed to be linear.

4 A New Approach for Intra-criterion Evaluation with Partial Information

Since the value function should represent the preferences of a decision maker measurably, in terms of aspiration, the bisection method is applied to determine points on the scale considered, outlining the partial value functions. And finally, to identify the behavior described by a criterion when it is elicited.

The proposed approach follows a dynamic similar to that found in the literature for the traditional bisection method (Belton and Stewart 2002; Groothuis-Oudshoorn et al. 2017; Bertani et al. 2020), however considering partial information from the DM. Two reference values are compared and the decision maker is asked why there is a greater predilection. However, instead of a point of indifference, want to find ranges of values through strict preference statements.

So, initially, the question has the basic structure: "What do you prefer, increase the value of the consequence in the Ci criterion from A to X or from X to B?". For minimization criteria, the term increase is replaced by decrease/minimize. Concerning the reference value X, it is updated to reduce the interval between the lower and upper bounds obtained with each answer given. For illustrative purposes, updates based on the answers given by the decision maker are made using the following logic:

> *Question 1: "What do you prefer, increase the value of the consequence in the Ci criterion from A to $X_n$or from $X_n$to B? DM: I prefer to increase from A to X_n". Range1 → A to X_n.*
>
> *Question 2: "What do you prefer, increase the value of the consequence in the Ci criterion from A to $X_{n/2}$or from $X_{n/2}$to B? DM: I prefer to increase from $X_{n/2}$to B". Range 2 → $X_{n/2}$to X_n.*

In this case, there was an update of the lower bound, because when answering, the decision maker migrated his preference interval to the upper segment of reference X. Similarly, the upper bound is updated when the chosen interval returns to the lower segment of the reference. And so, successively, until the stopping criterion is met or the decision maker does not wish to proceed. This procedure is performed until the last point is inferred.

About the number of points, the literature usually considers that five points provide sufficient information for the shape of a value function to be identified (Belton and Stewart 2002). In this proposal for the bisection method with partial information, the first and last points of the scale (0–1) will be determined at the local scale. Thus, the worst and best values of the consequences reported in the problem will be adopted as X = 0 and X = 1, depending on the direction of the criterion (minimization or maximization). Remaining the elicitation of points X = 0.25, X = 0.5 and X = 0.75.

4.1 Intra-criterion Elicitation Procedure

After declaring the values of the consequence matrix, the DM provides information for three rounds j, each with two stages, to identifying three points, in addition to the local extremes of the scale. However, the elicitation not be conducted to determine indifference statements, but an admissible range of values for the DM, decreasing his cognitive effort by request only strict preference statements.

The stopping criterion to change between the rounds can occur in two ways: i) assuming a percentage margin (P) of 5%, 10%, 15%, or 20% over the range R, between the maximum and minimum limits of the consequence values for a criterion Ci. The decision maker should define it before starting the elicitation; or ii) Anytime the decision maker wants to stop answering the intra-criteria elicitation questions, as the procedure supports partial information and is flexible. In this way, the margin admitted for variation is defined as a stopping criterion in Step1 of all rounds of the intra-criterion elicitation procedure. Initially, the interval analyzed for asking the questions will vary from A to B.

For each answer given, the lower and upper limits of the interval are checked and updated, when possible, i.e., each question is generated to decrease the numerical value between the lower limit and the upper limit of the range generated with the bisection method using partial information. Until a value equal to or less than the stopping criterion is reached. If the DM has not interrupted the process and the value is to be true, Step 2 of the procedure begins.

This step consists of presenting a graph with three shapes that describe possible behaviors of the criterion under analysis so that the decision maker chooses the one that he/she judges closest to your preferences. The series of round 1, for the point $X_{0.5}$, are built with as illustrated in Fig. 1.

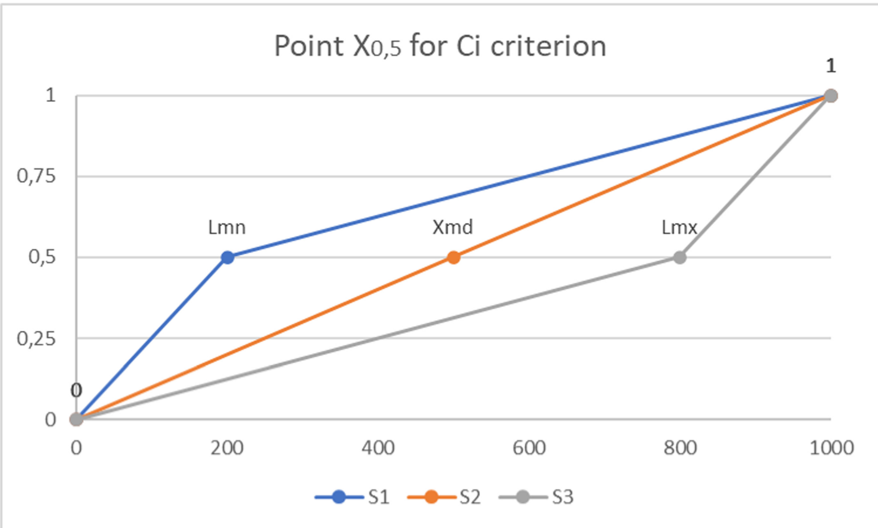

Fig. 1. Graph example with series of point $X_{0.5}$

Where the value 0 is the lower bound of the local scale of consequences. It is the worst consequence value declared in the matrix; the value 1 is the upper bound of the local scale of consequences. It is the best consequence value declared in the matrix. And, obtained in Step 1 of the round, LMn: Minimum range limit, LMx: Maximum range limit, and Xmd: Midpoint of the range.

Once the series is selected, the point $X_{0,5}$ will assume the value of LMn or LMx or Xmd, depending on the choice made, starting round 2. In this step, the elicitation process of Step 1 occurs similarly to that described for round 1, however, questions are asked to identify an intermediate value in the section below the midpoint ($X_{0.5}$) of the value function scale. Identifying the reference of $X_{0.25}$. That, the analyzed interval to ask the questions will vary from A to $X_{0.5}$.

For each answer given, the lower and upper limits are checked and updated, when possible. Until a value equal to or less than the stopping criterion is reached or the decision maker interrupts the process. Thus, Stage 2 of round 2 is initiated and again a graph is presented so that the DM chooses the best. The series for round 2 is built with the following references:

Shape1 (S1): X_0, Lmn, $X_{0,5}$, X_1
Shape2 (S2): X_0, Xmd, $X_{0,5}$, X_1
Shape3 (S3): X_0, Lmx, $X_{0,5}$, X_1

Where $X_{0,5}$ is the value chosen in round 1, being the midpoint in terms of local scale. The other parameters remain with the same interpretation. Once the series is selected, point $X_{0,25}$ will assume the value of LMn or LMx or Xmd, depending on the choice made, starting round 3. Finally, the last point of Step 1 in the process is elicited, but now the questions are made to identify asn intermediate value in the section above the midpoint ($X_{0.5}$) of the value function scale, determining $X_{0.75}$. That is, the interval analyzed to ask the questions will vary from $X_{0.5}$ to B. Thus, the smallest range between the values is identified, the last graph is displayed. The series for round 3 is built with the following references:

Shape1 (S1): X_0, $X_{0.25}$, $X_{0,5}$, Lmn, X_1
Shape2 (S2): X_0, $X_{0.25}$, $X_{0,5}$, Xmd, X_1
Shape3 (S3): X_0, $X_{0.25}$, $X_{0,5}$, Lmx, X_1

Thus, obtaining the final behavior of the value function for the Ci criterion (Fig. 2).

Figure 3 shows the flowchart of the intra-criterion elicitation process, highlighting the procedure's execution logic. Where the blue squares represent the input of the information by the decision maker and the black squares the systematics performed in the procedure. Stages 1 and 2 are highlighted, allowing the visualization of the steps for each one.

Where CriCont is the number of criteria, i is the counter to increment the number of criteria, P is the percentage value chosen by the decision maker, DA is the value calculated to be the stopping criterion, Q is the counter to increase the number of questions, n is the number of rounds, R is the range between high and low bounds. And J is the counter to increase the number of rounds, where, X1 equivalent to $X_{0.5}$; X2 to $X_{0.25}$, and X3 corresponds to the $X_{0.75}$.

After the decision maker inputs the matrix of consequences for the problem, Stage 1 of the intra-criterion elicitation procedure is started. Initially, the DM will define the

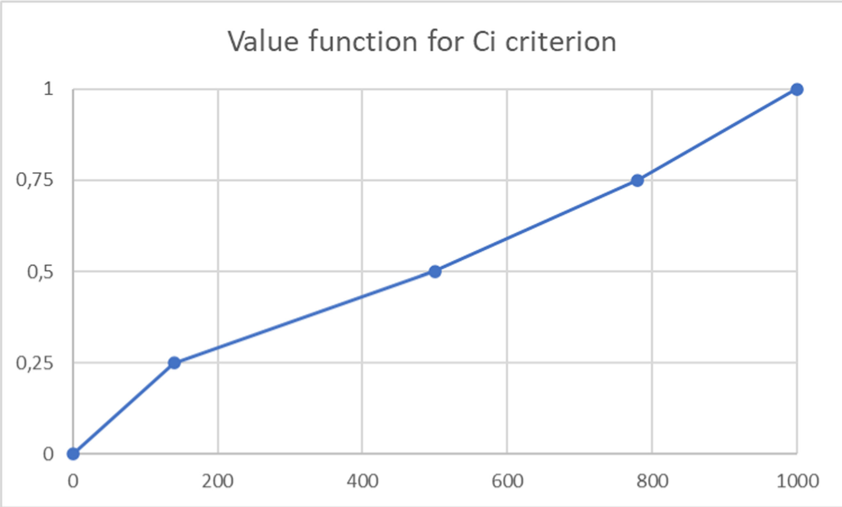

Fig. 2. Final graph example with Ci criterion behavior.

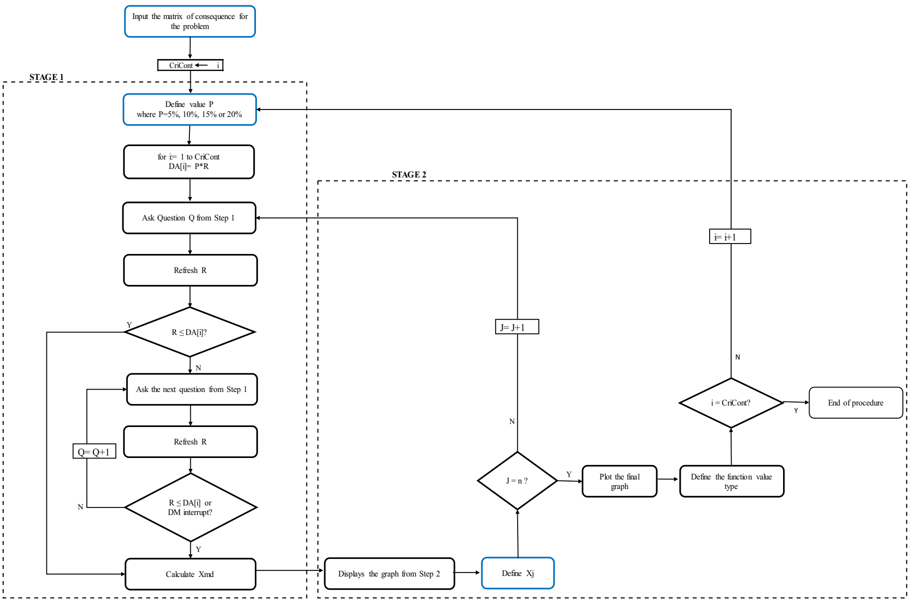

Fig. 3. Flowchart of procedure for intra-criterion evaluation.

percentage value used for the problem stopping criterion. Afterward, from i to the total number of criteria considered, the DA value is calculated and the first question is asked to the decision maker, obtaining the first range R of the space of actions. Thus, the stopping criterion is verified, if false, a new question is performed so that the interval is updated again. This step is repeated until the stopping criterion is met or the DM decides to stop the elicitation of that point.

In possession of the minimum and maximum bounds of the range obtained, for the first round, the average value of the interval (Xmd) is calculated, starting Stage 2 of the approach. Where a graph is displayed to the decision maker so that he/she can choose which of the three curves is preferred (Lmn, Xmd, or Lmx), defining the value of the first point xj, of the three that should be selected. If the round performed is not the last, it is incremented, restarting the elicitation, until the last inferred point is reached ($X_{0.75}$).

When the five points are known, a new graph is displayed to the decision maker, now with the final shape of the value function elicited for criterion Ci. The process is repeated until the last elicited criterion is reached, and thus, all functions have value been identified. Ending the procedure.

5 Numerical Example

In order to illustrate the applicability of the proposed approach, let us consider a multicriteria problem when deciding on renting an apartment. The process of eliciting the continuous maximization criterion Valuation/year is illustrated. Three rounds of questions were realized to identify three intermediate points, in addition to the limits known, to determine the shape of the marginal value function. The values of the consequences for the six alternatives (Table 1), as well a detailed description of the procedure is presented. A local scale is considered.

Table 1. Consequence values for the criteria 'Valuation /Year'.

Alternative	Apto1	Apto2	Apto3	Apto4	Apto5	Apto6
Valuation/year ($)	1000	2000	1500	2500	500	3500

Initially, the possible percentage variations P of 5%, 10%, 15%, and 20% for the range R of the criterion were presented to the decision maker, asking which one considered acceptable so that the value of the stop criterion used was calculated during the elicitation for the Valuation/year criterion. When observing the possible values, the DM declared to vary his elicitation margin by 10%, i.e., that the result would vary at most by $300 (Table 2). Upon reaching it, the DA stop criterion was considered to be true.

In the first round, questions were asked to identify the midpoint of the value function, represented as $X_{0.5}$. The minimum bound is $500 and the maximum is $3500. Once the procedure was initiated, the first question asked in Stage 1 was "*What do you prefer, increase the value from $500 to $2000 or from $2000 to $3500?*" The decision maker declared that he preferred the increase from $500 to $2000. Determining the first range (I1) from $500 to $2000.

Table 2. Calculation of the DA value

P Value (%)	DA Value ($)
10	(3500–500) * 0,1 = 300

Then was asked, "*What do you prefer, increase the value from $500 to $1500 or from $1500 to $3500?*" The decision maker answer that he preferred the increase from $1500 to $3500. Thus, as the response migrated the interval to the upper section of the midpoint of the range, the lower bound of I1 was updated. And the new range I2 being $1500 to $2000.

The third question asked was "*What do you prefer, increase the value from $500 to $1600 or from $1600 to $3500?*". The DM declared that he preferred the increase from $1600 to $3500. Thus, again the lower limit of the admissible space has been updated and the new range I3 ranging from $1600 to $2000, respectively, the lower and upper bounds.

In the fourth question, it was asked *"What do you prefer, increase the value from $500 to $1900 or from $1900 to $3500?"* The decision maker replied that he preferred the increase from $500 to $1900. Thus, the interval returned to the lower section of the midpoint of the range, updating the upper bound. And the range I4 staying $1600 to $1900. At the fourth question, it was verified that the DA value for interval I4 was true. Finishing Step 1 of the elicitation for point $X_{0.5}$, calculating the Xmd value.

In this way, the stage 2 of round 1 was started, where the graph with the plot of the three points known in I4 (Lmn, Lmx, Xmd) was displayed to the decision maker (Fig. 4) so that he could choose the best shape, setting the value to $X_{0.5}$.

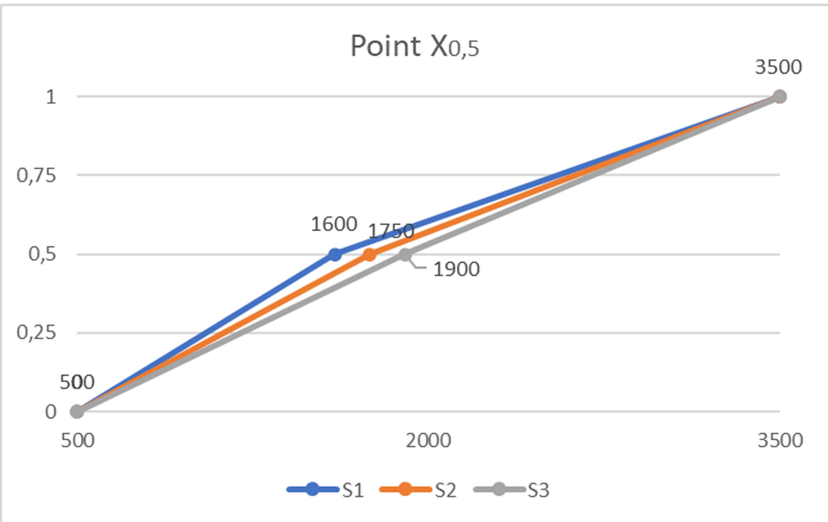

Fig. 4. Graph with series of point $X_{0.5}$

Observing the graph, the DM opted for the behavior expressed with the value of \$1900 to $X_{0.5}$. Justifying being the one with the lowest convexity. Then, round 2 of the procedure was initiated, determining the point $X_{0.25}$.

For the second round, in Step 1, questions were asked to identify the intermediate value in the section below the midpoint $X_{0.5}$. The range considered for asking the questions ranged from \$500 to \$1900, respectively, the lower and upper bounds observed. Where \$1900 was taken from the I4 range, round 1.

The first question asked was "*What do you prefer, increase the value from \$500 to \$1200 or from \$1200 to \$1900?*" The decision maker answer that he preferred the increase from \$500 to \$1200. Thus, the interval I1 was defined between \$500 and \$1200, respectively, with the lower and upper limits of the first interval. Then was asked, "*What do you prefer, increase the value from \$500 to \$1100 or from \$1100 to \$1900?*" The DM declared that he preferred the \$500 to \$1100 increase. In this way, the upper limit of the R range has been updated and the value obtained for the new range I2 from \$500 to \$1100.

Finally, the last question was "*What do you prefer, increase the value from \$500 to \$1000 or from \$1000 to \$1900?*" The decision maker stated that he preferred the increase from \$1000 to \$1900. Thus, the answer was moved to the upper section of the reference and the lower bound considered was updated. In the end, the range I3 was \$1000 to \$1100.

In this round, with one less question in relation to round 1, it was verified that the DA value for the interval I3 was reached, being below the stopping criterion definite. At the end of Step 1 of the elicitation for point $x_{0.25}$, the value of Xmd was calculated. Thus, stage 2 of round 2 was initiated, where the graph with the plot of the three points known in I3 (Lmn, Lmx, Xmd) was displayed to the DM (Fig. 5).

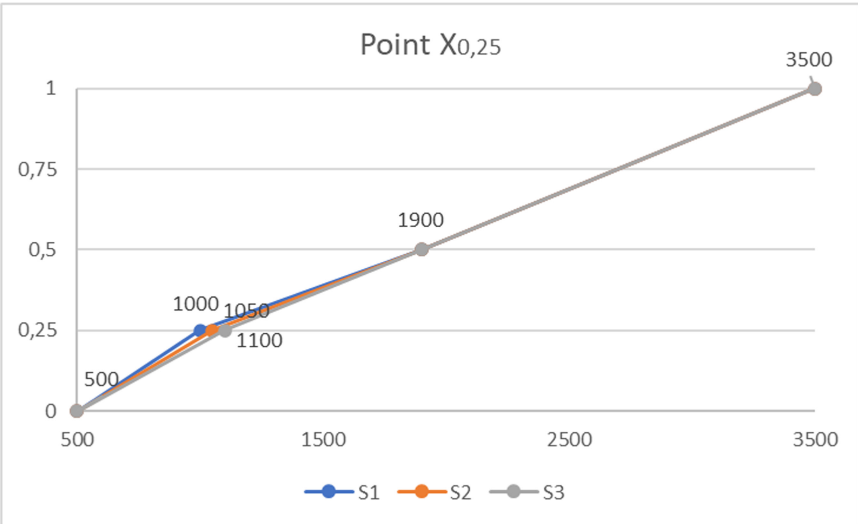

Fig. 5. Graph with series of point $X_{0.25}$

As noted, the elicitation of this point reached a very small variation between the limits of the interval. And when analyzing the graph, the decision maker opted for the behavior expressed with the value of \$1100 to $X_{0.25}$. Again, choosing the curve with the smallest convexity. Then, the last round is described, identifying the point $x_{0.75}$.

Finally, in the third round, questions were asked to identify an intermediate value in the section above the midpoint of the value function scale. Thus, the interval considered for performing the questions in Step 1 ranged from \$1900 to \$3500, the upper and lower bounds, respectively.

Initially, the decision maker was asked, *"What do you prefer, increase the value from \$1900 to \$2700 or from \$2700 to \$3500?"* The DM declared that he preferred the increase from \$1900 to \$2700, respectively, the lower and upper bounds of the first range I1. The second and final question was "*What do you prefer, increase the value from \$1900 to \$2600 or from \$2600 to \$3500?"* The decision maker said preferred the increase from \$2600 to \$3500. Thus, with the answer given, the interval changed to the lower section of the reference, updating the lower limit of the space considered. In the end, the range I2 for point $x_{0.75}$ was between \$2600 and \$2700.

With two questions, the DA value was reached in round 3, presenting a range of only \$100.00, i.e., 2/3 below the value determined by the decision maker. In this way, Step 1 of elicitation for point $X_{0.75}$ was completed and the Xmd was calculated. Starting stage 2 of round 3, where the graph with the plot of the three points known in I2 (Lmn, Lmx, Xmd) was displayed to the decision maker (Fig. 6).

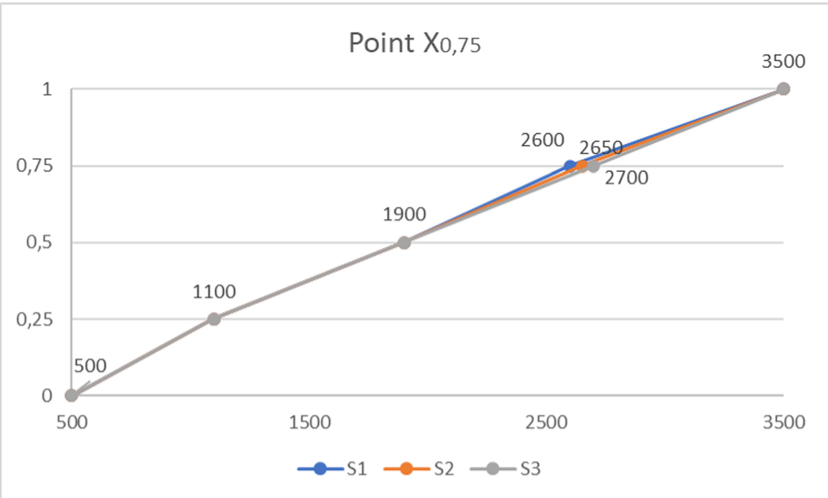

Fig. 6. Graph with series of point $X_{0,75}$.

As in the previous round, the elicitation allowed a small gap between the limits of I2. This being one of the reasons why the decision maker chose the behavior of the curve with the value of $X_{0.75} = \$2.650$, the midpoint. After all rounds and stages were completed, the final graph (Fig. 7) in the form of the value function for the maximization criterion

'Valuation/year' was displayed to the decision maker, presenting that the function can correspond to a logarithmic behavior. Ending the intra-criterion elicitation.

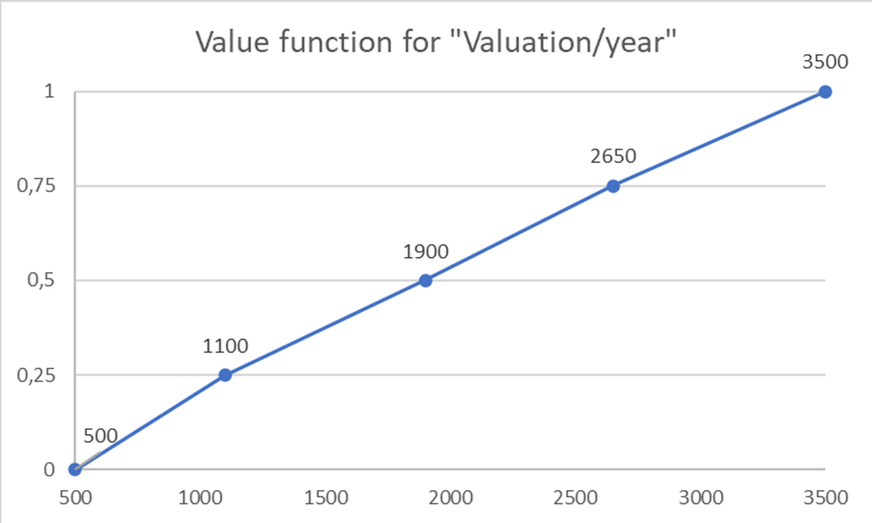

Fig. 7. Final graph with 'Valuation/year' criterion behavior.

5.1 Discussion

To compare performances, the same criterion was evaluated by the same decision maker, however using the traditional bisection method. That is, each question asked had the ultimate goal of making the decision maker declare a point of indifference between the compared values. Table 3 shows a comparison between the number of responses given with the "proposed approach" *versus* "bisection method", for each of the three intermediate points elicited.

Table 3. Comparison between traditional and adapted approaches

Approaches					
Proposed approach			Traditional bisection method		
Point	Number of questions	Final value	Point	Number of questions	Final value
$X_{0.25}$	3	$1100	$X_{0.25}$	7	$1095
$X_{0.5}$	4	$1900	$X_{0.5}$	8	$1825
$X_{0.75}$	2	$2650	$X_{0.75}$	5	$2675

Initial impressions reveal that, as expected, realize the intra-criterion elicitation using the traditional bisection method meant that the decision maker needed to answer a major number of questions compared to the approach proposed. Observing at point $X_{0.5}$, for example, it is possible to see that twice as many answers were necessary to obtain the final value. And when comparing the final values in both approaches, the bisection method with partial information differed by only $75 from that found in the traditional method.

For $X_{0.25}$ and $X_{0.75}$ references, the increase in the questions asked was greater than fifty percent. This clearly demanded more time to perform the procedure, as well as demands more cognitive effort on the part of the DM. Figure 8, presents the graph with the final behavior obtained with the traditional bisection method, where additional considerations can be explored.

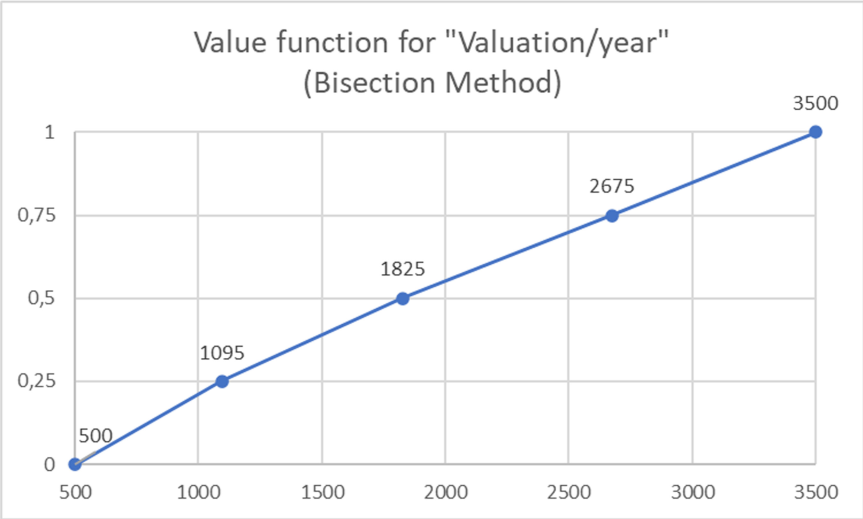

Fig. 8. Final graph using a traditional approach.

Analyzing Fig. 8, it is possible to verify that the final form identified through the elicitation process is visually similar to the behavior illustrated in Fig. 7. Including the final values found for each of the three points elicited. In $X_{0.25}$, for example, a difference of only $5 was identified.

Thus, establishing a parallel between the DA value declared by the decision maker in the elicitation using partial information, the difference between the $1100 found in the approach proposed and the $1095 obtained with the bisection method can be considered acceptable and consistent with the information provided by the decision maker.

Consequently, it was possible to verify that the bisection method with the use of partial information, proposed in the study, had a good performance, in a flexible process of elicitation. That presents advantages in terms of the effort and the time required and the structuring of the elicitation procedure.

6 Final Remarks

Initially, in opposition to models found in the literature, this study uses the performance values of the criteria of a multicriteria problem, to determine the space of admissible consequences. Defining a local measurement scale. Thus, the model is applied according to the circumstances, dynamically and seeking in fewer steps that the decision maker can express his preferences, using strict preference statements in a flexible procedure.

Once the intra-criteria evaluation in additive models consists in establishing the value function of each criterion, the proposal presented can be implemented in other methods that belong to this MCDM/A category. However, the axiomatic structure of these must support linearized and nonlinear functions, ensuring that the elicited behavior reflects the decision-maker preference.

Another aspect is related to the ability to design a procedure that makes use of partial information. Since is the great differential of the improved proposal. Thus, the development of intra-criteria elicitation procedures that reconciles the application of the bisection method to the use of partial information may be relevant.

For the fact the FITradeoff method has the axiomatic structure of the traditional tradeoff procedure, the method itself admits non-linear marginal value functions. Thus, the proposed approach improves the intra-criteria evaluation process, in the sense that specifying non-linear value functions directly (form and parameters) are no longer necessary. Instead, strict preference questions based on the structure of the bisection method are made to elicit those functions.

Additionally, as the method is embedded in a Decision Support System- FITradeoff DSS, the proposed procedure will be implemented computationally. Where the stage of model programming is being developed, along with validation tests.

Regarding the results obtained, it was possible to observe the efficiency of the approach adopted to the bisection method, which in relation to the traditional method, proved to be more agile, and less demanding in terms of cognitive effort.

For future research, other applications can be made considering improvements in the procedure, making the elicitation of discrete criteria also be included in the proposed approach. And for problems with a large number of evaluation criteria, it is interesting to investigate ways to reduce the number of criteria in the intra-criterion evaluation stage.

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