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Application of Fuzzy Hybrid Analytic Network Process in Equipment Selection of Open-Pit Metal Mines

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A B S T R A C T

Equipment selection is one of the most important aspects of open pit design. The selection of equipment for mining applications is not a well-defined process and because it involves the interaction of several subjective factors or criteria, decisions are often complicated and may even embody contradictions. The aim of this study is introducing a multi-criteria decision making method for selecting the most appropriate combination of drilling, loading and haulage equipment using a state of the art comprehensive model. The proposed method consists of two stages, first is determining the weight of each criteria which affects the decision using fuzzy analytic network process (FANP), the next step is calculating the score of each possible combination of mining equipment using Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The proposed methodology is applied for Sungun copper mine which is the largest open-cast copper mine in Iran and is among the most important copper deposits in Middle East and finally the most appropriate combination of mining equipment is determined for this open-pit mine.

1. Introduction

Mining costs are a function of operational conditions, operating scale and the cost of equipment. As the capital and operational costs of loading and hauling equipment constitute more than half the total costs in an open pit mine, appropriate equipment selection is an important challenge to the management. The equipment selection problem arises in the initial conception of mine development. As the large equipment are used in large open pit mines, their optimum selection not only leads to decreasing costs but may change the scope and design of the pit.

Equipment selection is a multi-criteria problem, affected by both quantitative and qualitative parameters. Different multi criteria decision making methods have been introduced to solve the problem. The aim of this study is introducing a novel comprehensive model, which resembles the complexity of the nature of equipment selection procedure. The proposed model consists of four main criteria with their twenty eight relative sub-criteria. Twenty three

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different combinations of drilling, loading and hauling feasible combinations of equipment are chosen in this paper among 48 options by a group of experts as the options in the model. Drilling equipment is taken into account in these combinations, as their type and size affect the characteristics of loading and consequently the type and size of the hauling equipment. An approach based on fuzzy analyticnetwork process-fuzzy TOPSIS (FANP-FTOPSIS) is therefore used in the paper, in order to solve the problem.

The reminder of this paper is organized as follow. In section 2 a brief review is done on the concept of equipment selection in open-pit mines, this section is also included the literature review of the different equipment selection methods that had been used. The proposed methodology of FANP-FTOPSIS is reviewed in section 3 alongside with fundamentals of fuzzy set theory, fuzzy ANP, and fuzzy TOSIS. Section 4 is allocated to applying the proposed method in Sungun copper mine in Iran. First, the expert's judgments based on fuzzy linguistic scale were gathered using a well-designed questionnaire. After performing pair-wise comparisons, the consistency of the judgments was checked, the judgments were defuzzified using Converting Fuzzy data into Crisp Score (CFCS) method, and after establishing unweighted, weighted and limited super-matrixes the global weight of each sub-criterion was calculated. Finally these weights were imported to fuzzy TOPSIS algorithm for ranking the alternatives and the one with the highest score was selected as the final solution. Finally these weights were imported to fuzzy TOPSIS algorithm for ranking the alternatives and the one with the highest score was selected as the final solution.

Finally in the section 5 the conclusions of the study are stated and this section concludes the paper.

2. Literature Survey

The equipment selection problem (ESP) in surface mines, especially open-pit mines, is a complex problem which is affected by different criteria and many features and restrictions must be considered for solving such problem [1].

The methods for selecting the appropriate type of mining equipment can be divided into seven different groups. These methods are Integer Programming, Simulation, Artificial Intelligence, Rank-Order Algorithm, Multi Criteria Decision Making Methods (MCDM Methods), Shovel-Truck Productivity, and Queuing Theory [2].

Integer programming which is a mathematical optimization method is used for solving ESP n numerous studies, but its focus is on the fleet size of equipment rather than selecting their type [3]. Jayawardane and Harris place importance on early project completion time for earthwork operations [4].

The methods based on simulation are usually used for analyzing the earth moving system, but there are also studies which used simulation for equipment selection. Hrebar and Dagdelen [5] developed a simulation method for dragline stripping equipment selection.

The methods based on different artificial intelligence methods had the most application in mining equipment selection [2]. The most common sub-sets of this method are expert systems and genetic algorithm based methods. The expert systems approach is often preferred for complex systems [6]. Amirkhanian and Baker [7] developed an expert system for equipment selection in construction incorporating 930 rules. Denby and Schofield [8] used expert systems for assign and select the equipments and introduced software. Naoum and Haidar [1] have used a model based on genetic algorithm for solving the equipment selection problem.

Rank-order algorithm is a method based on different operational research methods and fuzzy theory which was introduced by Bandopadhayay [9]. The main advantages of this method are consideration of qualitative and quantitative factors in optimized equipment selection, collective decision making, utilizing the dominance matrix, and eliminating some of the options before final decision making [2].

Multi-criteria decision making (MCDM) methods are among operational research methods that explicitly considers multiple criteria in decision-making environments. Samanta et al. [10] used analytical hierarchy process (AHP) which is a sub-discipline of MCDM methods for solving ESP in open cast mines.

Morgan and Peterson used shovel-truck productivity for predicting the travel times on haul and return portions of the truck cycle, and the prediction of the interaction effect between the shovel and truck at the loading point [11]. The equipment selection methods based on shovel-truck productivity can be divided into two sub-groups of match factor method and bunching theory [2].

Queuing theory is the study of the waiting times, lengths, and other properties of queues [2]. Equipment selection based on this method has been introduced by Karshenas [12] and Huang and Kumar [13] with different approaches.

3. Methodology

3.1. Fuzzy Set Theory and Fuzzy Numbers

Zadeh [14] introduced the fuzzy asset theory, which was oriented to the rationality of uncertainty due to imprecision or vagueness. A fuzzy set is an extension of a crisp set. Crisp set only allow full membership or non-membership at all, whereas fuzzy sets allow partial membership.

Fuzzy numbers are the special classes of fuzzy quantities. A fuzzy number is a fuzzy quantity M that represents a generalization of a real numberr. Intuitively, M(x) should be a measure of how well M(x) “approximates”. A fuzzy number M is a convex normalized fuzzy set. A fuzzy number is characterized by a given interval of real numbers, each with a grade of membership between 0 and 1. It is possible to use different fuzzy numbers according to the situation. Generally in practice triangular and trapezoidal fuzzy numbers are used. In applications it is often convenient to work with triangular fuzzy numbers (TFNs) because of their computational simplicity, and they are useful in promoting representation and information processing in a fuzzy environment. A triangular fuzzy number is shown in Figure 1.

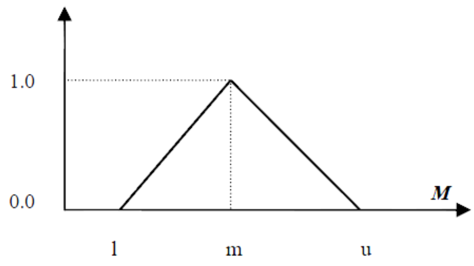

Figure 1. A Triangular Fuzzy Number

TFNs are defined by three real numbers, expressed as(l, m, u). The parameters l, m and u, respectively indicate the smallest possible value, the most promising value, and the largest possible value that describe a fuzzy event. Their membership functions are described as equation 1.

$$\mu(x/\widetilde{M}) = \begin{cases} 0 & x < l \\ \dfrac{x-l}{m-l} & l \le x \le m \\ \dfrac{r-x}{r-m} & m \le x \le r \\ 0 & x \ge r. \end{cases} \quad (1)$$

3.2.Fuzzy Analytic Network Process (FANP)

The analytic network process (ANP) method which was introduced by Saaty (1996) only uses the pair-wise comparison matrix to evaluate the ambiguity in multi-criteria decision making problems as it can be seen in equation 2. Assume that we have n different and independent criteria $(C_1, C_2, C_3, \dots, C_n)$ and they have the weights$(W_1, W_2, W_3, \dots, W_n)$, respectively. The decision-maker does not know in advance the values of$W_i, i = 1,2,3, \dots, n$, but he is capable of making pair-wise comparison between the different criteria. Also, assume that the quantified judgments provided by the decision-maker on pairs of criteria (C_i, C_j) are represented in a $n \times n$ matrix as in the equation 2 [15], [16].

$$A = [a_{ij}] = \begin{array}{c} C_1 \\ C_2 \\ \vdots \\ C_n \end{array} \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ 1/a_{12} & 1 & & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix} \quad (2)$$

where $a_{ii} = 1$ and $a_{ij} = \frac{1}{a_{ji}}, i = 1,2, \dots, n$. This research uses a methodology which combines the ANP method with fuzzy set theory which discussed before [17].

The steps of FANP are as following:

- Step 1: Establishing the model and the problem.
- Step 2: Establishing the triangular fuzzy numbers.
- Step 3: Establishing the fuzzy pair-wise comparison matrix (independent and interdependent) and deffuzzification.
- Step 4: Determining eigenvector and supermatrix formation.
- Step 5: Evaluating the Decision.

There are several methods for deffuzification, but in this study we used the Opricovic and Tzeng (2003) method which is called CFCS (Converting Fuzzy data into Crisp Score) method. The procedure of this method is as below:

- Developing the normalized matrix using equations 3 to 6:

$$xl_{ij}^{k} = (l_{ij}^{k} - minl_{ij}^{k})/\Delta_{min}^{max} \quad (3)$$

$$xm_{ij}^{k} = (m_{ij}^{k} - minl_{ij}^{k})/\Delta_{min}^{max} \quad (4)$$

$$xr_{ij}^{k} = (r_{ij}^{k} - minl_{ij}^{k})/\Delta_{min}^{max} \quad (5)$$

$$\Delta_{min}^{max} = maxr_{ij}^{k} - minl_{ij}^{k} \quad (6)$$

- Calculating the left and right normal scores (ls, rs) using the equations 7 and 8:

$$xls_{ij}^{k} = xm_{ij}^{k}/(1 + xm_{ij}^{k} - xl_{ij}^{k}) \quad (7)$$

$$xrs_{ij}^{k} = xr_{ij}^{k}/(1 + xr_{ij}^{k} - xm_{ij}^{k}) \quad (8)$$

- Calculating the final certain normal score using equation 9:

$$x_{ij}^{k} = \left[xls_{ij}^{k}\left(1 - xls_{ij}^{k}\right) + xrs_{ij}^{k}xrs_{ij}^{k}\right]/[1 - xls_{ij}^{k} + xrs_{ij}^{k}] \quad (9)$$

- Calculating the certain scores using equation 10:

$$z_{ij}^{k} = minl_{ij}^{k} + x_{ij}^{k}\Delta_{min}^{max} \quad (10)$$

- Step 6: Calculating the final weights:

Finally for calculating the weights, the geometric mean of the eigenvector of the aggregation matrix of the expert's opinions which was introduced by Saaty (1980) is used as equation 11.

$$W_i = \frac{\left(\prod_{j=1}^{n} a_{ij}^{*}\right)^{1/n}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} a_{ij}^{*}\right)^{1/n}} i, j = 1,2, \dots, n \quad (11)$$

3.3. Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS)

TOPSIS defines an index called similarity to the positive-ideal solution and the remoteness from the negative-ideal solution. Then the method chooses an alternative with the maximum similarity to the positive-ideal solution [18]. In FTOPSIS both the arrays in decision making matrix, the weights of criteria, or one of them is described in fuzzy format [19, 20].

The steps of FTOPSIS are as following:

The steps of FTOPSIS are as below [21, 22]:

- Step 1: Constructing the Fuzzy Decision Matrix:

Construct the fuzzy decision matrix as equation 12 and choose the appropriate linguistic variables for the alternatives with respect to criteria.

$$\tilde{D} = \begin{array}{c} \\ A_1 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccccc} x_1 & \ldots & x_j & \ldots & x_n \end{array} \\ \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1j} & \cdots & \tilde{x}_{1n} \\ \vdots & & \vdots & & \vdots \\ \tilde{x}_{i1} & \cdots & \tilde{x}_{ij} & \cdots & \tilde{x}_{in} \\ \vdots & & \vdots & & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mj} & \cdots & \tilde{x}_{mn} \end{bmatrix} \end{array} \qquad i = 1,2,\ldots,m;\ j=1,2,\ldots,n \tag{12}$$

where $\tilde{x}_{ij}^{k}$ is the rating of alternative A_i with respect to criterion x_i evaluated by expert and $\tilde{x}_{ij}^{k} = (a_{ij}^{k}, b_{ij}^{k}, c_{ij}^{k})$. For uniting the fuzzy performance of k experts the mean value is used as equation 13.

$$\tilde{x}_{ij} = \frac{1}{k}(\tilde{x}_{ij}^{1}, \tilde{x}_{ij}^{2}, \ldots, \tilde{x}_{ij}^{k}) \tag{13}$$

- Step 2: Normalization of the Fuzzy Decision Making Matrix:
The normalized decision matrix denoted $\widetilde{R}$ is shown as equation 14. Then the normalization process can be performed by equation 15. This equation can be used for both triangular and trapezoidal fuzzy numbers.

$$\widetilde{R} = [\tilde{r}_{ij}]_{m\times n}; i = 1,2,\ldots,m; j = 1,2,\ldots,n \tag{14}$$

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}\right); c_j^+ = \max_i c_{ij} \tag{15}$$

- Step 3: Constructing the Weighted Fuzzy Normalized Decision Matrix:
The weighted fuzzy normalized decision matrix can be calculated from equation 16 and 17 where $\widetilde{w}_j$ is the weight of criteriaj.

$$\widetilde{V} = [\tilde{v}_{ij}]_{m\times n}\ ; i = 1,2,\ldots,m\ ; j = 1,2,\ldots,n \tag{16}$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \widetilde{w}_j \tag{17}$$

- Step 4: Determining the Fuzzy Positive-Ideal Solution (FPIS) and Fuzzy Negative-Ideal Solution (FNIS):
According to the weighted normalized fuzzy decision matrix, we know that the elements $\widetilde{V}_{ij}$ are normalized positive TFNs and their ranges belong to the closed interval [0, 1]. Then, we can define FPIS A^+ and FNIS A^- as equation 18 to 21 where $\widetilde{V}_j^+ = (1,1,1)$ and $\widetilde{V}_j^- = (0,0,0)$for $j = 1,2,\ldots,n$.

$$\begin{aligned} A^+ &= \left(\widetilde{V}_1^+, \widetilde{V}_2^+, \ldots, \widetilde{V}_n^+\right) \\ &= \{(\max_i v_{ij} \big| j \\ &\in J), (\min_i v_{ij} \big| j \in J_i') \big| i = 1,2,\ldots,m\} = \{v_1^+, v_2^+, \ldots, v_j^+ \ldots, v_n^+\} \end{aligned} \tag{18}$$

$$A^- = \left(\tilde{V}_1^-, \tilde{V}_2^-, \dots, \tilde{V}_n^-\right) = \{(\min_i v_{ij} | j \in J), (\max_i v_{ij} | j \in J_i') | i = 1,2,\dots,m\} = \{v_1^+, v_2^+, \dots, v_j^+ \dots, v_n^+\} \quad (19)$$

$$J = \{j = 1,2, \dots, n\}\ ; \text{j belongs to the profit feature} \quad (20)$$

$$J' = \{j = 1,2, \dots, n\}\ ; \text{j belongs to the cost feature} \quad (21)$$

- Step 5: Calculating the Distance of Each Alternative from FPIS and FNIS:
The distances ($d_i^+$and d_i^-) of each alternative A^+ and A^- can be currently calculated by the area compensation method as equation 22 and 23.

$$d_i^+ = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{V}_j^+\right); i = 1,2, \dots, m\ ; j = 1,2, \dots, n \quad (22)$$

$$d_i^- = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{V}_j^-\right); i = 1,2, \dots, m\ ; j = 1,2, \dots, n \quad (23)$$

Consider the point that if we have two fuzzy numbers of $M(m_1, m_2, m_3)$ and $N(n_1, n_2, n_3)$ then the distance between them can be obtained from equation 24.

$$d(M, N) = \sqrt{\frac{1}{3}[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)]^2} \quad (24)$$

- Step 6: Obtaining the Closeness coefficient and Rank the Order of Alternatives:
The CC_i is defined to determine the ranking order of all alternatives once d_i^+ and d_i^- of each alternative have been calculated. This step solves the similarities to an ideal solution by the equation 25.

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+}\ ; i = 1,2, \dots, m \quad (25)$$

According to the CC_i we can determine the ranking order of all alternatives and select the best one from among a set of feasible alternatives.

4. Results

As the criteria, sub-criteria, and alternatives for solving the equipment selection problem (ESP) have been chosen and the network model have been constructed as Figure 2, in this section we used the proposed model for solving the equipment selection problem in Sungun copper mine, Iran.
The first step is gathering the expert judgments by using a well-designed questionnaire. After performing the pair wise comparisons, the next step is checking the consistency of the judgments, then the judgments will be defuzzified using the CFCS method. Then the unweighted, weighted and limited supermatrix will be established. The next step is importing

the sub criteria's weights to FTOPSIS method for ranking the alternatives. The final rank of alternatives based on proposed method is shown in Table 2. The combination of the down the hole drill wagon, electric mining shovel, and diesel truck was chosen as the most appropriate equipment as the result of the proposed model.

5. Conclusion

The selection of equipment for mining applications is not a well-defined process and because it involves the interaction of several subjective factors or criteria, decisions are often complicated and may even embody contradictions.

This research contains a comprehensive state of the art method for modeling equipment selection in surface metal mines which have been conducted in a case study in Sungun copper mine, Iran.

The model used in this study is detailed and comprehensive and includes 28 different attributes and their relative parameters which affect the process of equipment selection in surface metal mines and 23 different options for combination of equipment system as the alternatives.

The problem associated with utilizing a large model in equipment selection is the fact that when the number of the attributes and their relative parameters increases, the risk of occurring interaction between these attributes will increase. By neglecting these interactions, the model and the results will be in conflict with reality. Fuzzy ANP-Fuzzy TOPSIS method not only can solve the problem of modeling equipment selection with large number of attributes, relative parameters, and alternatives, but by considering the interaction between these parameters as it is in the reality, can offer highly reliable results which can easily be used in the mining industry.

The results of this study demonstrates that for comprehensive models of equipment selection in surface mines, resembling the complexity of mining procedure with considering the interaction among criteria and sub-criteria, and also the large number of alternatives the FANP-FTOPSIS can be a reliable approach which provides accurate and realistic results.

Table 1. List of Different Options for Equipment Selection in Iranian Surface Metal mines

No#	Drilling	Loading	Haulage
A	DTH Wagon Drill	Electric Mining Shovel	Wheel Motor
B	DTH Wagon Drill	Diesel-Hydraulic Mining Shovel	Wheel Motor
C	DTH Wagon Drill	Electric Mining Shovel	Diesel Truck
D	DTH Wagon Drill	Diesel-Hydraulic Mining Shovel	Diesel Truck
E	DTH Wagon Drill	Electric Mining Shovel	Articulated Truck
F	DTH Wagon Drill	Diesel-Hydraulic Mining Shovel	Articulated Truck
G	Top Hammer Wagon Drill	Pay Loader	Wheel Motor
H	Top Hammer Wagon Drill	Pay Loader	Diesel Truck
I	Top Hammer Wagon Drill	Pay Loader	Articulated Truck
J	Rotary Drilling Equipment	Electric Mining Shovel	Wheel Motor
K	Rotary Drilling Equipment	Diesel-Hydraulic Mining Shovel	Wheel Motor
L	Rotary Drilling Equipment	Electric Mining Shovel	Diesel Truck
M	Rotary Drilling Equipment	Diesel-Hydraulic Mining Shovel	Diesel Truck
N	DTH Wagon Drill	Pay Loader	Wheel Motor

Table 1. Continued

O	DTH Wagon Drill	Pay Loader	Diesel Truck
P	DTH Wagon Drill	Pay Loader	Articulated Truck
Q	Top Hammer Wagon Drill	Back Hoe Excavator	Wheel Motor
R	Top Hammer Wagon Drill	Back Hoe Excavator	Diesel Truck
S	Top Hammer Wagon Drill	Back Hoe Excavator	Articulated Truck
T	DTH Wagon Drill	Pay Loader	Belt Conveyor
U	Top Hammer Wagon Drill	Pay Loader	Belt Conveyor
W	DTH Wagon Drill	Back Hoe Excavator	Belt Conveyor
X	Rotary Drilling Equipment	Back Hoe Excavator	Belt Conveyor

Table 2. Final Rank of Alternatives Obtained from FAHP-FTOPSIS Method in Songun Mine

Alternative	**Sigma D-**	**Sigma D+**	**CCI**	**Final Rank**
A	0.297218	0.139514	0.68055	6
B	0.394802	0.183222	0.68302	4
C	0.414423	0.170905	0.708019	1
D	0.390745	0.202574	0.658575	8
E	0.339914	0.222902	0.603952	11
F	0.331482	0.237914	0.582164	12
G	0.247367	0.246272	0.501109	19
H	0.309455	0.257881	0.545453	16
I	0.26254	0.249067	0.513167	18
J	0.375055	0.178336	0.67774	7
K	0.381007	0.173933	0.686574	2
L	0.388423	0.179926	0.683424	3
M	0.400472	0.186026	0.68282	5
N	0.262091	0.21725	0.546774	15
O	0.3127	0.18862	0.623754	10
P	0.254623	0.229524	0.525921	17
Q	0.30249	0.226927	0.571364	13
R	0.341268	0.189999	0.642367	9
S	0.294669	0.230635	0.560949	14
T	0.236143	0.265369	0.470862	20
U	0.218288	0.286343	0.43257	22
W	0.235366	0.265036	0.470354	21
X	0.214542	0.283452	0.430812	23

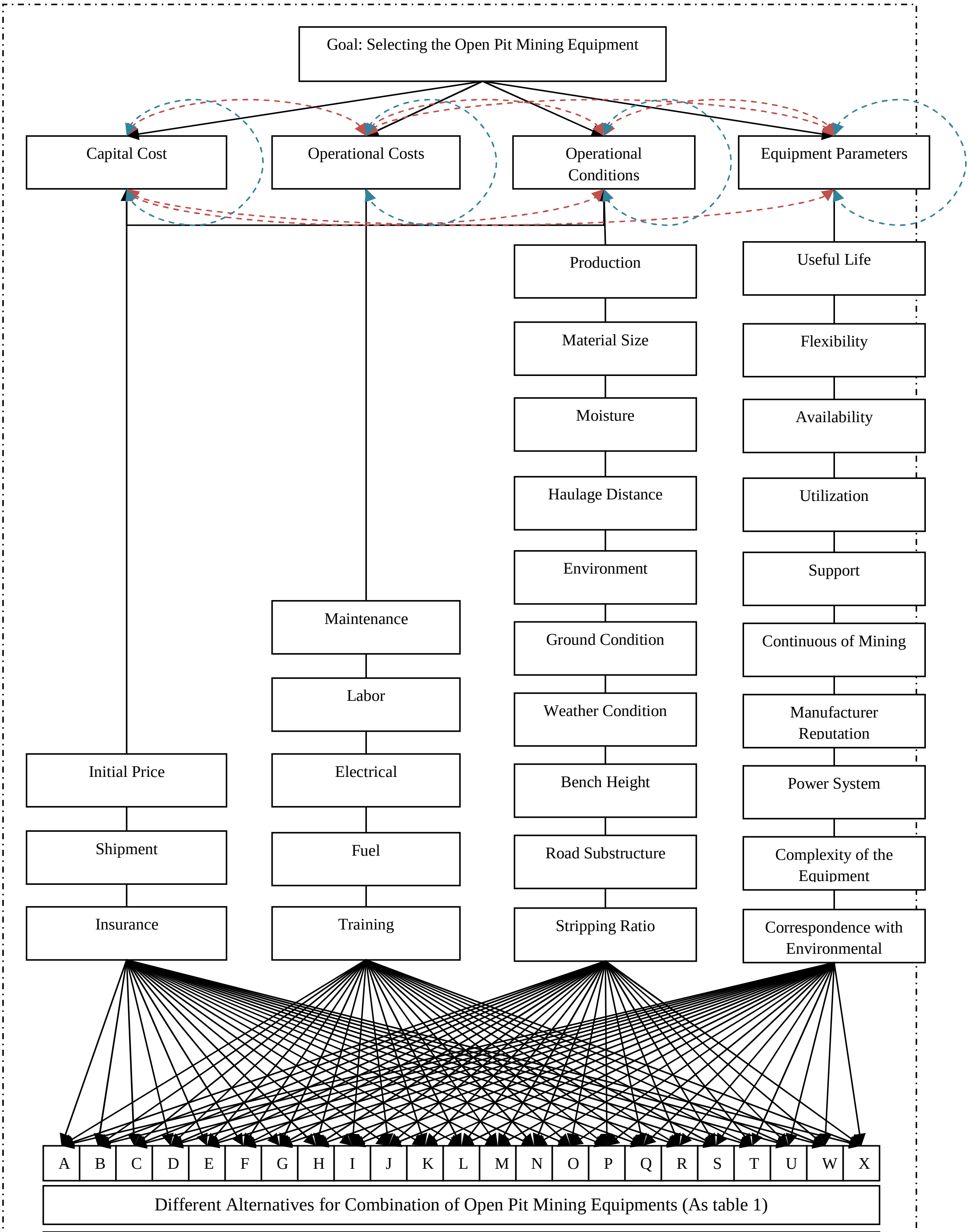

Figure 2. The Fuzzy ANP-Fuzzy TOPSIS Model for Equipment Selection in Sungun Mine

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