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BIPOLAR MIX – A METHOD FOR MIXED EVALUATIONS AND ITS APPLICATION TO THE RANKING OF EUROPEAN PROJECTS

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Abstract

A great variety of multi-criteria decision aiding (MCDA) methods has already been developed but few papers have dealt with mixed data (qualitative and quantitative). MCDA techniques accepting different types of evaluations (such as deterministic, stochastic and/or fuzzy ones) are rather rare and not very well known, even though this issue is crucial from a practical point of view, since mixed evaluations occur very frequently in appraising and selecting projects and organizations, as well as in risk management modelling, among other fields.

This paper presents a new discrete MCDA tool developed for mixed performances of alternatives called BIPOLAR MIX. It is based on the classical BIPOLAR method proposed by Konarzewska-Gubała (1989), and on its modification, namely the BIPOLAR method with stochastic dominance (SD) rules, proposed by Górecka (2009). A numerical example at the end of the paper illustrates the problem of ordering projects applying for co-financing from the European Union (EU).

Keywords: decision analysis, MCDA, mixed data, BIPOLAR MIX, uncertainty modelling, European Union.

1 Introduction

The case of mixed data is not frequently discussed in the literature and MCDA methods accepting different types of evaluations (e.g. ordinal and cardinal as well as deterministic, stochastic and/or fuzzy) are rather rare and not very well known. Nev-

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ertheless, this issue is vital from a practical point of view since mixed evaluations are frequent in real-life decision-making problems. They may occur:

- in appraising and selecting projects and organizations for various purposes,
- in the assessment of environmental impact,
- in establishing quality-of-living city rankings,
- in risk management modelling.

Examples of multi-criteria models that can be applied in such situations are:

- NAIADE (Munda, 1995; Munda et al., 1995),
- PAMSSEM (Martel et al., 1997; Guitouni et al., 1999),
- EVAMIX (Voogd, 1982; 1983),
- EVAMIX method with stochastic dominance rules (Górecka, 2010b; 2012),
- EVAMIX method for mixed evaluations (Chojnacka, Górecka, 2016).

Mixed evaluations have been also considered by Zaras (2004) and Ben Amor et al. (2007).

In some cases, though, these approaches are not well-suited for decision-making. Therefore, this paper presents a new discrete MCDA tool developed for mixed performances of alternatives, called BIPOLAR MIX. It is based on the classical BIPOLAR method proposed by Konarzewska-Gubała (1989) and on its modification, namely the BIPOLAR method with stochastic dominance (SD) rules, proposed by Górecka (2009).

The paper contains an introduction, three sections, and a conclusion. In Section 2, a general modelling framework is presented to clarify the context in which the proposed method can be applied. Section 3 presents the BIPOLAR MIX technique. Finally, Section 4 provides an example illustrating the problem of ordering projects which apply for co-financing from the European Union funds.

2 The context of problem modelling

Because of the very large amount of money channelled into the Regional Policy of the European Union (Cohesion Policy funding for 2014-2020 amounts to EUR 351.8 billion (www 1)), it is extremely important to allocate the financial means in the most effective way possible. That depends, among other things, on the appropriate choice of projects that are going to be co-financed. To help the decision-makers in this challenging task, MCDA methods, methods for making decisions in the presence of multiple, usually conflicting criteria, should be used, since the evaluation of the projects which apply for funding from the EU requires taking into account many different aspects: economic, financial, environmental, ecological, technical, technological, social and legal (Górecka, 2011; 2012).

The development of the BIPOLAR MIX method was driven by the distinctive features of the analysed decision-making problem, as well as the expectations and needs of the decision-makers engaged in the realisation of the EU Regional Policy, which are as follows (Górecka, 2011):

- the decision-making problem should be formulated as a problem of providing a complete order of the alternatives – it is essential for each applicant to be classified in the ranking and to know its own result (overall score), preferably a numerical one (points), since otherwise the results may be unconvincing for them;
- there is no room for the incomparability of the alternatives – the ranking should be complete as the argumentation that the project has not been selected for co-financing as incomparable with others will not be acknowledged by the applicants;
- the occurrence of ties in the ranking should be limited since this may create problems with dividing the funds;
- the problem is a group decision-making problem – experts involved in the appraisal of projects separately and independently evaluate a finite number of competing projects, and their diverse individual views must be incorporated into a joint final decision;
- there should be a possibility to employ both quantitative and qualitative criteria, and to use mixed data (deterministic and stochastic);
- decision-makers are able to reveal their preferences, but they do not have much time for the interaction and cooperation with the analyst;
- the possibility of the occurrence of complete compensation should be removed – in the case of some criteria it may be risky and in the case of others, projects should satisfy the so-called 'minimal quality';
- on the one hand, the decision aiding technique should not be too complicated so that decision-makers can explain to the applicants how it works and clarify the reasons for the rejection of their projects; on the other hand, the decision-making method should not be too simple to limit the possibilities of manipulating the results;
- it is desired that the decision aiding method allows us to determine whether the highly ranked projects are really good or just better than the weak ones.

The BIPOLAR MIX method responds to all these requirements (properties of the decision-making problem analysed and its participants)[1]. It is presented in the next section.

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1 Advantages and disadvantages of various MCDA techniques in the context of the European projects selection are presented in Górecka (2010b; 2011). Main strengths and weaknesses of selected MCDA approaches in the context of choosing a wedding venue are described in Górecka (2013).

3 The BIPOLAR MIX method

The BIPOLAR MIX technique is based on the BIPOLAR method (Konarzewska-Gubała, 1989; 1991) and on the modified BIPOLAR method with stochastic dominance rules (Górecka, 2009; 2010a; 2014a). As required, it allows us, among other things:

- to obtain a complete order of the alternatives;
- to use mixed data;
- to determine whether highly ranked alternatives are really good or just not bad – it allows for ranking and sorting alternatives as well as for determining their quality, taking into account what is good and undesirable from the decision-maker's point of view in the decision-making problem (reference system);
- to eliminate both the phenomenon of full compensation and the problem of the incomparability of the alternatives.

In this paper it is assumed that the performance of alternatives is given in a deterministic and stochastic way, and that the decision-maker(s) are risk-averse. Thus, if the evaluations are stochastic, we will use FSD/SSD[2] (see Quirk, Saposnik, 1962; Hadar, Russel, 1969) and AFSD/ASSD rules (see Leshno, Levy, 2002) for modelling preferences with respect to criteria measured on a cardinal scale, and OFSD/OSSD (see Spector et al., 1996) and OAFSD/OASSD rules (see Górecka, 2009; 2011; 2014c) for criteria measured on an ordinal scale.

We assume that when comparing alternatives a_i and a_l with respect to a single criterion, the following situations are distinguished: strict preference, weak preference and non-preference (see Roy, 1990; Górecka, 2009; 2014b; cf. Nowak, 2004; 2005):

- alternative a_i is strictly preferred to alternative a_l:

$$a_i \, P \, a_l \Leftrightarrow F_k^i \, SD \, F_k^l \quad \text{and} \quad \mu_k(a_i) - \mu_k(a_l) > p_k \,, \tag{1}$$

- alternative a_l is strictly preferred to alternative a_i:

$$a_l \, P \, a_i \Leftrightarrow F_k^l \, SD \, F_k^i \quad \text{and} \quad \mu_k(a_l) - \mu_k(a_i) > p_k \,, \tag{2}$$

- alternative a_i is weakly preferred to alternative a_l:

$$a_i \, Q \, a_l \Leftrightarrow F_k^i \, SD \, F_k^l \quad \text{and} \quad q_k < \mu_k(a_i) - \mu_k(a_l) \le p_k \,, \tag{3}$$

- alternative a_l is weakly preferred to alternative a_i:

$$a_l \, Q \, a_i \Leftrightarrow F_k^l \, SD \, F_k^i \quad \text{and} \quad q_k < \mu_k(a_l) - \mu_k(a_i) \le p_k \,, \tag{4}$$

[2] If a decision-maker has also a decreasing absolute risk aversion, then the TSD rule (see Whitmore, 1970) should be additionally applied. If a decision-maker is risk-seeking, then FSD/SISD/TISD1/TISD2 rules (see Goovaerts et al., 1984; Zaras, 1989) should be used.

- non-preference – otherwise,
  where:
- F_k^i, F_k^l – distribution of the evaluations of alternative a_i and alternative a_l, respectively, with respect to criterion f_k,
- *SD* – stochastic dominance relation: FSD/SSD/AFSD/ASSD or OFSD/ OSSD/OAFSD/OASSD,
- $\mu_k(a_i)$, $\mu_k(a_l)$ – average performance (expected value of the distribution of the evaluations) of a_i and a_l, respectively, on criterion f_k,
- q_k – indifference threshold for criterion f_k,
- p_k – preference threshold for criterion f_k.

We assume that:

- $F = \{f_1, f_2, \ldots, f_n\}$ is a finite set of n examined criteria (it is assumed that all criteria are maximized),
- $A = \{a_1, a_2, \ldots, a_m\}$ is a finite set of m alternatives,
- $R = \{r_1, r_2, \ldots, r_r\}$ is a reference set consisted of two subsets:
  - $D = \{d_1, d_2, \ldots, d_d\}$ – 'good' reference alternatives,
  - $Z = \{z_1, z_2, \ldots, z_z\}$ – 'bad' reference alternatives,
  - $D \cup Z = R$, $D \cap Z = \emptyset$,
  - $\forall d_g \in D \;\; \forall z_h \in Z \;\; \forall k = 1,2,\ldots,n \;\; \mu_k(d_g) \geq \mu_k(z_h)$,
  - $\forall d_g \in D \;\; \forall z_h \in Z \;\; \forall k = 1,2,\ldots,n \;\; f_k(d_g) \geq f_k(z_h)$,

where:

- $\mu_k(d_g), \mu_k(z_h)$ – average performance (expected value) of reference alternatives d_g and z_h, respectively, on criterion f_k,
- $f_k(d_g), f_k(z_h)$ – performance of reference alternatives d_g and z_h, respectively, on criterion f_k.

The BIPOLAR MIX procedure consists of the following steps:

<u>Step 1: Comparison of considered alternatives (a_i) with reference alternatives (r_j) to determine the decision-maker(s)' preference model</u>

A. Calculation of aggregated preference index $c(a_i, r_j)$ for each pair (a_i, r_j), where $a_i \in A$, $r_j \in R$:

$$c(a_i, r_j) = \sum_{k=1}^{n} w_k \varphi_k(a_i, r_j) \tag{5}$$

where:

$$\varphi_k(a_i, r_j) = \begin{cases} 1, & if \quad F_k^i \; SD \, F_k^j \wedge \mu_k(a_i) - \mu_k(r_j) > p_k \\ -1, & if \quad F_k^j \; SD \, F_k^i \wedge \mu_k(r_j) - \mu_k(a_i) > p_k \\ \dfrac{\mu_k(a_i) - q_k - \mu_k(r_j)}{p_k - q_k}, & if \;\; F_k^i \; SD \, F_k^j \wedge q_k < \mu_k(a_i) - \mu_k(r_j) \le p_k \\ -\dfrac{\mu_k(r_j) - q_k - \mu_k(a_i)}{p_k - q_k}, & if \;\; F_k^j \; SD \, F_k^i \wedge q_k < \mu_k(r_j) - \mu_k(a_i) \le p_k \\ 0 & otherwise \end{cases} \quad (6)$$

or:

$$\varphi_k(a_i, r_j) = \begin{cases} 1, & if \quad f_k(a_i) - f_k(r_j) > p_k \\ -1, & if \quad f_k(r_j) - f_k(a_i) > p_k \\ \dfrac{f_k(a_i) - q_k - f_k(r_j)}{p_k - q_k}, & if \quad q_k < f_k(a_i) - f_k(r_j) \le p_k \\ -\dfrac{f_k(r_j) - q_k - f_k(a_i)}{p_k - q_k}, & if \quad q_k < f_k(r_j) - f_k(a_i) \le p_k \\ 0 & otherwise \end{cases} \quad (7)$$

depending on data, where:

- w_k – coefficient of importance for criterion f_k, $\sum_{k=1}^{n} w_k = 1$,
- F_k^i, F_k^j – distribution of the evaluations of alternative a_i and reference alternative r_j, respectively, with respect to criterion f_k,
- SD – stochastic dominance relation,
- $\mu_k(a_i), \mu_k(r_j)$ – average performance (expected value of the evaluations' distribution) of a_i and r_j, respectively, on criterion f_k,
- $f_k(a_i), f_k(r_j)$ – performance of alternative a_i and reference alternative r_j, respectively, on criterion f_k,
- q_k, p_k – indifference and preference thresholds for criterion f_k.

B. Calculation of credibility index $\omega(a_i, r_j)$ for each pair (a_i, r_j), where $a_i \in A$, $r_j \in R$:

$$\omega(a_i, r_j) = \begin{cases} c(a_i, r_j) & if \;\; c(a_i, r_j) > 0 \;\; and \;\; \forall k \in I^- \;\; \mu_k(a_i) \ge v_k \\ c(a_i, r_j) & if \;\; c(a_i, r_j) < 0 \;\; and \;\; \forall k \in I^+ \;\; \mu_k(r_j) \ge v_k \\ 0 & otherwise \end{cases} \tag{8}$$

or:

$$\omega(a_i, r_j) = \begin{cases} c(a_i, r_j) & if \;\; c(a_i, r_j) > 0 \;\; and \;\; \forall k \in I^- \;\; f_k(a_i) \ge v_k \\ c(a_i, r_j) & if \;\; c(a_i, r_j) < 0 \;\; and \;\; \forall k \in I^+ \;\; f_k(r_j) \ge v_k \\ 0 & otherwise \end{cases} \tag{9}$$

depending on data, where:

- $I^+(a_i, r_j) = \{k : \varphi_k(a_i, r_j) > 0\}$,
- $I^-(a_i, r_j) = \{k : \varphi_k(a_i, r_j) < 0\}$,
- v_k – veto threshold for criterion f_k.

Hypothesis 'a_i is preferred to r_j' is accepted when both the concordance and the non-discordance conditions are satisfied. The concordance condition is satisfied if aggregated preference index $c(a_i, r_j)$ is greater than 0, whereas the non-discordance condition is satisfied if $\forall k \in I^- \;\; \mu_k(a_i) \ge v_k$ or $f_k(a_i) \ge v_k$ (depending on data), where v_k is the lowest acceptable expected value of the distribution of the evaluations on criterion f_k or the lowest acceptable evaluation on criterion f_k (depending on data). Hypothesis 'r_j is preferred to a_i' is accepted if aggregated preference index $c(a_i,r_j)$ is smaller than 0 and $\forall k \in I^+ \;\; \mu_k(r_j) \ge v_k$ or $f_k(r_j) \ge v_k$ (depending on data). If the non-discordance condition is not satisfied and/or aggregated preference index $c(a_i, r_j)$ is equal to 0, both hypotheses are rejected.

Step 2: Determining the position of considered alternatives (a_i) in relation to the bipolar reference system (D,Z) and drawing final conclusions about them, i.e. preparing recommendations for the decision-maker(s)

A. Comparison of considered alternatives (a_i) with 'good' reference alternatives (d_g) from subset D – calculation of success index d_{iS} for each alternative a_i:

$$d_{iS} = \frac{1}{d}\sum_{g=1}^{d} \omega(a_i, d_g), \;\; d_{iS} \in [-1,1]. \tag{10}$$

Mono-sorting:

- category S1: alternatives a_i for which $d_{iS} > 0$ (type: *overgood*),
- category S2: alternatives a_i for which $d_{iS} = 0$,
- category S3: alternatives a_i for which $d_{iS} < 0$ (type: *undergood*).

Mono-ranking: according to the descending value of d_{iS}.

B. Comparison of considered alternatives (a_i) with 'bad' reference alternatives (z_h) from subset Z – calculation of anti-failure index d_{iN} for each alternative a_i:

$$d_{iN} = \frac{1}{z}\sum_{h=1}^{z}\omega(a_i, z_h)\,,\ d_{iN} \in [-1,1]. \tag{11}$$

Mono-sorting:

- category N1: alternatives a_i for which $d_{iN} > 0$ (type: *overbad*),
- category N2: alternatives a_i for which $d_{iN} = 0$,
- category N3: alternatives a_i for which $d_{iN} < 0$ (type: *underbad*).

Mono-ranking: according to the descending value of d_{iN}.

C. Cumulative assessment of considered alternatives (a_i) in terms of success achievement and failure avoidance – calculation of final score d_{iSN} for each alternative a_i:

$$d_{iSN} = \frac{d_{iS} + d_{iN}}{2}\,,\ d_{iSN} \in [-1,1]. \tag{12}$$

Indices d_{iS} and d_{iN} induce two independent orders on the set of considered alternatives: a success-oriented one and an anti-failure-oriented one, respectively. Using both indices simultaneously we can rank and sort alternatives a_i bipolarly.

Bipolar-sorting:

- category B1: alternatives a_i for which $d_{iS} + d_{iN} > 0$ (type: *good*),
- category B2: alternatives a_i for which $d_{iS} + d_{iN} = 0$,
- category B3: alternatives a_i for which $d_{iS} + d_{iN} < 0$ (type: *bad*).

Bipolar-ranking: according to the descending value of d_{iSN}.

4 Illustrative example

This paper shows an application of the BIPOLAR MIX method to the mock-up process of appraising and ranking applications for financial aid from the European Regional Development Fund.

Sixteen infrastructure projects were considered. They concern the protection of surface waters, waste management and flood control, and include:

- construction and modernisation of wastewater and rainwater collection networks and wastewater treatment plants,
- implementation of a system of communal waste management, which includes the construction of sorting and composting plants and recultivation of landfills,
- modernisation of dikes.

These projects were evaluated using 11 criteria[3]: 1 deterministic (total cost) and 10 stochastic. Regarding the latter, five experts − specialists in environmental protection infrastructure − scored them[4] from 0 (the lowest evaluation) to 10 (the highest evaluation).

The model of preferences for the decision-making problem is presented in Table 1[5], while Table 2 provides the performance matrix for 16 projects from the case study and 4 reference projects (two 'good' and two 'bad'[6]). The results obtained using the BIPOLAR MIX method are shown in Table 3.

[3] The set of 11 criteria was constructed as follows: a list of the criteria (based, among other things, on the data available in the applications considered for project co-financing and on information from official documents related to the EU funds) was presented to five specialists on environmental protection infrastructure and European Union funds who could accept or reject each of them. They also had a possibility to add their own criteria to the preliminary list.

[4] To keep the classified data secret while allowing for objective evaluation, the descriptions of the projects were truncated and standardised.

[5] Weighting coefficients for evaluation criteria were established by the five experts on environmental protection infrastructure and EU funds with the help of the REMBRANDT system (Lootsma et al., 1990; Olson et al., 1995). The experts were also asked to determine values of indifference and preference thresholds for stochastic criteria. Two extreme opinions were disregarded and from the remaining three, the arithmetic mean was calculated. It was subsequently rounded to the nearest integer. Indifference and preference thresholds for the deterministic criterion (total cost) as well as veto thresholds for all criteria were set by the present author.

[6] The reference set was constructed by the present author. For stochastic criteria it was assumed that desirable performances of alternatives (experts' appraisal scores) are high (higher than or equal to 60% of points available, i.e. 6) and not too diversified, while undesirable performances are low and/or diversified. In the case of total cost (deterministic criterion) it was assumed that values less than or equal to PLN 5 million are desired, while values higher than or equal to PLN 20 million are undesired.

Table 1: Model of preferences

f_k	Criterion	Min/max	Type of data	w_k	q_k	p_k	v_k
f_1	Total cost [PLN million]	min	deterministic	0.12	1	3	30
f_2	Efficiency [0-10; 5 experts]	max	stochastic	0.19	1	3	3
f_3	Influence on environment [0-10; 5 experts]	max	stochastic	0.15	2	4	3
f_4	Influence on employment [0-10; 5 experts]	max	stochastic	0.05	3	4	2
f_5	Influence on inhabitants' health [0-10; 5 experts]	max	stochastic	0.14	3	5	2
f_6	Influence on investment attractiveness [0-10; 5 experts]	max	stochastic	0.07	2	4	2
f_7	Influence on tourist attractiveness [0-10; 5 experts]	max	stochastic	0.06	2	5	2
f_8	Validity of the technical solutions [0-10; 5 experts]	max	stochastic	0.08	1	3	2
f_9	Sustainability and institutional feasibility of the project [0-10; 5 experts]	max	stochastic	0.06	1	3	2
f_{10}	Complementarity with other projects [0-10; 5 experts]	max	stochastic	0.04	2	4	2
f_{11}	Comprehensiveness [0-10; 5 experts]	max	stochastic	0.04	2	4	2

Table 2: Performance matrix

f_k	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}
a_i	$f_k(a_i)$	$\mu_k(a_i)$									
a_1	8.42	5.6	7.2	4.4	4.8	4.6	4.6	7.8	7.4	7.0	4.8
a_2	31.55	7.2	9.2	7.8	5.8	7.8	9.0	8.4	8.4	8.6	9.0
a_3	9.24	7.0	8.4	3.8	5.0	5.8	6.2	7.6	6.4	3.4	4.0
a_4	9.25	7.6	8.8	7.2	5.6	7.6	8.4	8.4	7.4	3.8	4.6
a_5	5.93	5.8	8.4	7.4	5.8	7.2	4.6	8.2	8.6	7.4	5.6
a_6	20.00	6.8	6.6	8.4	6.0	7.6	6.8	6.6	9.0	7.0	5.4
a_7	26.01	4.6	7.6	6.2	6.0	6.6	6.6	8.2	8.0	7.4	5.8
a_8	5.85	7.0	8.4	5.4	7.0	5.8	6.4	8.6	8.2	6.2	5.6
a_9	5.6	7.0	7.4	3.6	5.6	5.0	5.0	7.6	7.6	8.6	5.8
a_{10}	7.00	6.0	8.0	4.0	5.6	6.8	7.2	8.4	8.0	8.4	6.2
a_{11}	6.22	5.4	7.6	3.2	5.0	5.6	6.2	7.2	7.4	8.4	7.4
a_{12}	33.95	6.2	7.8	6.2	5.8	5.4	4.4	7.6	7.0	8.4	7.4
a_{13}	7.00	7.2	9.0	5.6	7.8	6.4	6.2	8.8	7.0	6.2	6.8
a_{14}	13.87	6.8	8.0	7.2	6.8	4.6	4.0	7.8	7.0	4.0	7.8
a_{15}	10.53	6.6	7.4	7.8	6.8	6.4	7.0	7.8	7.6	3.8	6.8
a_{16}	9.02	9.0	7.2	1.0	6.0	6.2	6.8	9.2	8.6	8.6	5.4
r_j	$f_k(r_j)$	$\mu_k(r_j)$									
d_1	5.00	9.0	9.0	7.0	7.0	7.0	7.0	7.0	7.0	8.0	8.0
d_2	3.00	7.2	7.4	6.6	7.8	7.6	7.4	7.2	8.0	6.4	6.8
z_1	20.00	4.0	5.0	4.0	6.0	6.0	4.0	5.0	5.0	4.0	4.0
z_2	30.00	4.6	3.8	5.6	4.8	5.4	4.4	4.2	4.0	5.0	5.2

Table 3: Rankings of the projects

No.	Monorankings of the projects				Bipolar ranking of the projects	
	a_i	Success indices d_{iS}	a_i	Anti-failure indices d_{iN}	a_i	Final score d_{iSN}
1	a_{16}	-0.083	a_4	0.636	a_{13}	0.238
2	a_8	-0.084	a_{13}	0.576	a_8	0.236
3	a_{13}	-0.100	a_8	0.555	a_4	0.234
4	a_9	-0.120	a_{14}	0.525	a_9	0.199
5	a_2	-0.136	a_9	0.519	a_{10}	0.156
6	a_4	-0.169	a_3	0.510	a_5	0.144
7	a_5	-0.175	a_{10}	0.495	a_{15}	0.140
8	a_{10}	-0.183	a_{15}	0.493	a_{14}	0.138
9	a_6	-0.183	a_5	0.463	a_3	0.135
10	a_{15}	-0.213	a_{11}	0.396	a_6	0.100
11	a_{12}	-0.225	a_6	0.383	a_{16}	0.089
12	a_{11}	-0.230	a_1	0.317	a_{11}	0.083
13	a_3	-0.240	a_{16}	0.261	a_1	0.013
14	a_{14}	-0.250	a_7	0.256	a_7	-0.017
15	a_7	-0.289	a_2, a_{12}	0.000	a_2	-0.068
16	a_1	-0.292			a_{12}	-0.113

According to the analysis, all the projects in the case study belong to the category S3 (*undergood*) and none belongs to the category N3 (*underbad*). The final scores show that 13 projects were classified into category B1 (so-called 'good alternatives'), namely: a_{13}, a_8, a_4, a_9, a_{10}, a_5, a_{15}, a_{14}, a_3, a_6, a_{16}, a_{11} and a_1. Project a_{13} turned out to be the strongest and project a_8, second-strongest. The worst project for subsidising was a_{12}. This project, as well as a_2 and a_7, have been classified into category B3 (so-called 'bad alternatives') and should definitely not be recommended for co-financing. This is because a_2 and a_{12} are very expensive (they cost PLN 31.55 million and PLN 33.95 million, respectively), which was clearly caught by the BIPOLAR MIX method thanks to the veto procedure applied in this technique. Project a_7 scored low (it was almost always worse or not better than both 'good projects' and in many cases even not better than 'bad projects'). Moreover, it is also quite costly (PLN 26.01 million).

5 Conclusions

The BIPOLAR MIX method proposed in this paper is an efficient and fully operable technique that can enhance the European project evaluation procedure and improve the decision-making process since the existing procedure, based most frequently on the weighted sum, is not free of drawbacks (see Górecka, 2009; 2010a; 2010b; 2011). On the one hand, it is not too simple (to limit the temptation of manipulating the results), and, on the other hand, it is not too complicated (to enable decision-maker(s) to understand how it works). Furthermore, it allows us to use mixed information (ordinal and cardinal as well as deterministic and stochastic evaluations) and it eliminates both the possibility of full compensation and the problem of the incomparability of the alternatives. In addition, it allows us to rank and sort the alternatives and to determine their quality, using the reference system determined by the decision-maker(s). Finally, it allows us to obtain a numerical final score and it is not labour-intensive or time-consuming for the decision-makers.

The BIPOLAR MIX method can also be used to solve other decision-making problems, such as the evaluation and selection of public service organizations all over the world (cf. Chojnacka, Górecka, 2016). In the not-too-distant future we will apply it to charities operating in Poland and other countries, for instance, in Australia and Great Britain.

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