POST-MINING LAND-USE METHODS OPTIMUM RANKING, USING MULTI ATTRIBUTE DECISION TECHNIQUES WITH REGARD TO SUSTAINABLE RESOURCES MANAGEMENT

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Abstract: Developing of mining areas should comply with sustainable development principles so as to ensure sustainable development of mine, to unify social, economical and the ecological efficiency. The selection of reclamation method is a complex multi-person, multi-criteria decision problem while sustainable development challenges facing the minerals and metals industry need a comprehensive and interdisciplinary approach based upon reliable data and transparent methodical approaches. The aim of this study is to propose a combined Multi-Criteria Decision-Making approach (MCDM) to evaluate the post-mining land-use methods with the use of effective and major criteria in respect to the user's preference orders. In this paper, a Mined Land Suitability Analysis (MLSA) framework containing fifty numbers of leading evaluation attributes and also eight possible groups of post mining land uses for a mined land is used. This study utilizes entropy, weighted least square and AHP techniques to obtain the relative weights of attributes. Once the global weight vector of the attributes is calculated using these three methods, they are incorporated into the decision matrices and passed to the ranking techniques. SAW (Simple Additive Weighting), TOPSIS (Technique for Order Performance by Similarity to Ideal Solution) and Compromise Programing are used for ranking the alternatives. In other words the post-mining land-use methods ordered with nine ranking procedures. Due to specific approach of each of the above methods, and their advantages and disadvantages; the set of orders are not the same and for further aggregation, three ordering techniques employed to final ranking of the alternatives. Based on the statistical analysis two ranking methods excluded from nine procedures and average aggregated approach employed to rank the options. This procedure has been used for ordering the post-mining land use methods in a hypothetical mine. Accordingly construction of the mined land is the most appropriate method for the hypothetical mine in this article.

Keywords: AHP, entropy, post-mining land-use, statistical analysis, TOPSIS.

INTRODUCTION

To put mining operation in line with sustainable development throughout its life especial arrangements must be made. Mine-closure has adverse impacts on sustainability of a region. Decline in local and national economic can be named as one of the most significant impacts of mine-closure which may cause other problems like job loss and increases in migration. To prevent these unwanted impacts, a suitable reclamation plan must be utilized. An appropriate post-closure land-use will mitigate the adverse effects of mine-closure and improve the sustainability of surrounding area [1]. In general, mine site should be reclaimed so that the ultimate land-use and morphology of the site are compatible with either the current land-use in the surrounding area, or with the pre-mining environment. Adoption of most suitable post mining land use is a problem with multi-dimensional nature and there are so many factors in this problem which seriously influence on the decision judgments. Multi-Attribute Decision-Making (MADM) can be very useful for analysis of such issues [2]. Sometimes due to lack of knowledge and information, limited accuracy and ability of the decision makers and in conditions of uncertainty; cannot be confine to one method for quantification of qualitative criterion, weighting and scale down of attributes and ranking the alternatives. So survey of the various methods, the sensitivity analysis of each of the methods and using engineering judgments; is necessary for prioritization of the options. Accordingly this paper propose a combined multi criteria decision making approach to evaluate the post-mining land-use methods with the use of effective and major criteria in respect to the user's preference orders.

In this paper, a Mined Land Suitability Analysis (MLSA) framework containing fifty numbers of leading evaluation attributes and also eight possible groups of post mining land uses (agriculture, forestry, lake or pool, intensive recreation, non-intensive recreation, construction, conservation, and backfilling) for a mined land is used. In the mentioned MLSA framework, evaluation attributes is categorized into four criteria groups; economical, social, technical, and mine site factors. Each criteria group in turn extends to lower levels consisted of the fifty attributes in a protracted hierarchical structure. This framework has been devised to be used in combination with MADM methods [3, 4, and 5]. MADM is a technique employed to solve problems involving selection from among a finite number of alternatives. The aim of the MADM is to obtain the optimum alternative that has the highest degree of satisfaction for all of the relevant attributes. These techniques can assure sustainability of the total system and objectivity of the solution because they are based on mathematical methods [6].

Since the criteria of evaluation have diverse significance and meanings, we cannot assume that each evaluation criteria is of equal importance. There are many methods that can be employed to determine weights, such as the eigenvector method, weighted least-square method, entropy method, analytical hierarchy process (AHP), and linear programming techniques for multidimensional analysis of preference (LINMAP). The weights of attributes are subdivided into objective and subjective. Objective weights obtained by mathematical methods and subjective weights reflect subjective judgments of a person resulting in ranking of the alternatives of the particular problem. Later they acquire less rigorous values [7]. The selection of method depends on the nature of the problem. In this study; entropy, weighted least square method and AHP techniques used to obtain the relative weights of attributes.

Entropy works based on the decision matrix and as an objective method, whereas weighted least square and AHP follow a set of judgment-based pair-wise comparisons of attributes. Since in many engineering problems there is direct access to the values of the decision matrix, the first method can be commensurate.

Entropy is a general concept in statistical applications exposing unreliability/disorder of a set of data using a discrete probability analysis given a data distribution. Accordingly, it can accommodate many engineering experiments where the input data are obtained within reasonable errors. Weighted least square method as a subjective has the advantage that it involves the solution of a set of simultaneous linear algebraic equations and is thus conceptually easier to understand than the eigenvector method [7].

That is mainly because using the AHP, evaluation team can systematically compare and determine the global weights of the mined land attributes [8]. 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 [9].

One the global weight vector of the attributes is calculated using these three methods, they are incorporated into the decision matrices composed by stakeholders and passed to the ranking techniques. Three ranking techniques include TOPSIS (Technique for Order Performance by Similarity to Ideal Solution), SAW (Simple Additive Weighting) and Compromise programing used for ranking the post-mining land-use methods. SAW can be considered the most intuition and easy way to deal with Multiple Criteria Decision-Making (MCDM) problems, because the linear additive function can represent the preferences of Decision Makers (DM) [10].

TOPSIS was proposed by Hwang and Yoon (1981) to determine the best alternative based on the concepts of the compromise solution. The compromise solution can be regarded as choosing the solution with the shortest Euclidean distance from the ideal solution and the farthest Euclidean distance from the negative ideal solution [10].

In compromise programming, the best or satisfying solution is defined as one that minimizes the distance from the set of Pareto optima to the so-called "ideal solution". This ideal solution is defined as the solution that yields minimum (or maximum) values for all objectives. Such a solution does not exist, but is introduced in compromise programming as a target or a goal to get close to, although impossible to reach [10]. Due to the different conceptual assumptions of the methods, the set of orders is not the same. Thus for further aggregation, three ordering techniques, the average ranking procedure, Copeland and Borda were employed to final ranking of the alternatives. The average ranking procedure ranks alternatives according to their mean rankings, while the another technique is based on a voting concept. Thus, post-mining land-use methods with the thirteen combined

Table 1 : Possible alternative for post-mining land-uses

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

approach are prioritized and must be examined whether there are significant differences between the categories provided, or not? The answer to this question through statistical tests performed. For this purpose, since the data of this study are ordinal, Kendall`s tau-b and Spearman's correlation coefficient was used. Kendall`s tau-b correlation coefficient obtained from interaction between concordant and discordant pairs. Spearman correlation coefficient is defined as the Pearson correlation coefficient between the ranked variables [12]. Both of these tests calculated with SPSS software. The results of these tests show that between the results of three aggregated methods, there is a high correlation coefficient. Also correlation between the results of SAW methods, entropy-TOPSIS and aggregate methods is moderate to high. AHP-Compromise programming and entropy-compromise programming methods have no correlation with other methods. Given all the above points with removing AHP-Compromise programming and entropy-Compromise programming methods the average of remaining seven procedures can be calculated. Finally the results shown that construction is the most appropriate post-mining land-use for the hypothetical mine.

MATERIALS AND METHODS

The main criterion and possible alternatives in mine reclamation

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. Closer studies showed that in cases without mined-land suitability analysis (MLSA) process, sometimes obtained result are not acceptable. There are many well-reported instances failed due to lack of such an analytic process. 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. 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).

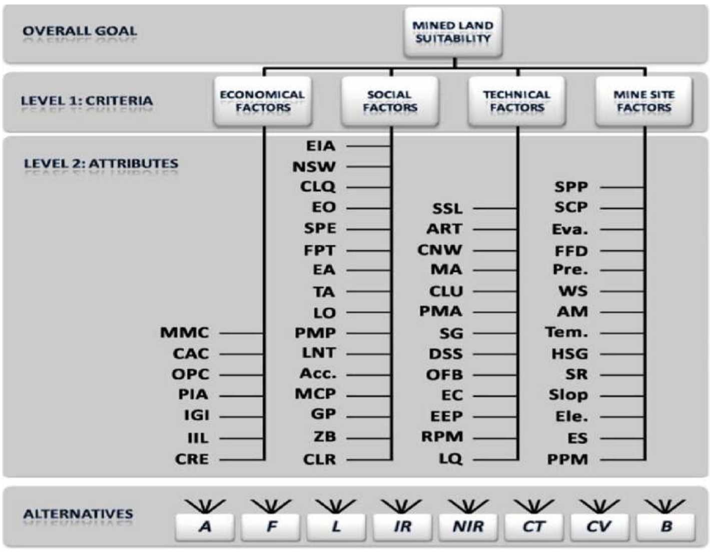

Figure. 1: Hierarchical structure of MLSA 50-attribute framework

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 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).

In this article, a relatively simple example of a typical mined land with hypothetical data and information is analyzed with the intention of illustrating the way of applying the proposed approach for mined land suitability analysis. In the considered example, pre-mining land-use of the mine site has been wildlife habitat, but mining activities have now severely damaged major portions of it. Mine is supposed to be located in the desert region with warm and dry weather. The original ecosystem is assumed to have been rich in native flora, and that some rare medicinal plants still exist in the area.

Methods of weighting the criteria

entropy weighting

Entropy weighting is a MADM method used to determine the importance weights of decision attributes by directly relating a criterion's importance weighting relative to the information transmitted by that criterion. For example, given a MADM decision matrix with column vector $x_j = (x_{1j}, x_{2j}, \ldots, x_{mj})$ that shows the contrast of all alternatives with respect to j^{th} attribute, an attribute has little importance when all alternatives have similar outcomes for that attribute. Moreover, if all alternatives are the same in relation to a specific attribute then that attribute should be eliminated because it transmits no information about decision-makers preferences. In contrast, the attribute that transmits the most information should have the greatest importance weighting. Mathematically this means that the projected outcomes of attribute j, P_{ij}, are defined as:

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{1}$$

The entropy E_j of the set of projected outcomes of attribute j is:

$$E_j = -\left(\frac{1}{\ln m}\right)\sum_{i=1}^{m} P_{ij} \ln P_{ij} \tag{2}$$

Where m is the number of alternatives and guarantees that E_j lies between zero and one. The degree of diversification d_j of the information provided by outcomes of attribute j can be defined as d_j = 1 - E_j. Hence, the entropy weighting of an attribute is calculated as follows:

$$W_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \tag{3}$$

Whereas entropy weighting provides a dynamic and objective assessment of a decision maker's attribute preference relative to the decision-making process, a priori weighting methods such as the AHP deceptively determine attribute importance statically and independently of the decision-making process [10].

Table 2: Attribute weights based on entropy method

attribute	CAC	OPC	MMC	PIA	IGI	IIL	CRE	EIA	NSW	CLQ
w_j	0.0155	0.0145	0.0145	0.0169	0.0166	0.0162	0.0168	0.0209	0.0211	0.0208
attribute	EO	SPE	EA	TA	LO	PMP	LNT	Acc.	MCP	GP
w_j	0.0211	0.0166	0.0175	0.0168	0.0235	0.0134	0.0134	0.0206	0.0235	0.0235
attribute	CLR	ZB	SSL	ART	CNW	MA	CLU	SG	DSS	PMA
w_j	0.0175	0.0235	0.0174	0.0158	0.0202	0.0149	0.0173	0.0259	0.0211	0.0171
attribute	OFB	EC	RPM	LQ	EEP	SPP	SCP	Eva	FFD	Pre
w_j	0.0174	0.0157	0.0118	0.0214	0.0192	0.0110	0.0110	0.0113	0.0113	0.0110
attribute	WS	Tem	HSG	SR	Slop	Ele.	ES	PPM	AM	
w_j	0.0117	0.0115	0.0083	0.0078	0.0095	0.0078	0.0142	0.0194	0.0124	

Weighted least square method

Suppose the DM gives his/her pairwise comparison matrix D = $[d_{kj}]$ on the attribute set *R* according to certain rules, for example, with elements of matrix D satisfying

$$d_{kj} > 0, \quad d_{kj} = \frac{1}{d_{kj}}, \quad d_{kk} = 1, \quad k, j = 1, 2, \ldots, n \tag{4}$$

Where d_{kj} denotes the relative weight of the attribute R_k with respect to the attribute R_j where:

$$w_j \in G = \left\{ w_j \geq 0, j = 1, 2, \ldots, n; \sum_{j=1}^{n} w_j = 1 \right\} \tag{5}$$

As a subjective approach, the weights w_j (j = 1,2,…,n) are obtained by solving the following model (6), which is the Weighted Least Square Method given by Chu et al. (1979) [10].

Minimize $z_1 = \sum_{k=1}^{n}\sum_{j=1}^{n}\left(d_{kj}\, w_j - w_k\right)^2$

s.t. $\sum_{j=1}^{n} w_j = 1$ (6)

$w_j \geq 0, \quad j = 1, 2, \dots, n$

Table 3: Attribute weights based on weighted least square method

attribute	CAC	OPC	MMC	PIA	IGI	IIL	CRE	EIA	NSW	CLQ
w_j	0.0911	0.0478	0.0129	0.0359	0.0331	0.0187	0.0188	0.0120	0.0172	0.0181
attribute	EO	SPE	EA	TA	LO	PMP	LNT	Acc.	MCP	GP
w_j	0.0207	0.0132	0.0369	0.0102	0.0084	0.0065	0.0064	0.0093	0.0097	0.0167
attribute	CLR	ZB	SSL	ART	CNW	MA	CLU	SG	DSS	PMA
w_j	0.0102	0.0088	0.0065	0.0239	0.0205	0.0276	0.0056	0.0081	0.0056	0.0057
attribute	OFB	EC	RPM	LQ	EEP	SPP	SCP	Eva	FFD	Pre
w_j	0.0160	0.1267	0.0046	0.0061	0.0118	0.0219	0.0216	0.0198	0.0166	0.0204
attribute	WS	Tem	HSG	SR	Slop	Ele.	ES	PPM	AM	
w_j	0.0164	0.0204	0.0205	0.0183	0.0180	0.0178	0.0194	0.0168	0.0208	

Table 4: Scale for pair-wise comparisons.

Numerical assessment	Linguistic meaning
1	Equal important
3	Moderately more important
5	Strongly more important
7	Very strongly important
9	Extremely more important
2, 4, 6, 8	Intermediate values of importance

Table 5: Attribute weights based on weighted least square method

attribute	CAC	OPC	MMC	PIA	IGI	IIL	CRE	EIA	NSW	CLQ
w_j	0.124	0.074	0.007	0.021	0.024	0.011	0.01	0.002	0.003	0.005
attribute	EO	SPE	EA	TA	LO	PMP	LNT	Acc.	MCP	GP
w_j	0.009	0.004	0.007	0.003	0.002	0.002	0.003	0.004	0.006	0.014
attribute	CLR	ZB	SSL	ART	CNW	MA	CLU	SG	DSS	PMA
w_j	0.005	0.003	0.02	0.072	0.068	0.032	0.008	0.024	0.021	0.009
attribute	OFB	EC	RPM	LQ	EEP	SPP	SCP	Eva	FFD	Pre
w_j	0.019	0.055	0.008	0.013	0.022	0.041	0.039	0.022	0.008	0.026
attribute	WS	Tem	HSG	SR	Slop	Ele.	ES	PPM	AM	
w_j	0.008	0.023	0.029	0.015	0.012	0.011	0.019	0.007	0.025	

Weighting with AHP

This method has been developed by Saaty (1990) and Saaty and Vargas (1994). The AHP structures the decision problem in levels which correspond to one understands of the situation: goals, criteria, sub-criteria and alternatives. By breaking the problem into levels, the DM can focus on smaller sets of decisions. In AHP technique the elements of each level compared to its related element in upper level inform by pair-wise comparison method. It must be noted that, in pair comparison of criterion if the priority of element i compared to element j is equal to w_{ij} then the priority of element j compared to element i is equal to 1/w_{ij}. The priority of element compared to it is equal to one. AHP method is applied in this research for criteria weighting. So, at first, set up n criteria in the rows and columns of n $\times$ n matrix. Then, Perform pair-wise comparisons of all the criteria according to the goal. The fundamental scale used for this purpose is shown in Table 1. Use average over normalized columns to estimate the Eigen values of the matrix. The redundancy of the pairwise comparisons (Table 2) makes the AHP much less sensitive to judgment errors; it also lets one measure judgment errors by calculating the consistency index of the comparison matrix, and then calculating the consistency ratio. 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.

Ordering procedures

SAW method

The SAW method is the simplest MADM method to handle cardinal data (Hwang et al. 1981). Since it is easy to use and easily understood by the decision maker, this method is widely used in many fields. First lineal' transformation is applied which normalizes the impact matrix. For each alternative, a utility value Ui is determined by multiplying the normalized impact value of each alternative by its importance weight. Then summation is taken of these products. Mathematically, the utility function can be written as:

$$u_i(x) = \sum_{j=1}^{n} w_j r_{ij}(x) \tag{9}$$

Where w_i is importance weight of the attributes and r_{ij} is the normalized impact matrix. After the utility values are computed for each attribute, the alternative with the highest score (the highest weighted average) is the most preferable one for the decision maker. The underlying assumption of the SAW method is that attributes are preferentially independent. Therefore, the importance weight of one attribute is not influenced in any way by the weight of another attribute. Simplicity and ease of use are the main advantages of this method, however, a few disadvantages of using SWA can easily be found. Since complementarily often exists among attributes, the assumption of preferentially independence may be unacceptable, and ignoring the dependence among attributes may cause a misleading result (Hwang et al. 1992) [10].

TOPSIS method

Hwang and Yoon (1981) developed the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method based on the concept that the chosen alternatives should have the shortest distance from the positive ideal solution and the longest distance from the negative ideal solution. Descriptions of the fundamentals of TOPSIS method and related applications can be readily found (Hwang and Yoon, 1981). The procedure of determining utility value for each alternative using TOPSIS is shown as follows: (1) First, the impact matrix needs to be normalized so as to render the attributes into dimensionless values environment for inter-attribute comparison. (2) A set of weights is selected to form a weighted normalized impact matrix of v_{ij}. (3) After v_{ij} is calculated, ideal solution A* and negative-ideal solution A need to be defined. (4) Once the ideal and negative-ideal solutions are computed, the utility value Uj of each alternative j, which is defined as the relative closeness to the ideal solution (Hwang et al. 1981), can be calculated.

Finally, the alternatives can be ranked according to Uj in descending order and the one with maximum utility value is the most preferable solution. Similar to the advantages of using the SWA method, TOPSIS is a simple and an easily comprehensible method for the decision maker [10].

Compromise programming method

In compromise programming, the best or satisfying solution is defined as one that minimizes the distance from the set of Pareto optima to the so-called ideal solution. This ideal solution is defined as the solution that yields minimum (or maximum) values for all objectives. Such a solution does not exist, but is introduced in compromise programming as a target or a goal to get close to, although impossible to reach. The criterion used in compromise programming is the minimization of the normalized deviation from the ideal solution f^* measured by the family of L_p metrics defined as follows:

Min

$$L_p(x) = \min_{x \in \Omega} \left[\sum_{i=1}^{m} \left| \frac{f_i(x) - \min f_i(x)}{\max f_i(x) - \min f_i(x)} \right|^p \right]^{1/p} \tag{10}$$

This family of L_p metrics indicates how close the satisficing solution is to the ideal solution, which for p= 2, and p= 2 define the *Euclidean distance* and the maximum distance, respectively [10].

Aggregate methods

For further aggregation, two ordering techniques, the average ranking procedure and the Copeland, were employed to final ranking of the alternatives. The average ranking procedure ranks alternatives according to their mean rankings, while the another technique is based on a voting concept [11].

Average Ranking Procedure

The average ranking procedure is the simplest technique among the three aggregation methods. This technique is based on the concept of statistical calculation and ranks the alternatives according to the average rankings from the MADM methods. First the rank position of each alterative is taken as its index value. After that, the average index numbers are calculated and the average index value for each alterative is determined in the last [11].

Copeland method

The Copeland method is based on a voting concept. This method is an extension of the Borda method. It is believed that the aggregation utility of A_j does not only depend on the number of "wins", but the number of "losses" also needs to be taken into account. The number of losses, denoted as S'j, is used to compensate the utility value of Sj. S'j is calculated by summing the values of each column of the matrix. The aggregation utility is simply defined as the difference of Sj from S'j [11].Ranking of the possible post-mining land-use methods based on each of the methods shown in table 6.

Table 6: Ranking of the methods based on each of the procedures

weighting methods	entropy	Weighted least square method	ahp	entropy	Weighted least square method	ahp	entropy	Weighted least square method	ahp	aggregate methods		
ranking methods	TOPSIS			CP			SAW			Average Ranking Procedure	copeland	borda
A-F	10	8	13	1	2	9	4	4	4	6	1	3
A-G	16	14	11	3	3	6	13	12	12	15	6	9
A-P	9	4	6	3	2	3	10	9	8	9	4	6
A-N	17	11	15	3	8	13	14	14	11	18	11	13
F-L	18	7	12	3	6	12	16	15	15	17	9	11
F-W	15	5	8	3	3	5	15	17	16	15	6	8
F-S	8	2	4	3	1	4	6	8	7	7	3	5
L-A	14	10	10	3	8	14	19	19	19	19	11	13
L-S	12	9	9	3	8	15	18	18	18	18	10	12
L-W	13	6	5	3	6	10	20	20	20	17	9	11
IR-S	7	15	16	3	8	16	5	6	6	14	5	7
IR-H	4	1	3	3	4	7	6	10	9	8	2	4
NIR-P	19	12	14	3	7	11	12	13	13	17	7	9
NIR-M	5	13	7	3	5	8	7	7	10	11	5	6
CT-R	6	19	19	3	8	18	7	5	5	15	4	6
CT-C	2	17	18	3	8	19	2	2	2	12	1	2
CT-I	3	20	20	3	8	20	1	1	1	13	3	6
CT-E	1	18	17	3	8	17	3	3	3	12	1	1
CV-W	11	3	1	3	1	2	11	11	14	10	1	1
B	20	16	2	2	8	1	17	16	17	17	8	10

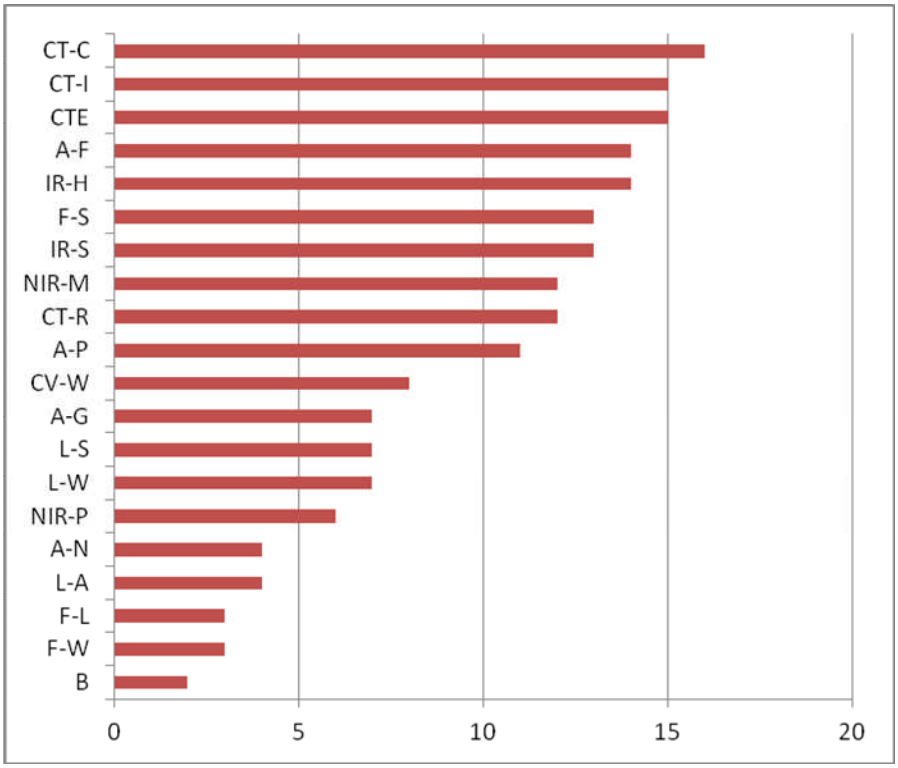

Figure 3: Final ranking of the post-mining land-use options with average ranking method

RESULTS AND DISCUSSION

In statistics, the Kendall rank correlation coefficient, commonly referred to as Kendall's tau (τ) coefficient, is a statistic used to measure the association between two measured quantities. A tau test is a non-parametric hypothesis test which uses the coefficient to test for statistical dependence. Specifically, it is a measure of rank correlation: that is, the similarity of the orderings of the data when ranked by each of the quantities.

The denominator is the total number of pairs, so the coefficient must be in the range $-1 \leq \tau \leq 1$. (1) If the agreement between the two rankings is perfect (i.e., the two rankings are the same) the coefficient has value 1. (2) If the disagreement between the two rankings is perfect (i.e., one ranking is the reverse of the other) the coefficient has value −1. (3) If X and Y are independent, then we would expect the coefficient to be approximately zero.

The Spearman correlation coefficient is defined as the Pearson correlation coefficient between the ranked variables and is a non-parametric measure of statistical dependence between two variables. It assesses how well the relationship between two variables can be described using a monotonic function The sign of the Spearman correlation indicates the direction of association between X (the independent variable) and Y (the dependent variable). If Y tends to increase when X increases, the Spearman correlation coefficient is positive. If *Y* tends to decrease when *X* increases, the Spearman correlation coefficient is negative. A Spearman correlation of zero indicates that there is no tendency for *Y* to either increase or decrease when *X* increases [12].

The results of Kendall`s tau-b and Spearman's correlation coefficient shown in table 7 and 8 respectively. These results using SPSS software and with paired comparison of results of 13 ranking method used in this article obtained. According to Table 7 and 8 can be said: (1) The results of entropy- TOPSIS method, SAW and aggregate methods have moderate to high correlation coefficient. In other words, when possible reclamation methods ranked with TOPSIS provided that attribute weights calculated with entropy procedure; ratings obtained for each of the post-mining land-use methods with SAW is as the same as and is independent of weighting method. (2) When attribute weights calculated with AHP or weighted least square method, the results of rating with TOPSIS and Compromise programming are almost identical and have high correlation. Thus we can conclude: (a) obtained weights from AHP and weighted least square method are almost the same (closeness of two weighting method). (b) results from

Table 7: Kendall's tau-b correlation coefficient

Correlations				enttop	sqrtop	ahptop	entcp	sqrcp	ahpcp	entsaw	sqrsaw	ahpsaw	mean	kopland	borda
Kendall's tau_b	entropy-TOPSIS	enttop	Correlation Coefficient	1.000	-.074	-.147	-.203	-.036	-.305	.582**	.558**	.526**	.407*	.522**	.519**
			Sig. (2-tailed)	.	.650	.364	.285	.837	.060	.000	.001	.001	.014	.002	.002
			N	20	20	20	20	20	20	20	20	20	20	20	20
	Weighted least square method-TOPSIS	sqrtop	Correlation Coefficient	-.074	1.000	.632**	-.060	.592**	.495**	-.222	-.326*	-.295	.157	-.022	.011
			Sig. (2-tailed)	.650	.	.000	.753	.001	.002	.173	.044	.069	.343	.896	.948
			N	20	20	20	20	20	20	20	20	20	20	20	20
	AHP-TOPSIS	ahptop	Correlation Coefficient	-.147	.632**	1.000	.131	.486**	.716**	-.339*	-.400*	-.432**	.103	-.022	.011
			Sig. (2-tailed)	.364	.000	.	.489	.005	.000	.038	.014	.008	.535	.896	.948
			N	20	20	20	20	20	20	20	20	20	20	20	20
	entropy-compromise programming	entcp	Correlation Coefficient	-.203	-.060	.131	1.000	.054	.250	.012	.036	.012	.123	.099	.061
			Sig. (2-tailed)	.285	.753	.489	.	.792	.187	.950	.850	.950	.527	.613	.752
			N	20	20	20	20	20	20	20	20	20	20	20	20
	Weighted least square method-compromise programming	sqrcp	Correlation Coefficient	-.036	.592**	.486**	.054	1.000	.687**	.036	-.012	-.024	.482**	.294	.310
			Sig. (2-tailed)	.837	.001	.005	.792	.	.000	.837	.945	.891	.006	.098	.079
			N	20	20	20	20	20	20	20	20	20	20	20	20
	AHP-compromise programming	ahpcp	Correlation Coefficient	-.305	.495**	.716**	.250	.687**	1.000	-.254	-.284	-.316	.179	.022	.054
			Sig. (2-tailed)	.060	.002	.000	.187	.000	.	.119	.080	.052	.281	.896	.744
			N	20	20	20	20	20	20	20	20	20	20	20	20
	entropy-SAW	entsaw	Correlation Coefficient	.582**	-.222	-.339*	.012	.036	-.254	1.000	.899**	.868**	.561**	.678**	.647**
			Sig. (2-tailed)	.000	.173	.038	.950	.837	.119	.	.000	.000	.001	.000	.000
			N	20	20	20	20	20	20	20	20	20	20	20	20
	Weighted least square method-SAW	sqrsaw	Correlation Coefficient	.558**	-.326*	-.400*	.036	-.012	-.284	.899**	1.000	.905**	.483**	.620**	.573**
			Sig. (2-tailed)	.001	.044	.014	.850	.945	.080	.000	.	.000	.004	.000	.001
			N	20	20	20	20	20	20	20	20	20	20	20	20
	AHP-SAW	ahpsaw	Correlation Coefficient	.526**	-.295	-.432**	.012	-.024	-.316	.868**	.905**	1.000	.472**	.609**	.552**
			Sig. (2-tailed)	.001	.069	.008	.950	.891	.052	.000	.000	.	.004	.000	.001
			N	20	20	20	20	20	20	20	20	20	20	20	20
	Average Ranking Procedure	mean	Correlation Coefficient	.407*	.157	.103	.123	.482**	.179	.561**	.483**	.472**	1.000	.773**	.769**
			Sig. (2-tailed)	.014	.343	.535	.527	.006	.281	.001	.004	.004	.	.000	.000
			N	20	20	20	20	20	20	20	20	20	20	20	20
	kopland method	kopland	Correlation Coefficient	.522**	-.022	-.022	.099	.294	.022	.678**	.620**	.609**	.773**	1.000	.961**
			Sig. (2-tailed)	.002	.896	.896	.613	.098	.896	.000	.000	.000	.000	.	.000
			N	20	20	20	20	20	20	20	20	20	20	20	20
	borda method	borda	Correlation Coefficient	.519**	.011	.011	.061	.310	.054	.647**	.573**	.552**	.769**	.961**	1.000
			Sig. (2-tailed)	.002	.948	.948	.752	.079	.744	.000	.001	.001	.000	.000	.
			N	20	20	20	20	20	20	20	20	20	20	20	20

Table 8: Spearman's correlation coefficient

correlations

				enttop	sqrtop	ahptop	entcp	sqrcp	ahpcp	entsaw	sqrsaw	ahpsaw	mean	kopland	borda
Spearman's rho	entropy-TOPSIS	enttop	Correlation Coefficient	1.000	-.232	-.310	-.245	-.088	-.433	.800**	.785**	.756**	.634**	.735**	.732**
			Sig. (2-tailed)	.	.326	.184	.297	.711	.056	.000	.000	.000	.003	.000	.000
			N	20	20	20	20	20	20	20	20	20	20	20	20
	Weighted least square method-TOPSIS	sqrtop	Correlation Coefficient	-.232	1.000	.744**	-.075	.751**	.653**	-.323	-.448*	-.420	.262	-.032	.007
			Sig. (2-tailed)	.326	.	.000	.753	.000	.002	.165	.048	.066	.265	.894	.977
			N	20	20	20	20	20	20	20	20	20	20	20	20
	AHP-TOPSIS	ahptop	Correlation Coefficient	-.310	.744**	1.000	.157	.603**	.872**	-.466*	-.534*	-.594**	.166	-.097	-.033
			Sig. (2-tailed)	.184	.000	.	.508	.005	.000	.038	.015	.006	.483	.685	.892
			N	20	20	20	20	20	20	20	20	20	20	20	20
	entropy-compromise programming	entcp	Correlation Coefficient	-.245	-.075	.157	1.000	.064	.306	.019	.046	.019	.152	.120	.074
			Sig. (2-tailed)	.297	.753	.508	.	.787	.190	.937	.847	.937	.523	.615	.757
			N	20	20	20	20	20	20	20	20	20	20	20	20
	Weighted least square method-compromise programming	sqrcp	Correlation Coefficient	-.088	.751**	.603**	.064	1.000	.754**	.019	-.041	-.074	.612**	.335	.361
			Sig. (2-tailed)	.711	.000	.005	.787	.	.000	.938	.864	.756	.004	.148	.118
			N	20	20	20	20	20	20	20	20	20	20	20	20
	AHP-compromise programming	ahpcp	Correlation Coefficient	-.433	.653**	.872**	.306	.754**	1.000	-.336	-.380	-.421	.281	.000	.048
			Sig. (2-tailed)	.056	.002	.000	.190	.000	.	.147	.098	.064	.229	1.000	.840
			N	20	20	20	20	20	20	20	20	20	20	20	20
	entropy-SAW	entsaw	Correlation Coefficient	.800**	-.323	-.466*	.019	.019	-.336	1.000	.971**	.964**	.744**	.847**	.812**
			Sig. (2-tailed)	.000	.165	.038	.937	.938	.147	.	.000	.000	.000	.000	.000
			N	20	20	20	20	20	20	20	20	20	20	20	20
	Weighted least square method-SAW	sqrsaw	Correlation Coefficient	.785**	-.448*	-.534*	.046	-.041	-.380	.971**	1.000	.976**	.691**	.815**	.779**
			Sig. (2-tailed)	.000	.048	.015	.847	.864	.098	.000	.	.000	.001	.000	.000
			N	20	20	20	20	20	20	20	20	20	20	20	20
	AHP-SAW	ahpsaw	Correlation Coefficient	.756**	-.420	-.594**	.019	-.074	-.421	.964**	.976**	1.000	.648**	.759**	.711**
			Sig. (2-tailed)	.000	.066	.006	.937	.756	.064	.000	.000	.	.002	.000	.000
			N	20	20	20	20	20	20	20	20	20	20	20	20
	Average Ranking Procedure	mean	Correlation Coefficient	.634**	.262	.166	.152	.612**	.281	.744**	.691**	.648**	1.000	.887**	.888**
			Sig. (2-tailed)	.003	.265	.483	.523	.004	.229	.000	.001	.002	.	.000	.000
			N	20	20	20	20	20	20	20	20	20	20	20	20
	kopland method	kopland	Correlation Coefficient	.735**	-.032	-.097	.120	.335	.000	.847**	.815**	.759**	.887**	1.000	.989**
			Sig. (2-tailed)	.000	.894	.685	.615	.148	1.000	.000	.000	.000	.000	.	.000
			N	20	20	20	20	20	20	20	20	20	20	20	20
	borda method	borda	Correlation Coefficient	.732**	.007	-.033	.074	.361	.048	.812**	.779**	.711**	.888**	.989**	1.000
			Sig. (2-tailed)	.000	.977	.892	.757	.118	.840	.000	.000	.000	.000	.000	.
			N	20	20	20	20	20	20	20	20	20	20	20	20

two ranking methods named except for the entropy weighting are the same (closeness of two ranking procedure). (c) The results of SAW method have high correlation with aggregate methods and no matter what method of weighting procedure to be determined, namely this procedure is less affected by the method of weighting. (d) In each of the ranking procedures, due to closeness of AHP and weighted least square weights, the results of these methods have high correlation. (e) AHP-Compromise programming and entropy-Compromise programming methods have no correlation with other methods.

Given all the above points with removing AHP-Compromise programming and entropy-Compromise programming methods the average of remaining 7 procedures can be calculated. Final ranking of the possible post-mining land-use for hypothetical mine can be seen in figure 3. As can be seen in figure construction is the most appropriate post-mining land-use for hypothetical mine in this article.

CONCLUSION

Mining can provide an economic basis for sustainable development and a foundation for basic infrastructure for future development. Sustainable development is about economic activity in an environmental, technical and social context. The selection of reclamation method is a complex multi-person, multi-criteria decision problem while sustainable development challenges facing the minerals and metals industry need a comprehensive and interdisciplinary approach based upon reliable data and transparent methodical approaches. In this paper, a mined land suitability analysis (MLSA) framework containing fifty numbers of leading evaluation attributes and also eight possible groups of post mining land uses for a mined land is provided. This framework has been devised to be used in combination with Multi-Attribute Decision-Making (MADM) methods. This study utilized entropy, weighted least square method and AHP techniques to obtain the relative weights of attributes. SAW, TOPSIS, compromise programing and three aggregate method used for ranking the alternatives. Based on the results of statistical analysis two methods were excluded and finally the average of seven methods shown that construction is the most appropriate post-mining land-use for the hypothetical mine.

REFERENCE

[1] Abdi Oskouei, M., Osanloo, M., (2011). The effect of mine reclamation program implementation on sustainability of region. Fifth International Conference Sustainable Development in the Minerals Industry (SDIMI), Aachen, Germany, pp. 549-557.

[2] Bascetin, A., (2007). A decision support system using analytical hierarchy process (AHP) for the optimal environmental reclamation of an open-pit mine. Environmental Geology, 52, 663–672.

[3] Soltanmohammadi, H., Osanloo M., Aghajani Bazzazi, A., (2008). Achieving to some outranking relationships between post mining land uses through mined land suitability analysis. Int. J. Environ. Sci. Tech., 5 (4), 535-546.

[4] Soltanmohammadi, H., Osanloo M., Aghajani Bazzazi, A., (2009). Deriving preference order of post-mining land-uses through MLSA framework: application of an outranking technique. Environmental Geology, 58, 877–888.

[5] Soltanmohammadi, H., Osanloo M., Aghajani Bazzazi, A., (2010). Analytical approach with a reliable logic and a ranking policy for post-minig land-use determination., Land use policy 27, 324-337.

[6] Adam, F., Humphreys, P., (2008). Encyclopedia of Decision Making and Decision Support Technologies. United States of America: Information Science Reference.

[7] Ustinovichius, L., (2007). Methods of determining objective, subjective and integrated weights of attributes. Int. J. Management and Decision Making, 8, 540-554.

[8] Saaty, T.L., Vargas, L.G., (1994). Decision Making in Economic, Political, Social, and Technological Environments with the Analytic Hierarchy Process. Pittsburgh, RWS Publications.

[9] Eddie, W. L.; Heng, L.; Danny, C. K., (2002). Analytical hierarchy process (AHP); A defective tool when used improperly, Meas. Bus. Excellence, 6 (4), 33-37.

[10] Tzeng, G.H. Huang, J.J., (2011). Multiple Attribute Decision Making methods and Applications. United States of America: CRC Press, Taylor & Francis Group.

[11] Jin, L., (2005). A Fuzzy Multi-Criteria Decision Analysis fors Assessing Technologies of Air Pollution Abatement at Coal-Fired Power Plants. Submitted to the Faculty of Engineering in partial fulfillment of the Requirements for the Degree of Master of Engineering in Environment Systems Engineering University of Regina.

[12] Kruskal, W.H. (1958). "Ordinal Measures of Association". Journal of the American Statistical Association 53 (284): 814–861. doi:10.2307/2281954. MR100941 JSTOR 2281954.