International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-9 Issue-1, October, 2019

Optimal Extraction Methods Selection for Kakosa South Copper Ore Deposit Applying Modified Technique for Order of Preference by Similarity to Idea Solution Model

S. Kangwa, V. Mutambo

Abstract: ***Kakosa South copper deposit is located about 450km northwest of Lusaka between Chingola and Chililabombwe. A comprehensive study of Kakosa South deposit was carried out. In Kakosa area the footwall aquifer rocks comprising sandstone and conglomerates which are thin and as such are not expected to represent major aquifers. Copper mineralisation is found in the upper quartzite and ore-shale. The inclination of the deposit ranges from 25^0 up to 35^0. The hangingwall formations above the upper quartzite are represented by a sequence of dolomite and shale formations. Based on Kakosa geotechnical analysis and rock mass classification, fuzzy TOPSIS approach was employed for the selection of optimal extraction techniques. FTOPSIS approach has precise and specific quantities which are used in order to establish criteria and option weights. Triangular fuzzy numbers were determined to represent semantic variables. The fuzzy numbers for Kakosa South parameters were used as input data in the decision making model and matched against the criteria required for the mining method. Applying FDM model, extraction techniques were ranked. The results indicated that open pit extraction technique was ranked first with 78.90 scores followed by sublevel stoping with 66.88 scores. It is concluded that the Kakosa South copper ore deposit can optimally be extracted by open pit mining up to transition depth and transit from open pit mining to underground mining employing sublevel stoping.***

Keywords: Extraction technique, Kakosa, TOPSIS.

I. INTRODUCTION

Kakosa South copper deposit is located about 450km northwest of Lusaka, the capital city of Zambia. The deposit is located between Chingola and Chililabombwe and is approximately 4.0km south of Konkola Copper Mine and is a section of Konkola Division of the Zambian Copperbelt. The research submission to the journal, rectification is not possible. In the formatted paper, volume no/ issue no will be in the right top corner of the paper. In the case of failure, the papers will be declined from the database of journal and carried out a comprehensive study of Kakosa South deposit (a Greenfield mining project). The geotechnical study included classification of rock mass and estimation of grade and mineral resources.

Revised Manuscript Received on October 30, 2019.

* Correspondence Author

Sam Kangwa*, Lecturer and Assistant Dean Department of Mining Engineering and a holder of M.Sc. and B.Eng. Diploma in Education University of Zambia.

Dr. Victor Mutambo, Scientific Research Department of Mining Engineering and a holder of M.Sc. and B.Eng. Diploma in Education University of Zambia.

A. Geology of Kakosa area

Kakosa area is under Konkola Division of the Zambian Copperbelt. It consists of almost uninterrupted, north-west 20km long and 2 to 4km wide band of mineralisation within the Neoproterozoic Kitwe and Mindola formations. The band of mineralisation ranges from the northerly boundary of 'Kafue Anticline' basement rock-mass and is over-folded. It appears again on the edge of the Konkola basement dome in the north-west part [Hitzman et al., 2012]. 'Kafue Anticline' basement area is originally denoted by the West-North-West trending, 'partly-domal', Chililabombwe Anticline. The point at which the Lower Roan Subgroup laps and overlies basement that is where it hosts the Chililabombwe mineralisation, Fitwaola together with Kakosa copper deposits. The Konkola basement dome is largely composed of Palaeoproterozoic granioids. In Kakosa area the footwall aquifer rocks comprising sandstone and conglomerates which are thin and as such are not expected to represent major aquifers. Copper mineralisation is found in the upper quartzite and ore-shale formations (Figure 1). The inclination of ore deposit mostly ranges from 25 to 35 degrees. The hangingwall formations above the upper quartzite are represented by a sequence of dolomite and shale formations.

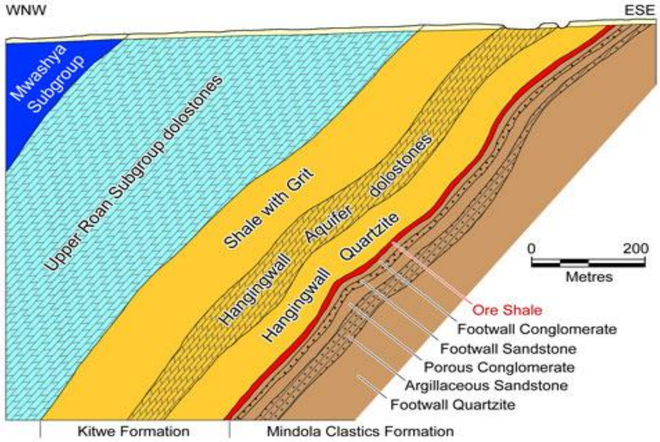

Figure 1: Konkola cross-section [Government of Republic of Zambia, 2001]

B. Kakosa rock mass classification

Classification of rock mass for Kakosa formation was based on raw data obtained from drill-holes numbers KAK0001 to KAK0028 and KLB0134 to KLB140.

The following different methods were applied for comparison purpose:
1. Rock Quality Designation (RQD)
2. Rock Mass Quality or Q- System
3. Rock Mass Rating (RMR)
4. Design Rock Mass Strength (DRMS)

Based on Kakosa geotechnical analysis, rock mass classification per rock type above and below ore zone was classified and the summary is indicated in Table 1.

Table 1: Summary of rock classification of Kakosa area

	RQD	Q	RMS	DRMS (MPa)
HWQ	82.2	18.2	68.1	73.0
OSU	52.1	1.9	48.1	24.0
FCS	40.4	5.4	59.1	49.5
AS	94.1	81.1	56.7	38.8
FWQ	61.0	38.9	48.2	65.7

Based on interpretation and analysis of raw data obtained from drill-holes, the technical parameters of Kakosa deposit were modeled and the summary is shown in Table 2.

Table 2: Technical parameters of Kakosa deposit

Parameter	Description
Hangingwall Quartzite (HWQ)	Competent and about 40m
Deposit shape	Tabular and spoon shaped
Ore Shale Unit (OSU)	Weak to moderate
Deposit dip	20^0 to 35^0
Deposit size	±25 metres
Average grade	1.17% TCu & 0.55% ASCu
Ore uniform	Moderate
Depth	80m to 250m (opened ended)
Footwall Conglomerate and Sandstone (FCS)	Weak to moderate and about 7m
Argillaceous Sandstone (AS)	Moderate and about 10m
Footwall quartzite (FWQ)	Competent and more than 100m thick

II. MODIFIED TECHNIQUE FOR ORDER PREFERENCE SIMILARITY TO IDEAL SOLUTION

After analysis of Kakosa geotechnical factors, the next stage was to select optimal extraction techniques. Selection of ore extraction technique is one of the most crucial and complicated decisions at the preliminary stage of mine planning process. Since there are many criteria involved in the process of ore extraction technique selection, the process is described as multiple criteria decision making analysis (MCDMA). The Technique for Order Preference Similarity to Ideal Solution (TOPSIS) is one of the most widely used techniques of MCDM [Yoon and Hwang, 1995] for selection of optimal alternative. In TOPSIS method, the Concepts of the "ideal solution" and "ideal similarity" are used and alternatives are ranked based on the similarity to the ideal solution. Therefore, the alternative which is more similar to the ideal solution is acceptable. At the similarity ideal, the alternative distance from the positive ideal and negative ideal solution is measured. The alternatives are then evaluated and ranked based on the distance from the positive ideal and the negative ideal solution [Yari et al, 2016; Hwang and Yoon, 1995].

A. Fuzzy sets theory in ore extraction

Since there are many uncertainties in geometric, geological and ore body characteristics involved in the process of ore extraction technique selection, using crisp numbers allocated to these uncertainties is imprecise and complicates the process. In order to address the uncertainties, it is suitable to apply the fuzzy numbers. The fuzzy sets theory in ore extraction is one of the contemporary methods which can sort-out the inaccuracies of input data by assigning simple and often sufficiently reliable approximations that would give the desired ranking of alternatives. The fuzzy sets theory is capable of transforming most erroneous and enigmatic concepts, variables and systems into a mathematical form. The conversion set is the context for reasoning, interpretation and decision-making at uncertainty conditions [Mohammadi & Vafaei, 2013]. When the TOPSIS and Fuzzy theory are used together, they form the FTOPSIS. FTOPSIS approach was applied for selecting the optimal extraction techniques for Kakosa copper ore deposit. In FTOPSIS, fuzzy numbers allow for the performance of the computational analysis and rank the alternatives [Rudnik and Kacprzak, 2017]. The fuzzy TOPSIS procedure involves the following steps [Wang & Chang, 2007; Javanshirgiv et al., 2017; Nădăban, 2016]:

Step 1. Identification of the evaluation criteria and alternatives.

Step 2. Choosing of the appropriate semantic variables.

The fuzzy set numbers can be applied to denote semantic variables as shown in Tables 3. The fuzzy numbers are used for the analysis of the importance weight of the criteria and the evaluation of options with regard to each criterion [Zadeh, 1975].

Table 3: Semantic variables for ranking the weight of each criterion

Semantic variables	Fuzzy set triangular numbers
Very weak (VW)	(0.0, 0.1, 0.3)
Weak (W)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
Strong (S)	(0.5, 0.7, 0.9)
Very Strong (VS)	(0.7, 0.9, 1.0)

Table 4: Semantic variables for the ratings

Semantic variables	Fuzzy set triangular numbers
Very bad (VB)	(0, 1, 3)
Bad (B)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Good (G)	(5, 7, 9)
Very Good (VG)	(7, .9, 10)

Step 3. Defining of the uncertainty decision-making matrix. A fuzzy multiple criteria decision-making challenge is stated in matrix format as:

$$\tilde{D} = \begin{pmatrix} \tilde{x}_{11} & \dots & \tilde{x}_{1j} & \dots & \tilde{x}_{1m} \\ \vdots & \dots & \vdots & \dots & \vdots \\ \tilde{x}_{i1} & \dots & \tilde{x}_{ij} & \dots & \tilde{x}_{in} \\ \vdots & \dots & \vdots & \dots & \vdots \\ \tilde{x}_{m1} & \dots & \tilde{x}_{mj} & \dots & \tilde{x}_{mn} \end{pmatrix}$$

Where $\tilde{x}_{ij}$ are semantic variables that can be expressed by fuzzy set triangular numbers as:

$$\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$$

Step 4. Normalising of the fuzzy decision matrix $\tilde{R}$ $[\tilde{r}_{ij}]$
The multiple criteria decision matrix $(\tilde{D})$ was normalised in order to adjust values measured on different scales to a notionally common measurable scale or to convert to unit less. The purpose is to allow evaluation or pairwise comparison of different criteria on a relative scale. The vector normalisation method is applied for evaluating element ijr of the normalised multiple criteria decision matrix, which is expressed as normalised decision making matrix. The linear scale conversion is used to transform the different criteria scales into comparable measurable units. Applying this process, it is possible to obtain a normalised fuzzy decision making matrix expressed as $\tilde{R}$ [Safari et al., 2010]:

$$\tilde{R} = [\tilde{r}_{ij}]_{mxn} \quad i = 1, 2, \dots, m \text{ and } j = 1, 2, \dots, n$$

$$\tilde{R} \begin{pmatrix} \tilde{r}_{11} & \dots & \tilde{r}_{1j} & \dots & \tilde{r}_{1m} \\ \vdots & \dots & \vdots & \dots & \vdots \\ \tilde{r}_{i1} & \dots & \tilde{r}_{ij} & \dots & \tilde{r}_{in} \\ \vdots & \dots & \vdots & \dots & \vdots \\ \tilde{r}_{m1} & \dots & \tilde{r}_{mj} & \dots & \tilde{r}_{mn} \end{pmatrix}$$

where:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j}*, \frac{b_{ij}}{c_j}*, \frac{c_{ij}}{c_j}*, \quad c_j* = Max_j\{c_{ij}\}\right) s, \text{ if } j\in B;$$

$$\tilde{r}_{ij} = \left(\frac{a_j-}{c_{ij}}, \frac{a_j-}{b_{ij}}*, \frac{a_j-}{a_{ij}}*, \quad a_j- = \right) Min_j\{a_{ij}\}, \text{ if } j\in C;$$

The benefit and cost criteria are expressed by B and C sets respectively. Upon obtaining the benefit and the cost attributes, the discrimination between maximisation or minimisation criteria desired to achieve by a decision maker would be possible.

Step 5. Establishing of multiple decision making criteria weighted matrix ($\tilde{W}$).
In this step, the purpose is to establish weight of each criterion as it is not possible for each evaluation criterion to be of equal importance because each evaluation criteria has a different meaning.

$$\tilde{w}_j = [\tilde{w}_1, \tilde{w}_2, \dots, \tilde{w}_n]$$

Where $\tilde{w}_j$ represents semantic variables that can be indicated by the triangular fuzzy set numbers as:

$$\tilde{w}_j = (w_{j1}, w_{j2}, w_{j3}).$$

Step 6. Computing of the normalised weighted fuzzy decision matrix.
The determination of the weight of each criterion provides normalised fuzzy decision making matrix A as:

$$A = \begin{pmatrix} \tilde{v}_{11} & \tilde{v}_{12} & \dots & \tilde{v}_{1n} \\ \tilde{v}_{21} & \tilde{v}_{22} & \dots & \tilde{v}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{v}_{m1} & \tilde{v}_{m2} & \dots & \tilde{v}_{mn} \end{pmatrix}$$

where: $\tilde{v}_{ij} = \tilde{r}_{ij} . \tilde{w}_{ij}$

Step 7. Computing of the Fuzzy Positive Ideal Solution (FPIS) and the Fuzzy Negative Ideal Solutions (FNIS). FPIS designates the best preferable alternative, and FNIS designates the least preferable alternative. FPIS (A^+) and FNIS (A^-) can be determined as follows [Chen, 2000; Chen & Tzeng, 2006]:

$$A^+ = \{\tilde{v}_1*, \tilde{v}_2*, \dots, \tilde{v}_n*\}, \quad \tilde{v}_1* = Max_j\{\tilde{v}_{ij}\},$$
$$i = 1, 2, \dots, m; \ j = 1, 2, \dots, n$$

$$A^- = \{\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-\}, \quad \tilde{v}_1^- = Min_j\{\tilde{v}_{ij}\},$$
$$i = 1, 2, \dots, m; \ j = 1, 2, \dots, n$$

Step 8. Computation of how far each alternative is from FPIS and FNIS.
The distances of each alternative from FPIS and FNIS are computed as:

$$S_i^* = \sum d_v(v_{ij}, v_j^*), \quad i = 1, 2, \dots, m$$

$$S_i^- = \sum d_v(v_{ij}, v_j^-), \quad i = 1, 2, \dots, m$$

$$d_v(v_{ij}, v_j^*) = \sqrt{\frac{1}{3}(\Sigma(v_{ij} - v_j^*))^2}$$

$$d_v(v_{ij}, v_j^-) = \sqrt{\frac{1}{3}(\Sigma(v_{ij} - v_j^-))^2}$$

Where d_v is the distance computed between two fuzzy sets of triangular numbers.

Step 9. Computation of closeness coefficient.
For each alternative A_i, the closeness coefficient (CC_i) is calculated as:

$$CC_i = \frac{s_i}{s_i^{*} + s_i}, \quad i = 1, 2, \ldots, m$$

Step 10. Ranking alternatives.
Alternative with highest closeness coefficient represents the best alternative.

III. SELECTION OF OPTIMAL EXTRACTION TECHNIQUES FOR KAKOSA DEPOSIT

Selection of extraction techniques for Kakosa South deposit was based on the fuzzy TOPSIS model. The fuzzy TOPSIS methodology flowchart is presented in Figure 2.

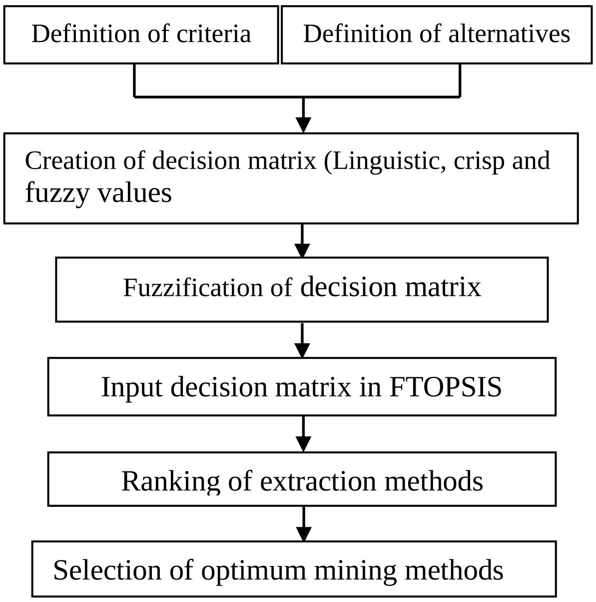

Figure 2: Flowchart of the modified FTOPSIS model for mining method selection

Before the application of FTOPSIS model, the semantic and crisp values in Tables 1 and 2 were converted to fuzzy numbers by the use of fuzzy triangular functions as shown in Table 5. The fuzzy numbers for Kakosa South parameters were used as input in the decision making model and matched against the criteria required for the extraction technique.

Table 5: Semantic variables for ranking the weight of each criterion

Semantic variables	Fuzzy set triangular numbers
Very low	(0.000, 0.125, 0.250)
Low	(0.125, 0.250, 0.375)
Moderately low	(0.250, 0.375, 0.500)
Medium	(0.375, 0.500, 0.625)
Moderately high	(0.500, 0.625, 0.750)
High	(0.625, 0.750, 0.875)
Very high	(0.750, 0.875, 1.000)

There are eighteen traditional extraction techniques, each of which may be divided into several various variations. In order to determine the optimal extraction technique for Kakosa South ore body, eleven techniques were chosen for evaluation and competition. The eleven techniques were considered because of the software limitation in the number of alternatives. The eleven techniques are universally accepted and are:

1. Open pit mining;
2. Room and pillar;
3. Stope and pillar;
4. Cut and fill stoping;
5. Sublevel stoping;
6. Sublevel caving;
7. Block caving;
8. Longwall mining;
9. Shrinkage stoping;
10. Square set stoping, and
11. Top slicing.

Among the techniques not considered for Kakosa deposit include vertical crater retreat, stripping mining and conceptual mining techniques such as hydraulic mining and borehole mining. Extraction techniques including long-wall may be executed in reverse or advance mode. The ground stability may be achieved by caving or back filling. Therefore options in the extraction technique selection process are much more several than the eleven techniques which were considered. Eleven universal techniques were entered into fuzzy decision making (FDM) model as alternatives. Criteria involved in the selection of the optimum extraction technique include Kakosa rock mass classification parameters for hanging wall, ore body and footwall formations, ore deposit characteristics, projected recovery and production capacity. These parameters were input data for FDM as attributes. The decision matrix for Kakosa South copper deposit was considered in the FDM model according to Tables 6 and 7. FDM results are indicated in Table 8.

Table 6: Geometric and geo-mechanical input data for Kakosa South copper ore deposit

	Attribute Name	Deposit shape	Grade distribution	Ore dip	Ore thickness	Depth	Hangwall RMR	Ore RMR	Hangwall RSS
No.	Attribute Data Type	Linguistic	Linguistic	Linguistic	Linguistic	Linguistic	Linguistic	Linguistic	Linguistic
	Attribute Weight	Medium	MoL Low	MoL High	MoL High	MoL High	MoL High	Medium	MoL High
1	Block caving	Medium	Medium	Medium	MoL High	MoL High	MoL High	Low	High
2	Cut & fill	High	MoL High	MoL High	MoL Low	MoL High	High	MoL High	MoL High
3	Longwall	High	MoL Low	Low	Very Low	Medium	High	Medium	Very High
4	Open pit	Medium	MoL High	MoL High	High	Low	High	MoL High	MoL High
5	Room & pillar	High	Medium	Low	Very Low	MoL High	MoL High	Very High	Low
6	Shirinkage	High	Medium	Low	Very Low	MoL High	Medium	MoL High	Low
7	Square-set	MoL Low	MoL Low	MoL High	Low	MoL Low	MoL Low	Low	High
8	Stope & pillar	High	MoL High	Medium	MoL High	MoL High	MoL High	Very High	Low
9	Sublevel caving	High	Medium	MoL Low	High	Medium	MoL High	MoL Low	High
10	Sublevel stoping	High	High	MoL Low	High	High	MoL High	High	Low
11	Top slicing	Medium	MoL Low	Medium	Medium	MoL Low	Medium	MoL Low	High

Table 7: Input data for Kakosa South copper ore deposit

	Attribute name	Ore RSS	Footwall RSS	Recovery	Skilled personnel	Output	HQW RQD
No.	Attribute (Data)	Semantic	Linguistic	Deterministic	Semantic	Deterministic	Semantic
	Attribute weight	Medium	Medium	High	High	Mod. High	Medium
1	Open pit mining	Mod high	High	95	High	85	Very high
2	Room and pillar	Mod. low	Medium	70	Mod. high	40	Mod. low
3	Stope and pillar	Mod. low	Medium	65	Mod. low	45	Mod. low
4	Cut & fill stoping	Mod. low	medium	95	Medium	35	Low
5	Sublevel stoping	Medium	High	85	Mod high	50	Mod. low
6	Sublevel caving	Mod. high	Medium	85	Mod low	40	High
7	Block caving	Medium	medium	90	Medium	90	Very high
8	Longwall mining	Very high	Mod high	90	Medium	40	High
9	Shrinkage	Mod. low	Mod high	80	Mod. high	15	Very high
10	Square set	Mod hogh	Low	90	Mod. low	10	High
11	Top slicing	Medium	Mod low	90	Medium	15	High

Table 8: FDM scores obtained by each extraction technique for Kakosa South deposit

Rank	Name	Score
1	Open pit	78.90
2	Sublevel stoping	66.88
3	Cut and fill	60.46
4	Shrinkage	53.91
5	Block caving	53.61
6	Longwall	53.55
7	Stope and pillar	51.96
8	Sublevel caving	51.73
9	Room and pillar	50.95
10	Top slicing	37.91
11	Square-set	28.03

IV. CONCLUSION

The process of selecting an optimal extraction technique is based on many criteria, and therefore cardinal to employ appropriate extraction technique. The results of FTOPSIS as indicated in Table 8 show that open pit extraction technique was ranked first with 78.90 scores followed by sublevel stoping with 66.88 scores and cut and fill with 60.46. The least ranked extraction technique was square set with 28.03 scores. It is concluded that the Kakosa South copper ore deposit can optimally be extracted by open pit mining technique up to the transition depth and transit from open pit mining to underground mining employing sublevel stoping.

ACKNOWLEDGEMENT

This paper forms part of the initial research work on techno-economic potential for mining Zambia's low grade-copper ore deposits, which was funded by the African Development Bank under its Support to Science and Technology Education Project. The project was partly supported by Konkola Copper Mines Plc.

REFERENCES

1. Chen, C. T. 2000. Extension of the group decision –making under fuzzy environment. Fuzzy sets and systems. Pp114, 1 – 9.
2. Chen, M.F. and Tzeng, G. H. 2006. Combining grey relation and TPOSIS concepts for selecting an expatriate host country. Mathematical and Computer Modelling. 40: 1473-1490.
3. Government of Republic of Zambia 2001. Geologocal maps. Geological Survey of Zambia, Lusaka.
4. Hitzman, M., Broughton, D., and Selley, D. 2012. The Central African Copperbelt: Diverse stratigraphic, structural and temporal settings. Society of Economic Geologists, Speacial publication, department of Geology and Geological Engineering, Colorado School of Mines, Golden, Colorado, 8040.
5. Hwang, C., and Yoon, K. 1995. Multiple Attribute Decision Making: Methods and Application. Springer, New York. http://dx.doi.org/10.1007/978-3-642-48318-9.
6. Javanshirgiv, M., Moghadder, M.T. and Safari, M. 2017. 'The selection of appropriate mining
7. method for the Deh Gheybi Granite Quarry Mine using the FTOPSIS method', International Journal of Mining and Mineral Engineering, Vol. 8, No. 2, pp.113–130.
8. Selection of Optimal Contractor to Execute Project Using FTOPSIS Method (Case Study: Kermanshash Gas Company), International Research Journal of Applied and Basic Sciences, Vol. 6, No. 4, 450 – 459.
9. Nădăban S. 2016. Fuzzy b-Metric Spaces. Department of Mathematics and Computer Science, Aurel Vlaicu University of Arad, Romania. International Journal of Computers Communication and Control ISSN 1841-9836, 11(2):273-281.
10. Rudnik, K. and Kacprzak, D. 2017. Fuzzy TOPSIS with ordered fuzzy numbers for flow control in engineering system. Applied Soft Computing Vol. 52. pp. 1020 – 1041.
11. Safari, M., R. Kakaei, M. Ataei, M. Karamoozian. TOPSIS, Arabian Journal of Geosciences, 2010
12. Wang, Y., and Chang, H. 2007. Generalizing TOPSIS for fuzzy multiple-criteria group decision-making. Computer and Mathematics with Applications 53 (11): 1762 – 1772.
13. Yari, M., Bagherpour, R. and Almasi, N. 2016. An Approach to the Evaluation and Classification of Dimensional Stone Quarries with an Emphasis on Safety Parameters. Rudarsko-geološko-naftni zbornik (The Mining, Geology and Petroleum Engineering Bulletin), 31,3,15-26.
14. Yoon, K. P. and Hwang, C. L. 1995. Multiple attribute decision making: an introduction. Volume 104.
15. Zadeh L. A. 1975. Outline of a new approach to the analysis of complex systems and decision process. IEEE Trans., 3, pp. 28-44.

AUTHORS PROFILE

Sam Kangwa - Lecturer at The University of Zambia, School of Mines, Mining Engineering Department and a holder of M.Sc. and B.Eng. in Mining Engineering, anf Diploma in Education. Worked as a mining engineer at Mufulira copper mines and later joined the Copperbelt University as a Lecturer and Assistant Dean. He worked as Principal of Evelyn Hone College from 2005 to 2013 and in 2015; he joined the University of Zambia as a Lecturer. He has been involved in local and international projects related to education, skills development and mining engineering. He is currently pursuing PhD research studies.

Dr. Victor Mutambo is a holder of M. Sc., and PhD in Mining Engineering. He worked as Scientific Research officer in the Department of underground Mining from 1999 to 2000. In 2001 he joined the University of Zambia as Lecturer. He was a visiting Lecturer at the University of Zimbabwe. From 2011 to 2014, he served as Permanent Secretary in the Ministry of Mines, Energy and Water Development. He is a member to Engineering Institution of Zambia, Mining International Quality, and Association of Industrial Hygienist of America International Affairs Subcommittee for SAIMM. He has published several papers.