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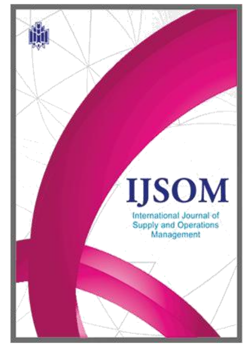

EDAS-Sort-B: An Extension of the EDAS Method for Sorting Problems through Boundary Profiles

Maroua Ghram [a*] and Hela Moalla Frikha [a]

[a] *Laboratory "Optimisation, Logistique et Informatique Décisionnelle" (OLID), University of Sfax, Tunisia*

Abstract

Multiple Criteria Decision Analysis (MCDA) sorting models are highly relevant for solving real-world problems. Thus, in the literature, the great majority of MCDM methods tackled the choice or ranking problems unlike the sorting approaches although assigning alternatives to predefined homogeneous categories (classes) presents a complex problem. Thus, in this paper, we tackled the sorting problematic using the EDAS "Evaluation based on Distance from Average Solution" method. It is used for ranking alternatives, in a decreasing order, according to their Appraisal Scores (AS). Nevertheless, the current version of EDAS method cannot deal with sorting problems. Since a great majority of real-world decision-making problems are modeled as sorting ones, we proposed a new sorting MCDM method called EDAS-Sort to cope with decision problems requiring assigning alternatives to predefined and ordered classes. Given that we dealt with classes defined by their boundary profiles, the proposed method is called EDAS-Sort-B. To demonstrate and underline it, we presented a case study on a bank agency located in Sfax, Tunisia which aims to assign clients requesting loans to three predefined and ordered categories: very solvent, solvent, and doubtful according to various criteria. Therefore, the head of the bank agency (decision maker) will gain insight on the client's profile and whether he is trustful or not to repay the loan. Thus, the EDAS-Sort-B is effective for solving problems requiring assigning alternatives to predefined and ordered categories. Thereupon, the main advantage of EDAS-Sort-B is to help the DM "Decision Maker" to take a real-time decision related to alternatives' assignment.

Keywords: Multiple Criteria Decision Making; Sorting; EDAS; Boundary Profiles; Assignment.

Introduction

The MCDM process attend to support DMs in making effective and consistent decisions. In fact, in MCDM field, we distinguish between these problematics: ranking, sorting, choice, and description (Roy, 1981). Actually, the ranking and choice problematics are the most addressed ones by researchers. On the other hand, the sorting problematic deals with situations requiring assigning actions to predefined classes based on their performance on a set of criteria. The sorting problematic is also called a classification or an assignment procedure or the problematic β. In fact, there are two types of sorting: ordinal MCDM classification problem (ordered classes) and nominal MCDM classification problem (non-ordered classes) (Belacel, 2000). Howbeit, the multi-criteria sorting problematic considers the first type i.e. classes are already defined and ordered, by the DM, from the most to the least preferred. In fact, the sorting

*Corresponding author email address: maroua.ghram@gmail.com
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problematic consists in assigning alternatives to one class (category) denoted by C_j regard a set of criteria. For each category C_j, the DM assigns a reference profile, which can be either a boundary (limiting) or central profile. The class C_j is delimited by its lower and upper boundary profiles l_j and l_{j+1} respectively. Actually, the upper boundary profile of category C_j presents the lower limit profile of the next category C_{j+1} (Alvarez et al., 2021). As a matter of fact, the application of MCDM sorting methods encompasses the areas including: financial management, risk assessment, project evaluation, facility location, inventory management, materials management, maintenance management, environmental assessment, theoretical foundations and transportation, health, education, human resources, supplier selection.

Howbeit, in the literature, very few methods were developed to deal with sorting problematic. Therefore, we developed EDAS-Sort-B to assign actions into predefined and ordered categories from the most preferred to the least preferred. Actually, the proposed method can be applied to several fields. The principal of the EDAS-Sort-B method is based on comparing the appraisal scores (AS) of the actions with the AS of the limiting (boundary) profiles since the categories are specified independently of the considered alternatives. The main advantage of EDAS-Sort-B method compared to the existing ones is that it is easy to use by stakeholders since it requires from the DM to determine only the decision matrix (including the limiting profiles) and the classes. Thus, the purpose of the EDAS-Sort-B method is to organize a given set of alternatives (example: clients) to homogenous groups to facilitate the decision making process for stakeholders since each class has its own specific characteristics.

The manuscript is divided into five sections. In section 1, we will exhibit a literature review on MCDM sorting methods. We will present, in section 2, the EDAS method. In section 3, we will tackle the steps of the EDAS-Sort-B method. In section 4, we will emphasize an empirical example to discuss the feasibility of EDAS-Sort-B. In section 5, we will conclude and we will highlight our perspectives.

Literature Review

Classification methods are of a great importance to support decision making process in several fields. Solving sorting or classification problems is indeed relevant for analyzing groups including the most preferred actions and those including the least preferred actions. In the literature, ranking and outranking methods turned out to sorting ones by exploiting their ranking or outranking relations to cope with cases requiring assigning alternatives to classes defined either by their boundary or central profiles. In this context, the PROMETHEE “Preference Ranking Organization Method for Enrichment Evaluation” (Brans and Vincke, 1985) was extended to sorting methods : PROMSORT method (Araz and Ozkarahan 2005; 2007), FlowSort method (Nemery and Lamboray, 2008) and PROMETHEE TRI (Figueira et al., 2005). Additionally, the PROMETHEE II (Brans and Vincke, 1985) method was extended to P2CLUST to tackle the problem of ordered multicriteria clustering by combining the k-means algorithm with the FLOWSORT method (De Smet, 2013). In like manner, ELECTRE III method (Roy, 1978) was extended to ELECTRE TRI (Yu, 1992; Mousseau et al., 2000) and ELECTRESORT (Ishizaka and Nemery, 2014) to assign actions to categories (Mousseau et al., 2000). In ELECTRE TRI methods, we distinguish between ELECTRE Tri C (Almeida-Dias et al., 2010), defined by central profiles to handle decision aiding sorting problems, and ELECTRE Tri B (Roy and Bouyssou, 1993) which is based on limiting profiles. On the other hand, Bouyssou and Marchant (2015) extended the ELECTRE TRI-B method. In fact, the ELECTRE Tri-nC (Almeida-Dias et al., 2012) is an extension of ELECTRE Tri C. On the other hand, Ishizaka et al. (2012) proposed AHPSort method to deal with sorting problematic. By the same token, Sabokbar et al. (2016) proposed TOPSIS Sort to assign actions into categories. Fernandez and Navarro (2011) proposed the THESEUS method to evaluate action’s assignment. The THESEUS method handles the preference information contained in the presence of large reference sets. Moreover, Doumpos et al. (2015) developed the PAIRCLAS method. Demir et al. (2018) extended VIKOR method (Opricovic and Tzeng 2004) to VIKORSORT for Multiple Criteria Ordinal Classification problems. Additionally, Belacel (2000) developed a fuzzy multicriteria classification method called PROAFTN for clinical application, precisely, for medical diagnostics. Dias and Mousseau (2003) developed a DSS “Decision Support System” designed to sort actions into an ordered and priori defined set of categories called IRIS “Interactive Robustness analysis and parameters’ Inference for multicriteria Sorting problems” based on ELECTRE TRI. On the other side, Karasakal and Aker (2017) proposed a sorting approach based on DEA “Data Envelopment Analysis” (Charnes et al., 1978) for the evaluation of R&D “Research and Development” projects. Devaud et al. (1980) extended UTA “UTilités Additives” method (Jacquet-Lagreze and Siskos 1982) to UTADIS “UTilités Additives DIScriminantes” for multicriteria sorting problematic. Moreover, Ouhibi and Frikha (2019) extended the Combinative Distance-based ASsement (CODAS) method (Keshavarz Ghorabaee et al., 2016) to

CODAS Sort to assign actions into one of the predefined and ordered classes bounded by reference actions (low and upper limit profiles). Furthermore, Liu et al. (2019) extended the Best Worst Method (BWM) (Rezaei 2015) to BWMSort II, in a context of a fuzzy environment dealing with Interval Type-2 fuzzy sets to overcome unclear class assignments, all in reducing pairwise comparisons between the representative points and boundary profiles. The most recent sorting papers tackled: Bipolar sorting (Trzaskalik, 2021), ELECTRE TRI-nC (Madhooshiarzanagh and Abi-Zeid, 2021), Probabilistic Linguistic Term Set (PLTS) sorting method (Peng and Wang, 2020), Hierarchical Stochastic Multicriteria Acceptability Analysis (SMAA) Fuzzy–FlowSort (FFS) (SMAA–FFS–H) (Pelissari et al., 2020), Contingent Sort (CORT) (Kadzinski et al., 2020), Flexible and Interactive Tradeoff Elicitation sorting (Kang et al., 2020), Preference learning framework for multiple criteria sorting problems (Liu et al., 2020), Non-Additive Robust Ordinal Regression for Hierarchical Criteria (NAROR-HC) (Arcidiacono et al., 2020), Sorting with partial monotonicity constraints (Kadzinski et al., 2020a), non-monotonic sort (Guo et al., 2019), AHP-Fuzzy Sorting (Ishizaka et al., 2019). In addition, de Lima Silva and de Almeida Filho (2020) developed TOPSIS-Sort-B, established from boundary profiles, and TOPSIS-Sort-C, established from centroides. On the other hand, Mouhib and Frini (2021) proposed the TSMAATri method for assigning actions to predefined class. It is a generalization of SMAA-Tri (Tervonen et al., 2009) to a temporal context where alternative evaluations are stochastic based on Monte Carlo simulations for generating stochastic evaluation values.

The EDAS Method

The EDAS (Keshavarz Ghorabaee et al. 2015), is a ranking multicriteria method for evaluating alternatives on the basis of higher values of PDA “Positive Distance from Average” and lower values of NDA “Negative Distance from Average” to rank them in a decreasing order of the AS “Appraisal Score” following these steps:

Step 1

Constructing the performance matrix for “m” alternatives and “n” criteria.

Step 2

Determining the AV “AVerage solution” regarding all criteria such that: $AV_j = \frac{\sum_{i=1}^{m} x_{ij}}{m}$

Step 3

Constructing the PDA “Positive Distance from Average” and the NDA “Negative Distance from Average” matrixes regarding the type (benefit or cost criterion).

For benefit criteria:

$$\mathrm{PDA}_{ij} = \frac{\max(0,(x_{ij} - AV_j))}{AV_j}$$

$$\mathrm{NDA}_{ij} = \frac{\max(0,(AV_j - x_{ij}))}{AV_j}$$

For cost criteria:

$$\mathrm{PDA}_{ij} = \frac{\max(0,(AV_j - x_{ij}))}{AV_j}$$

$$\mathrm{NDA}_{ij} = \frac{\max(0,(x_{ij} - AV_j))}{AV_j}$$

Where:

PDA_{ij} : the “positive distance” of the alternative "i" from AV_j;

NDA_{ij} : the “negative distance” of the alternative "i" from AV_j.

Step 4

Determining the “weighted sum” of PDA and NDA for the actions.

$$SP_i = \sum_{j=1}^{n} w_j \mathrm{PDA}_{ij} \;;\quad \forall i = 1,\dots,m$$

$$SN_i = \sum_{j=1}^{n} w_j \mathrm{NDA}_{ij} \;;\quad \forall i = 1,\dots,m$$

Where w_j : the weight of the criterion j.

Step 5

Normalizing the values of SP and SN for the actions.

$$NSP_i = \frac{\mathrm{SP}_i}{max_i\,(\mathrm{SP}_i)} \quad ;\ \forall i = 1,\dots, m$$

$$NSN_i = 1 - \frac{\mathrm{SN}_i}{max_i\,(\mathrm{SN}_i)} \quad ;\ \forall i = 1,\dots, m$$

Step 6

Calculating the "AS" for the actions such that: $AS_i = \frac{1}{2}\left(NSP_i + NSN_i\right)$

With $0 \leq AS_i \leq 1$

Step 7

Ranking the actions in a decreasing order of the "AS".

The Proposed EDAS-Sort-B Method

We extended the EDAS method to tackle with the sorting problematic. The assignment rule of the EDAS-Sort-B method consist of comparing the Appraisal Score of each action A_i with the Appraisal Scores of the boundary (limiting) profiles l_h of k ordered classes decreasingly (optimistic assignment) such that each category C_h is bounded by a "lower limit profile" l_h and an "upper limit profile" l_{h+1}. We note that, for k categories, there is $k-1$ boundary profiles. For the class C_1, we define only the upper limit profile l_1. For the class C_k, we define only the lower limit profile l_{k-1}.

Step 1

Constructing the decision matrix.

$$X=\begin{bmatrix} x_{11} & \dots x_{1j} & \cdots x_{1n} \\ \vdots & \ddots \ \vdots & \ddots \ \vdots \\ x_{i1} & \dots x_{ij} & \dots x_{in} \\ \vdots & \ddots \ \vdots & \ddots \ \vdots \\ x_{m1} & \dots x_{mj} & \dots x_{mn} \end{bmatrix} \text{ For all } z= 1,\dots, m \ ; j= 1, \dots, n$$

Where

x_{zj} : the performance value of the action z according to criterion j;

m: the number of actions;

n: the number of criteria.

Step 2

Determining boundary profiles $l_j = \{l_1, \dots, l_{k-1}\}$ by the DM and integrate them to the performance matrix as alternatives.

Step 3

Determining AV of the actions and profiles such that:

$$AV_j = \frac{\sum_{z=1}^{m+k-1} x_{zj}}{m+k-1} \tag{1}$$

Step 4

Constructing the PDA and NDA matrixes such that:

For benefit criteria:

$$\text{PDA}_{zj} = \frac{\max(0,(x_{zj} - AV_j))}{AV_j} \tag{2}$$

$$\text{NDA}_{zj} = \frac{\max(0,(AV_j - x_{zj}))}{AV_j} \tag{3}$$

For cost criteria:

$$\text{PDA}_{zj} = \frac{\max(0,(AV_j - x_{zj}))}{AV_j} \tag{4}$$

$$\text{NDA}_{zj} = \frac{\max(0,(x_{zj} - AV_j))}{AV_j} \tag{5}$$

Where:

PDA_{zj} : the positive distance of action z or boundary profile l_j from average solution according to the criterion j;

NDA_{zj} : the negative distance of action z or boundary profile l_j from average solution according to the criterion j.

Step 5

Determining the "weighted sum" of PDA and NDA for actions and boundary profiles.

$$SP_z = \sum_{j=1}^{n} w_j \text{PDA}_{zj} \ ; \quad \forall z = 1,\dots,m+k-1 \tag{6}$$

$$SN_z = \sum_{j=1}^{n} w_j \text{NDA}_{zj} \ ; \quad \forall z = 1,\dots,m+k-1 \tag{7}$$

Where w_j: criterion weight determined directly by the DM such that :

$$\sum_{j=1}^{n} w_j = 1 \tag{8}$$

Step 6

Normalizing the values of SP and SN for actions and boundary profiles.

$$NSP_z = \frac{\mathrm{SP}_z}{max_z\,(\mathrm{SP}_z)} \quad ; \qquad \forall z = 1,\ldots, m+k\text{-}1 \tag{9}$$

$$NSN_z = 1 - \frac{\mathrm{SN}_z}{max_z\,(\mathrm{SN}_z)} \quad ; \ \forall z = 1,\ldots, m+k\text{-}1 \tag{10}$$

Step 7

Calculating the AS for actions and boundary profiles.

$$AS_z = \frac{1}{2}\,(NSP_z + NSN_z) \tag{11}$$

With $0 \leq AS_z \leq 1$

Step 8

Assigning the actions to one of the categories ordered decreasingly from C_1 to C_k ($C_1 \succ \cdots \succ C_h \succ \cdots \succ C_k$) such as $l_1 < \cdots < l_h < \cdots < l_{k-1}$, according to these optimistic assignment rules:

- If $AS_{A_i} < AS_{\,l_1}$, then the action A_i is assigned to the class C_1.
- If $AS_{\,l_h} < AS_{A_i} < AS_{\,l_{h+1}}$, then the action A_i is assigned to the class C_h.
- If $AS_{A_i} > AS_{\,l_{k-1}}$, then the action A_i is assigned to the class C_k.

A Case Study

The aim of this case study conducted at a bank agency located at Sfax, Tunisia is to assign 20 clients demanding loans to three predefined classes: very solvent, solvent and doubtful according to various criteria: age, seniority, fixed and regular income, guaranties, credit amount, credit term, solvency and repayment capacity. All of them are benefit criteria except the age. Consequently, we presented in the decision matrix (table 1) the assessments of clients (alternatives) as well as the two limiting profiles l_1 and l_2 and we calculated the AVerage solution (step 3 of the EDAS-Sort-B method).

Table 1. Decision matrix

	Age	**Seniority**	**Fixed and regular income**	**Guaranties**	**Credit amount**	**Credit term**	**Solvency**	**Repayment capacity**
W_j	0.06	0.05	0.15	0.1	0.13	0.13	0.2	0.18
A1	67	40	970	3	15000	36	3	388
A2	57	21	3200	3	40000	60	1	1920
A3	50	10	1400	2	40000	60	3	700
A4	58	3	1270	2	30000	60	2	635
A5	48	27	1300	2	7000	24	1	650
A6	47	0	605	2	12000	60	2	242
A7	38	10	1100	2	19000	60	1	550
A8	55	51	2000	3	15000	60	1	1200
A9	60	30	1200	2	15000	60	1	600

Table 1. Decision matrix (*Continued*)

	Age	**Seniority**	**Fixed and regular income**	**Guaranties**	**Credit amount**	**Credit term**	**Solvency**	**Repayment capacity**
A10	34	10	3000	2	30000	60	1	1800
A11	20	0	600	2	50000	60	2	240
A12	50	20	1200	2	40000	60	2	600
A13	34	8	2200	2	40000	60	1	1320
A14	70	35	1600	2	30000	60	2	800
A15	50	15	1100	2	25000	60	2	550
A16	60	25	1200	2	10000	60	1	600
A17	42	12	3000	3	40000	60	1	1800
A18	38	8	1500	2	10000	36	3	750
A19	27	9	700	2	14000	60	2	280
A20	52	18	2500	2	25000	60	1	1500
$\boldsymbol{l_1}$	30	5	970	1	5000	24	1	500
$\boldsymbol{l_2}$	60	15	2000	1	20000	36	1	1500
AV_j	47.818	16.909	1574.773	2.136	24181.818	53.455	1.727	869.318

The sample is small since it was taken during a period of a lockdown due to COVID'19 pandemic. Each class is bounded by a lower limiting profile and an upper one. In our case, since we have three classes, we defined two limiting profiles l_1 and l_2 as illustrated in figure 1.

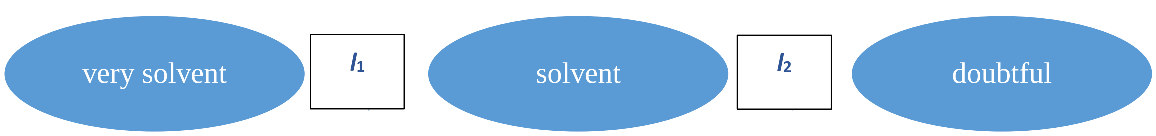

Figure 1. the classes and their boundary profiles

After that, we constructed the PDA and the NDA matrixes (step 4 of the EDAS-Sort-B method). Then, we applied steps 5, 6 and 7 respectively of the EDAS-Sort-B method as presented in table 2.

Table 2. The calculation of Appraisal Scores (AS)

	SP_z	SN_z	NSP_z	NSN_z	AS_z
A1	0.26	0.27	0.49	0.31	0.4
A2	0.53	0.1	1	0.76	0.88
A3	0.25	0.08	0.47	0.79	0.63
A4	0.08	0.14	0.15	0.65	0.4
A5	0.03	0.33	0.06	0.17	0.115
A6	0.05	0.34	0.09	0.13	0.11
A7	0.03	0.25	0.05	0.37	0.21
A8	0.27	0.14	0.51	0.64	0.575
A9	0.05	0.25	0.1	0.37	0.235
A10	0.39	0.11	0.75	0.72	0.735
A11	0.22	0.28	0.42	0.29	0.355
A12	0.14	0.1	0.27	0.74	0.505
A13	0.27	0.12	0.52	0.7	0.61
A14	0.13	0.05	0.26	0.88	0.57
A15	0.05	0.13	0.1	0.68	0.39
A16	0.04	0.27	0.08	0.31	0.195
A17	0.48	0.1	0.91	0.75	0.83
A18	0.16	0.18	0.3	0.54	0.42
A19	0.07	0.29	0.14	0.27	0.205
A20	0.24	0.1	0.46	0.76	0.61
l_1	0.02	0.39	0.03	0	0.015
l_2	0.32	0.09	0.61	0.78	0.695

Each action is assigned to either class C1 (very solvent) or C2 (solvent) or C3 (doubtful) such as:

- If $AS_{A_i} < 0.015$, then the action A_i is assigned to the class C_1 i.e. the client is considered very solvent.
- If $0.015 < AS_{A_i} < 0.695$, then the action A_i is assigned to the class C_2 i.e. the client is considered solvent.
- If $AS_{A_i} > 0.695$, then the action A_i is assigned to the class C_3 i.e. the client is considered doubtful.

As an illustration, the clients' assignment into classes (C_1, C_2 and C_3) is presented in figure 2.

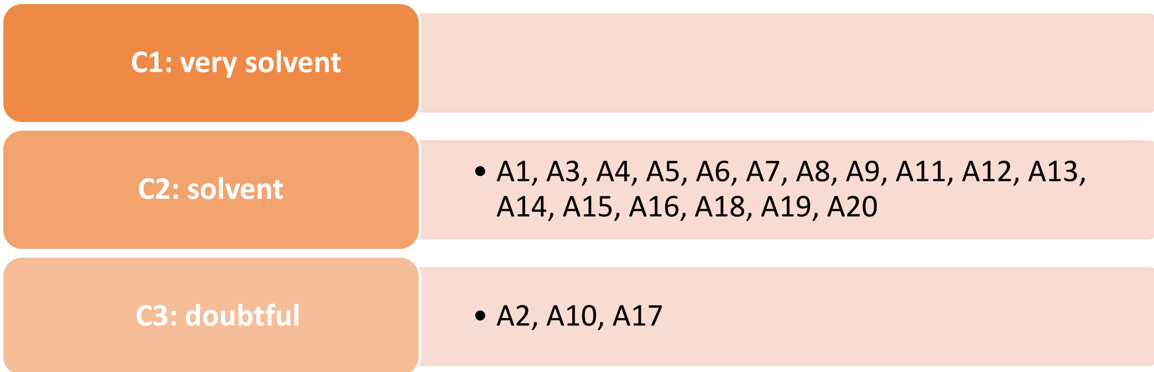

Figure 2. The assignment of clients

As can been noticed, most of this bank agency clients are solvent except three of them (A2, A10 and A17) who are considered doubtful.
In a final analysis, a comparison between the proposed EDAS-Sort-B with different MCDM sorting methods based on boundary profiles was conducted to discuss the generated assignments in table 3 and figure 3.

Table 3. Comparison between different sorting methods

	EDAS-Sort-B	TOPSIS-Sort-B	CODAS-Sort	VIKOR-Sort	AHP-Sort
A1	2	2	2	2	2
A2	3	3	2	2	2
A3	2	2	2	2	2
A4	2	2	2	2	2
A5	2	1	1	2	1
A6	2	2	1	2	2
A7	2	2	2	2	2
A8	2	2	2	2	2
A9	2	2	2	2	2
A10	3	2	2	2	3
A11	2	2	2	2	2
A12	2	2	2	2	2
A13	2	2	2	2	2
A14	2	2	2	2	2

Table 1. Comparison between different sorting methods (*Continued*)

	EDAS-Sort-B	TOPSIS-Sort-B	CODAS-Sort	VIKOR-Sort	AHP-Sort
A15	2	2	2	2	2
A16	2	2	1	2	2
A17	3	3	2	2	3
A18	2	2	1	2	2
A19	2	2	1	2	2
A20	2	2	2	2	2

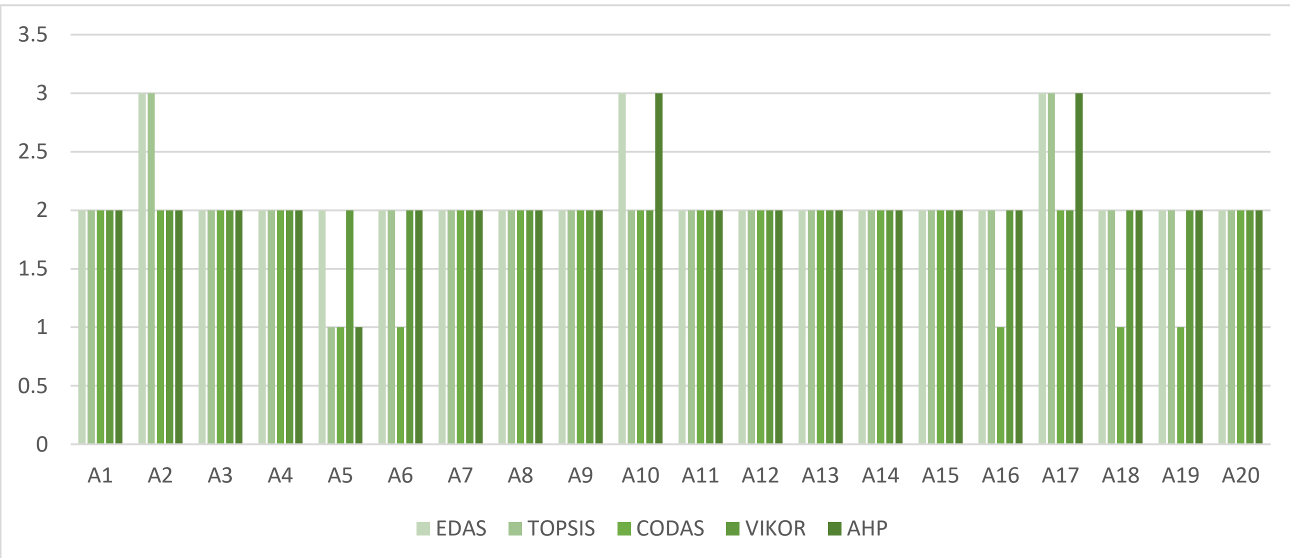

Figure 3. Comparison between different MCDM sorting methods

From table 3 and figure 3 (generated from excel spread sheet), we remarked that clients' assignment according to different MCDM sorting methods addressed above, are similar except for eight clients A2, A5, A6, A10, A16, A17, A18 and A19 (a slight difference). On the other side, the CODAS Sort method gave different results from the other sorting methods for clients A6, A16, A18, A19. For the VIKOR Sort method, all clients are assigned to the same category (solvent). As a matter of fact, the sorting MCDA approaches do not conduct, usually, to the same assignment. However, the clients 'assignment of the EDAS-Sort-B method satisfied the most the head of the bank agency.
In addition, we carried out a sensitivity analysis of the EDAS Sort-B method to study the effect of a change in boundary profiles on the clients 'assignment. For that, we established 4 scenarios presented respectively in tables 4, 5, 6 and 7.

Table 4. Scenario 1

l_1	30	5	970	1	5000
l_2	60	15	2000	1	20000

Table 5. Scenario 2

l_1	40	10	1500	2	5500
l_2	55	20	2500	3	25000

Table 6. Scenario 3

l_1	45	15	1200	1	7000
l_2	65	25	2200	2	40000

Table 7. Scenario 4

l_1	27	3	600	2	7000
l_2	67	18	2500	4	30000

Table 8. Sensitivity analysis

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
A1	2	2	2	2
A2	3	2	3	3
A3	2	2	2	2
A4	2	2	2	2
A5	2	1	2	2
A6	2	1	2	2
A7	2	1	2	2
A8	2	2	2	2
A9	2	1	2	2
A10	3	2	2	2
A11	2	2	2	2
A12	2	2	2	2
A13	2	2	2	2
A14	2	2	2	2
A15	2	2	2	2
A16	2	1	2	2
A17	3	2	2	2
A18	2	2	2	2
A19	2	1	2	2
A20	2	2	2	2

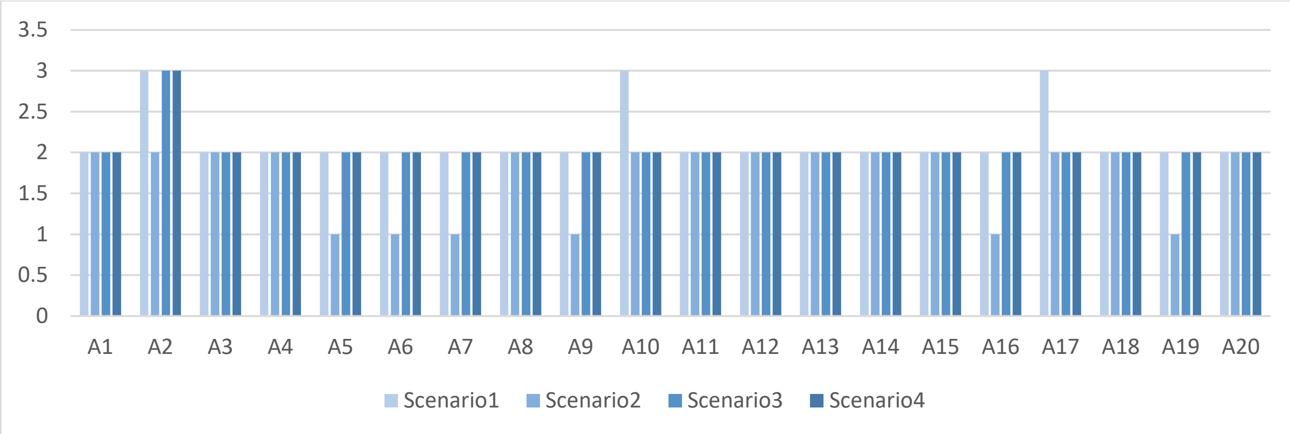

Figure 4. Sensitivity analysis

As an illustration, and from table 8 and figure 4 (generated from excel spread sheet), we point out that scenario 1 gave different assignment for both clients A10 and A17. On the other side, scenario 2 gave different assignment for seven clients A2, A5, A6, A7, A9, A16 and A19. Scenarios 3 and 4 gave exactly the same result. In essence, we can conclude that the EDAS-Sort-B method is slightly sensitive in a change of limiting profiles' values.

Discussion

The presented case study highlighted the efficiency of the EDAS-Sort-B method. The proposed method helped the head of a bank agency to classify clients demanding loans to categories ordered according to their solvency using a set of criteria. The result showed that most of the bank agency's clients belong to the solvent category. In addition, we conducted a sensitivity analysis to study the effect of a change in the limiting profiles values of the clients 'assignment. Therefore, we concluded that the EDAS-Sort-B method is slightly sensitive in a change of limiting profiles' values. The major advantage of the EDAS-Sort-B compared to other sorting multicriteria methods is that it is easy to use by DMs since it requires only, as data, the decision matrix and the ordered categories. Furthermore, it gave more satisfied results.

Conclusion

The EDAS Sort-B, proposed, in this paper, is an extension of EDAS method for multicriteria sorting problems. It consists of assigning alternatives into predefined categories ordered from the most to the least preferred (optimistic assignment). Since the method is based on boundary (limiting) profiles, it is called EDAS-Sort-B. Each class is bounded by a lower limiting profile and an upper one except for the first class (defined only the upper boundary profile) and the last class (defined only the lower boundary profile). The major advantage of EDAS-Sort-B, is that it is easy to use by DMs. As a matter of fact, the EDAS-Sort-B method requires from the DM only to determine the decision matrix in which the actions and the limiting profiles are evaluated according to a family of criteria, criteria weights and the ordered categories. To discuss the feasibility of our method, we presented a real case study conducted at a bank agency in Tunisia. Actually, the assignment procedure of the clients satisfied the head of the bank agency (the DM) and it reduced the time allocated for such a task. As a perspective, we intend to develop the EDAS-Sort-C method which it will be based on central profiles (or centroids) and comparing between results given by EDAS-Sort-B, and EDAS-Sort-C. Moreover, we intend to conduct a case study in renewable energies to assign solar photovoltaic panels to predefined categories. The EDAS-Sort approach is quite flexible and can be applied to numerous fields.

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