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ORIGINAL ARTICLE

Deriving preference order of post-mining land-uses through MLSA framework: application of an outranking technique

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Abstract This study intends to take advantage of a previously developed framework for mined land suitability analysis (MLSA) consisted of economical, social, technical and mine site factors to achieve a partial and also a complete pre-order of feasible post-mining land-uses. Analysis by an outranking multi-attribute decision-making (MADM) technique, called PROMETHEE (preference ranking organization method for enrichment evaluation), was taken into consideration because of its clear advantages on the field of MLSA as compared with MADM ranking techniques. Application of the proposed approach on a mined land can be completed through some successive steps. First, performance of the MLSA attributes is scored locally by each individual decision maker (DM). Then the assigned performance scores are normalized and the deviation amplitudes of non-dominated alternatives are calculated. Weights of the attributes are calculated by another MADM technique namely, analytical hierarchy process (AHP) in a separate procedure. Using the Gaussian preference function beside the weights, the preference indexes of the land-use alternatives are obtained. Calculation of the outgoing and entering flows of the alternatives and one by one comparison of these values will lead to partial pre-order of them and calculation of the net flows, will lead to a ranked preference for each land-use. At the final step, utilizing the PROMETHEE group decision support system which incorporates judgments of all the DMs, a consensual ranking can be derived. In this paper, preference order of post-mining land-uses for a hypothetical mined land has been derived according to judgments of one DM to reveal applicability of the proposed approach.

Keywords Mined land suitability analysis (MLSA) · Multi-attribute decision-making (MADM) · Post-mining land-use · Evaluation attributes · PROMETHEE · AHP

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Introduction

In an earlier study (Soltanmohammadi et al. 2008), a mined land suitability analysis (MLSA) framework containing 50 numbers of leading evaluation attributes and also eight groups of possible post-mining land-uses for a mined land, had been provided by reviewing reclamation practice reports of mines, disturbed lands and many other similar cases. In the proposed MLSA framework, the mined land evaluation attributes, were categorized into four criteria groups, including economical, social, technical, and mine site factors in a hierarchical structure. The MLSA framework had been introduced to be analyzed through a multi-attribute decision-making (MADM) technique.

During last few years, analytical hierarchy process (AHP) method which is a MADM technique has been addressed in the literature on the field of mined land suitability analysis (Uberman and Ostręga 2005; Osanloo et al. 2006; Bascetin 2007). That is mainly because using the AHP, evaluation team can systematically compare and determine the global weights of the mined land attributes (Saaty and Vargas 1994). But it has been affirmed that excluding weighting power of this method, it losses advantages against the other MADM methods when the problem is relatively complicated (Eddie et al. 2002). Especially in cases such as the 50-attribute MLSA framework, where most of attributes have a qualitative nature, outranking non-compensatory techniques such as ELECTRE (elimination et choix traduisant la realite) and PROMETHEE (preference ranking organization method for enrichment evaluation) will be more practical (Hong and Vogel 1991). Moreover, these methods do not necessitate subjective judgments of decision maker (DM), as much as the AHP does.

It can be proved that, outranking MADM techniques are well suited for conditions that exist in the MLSA framework. In a MLSA example, land-use alternatives can be very different. For instance, it happens frequently that an alternative has lots of economic advantages and serious environmental impacts, while another presents the opposite characteristics. In such a case, DM may be unable to rank them. These alternatives are thus considered as incomparable and outranking methods are the only methods that can take into account this situation (Joerin et al. 2001).

In this paper, an outranking MADM technique named PROMETHEE is applied to analyze a hypothetical mined land example through the MLSA framework. The PROMETHEE algorithm has been totally adopted here from a book by Mousseau and Roy (2005). This method was originally developed by Brans et al. (1986). It is an outranking method quite simple in conception and application compared to other methods for multi-attribute analysis. It is well adapted to problems such as MLSA where a finite number of alternatives are to be ranked considering several, sometimes conflicting, attributes (Goumas and Lygerou 2000).

However as the other MADM techniques, the PROMETHEE method has also some drawbacks which should be kept in mind during application. Some of the most serious weaknesses of this method have been discussed by Keyser and Peeters (1996) and Parreiras and Vasconcelos (2007). But evidently the major weakness of this method is lack of providing specific guidelines for determining weights of the evaluation attributes. Particularly, this disadvantage is more critical, when the number of attributes is too large (Macharis et al. 2004) and such a condition exists in the case of MLSA framework.

Macharis et al. (2004) have argued that this disadvantage can be eliminated by integrating into PROMETHEE, two elements usually associated with AHP namely: hierarchical structure of the attributes (property of the MLSA framework), and determination of the weights via pair-wise comparisons. The AHP-PROMETHEE integrated approach proposed by Macharis et al. (2004) has been recently applied successfully in equipment selection problem by Dagdeviren (2008).

In this study, with taking into account all the drawbacks studied by Keyser and Peeters (1996), the hybrid AHP-PROMETHEE tool was chosen to derive preference order of alternatives that would provide the optimum after use of a hypothetical mined land example from one DM's point of view (DM_x). However, as this problem is subject to the influence of at least four major groups of stakeholders (DMs), the PROMETHEE group decision support system (GDSS) procedure (developed by Macharis et al. 1998) was suggested to be incorporated in the PROMETHEE method.

MLSA framework

Eight groups of post-mining land-uses, containing 21 individual land-uses which have been exercised in mined lands of some different countries have been presented in Table 1. Some of the adopted land-uses had been reported as successful and some had been faced with failure. Closer studies showed that in cases without a mined land suitability analysis process, sometimes obtained result are not acceptable. There are many well-reported instances failed due to lack of such an analytic process (see e.g. Alexander 1996). This makes certain, merits of a standardized MLSA framework for post-mining land-use selection. Thus, developing a 50-attribute MLSA framework, including economical, social, technical and mine site factors, was taken into consideration to overcome this weakness (Soltanmohammadi et al. 2008).

Overall goal of the MLSA framework with hierarchical structure is mined land suitability. The criteria and attributes, respectively, place in first and second levels of the hierarchy and the eight groups of post-mining land-uses form its alternatives. The MLSA framework was built to allow analyzing the suitability of mined lands, with distinct characteristics, in conformity with a MADM approach (Fig. 1).

Economical factors

Economical factors are of a great importance in MLSA framework and include attributes such as; maintenance and monitoring costs (MMC), capital costs (CAC), operational costs (OPC), potential of investment absorption (PIA), increase in governmental incomes (IGI), increase in income of local community (IIL) and positive changes in real estate value (CRE). It is clear that these factors usually have a deterministic role due to their uncontrollability.

Social factors

As well as meeting the economic requirements, it is critical that the post-mining land-use is acceptable to the society. Social factors considered in this study include; effects on immigration to the area (EIA), need to specialist

Table 1 Some exercised post-mining land-uses (reproduced from Soltanmohammadi et al. 2008)

Land-use types	Exercised post-mining land-uses	Abbreviations
(1) Agriculture (A)	Arable farmland	A-F
	Garden	A-G
	Pasture or hay-land	A-P
	Nursery	A-N
(2) Forestry (F)	Lumber production	F-L
	Woodland	F–W
	Shrubs and native forestation	F–S
(3) Lake or pool (L)	Aquaculture	L-A
	Sailing, swimming, etc.	L-S
	Water supply	L-W
(4) Intensive recreation (IR)	Sport field	IR-S
	Sailing, swimming or fishing pond, etc.	L-S
	Hunting	IR-H
(5) Non-intensive recreation (NIR)	Park and open green space	NIR-P
	Museum or exhibition of mining innovations	NIR-M
(6) Construction (CT)	Residential	CT-R
	Commercial (shopping center, etc.)	CT-C
	Industrial (factory, brick and block making, etc.)	CT-I
	Educational (University, etc.)	CT-E
	A sustainable community	CT-S
(7) Conservation (CV)	Wildlife habitat	CV-W
	Water supply (surface and groundwater)	L-W
(8) Pit backfilling (B)	Possibility of landfill (as a last resort)	B

workforces (NSW), positive changes in livelihood quality (CLQ), employment opportunities (EO), serving the public education (SPE), frequency of passing through mine site (FPT), ecological acceptability (EA), tourism attraction (TA), land ownership (LO), proximity of mine site to population centers (PMP), location toward nearest town (LNT), accessibility or road condition (Acc.), mining company policy (MCP), government policy (GP), zoning by-laws (ZB) and consistency with local requirements (CLR).

Technical factors

A technical attribute corresponds to constraints that may lead each DM to prefer a specific individual post-mining land-use, based on the fact that it best satisfies some technological requirements, which are associated with those constraints. The technical factors considered in this study include: shape and size of mined land (SSL); availability of reclamation techniques (ART); closeness to nearest water supply (CNW); market availability (MA); current land-use in surrounding area (CLU); prosperity in the mine area (PMA); structural geology (SG); distance from special services (DSS); outlook of future businesses (OFB); environmental contaminations (EC); extreme events potential (EEP); reusing potential of mine facilities (RPM) and landscape quality (LQ).

Mine site factors

The mine site factors are intrinsic and site-specific attributes that affect the decision. They comprise three groups of attributes namely soil, climate and topography. In general, they include: soil's physical properties (SPP); soil's chemical properties (SCP); evaporation (Eva.); frost-free days (FFD); precipitation (Pre.); wind speed (WS); air moisture (AM); temperature (Tem.); hydrology of surface and groundwater (HSG); surface relief (SR); slope (Slop); elevation (Ele.); exposure to sunshine (ES) and physical properties of mine components (PPM).

Application of the proposed approach on a hypothetical mined land

The AHP-PROMETHEE integrated approach is applied here to analyze an illustrative example, on the basis of the MLSA framework. Fourteen possible post-miming land-use alternatives for the considered example include:

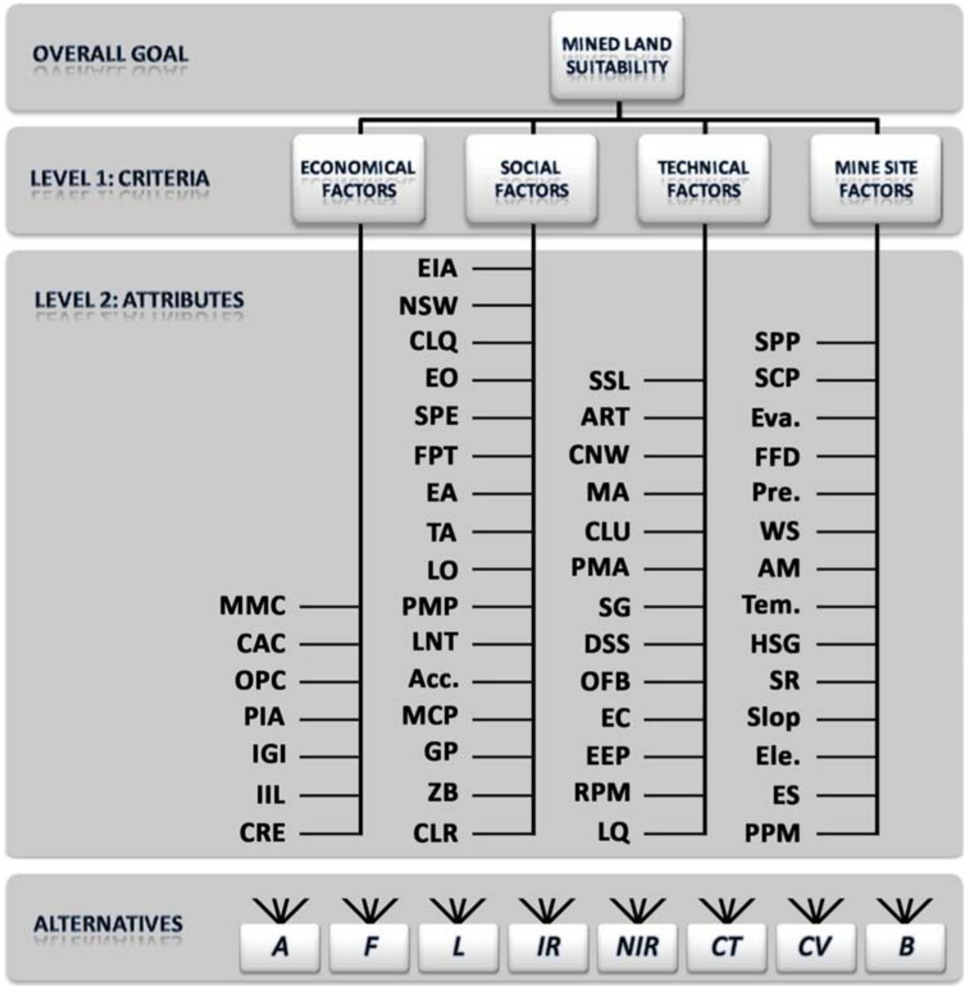


Fig. 1 Hierarchical structure of MLSA 50-attribute framework

farmland (A-F); pasture (A-P); nursery (A-N); forestry (F); lake (L); sport field (IR-S); park (NIR-P); residential (CT-R); commercial (CT-C); industrial (CT-I); educational (CT-E); sustainable community (CT-S); wildlife habitat (CV-W) and landfill (B).

Details of the proposed approach and applied steps on the considered example are discussed in the following sections.

Local evaluations according to judgments of each individual DM

In a real MLSA application, the most relevant stakeholders (DMs) are: (1) mining company representative, (2) government representative (probably a land manager), (3) environment agency, and (4) community representative. In this way, in the MLSA example studied in this paper, it is assumed that these four stakeholder groups participate in the required decision making judgments. Performance scores can be assigned to the attributes with respect to judgments of each DM on the mined land through the MLSA framework. Thus, for each alternative $j \in J$, the performance scores f_{ij} are assigned to attributes $i \in n$ by every four involved DMs (DM_1–DM_4) to form a decision matrix **F** for each DM, according to Eq. 1:

$$\mathbf{F} = \begin{bmatrix} f_{11} & f_{12} & \dots & f_{1J} \\ f_{21} & f_{22} & \dots & f_{2J} \\ \vdots & \vdots & \ddots & \vdots \\ f_{n1} & f_{n2} & \dots & f_{nJ} \end{bmatrix}, \quad i = 1, 2, \dots, n;\ j = 1, 2, \dots, J. \tag{1}$$

The authors have recommended here the fundamental nine-point scale defined by Saaty and Vargas (1994) be used by DMs to assess performance scores of the attributes. In the proposed scale of quantification, score equal to 1 signifies *extremely low* and score equal to 9 signifies *extremely high* condition of every attribute against each alternative (Table 2).

Some of the assumed performance scores for the studied example according to subjective judgments of DM_x have been cut in a fragmented decision matrix as shown in

Table 2 Manner of assigning performance scores to the attributes *i* against land-uses *j*

Extremely low →										***Extremely high***
Post-mining land-uses	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	Attributes
Farmland					■					Capital costs
Industrial		■								Ecological acceptability
Landfill									■	Environmental contaminations

Table 3 Scores of land-uses $j \in J$ assigned to the attributes $i \in n$ according to judgment by DM_x (the highlighted rows represent cost attributes)

i	*j*	*A-F*	*A-P*	*A-N*	*F*	*L*	*IR-S*	*NIR-P*	*CT-R*	*CT-C*	*CT-I*	*CT-E*	*CT-S*	*CV-W*	*B*	*Weights*
1	***MMC***	7	8	6	9	9	3	6	7	5	2	5	8	9	9	0.04060
2	***CAC***	5	3	2	4	2	6	5	7	8	8	7	9	4	1	0.03383
3	***OPC***	4	2	4	7	9	6	4	7	2	8	7	9	5	2	0.03383
4	***PIA***	2	2	7	1	8	8	7	4	8	9	4	3	9	2	0.02827
5	***IGI***	7	7	5	8	8	8	1	3	8	9	2	4	6	4	0.02274
46	***SR***	7	2	2	1	7	1	1	9	8	6	8	8	1	3	0.01214
47	***Slop***	7	2	1	1	1	1	2	9	7	2	7	8	2	8	0.02167
48	***Ele.***	5	3	3	3	8	9	3	5	5	3	5	6	2	8	0.00898
49	***ES***	8	8	8	8	7	8	8	5	5	5	5	8	8	5	0.01000
50	***PPM***	9	7	5	6	2	2	2	8	7	2	8	7	8	3	0.02165

Table 3. The highlighted rows represent cost attributes and must be minimized while the others represent benefit attributes and must be maximized in the MLSA process.

Weighting the attributes using AHP

The weights of attributes are calculated by means of AHP method developed by Saaty and Vargas (1994). The procedure of AHP weighting can be summarized as follows.

Firstly, pairs of elements of the *n*-attribute hierarchical framework are compared within pair-wise comparison matrixes **A**, according to Eq. 2

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix},$$

$$a_{iz} = \frac{1}{a_{zi}},\ a_{ii} = 1,\ i, z = 1, 2, \ldots, n. \tag{2}$$

where, the element a_{iz} can be interpreted as the degree of preference of *i*th attribute over *z*th attribute, and vice versa.

Secondly, each column of the pair-wise comparison matrix is divided by sum of entries of the corresponding column to obtain the normalized comparison matrix. The eigen-values λ_i of this matrix would give the relative weight of attribute *i*.

Finally, the obtained relative weight vector is multiplied by the weight coefficients of the elements at the higher levels, until the top of the hierarchy is reached. The result is global weight vector **W** of the attributes and can be shown as Eq. 3

$$\mathbf{W} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix}. \tag{3}$$

AHP also calculates an inconsistency index CI to reflect the consistency of DM's judgments during the evaluation phase. The inconsistency index in pair-wise comparison matrixes can be calculated by means of Eq. 4

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1}. \tag{4}$$

where $\lambda_{\max}$ is highest eigenvalue of the pair-wise comparison matrix. The closer the inconsistency index is to zero, the greater the consistency so the relevant index should be lower than 0.10 to accept the AHP results as consistent.

With standing to the fact that, such a procedure is common in mathematics, Expert Choice software was used in this study, which is a multi-objective decision support tool. Descending order of the calculated weights for the studied example according to subjective judgments of DM_x has been illustrated in Fig. 2. According to Eq. 4, an acceptable overall inconsistency index of 0.02 motivated the DM_x to accept final weighting result of the AHP method.

For the sake of simplicity, the above weighting result was accepted for the next calculations. But, it should be noted that, in a real situation, calculations of this phase must be performed by a team of DMs. There are different

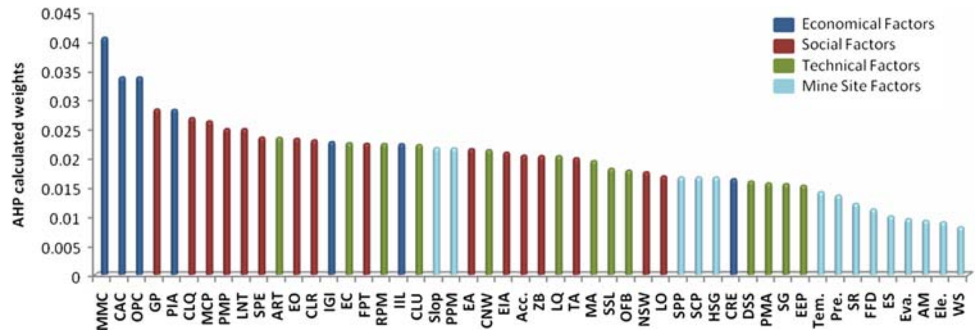


Fig. 2 Global weights of the evaluation attributes calculated using AHP method

ways for aggregation of individual judgments in AHP group decision making (Forman and Peniwati 1998, Escobar et al. 2004). Two methods, known to be most useful, are aggregation of individual judgments (AIJ) and aggregation of individual priorities (AIP). Owing to the fact that, in MLSA process the group decision has to be made as separate individual DMs, for this case, the AIJ is more suitable than the AIP (Forman and Peniwati 1998). Therefore, in this phase, the experts in the decision making team are given the task of forming individual pair-wise comparison matrix by using Saaty's nine-point scale. According to Eq. 5, weighted geometric mean of these judgments can be found to obtain the pair-wise comparison matrix on which there is a consensus.

$$a_{iz}^{g} = \prod_{x=1}^{X} \left(a_{iz}^{x}\right)^{w_x}. \tag{5}$$

In Eq. 5, a_{iz}^{g} refers to the group judgment on the relative importance of attributes i and z, a_{iz}^{x} refers to expert x's (DM_x) judgment on the relative importance of attributes i and z, w_x is the normalized weight of DM_x, and X is the number of DMs.

Normalization of the performance scores

Since the attributes are of benefit and cost types, a basic task in MADM is normalizing the decision matrix (Yoon and Hwang 1995). Thus, normalized rating for each element in the decision matrix **F** should be calculated. The normalized values r_{ji} can be calculated as:

$$\begin{cases} r_{ji} = \dfrac{f_{ij}}{\sqrt{\sum_{j=1}^{J} f_{ij}^2}}, \quad i = 1, \ldots, n;\ j = 1, \ldots, J, \\ \quad \text{for benefit attributes;} \\ r_{ji} = \dfrac{1/f_{ij}}{\sqrt{\sum_{j=1}^{J} \left(1/f_{ij}\right)^2}}, \quad i = 1, \ldots, n;\ j = 1, \ldots, J, \\ \quad \text{for cost attributes.} \end{cases} \tag{6}$$

The normalized decision matrix **R** can be written as Eq. 7:

$$\mathbf{R} = \begin{bmatrix} r_{11} & r_{12} & \ldots & r_{Jn} \\ r_{21} & r_{22} & \ldots & r_{Jn} \\ \vdots & \vdots & \ddots & \vdots \\ r_{J1} & r_{J2} & \ldots & r_{Jn} \end{bmatrix}, \quad i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, J. \tag{7}$$

Some normalized scores of the studied example obtained using Eq. 6, have been shown in Table 4 as a fragmented decision matrix.

Application of dominance rule on the normalized decision matrix

Dominance analysis narrows down the focus of the decision to the Pareto optimal set, which is the subset of alternatives consisting of those that are not dominated by other alternatives according to the evaluation attributes. The use of dominance analysis in choice-making is common in literature related to MADM (Naresh 2003); because it rationally should be verified if there is any dominated alternative among the possible solutions.

As stated by the dominance rule; alternative k dominates alternative l, if and only if k is at least as good as l in all the attributes, and there is at least one attribute, in which k is strictly better than l. In other words

$$(k \text{ dominates } l) \Leftrightarrow (r_{ik} \geq r_{il}) \wedge \exists z (r_{zk} > r_{zl}). \tag{8}$$

For the studied example, with reference to normalized decision matrix shown in Table 4 and also using Eq. 8 there has been no dominated alternative among the judged solutions by DM_x. As a result, the normalized values were confirmed for the next stages without decrease in the number of possible post mining land-uses.

Calculation of the deviation amplitudes

The amplitude of the deviations d_i between the evaluations of each alternative k and l within each attribute i is calculated as

Table 4 Normalized values in a fragmented decision matrix

	MMC	CAC	OPC	PIA	IGI	IIL	CRE	EIA	Tem.	HSG	SR	Slop	Ele.	ES	PPM
Farmland	0.1661	0.2313	0.3101	0.0518	0.3015	0.4015	0.3260	0.3449	0.2005	0.2675	0.0988	0.0926	0.2294	0.3106	0.0000
Pasture	0.0830	0.3470	0.4341	0.0518	0.3015	0.4015	0.2794	0.3449	0.3509	0.3121	0.3457	0.3243	0.3441	0.3106	0.1213
Nursery	0.2491	0.4048	0.3101	0.3111	0.2010	0.3513	0.0931	0.0493	0.4010	0.3121	0.3457	0.3706	0.3441	0.3106	0.2425
Forestry	0.0000	0.2892	0.1240	0.0000	0.3518	0.0000	0.3260	0.2463	0.3509	0.3567	0.3951	0.3706	0.3441	0.3106	0.1819
Lake or Pool	0.0000	0.4048	0.0000	0.3629	0.3518	0.0502	0.3260	0.2463	0.1003	0.1338	0.0988	0.3706	0.0574	0.2662	0.4244
Sport field	0.4983	0.1735	0.1861	0.3629	0.3518	0.3011	0.1863	0.0985	0.2005	0.3567	0.3951	0.3706	0.0000	0.3106	0.4244
Park	0.2491	0.2313	0.3101	0.3111	0.0000	0.0000	0.1863	0.1971	0.2506	0.3567	0.3951	0.3243	0.3441	0.3106	0.4244
Residential	0.1661	0.1157	0.1240	0.1555	0.1005	0.2509	0.3726	0.3449	0.1504	0.0000	0.0000	0.0000	0.2294	0.1775	0.0606
Commercial	0.3322	0.0578	0.4341	0.3629	0.3518	0.3513	0.3260	0.2956	0.2005	0.0892	0.0494	0.0926	0.2294	0.1775	0.1213
Industrial	0.5813	0.0578	0.0620	0.4148	0.4020	0.4015	0.2329	0.2956	0.3509	0.2675	0.1482	0.3243	0.3441	0.1775	0.4244
Educational	0.3322	0.1157	0.1240	0.1555	0.0503	0.2008	0.2794	0.3449	0.2005	0.3567	0.0494	0.0926	0.2294	0.1775	0.0606
Community	0.0830	0.0000	0.0000	0.1037	0.1508	0.2008	0.3726	0.3941	0.0000	0.0000	0.0494	0.0463	0.1721	0.3106	0.1213
Wildlife habitat	0.0000	0.2892	0.2481	0.4148	0.2513	0.1506	0.0931	0.1478	0.3509	0.3567	0.3951	0.3243	0.4015	0.3106	0.0606
Landfill	0.0000	0.4627	0.4341	0.0518	0.1508	0.1004	0.0000	0.0000	0.3008	0.0000	0.2963	0.0463	0.0574	0.1775	0.3638

$$d_i(k,l) = r_{ki} - r_{li} \quad k,l = 1,2,\ldots,J;\ i = 1,2,\ldots,n. \tag{9}$$

Therefore, the deviation amplitude matrix for an alternative j within n attributes can be written as:

$$\mathbf{D}_j = \begin{pmatrix} d_1(j,1) & d_2(j,1) & \ldots & d_n(j,1) \\ d_1(j,2) & d_2(j,2) & & d_n(j,2) \\ \vdots & & \ddots & \vdots \\ d_1(j,J) & d_2(j,J) & \cdots & d_n(j,J) \end{pmatrix}_{J\times n}, \quad j = 1,2,\ldots,J. \tag{10}$$

Table 5 shows fragmented deviation amplitudes matrix for the *Farmland* alternative within the attributes of the MLSA framework.

Indication of a generalized preference function

For each attribute i, a generalized preference function $P_i(d)$ is indicated. Brans et al. (1986) proposed four main types of preference functions (they presented two other types that can be derived from these ones), which cover most of the practical situations:

I. Quasi-attribute:

$$P_i(d) = \begin{cases} 0, & \text{if } d_i \le t; \\ 1, & \text{if } d_i > t. \end{cases} \tag{11}$$

II. Level attribute:

$$P_i(d) = \begin{cases} 0, & \text{if } d_i \le t; \\ 0.5, & \text{if } t < d_i \le q; \\ 1, & \text{if } d_i > q. \end{cases} \tag{12}$$

III. Linear attribute:

$$P_i(d) = \begin{cases} 0, & \text{if } d_i \le t; \\ (d_i - t)/(q - t), & \text{if } t < d_i \le q; \\ 1, & \text{if } d_i > q. \end{cases} \tag{13}$$

IV. Gaussian attribute:

$$P_i(d) = \begin{cases} 0, & \text{if } d_i \le 0; \\ 1 - \exp\left(-d_i^2/2\sigma^2\right) & \text{if } d_i > 0. \end{cases} \tag{14}$$

In Eqs 12 and 13, q is the lower bound of the strict preference interval, and in Eqs. 11–13, t is the upper bound of the indifference interval. In the case of the Gaussian attribute, σ is the distance between the origin and the inflexion point of the curve $P_i(d)$ (see Figs. 3, 4).

The Gaussian preference function was chosen to be used for all attributes in this study because this function has been proved to be the least sensitive to small variations of the PROMETHEE input values (Parreiras and Vasconcelos 2007).

In addition, because in this study, all the input values are qualitative and are varied natural numbers between 1 and 9 with a uniform distribution, deviations of the normalized values are also distributed uniformly. Thus, a reasonable way to find the threshold value σ_i is calculating arithmetic mean of the deviation amplitudes. The following formula is then proposed to find the threshold value σ_i for each attribute i, in such way that the inflexion point of the Gaussian curve lies on arithmetic mean of positive values of the deviation amplitudes:

$$\sigma_i = \frac{\sum_{\substack{k,l=1 \\ k\ne l}}^{k,l=J} |d_i(k,l)|}{J(J-1)}, \quad i = 1,2,\ldots,n;\ k,l = 1,2,\ldots,J. \tag{15}$$

Table 5 Deviation amplitude for normalized values of Farmland alternative in a fragmented decision matrix

	MMC	CAC	OPC	PIA	IGI	IIL	CRE	EIA	Tem.	HSG	SR	Slop	Ele.	ES	PPM
Farmland	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pasture	0.0830	−0.1157	−0.1240	0.0000	0.0000	0.0000	0.0401	0.0000	−0.1504	−0.0390	−0.2469	−0.2316	−0.1147	0.0000	−0.1213
Nursery	−0.0830	−0.1735	0.0000	−0.2223	0.0859	0.0432	0.2006	0.2531	−0.2005	−0.0390	−0.2469	−0.2779	−0.1147	0.0000	−0.2425
Forestry	0.1661	−0.0578	0.1861	0.0445	−0.0430	0.3452	0.0000	0.0844	−0.1504	−0.0779	−0.2963	−0.2779	−0.1147	0.0000	−0.1819
Lake or Pool	0.1661	−0.1735	0.3101	−0.2667	−0.0430	0.3021	0.0000	0.0844	0.1003	0.1169	0.0000	−0.2779	0.1721	0.0382	−0.4244
Sport field	−0.3322	0.0578	0.1240	−0.2667	−0.0430	0.0863	0.1204	0.2109	0.0000	−0.0779	−0.2963	−0.2779	0.2294	0.0000	−0.4244
Park	−0.0830	0.0000	0.0000	−0.2223	0.2577	0.3452	0.1204	0.1265	−0.0501	−0.0779	−0.2963	−0.2316	−0.1147	0.0000	−0.4244
Residential	0.0000	0.1157	0.1861	−0.0889	0.1718	0.1295	−0.0401	0.0000	0.0501	0.2337	0.0988	0.0926	0.0000	0.1145	−0.0606
Commercial	−0.1661	0.1735	−0.1240	−0.2667	−0.0430	0.0432	0.0000	0.0422	0.0000	0.1558	0.0494	0.0000	0.0000	0.1145	−0.1213
Industrial	−0.4152	0.1735	0.2481	−0.3112	−0.0859	0.0000	0.0803	0.0422	−0.1504	0.0000	−0.0494	−0.2316	−0.1147	0.1145	−0.4244
Educational	−0.1661	0.1157	0.1861	−0.0889	0.2148	0.1726	0.0401	0.0000	0.0000	−0.0779	0.0494	0.0000	0.0000	0.1145	−0.0606
Community	0.0830	0.2313	0.3101	−0.0445	0.1289	0.1726	−0.0401	−0.0422	0.2005	0.2337	0.0494	0.0463	0.0574	0.0000	−0.1213
Wildlife habitat	0.1661	−0.0578	0.0620	−0.3112	0.0430	0.2158	0.2006	0.1687	−0.1504	−0.0779	−0.2963	−0.2316	−0.1721	0.0000	−0.0606
Landfill	0.1661	−0.2313	−0.1240	0.0000	0.1289	0.2589	0.2809	0.2953	−0.1003	0.2337	−0.1975	0.0463	0.1721	0.1145	−0.3638

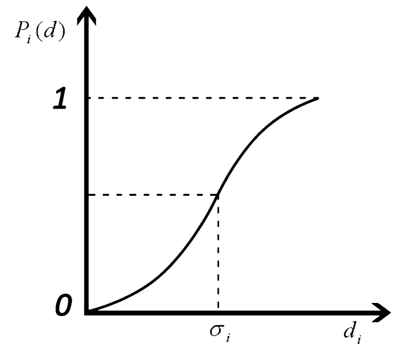


Fig. 3 Gaussian preference function

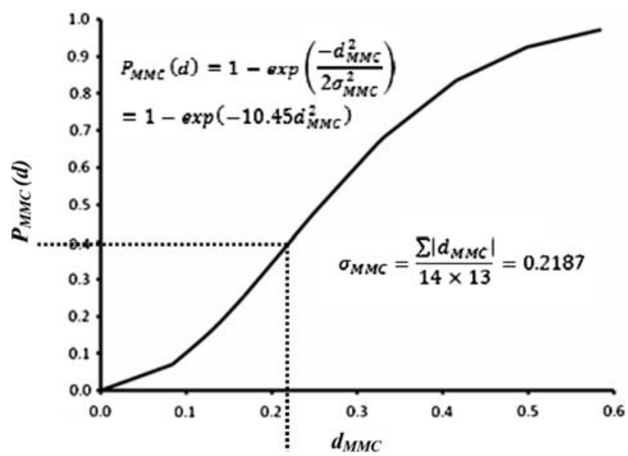


Fig. 4 Gaussian preference function of the MMC attribute

A schematic procedure for finding the threshold parameters σ of some attributes of the studied example, by using Eq. 15 has been shown in Table 6.

The diagram in Fig. 4 has also been illustrated to exemplify the proposed procedure. This figure shows the Gaussian preference function for the attribute MMC and the related calculations.

The preference function $P_i(k, l)$ for attribute i and alternatives k and l as a measure of the preference of a DM for alternative k as compared to alternative l can be defined as:

$$P_i(k,l) = \begin{cases} 0 & \text{if } r_{ki} \le r_{li} \Rightarrow d_i(k,l) \le 0; \\ p_i(d) & \text{if } r_{ki} > r_{li} \Rightarrow d_i(k,l) > 0. \end{cases} \quad (16)$$

The preference function is 0 if alternative k performs less well than alternative l according to attribute i, assumes a value between 0 and 1 if alternative k performs better than alternative l according to attribute i, and is closer to 1 the greater the preference of the DM for the disparity between the normalized attribute values r_{ki} and r_{li}.

Finally, according to Eq. 14 for an alternative j, the matrix of Gaussian preference function $P_j(d)$ can be defined as:

$$P_j(d) = \begin{pmatrix} 1-\exp\left(\frac{-d_1^2(j,1)}{2\sigma_1^2}\right) & 1-\exp\left(\frac{-d_2^2(j,1)}{2\sigma_2^2}\right) & \cdots & 1-\exp\left(\frac{-d_n^2(j,1)}{2\sigma_n^2}\right) \\ 1-\exp\left(\frac{-d_1^2(j,2)}{2\sigma_1^2}\right) & 1-\exp\left(\frac{-d_2^2(j,2)}{2\sigma_2^2}\right) & & 1-\exp\left(\frac{-d_n^2(j,2)}{2\sigma_n^2}\right) \\ \vdots & & \ddots & \vdots \\ 1-\exp\left(\frac{-d_1^2(j,J)}{2\sigma_1^2}\right) & 1-\exp\left(\frac{-d_2^2(j,J)}{2\sigma_2^2}\right) & \cdots & 1-\exp\left(\frac{-d_n^2(j,J)}{2\sigma_n^2}\right) \end{pmatrix}, \quad j = 1,2,\ldots,J. \tag{17}$$

Calculation of the preference indexes between alternatives

For all the alternatives $k,l \in J$ the preference index $\pi(k, l)$ is defined as:

$$\pi(k,l) = \sum_{i=1}^{n} w_i \cdot P_i(k,l). \tag{18}$$

$$\pi = \begin{pmatrix} 0 & \pi(1,2) & \ldots & \pi(1,J) \\ \pi(2,1) & 0 & \cdots & \pi(2,J) \\ \vdots & \vdots & \ddots & \vdots \\ \pi(J,1) & \pi(J,2) & \cdots & 0 \end{pmatrix}_{J\times J}. \tag{19}$$

This index is an intensity measurement of the total preference of the DM for an alternative k compared to an alternative l by taking into account all the attributes i simultaneously. The preference index matrix, given by Eq. 19, is calculated using Eq. 18. Table 7 shows the obtained matrix for all post-mining land-uses considered in the studied example.

These preference indexes are basically some weighted averages of the preference functions $P_i(d)$ and can be represented as a valued outranking graph as illustrated in Fig. 5.

Table 6 Procedure of calculating the threshold parameter σ

	MMC	CAC	OPC	PIA	Slop	Ele.	ES	PPM
$\|d(1,2)\|$	0.08305	0.11566	0.12403	0.00000	0.23162	0.11471	0.00000	0.12127
$\|d(1,3)\|$	0.08305	0.17349	0.00000	0.22228	0.27794	0.11471	0.00000	0.24254
$\|d(1,4)\|$	0.16609	0.05783	0.18605	0.04446	0.27794	0.11471	0.00000	0.18190
$\|d(12,13)\|$	0.08305	0.28916	0.24807	0.26673	0.27794	0.22942	0.00000	0.06063
$\|d(12,14)\|$	0.08305	0.46265	0.43412	0.04446	0.00000	0.11471	0.11454	0.24254
$\|d(13,14)\|$	0.00000	0.17349	0.18605	0.31119	0.27794	0.34412	0.11454	0.30317
Sum	39.36356	31.34467	32.99324	27.47345	30.20332	26.03869	10.46137	33.46992
σ	0.21869	0.17414	0.18330	0.15263	0.16780	0.14466	0.05812	0.18594

Table 7 Matrix of preference indexes for land-use alternatives

	A-F	A-P	A-N	F	L	IR-S	NIR-P	CT-R	CT-C	CT-I	CT-E	CT-S	CV-W	B
A-F	0.000	0.245	0.457	0.524	0.595	0.506	0.337	0.690	0.463	0.445	0.599	0.648	0.477	0.711
A-P	0.510	0.000	0.505	0.526	0.684	0.499	0.415	0.689	0.538	0.464	0.620	0.601	0.500	0.808
A-N	0.382	0.351	0.000	0.540	0.558	0.423	0.372	0.753	0.544	0.388	0.623	0.647	0.526	0.770
F	0.406	0.342	0.362	0.000	0.558	0.374	0.347	0.547	0.431	0.394	0.482	0.594	0.461	0.667
L	0.343	0.262	0.299	0.253	0.000	0.266	0.298	0.419	0.368	0.279	0.429	0.409	0.298	0.515
IR-S	0.434	0.423	0.427	0.491	0.496	0.000	0.395	0.691	0.523	0.383	0.587	0.690	0.450	0.754
NIR-P	0.484	0.353	0.429	0.442	0.566	0.385	0.000	0.711	0.492	0.347	0.570	0.647	0.441	0.724
CT-R	0.209	0.226	0.190	0.322	0.524	0.166	0.260	0.000	0.214	0.264	0.205	0.453	0.353	0.509
CT-C	0.399	0.294	0.362	0.448	0.484	0.268	0.384	0.601	0.000	0.270	0.390	0.606	0.511	0.677
CT-I	0.411	0.367	0.451	0.535	0.676	0.516	0.522	0.682	0.555	0.000	0.598	0.702	0.519	0.779
CT-E	0.277	0.246	0.299	0.326	0.498	0.213	0.293	0.357	0.282	0.321	0.000	0.515	0.437	0.614
CT-S	0.288	0.205	0.235	0.351	0.514	0.244	0.224	0.382	0.279	0.249	0.298	0.000	0.359	0.576
CV-W	0.423	0.346	0.424	0.251	0.544	0.392	0.358	0.557	0.434	0.406	0.477	0.554	0.000	0.667
B	0.245	0.130	0.199	0.259	0.322	0.178	0.214	0.329	0.171	0.104	0.269	0.312	0.270	0.000

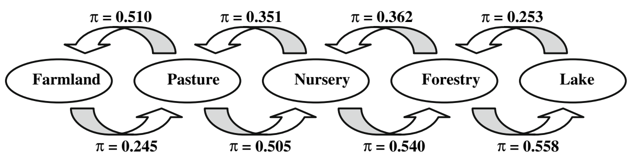


Fig. 5 Outranking graph of some land-uses of the given example based on the preference indexes

Calculation of the outgoing and entering flows

As a measure for strength of the alternatives j, the outgoing flow $\varphi_j{}^+$ is calculated according to Eq. 20

$$\varphi_j^+ = \frac{1}{J-1}\sum_{\substack{k=1\\k\neq j}}^{J} \pi(j,k)\ , \quad j,k = 1,2,\ldots,J. \tag{20}$$

The outgoing flow is the sum of the values of the arcs which leave node j and therefore yields a measure of the 'outranking character' of alternative j. The calculated outgoing flows φ_j^+ of the post-mining land-uses have been represented in Table 8.

Analogous to the outgoing flow φ_j^+, the entering flow φ_j^- which is a measure for the weakness of an alternative j, is calculated, measuring the 'outranked character' of alternative j:

$$\varphi_j^- = \frac{1}{J-1}\sum_{\substack{k=1\\k\neq j}}^{J} \pi(k,j)\ , \quad j,k = 1,2,\ldots,J. \tag{21}$$

Table 8 represents the entering flows φ_j^- of post-mining land-use alternatives for the studied example calculated using Eq. (21).

Deriving preference order of the alternatives

PROMETHEE I partial pre-order of the alternatives is illustrated within graphical evaluation of the outranking relations. Basically, in comparing two different alternatives, the higher the outgoing flow φ_j^+ and the lower the entering flow φ_j^-, the better the alternative; otherwise two alternatives are incomparable. In other words, an alternative k is preferred to alternative l when the following condition is satisfied:

$$\begin{array}{lll} \varphi_k^+ > \varphi_l^+ & \text{and} \quad \varphi_k^- < \varphi_l^- & \text{or,} \\ \varphi_k^+ > \varphi_l^+ & \text{and} \quad \varphi_k^- = \varphi_l^- & \text{or,} \\ \varphi_k^+ = \varphi_l^+ & \text{and} \quad \varphi_k^- < \varphi_l^- . & \end{array} \tag{22}$$

In the outranking graph, an arrow in direct or indirect form departs from alternative j to k, if j is preferred to k; and otherwise in case of incomparability between two alternatives j and k, no direct/indirect arrows are traced, showing that an alternative is preferred to the other (Fig. 6). As can be seen in the figure, there are five pairs of alternatives with incomparability relation for the studied example including: sport field-nursery; sport field-park; nursery-park; park-farmland; and wildlife habitat-commercial.

In case a complete pre-order is requested, PROMETHEE II yields the so-called net flows φ_j^{net} as the difference of the outgoing φ_j^+ and entering φ_j^- flows avoiding any incomparability:

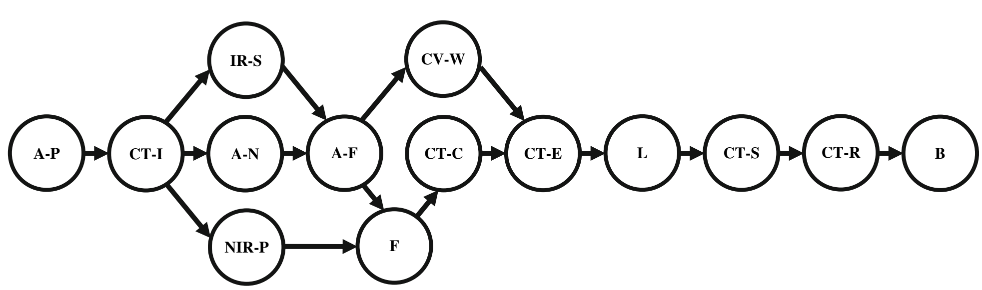
$$\varphi_j^{\text{net}} = \varphi_j^+ - \varphi_j^- . \tag{23}$$

The net flows φ_j^{net} of the alternatives in the studied example have been calculated according to Eq. 23 and represented in Table 8 accompanied by ranks of them.

Table 8 Outgoing, entering and net flows of the alternatives accompanied by their ranks

	A-F	A-P	A-N	F	L	IR-S	NIR-P	CT-R	CT-C	CT-I	CT-E	CT-S	CV-W	B
φ_j^+	0.515	0.566	0.529	0.459	0.341	0.519	0.507	0.300	0.438	0.563	0.360	0.323	0.449	0.231
φ_j^-	0.370	0.291	0.357	0.405	0.540	0.341	0.340	0.570	0.407	0.332	0.473	0.567	0.431	0.675
φ_j^{net}	0.145	0.275	0.172	0.054	−0.199	0.178	0.167	−0.270	0.031	0.231	−0.113	−0.244	0.018	−0.444
Ranks	6	1	4	7	11	3	5	13	8	2	10	12	9	14

Fig. 6 Outranking graph for PROMETHEE I partial pre-order of the alternatives



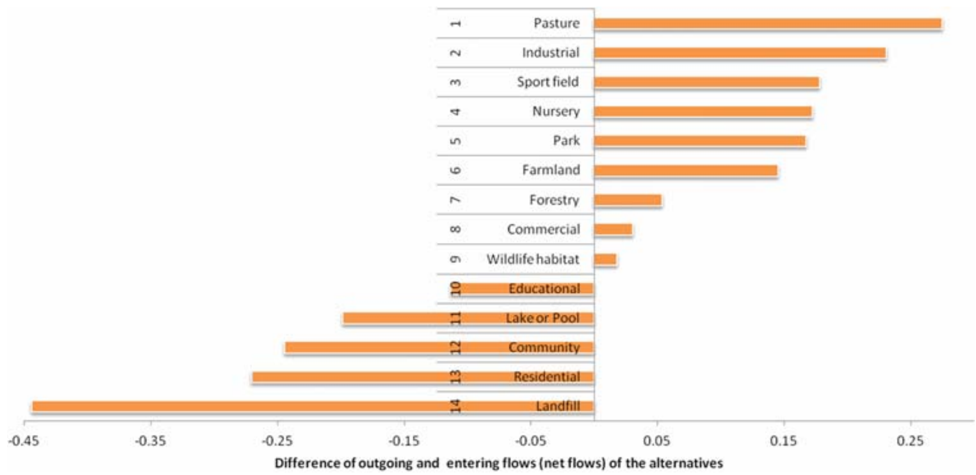


Fig. 7 Descending preference order of the alternatives according to PROMETHEE II complete preorder

Also, descending preference order of the land-uses is illustrated in Fig. 7.

In the outranking graph shown in Fig. 6, graphical visualization for 14 numbers of alternatives was not very complicated. However, some complexities may occur when the number of alternatives is more than usual. If this condition existed in a MLSA problem, using the ranking-distinctiveness (R-D) visualization tool introduced by Lewi and Hoof (1992) would be very meaningful.

Lewi and Hoof (1992) have argued that as the number of arrows in the non-metric outranking graph (Fig. 6) rapidly increases with the number of alternatives, it becomes difficult to interpret the graph, and also there will be no way of presenting connectivity of the alternatives in the graph. Therefore, Lewi and Hoof (1992) via combining concepts of Pareto optimality and PROMETHEE, proposed the R-D diagram which could show the information produced by both PROMETHEE I and II. In the metric bivariate diagram, the horizontal axis, R, is proportional to the net flow φ_j^{net}, while the vertical axis, D, is proportional to sum of the outgoing and entering flows. The two metric axes are calculated as follows:

$$\vec{R} = 50 + 50\left(\varphi_j^{+} - \varphi_j^{-}\right) = 50 + 50\varphi_j^{\text{net}}. \qquad (24)$$

$$\vec{D} = 100\left(\varphi_j^{+} + \varphi_j^{-}\right). \qquad (25)$$

In Eqs. 24 and 25, R is called the ranking of an alternative, and D represents its distinctiveness. The ranking, R, will produce a relative rank order of the alternatives which is equivalent to the ranking produced by PROMETHEE II and the distinctiveness, D, can determine how distinct an alternative is from all the others.

Global evaluation by a group of DMs

Macharis et al. (1998) developed a PROMETHEE GDSS procedure to provide decision aid to a group of DMs. In accordance with their proposed procedure, each of the four ($X = 4$) previously mentioned DMs will have a decision power given by a non-negative weight w_x where $\sum_{x=1}^{X} w_x = 1$. In the proposed procedure, after performing calculations of the preceding sections independently by each DM_x, the net flow vectors of each DM_x are collected by a facilitator and put in a ($X \times J$) decision matrix $\mathbf{F}'$ once again. Each element $\varphi^{\text{net}}(x, j)$ of this matrix expresses the viewpoint f'_{xj} of a particular DM_x. Each of the attributes x, has a weight w_x and an associated linear attribute preference function (Eq. 13; $t = 0$, $q = 2$). In the last step, the facilitator calculates the new deviation amplitudes $d_x(k, l)$, preference indexes $\pi'(k, l)$, and flows φ'_j so that, the PROMETHEE I and II consensual rankings are computed in a way precisely similar to the preceding sections.

Conclusions

The motivation for developing a decision aid MLSA framework was the necessity to have an analytical approach which possesses advantages such as:

(1) The participative stakeholder's preferences on different post-mining land-uses and also on assigned weights of the attributes is easily included.
(2) Analysis is through an algorithm comprehensible for all stakeholders.
(3) Analysis is by means of a mathematical procedure that can effectively take into account different and sometimes conflicting attributes in MLSA process and can yield a definitive result for DMs.

In this paper, the PROMETHEE method, in combination with AHP method applied on MLSA framework and satisfactorily produced the above desirable demands. The only ambiguous point in the applied technique was to indicate the most suitable preference function for all attributes. The

Gaussian attribute function (Fig. 3) was selected, expecting that, it is the least sensitive to variations of normalized scores. Being free of need to two distinct threshold parameters is another advantage of this function. Moreover, analysis by using other preference functions (Eqs. 11–13), which was performed in a separate study did not show much differences. The only difference in case of the studied example was small changes in the values of the final flows and therefore none of the other functions did not substantially change the obtained partial and complete ranking of the land-uses.

The authors suggested an equation (Eq. 15) to assume arithmetic mean of positive deviation amplitudes for threshold parameter of the Gaussian function. The net flows (Table 8; Fig. 7) of PROMETHEE II by avoiding any incomparability can lead to a complete ranking of the alternatives, from the best one (*Pasture* in the considered example) to the worst one (*Landfill* in the considered example). But the partial pre-order derived by PROMETHEE I may contain more realistic information through the indication of incomparabilities. With the help of the non-metric outranking graph (Fig. 6), some clusters of alternatives can be derived. It means a group of best (e.g. pasture, industrial, sport field, nursery, farmland, and park), worst (e.g. educational, lake, community, residential, and landfill), and mediocre (e.g. forestry, commercial, and wildlife habitat) post-mining land-uses can be identified for a considered mined land.

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