EQS: a computer software using fuzzy logic for equipment selection in mining engineering

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Synopsis

Equipment selection in mining engineering is one of the most important decisions that affects the mine design, production planning and economic parameters in open pit and underground mining. Mine planning engineers generally use their intuition and experiences in decision making. Mostly, linguistic variables (the weather is raining, soil is wet, etc.) come into question and decision-makers may not know how these variables are computed. Since the advent of the fuzzy set theory, these uncertainties are easily interpreted in the decision-making process. The development of computer technology and programming of colloquial language with expert systems have considerably reduced decision-makers' burden. This paper reviews the development of a computer programme software called EQS (EQuipment Selection) that automates equipment selection in mining engineering using fuzzy set theory. The EQS with an introduction of the concepts and theories of multiple attribute decision-making, the fuzzy set theory, and EQS applications to mining industry problems with case studies are presented

Introduction

In the last three decades, fuzzy logic methods have been advanced as a formal means to deal with implicit imprecision in a wide range of problems, e.g. in industrial control, military operations, economics, engineering, medicine, reliability, pattern recognition and classification. There are many studies related to these subjects, e.g. Maiers and Sherif (1985)[1], Kandel (1986)[2], Klir and Folger (1988)[3], Prade (1985)[4], Dubois *et al.* (1992)[5], Bandopadhyay and Chattopadhyay (1986)[6], Bandopadhyay (1987)[7–8], Gershon *et al.* (1993)[9], Herzog and Bandopadhyay (1996)[10], Alvarez Grima (2000)[11], Bruines (1998)[12], Clarke *et al.* (1990)[13], Nguyen (1985)[14], Başçetin and Kesimal (1999)[15], Kesimal and Başçetin (2002)[16] and Başçetin *et al.* (2004)[17]. Fuzzy logic synthesizes different solution alternatives, each of which need not be right or wrong but instead is possibly true to a certain degree (see, Zadeh (1965)[18]; Yager (1986)[19]).

Decision making may be characterized as a process of selecting a 'sufficiently good' alternative to attain a goal or goals, and it involves uncertainity. Thus, one of the most important aspects for a useful decision aid is to provide the ability to handle imprecise and vague information, such as 'large' profits, 'fast' speed and 'cheap' price. A decision model should cover processes for identifying, measuring and combining criteria and alternatives to build a conceptual model for decisions and evaluations in fuzzy environments. Mining engineers generally use their intuition and experiences in decision making. Mostly linguistic variables (the weather is raining, soil is wet, etc.) become questionable and decision-makers may not know how these variables are computed. Since the advent of the fuzzy set theory, these uncertainties are easily evaluated in the decision-making process. The development of computer technology and programming of colloquial language with expert systems have considerably reduced decision makers' burden. In this study, a computer software based on fuzzy set theory for automating equipment selection in mining operations is introduced.

Fuzzy set history

In using our daily language to impart knowledge and information, there is a great deal of imprecision and vagueness, or fuzziness. Such statements as 'John is tall' and 'Fred is young' are simple examples. Our main concern is representing, manipulating, and drawing inferences from such imprecise statements:

- The description of a human characteristic such as 'healthy'
- The classification of patients as 'depressed'

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- The classification of certain objects as 'large'
- The classification of people by age such as 'old'.
- A rule for driving such as 'if an obstacle is close, then brake immediately'.

In the examples above, terms such as 'depressed' and 'old' are fuzzy in the sense that cannot be sharply defined. However, as humans, we do make sense out of this kind information, and use it in decision making. These 'fuzzy notions' are in sharp contrast to such terms as 'married', 'over 39 years old', or 'under 6 feet tall'. In ordinary mathematics, we are used to dealing with collection objects, say certain subsets of a given set such as the subset of even integers in the set of all integers. But when we speak of the subset of depressed people in a given set of people, it may be impossible to decide whether a person is in that subset or not. Forcing a yes-or-no answer is possible and is usually done, but information may be lost in doing so because no account is taken of the degree of depression. Although this situation has existed from time immemorial, the dominant context in which science is applied is that in which statements are precise (say either true or false)—no imprecision is present. But in this time of rapidly advancing technology, the dream of producing machines that mimic human reasoning, which is usually based on uncertain and imprecise information, has captured the attention of many scientists. The theory and application of fuzzy concepts are central in this endeavour but remain to large extent in the domain of engineering and applied sciences.

With the success of automatic control and expert systems, we are now witnessing an endorsement of fuzzy concepts in technology. The mathematical elements that form the basis of fuzzy concepts have existed for a long time, but the emergence of application has provided a motivation for a new focus for the underlying mathematics. Until the emergence of fuzzy set theory as an important tool in practical applications, there was no compelling reason to study its mathematics. But because of the practical significance of these developments, it has become important to study the mathematical basis of this theory[20].

A fuzzy set F in a universe U is a collection of ordered pairs $\{(u, \mu_F(u)) / u \in U\}$ where $\mu_F: U \rightarrow [0, 1]$ is the membership function of F. Specifically, $\mu_F(u)$ is the membership grade of u in F, which measures the compatibility of u with F. $\mu_F(u)$ may also be regarded as the degree of truth, or possibility, that u belongs to F. This idea of sliding membership $(0 \leq \mu_F(u) \leq 1)$ contrasts with classical set theory in which an element of the universe either has full membership $(\mu_F(u) = 1)$ or no membership $(\mu_F(u) = 0)$ in a set. Conversely, in fuzzy set theory, the fact that whether u is a member of this set or not is measured by the membership grade between 0 and 1. Because u is not a member of a fuzzy set F $(u \notin F)$ if it has the membership grade $\mu_F(u) = 0)$. In case of the membership grade having $\mu_F(u) = 1$, it is a full member of a fuzzy set F $(u \in F)$. u is also a member of a fuzzy set F regarding the real values.

To clear the difference between these two sets, look at the following example: Supposed that a set K has various cycle times of three shovels (A, B, C). An optimum loading cycle time is considered to be 20 seconds in this mine site. Shovels A, B and C have 20, 23 and 28 seconds of loading cycle time respectively. K set is firstly evaluated a by crisp and subsequently by fuzzy a set.

From Figure 1, only the cycle time of shovel A is optimum and ıts the membership grade is $\mu_K(A)=1$. Since the cycle time of other shovels is far from the optimum, they have no chance in selection. Thus, the membership grades of these shovels have zero value $(\mu_K(B) = 0,\ \mu_K(C) = 0)$. According to fuzzy set theory, as the membership grade of shovel A complies with the optimum cycle time, it has the highest priority in selection and hence the membership grade of 1 $(\mu_K(A) = 1)$. The cycle time of shovel B is a little closer to the optimum, and whether it is a member of a fuzzy set or not depends upon the membership grade between 0 and 1. Shovel C is not a member of a fuzzy set and has zero value because of being rather far away the optimum.

Fuzzy multiple attribute decision making

There are many methods of decision making. The focus of this paper is on Yager's[21] method that is one of the methods of fuzzy multiple attribute decision making. Consider the problem of selecting a site from the set $\{A, B, C\}$ for a new in-pit crusher in a quarry, with the goal, G, of spending the minimum investment possible and for criteria evaluation to be located near the pit and the processing plant, respectively $C1$ and $C2$. The judgement scale used is 1—Equally important, 3—weakly more important, 5—strongly more important, 7—demonstrably more important and 9—absolutely more important. The values between (2, 4, 6, 8) show compromise judgments.

Formally, let $A = \{A_1, A_2, \ldots, A_n\}$ be the set of alternatives, $C = \{C_1, C_2, \ldots, C_m\}$ be the set of criteria which can be given as fuzzy sets in the space of alternatives and G the goal, which can also be given by a fuzzy set. Yager suggests the use of Saaty's method for pair-wise comparison of the criteria (attributes). A pair-wise comparison of attributes (criteria) could improve and facilitate the assessment of criteria importance. Saaty[22] developed a procedure for obtaining a ratio scale for the elements compared. To obtain the importance, the decision-maker is asked to judge the criteria in pair-wise comparisons and the values assigned are $\boldsymbol{w_{ij} = 1/w_{ij}}$. Having obtained the judgments, the mxm matrix B is constructed so that: (a) $b_{ii} = 1$; (b) $b_{ij} = w_{ij}$; (c) $b_{ji} = b_{ij}$. To sum up, Yager suggests that the resulting eigenvector should be used to express the decision maker's empirical estimate of importance (the reciprocal matrix in which the values are given by the decision maker) for each criteria in the decision and criteria 1 and 2, respectively $\boldsymbol{C_1}$ and $\mathbf{C_2}$, are three times as important as G, and the pair-wise comparison reciprocal matrix is:

$$\begin{array}{ccc} G & C_1 & C_2 \end{array}$$
$$\begin{bmatrix} 1 & 1/3 & 1/3 \\ 3 & 1 & 1 \\ 3 & 1 & 1 \end{bmatrix}$$

Hence, the eigenvalues of the reciprocal matrix are $\lambda = [0, 3, 0]$ and therefore $\lambda_{max} = 3$. All values except one are zero (as stated in Saaty[22]). The weights of the criteria are finally achieved in the eigenvector of the matrix,

$$eigenvector = \begin{bmatrix} 0.299 \\ 0.688 \\ 0.688 \end{bmatrix} with\ \lambda_{\max}.$$

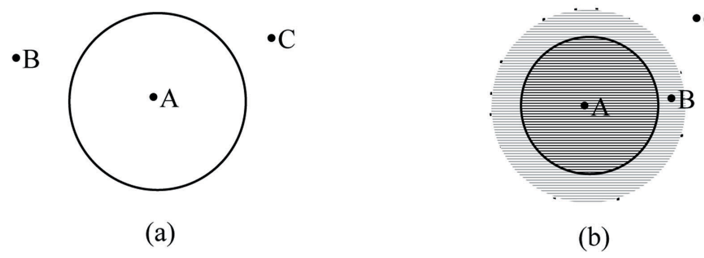

Figure 1—Crisp (a) and fuzzy set (b)

The eigenvector corresponds to the weights to be associated with the memberships of each attribute/feature/goal. Thus, the exponential weighting is α_1=1/3, α_2=2/3, α_3=2/3 and the final decision (membership decision function) about the site location is given as follows:

$$\mu_D(A) = D(A) = min \left\{\mu_G(X), \mu_{C1}(X),\ \mu_{C2}(X), \ldots \ldots, \mu_{CM}(X)\right\} \quad [1]$$

There are some cases where the importance of criteria is not equally alike and weighting coefficients are required. The decision function with the relative importance of criteria, omitting the membership signal μ for simplification, is:

$$D = min\left(\omega_o G,\ \omega_1 C_1,\ \omega_2 C_2, \ldots., \omega_m C_m\right)$$

$$with \sum_{j=1}^{m} \omega = 1$$

Thus, the fuzzy decision function in the example is

$$D(A) = min\left\{G^{1/3}, C_1^{2/3}, C_2^{2/3}\right\}$$

$$G = \left[0.5/A_1, 0.8/A_2, 0.3/A_3\right]^{0.229}$$

$$= \left[0.85/A_1, 0.95/A_2, 0.76/A_3\right]$$

$$C_1 = \left[0.7/A_1, 0.9/A_2, 0.5/A_3\right]^{0.688}$$

$$= \left[0.78/A_1, 0.93/A_2, 0.62/A_3\right]$$

$$C_2 = \left[0.4/A_1, 0.2/A_2, 0.9/A_3\right]^{0.688}$$

$$= \left[0.53/A_1, 0.33/A_2, 0.93/A_3\right]$$

$$D(A) = \left\{0.53/A_1, 0.33/A_2, 0.62/A_3\right\}$$

and the optimal solution,

$$D = \max\left\{(x_1, .24), (x_2, .2), (x_3, .12)\right\} \quad [2]$$

corresponding to the maximum membership 0.62, is A_3 $(D(A^*) = 0.62/A_3)$.

EQS program description

Aim of the EQS program

The EQS program compares the various mining systems and criteria in an open-pit or underground mines by using fuzzy logic algorithms, and then finds the optimum mining systems with a great accuracy. The general flow chart of the program is given in Figure 2.

EQS program working processes

The program consists of two different components: 1) Input parameters are taken by the EQS that is programmed in the Visual Basic Programming Language. 2) The criteria comparison matrix is solved by using Matlab v 6.0 software[23].

At the starting point, the sort of mine is selected as an open-pit or an underground type. All listed alternative systems and criteria can be taken from the separate files. For open-pit type mines, 'open-pit.txt' contains data about alternative systems, and 'open-pitcriteria.txt' has criteria data. Similarly, for underground type mines, 'underground.txt' contains data about alternative systems, and 'undergroundcriteria.txt' has criteria data. The system alternatives and their criteria are parameters that can be selected by the user after the mine type is chosen. Then, the user enters the membership grades of each alternative system. The membership grades of all alternative systems for each criterion are determined by conferring with experts on this subject. In order to compare the criteria with each other, a new data window that is a squared-matrix form has to be filled in or the user can easily select one of the default files. Also, the alternative systems and criteria data can be modified by the user.

The criteria matrix in m x m form is constructed to express the decision-makers' empirical estimate of importance for each criterion. After this, the matlab code (see Appendix I) is executed to obtain the eigenvalue and the eigenvector of the criteria matrix. The matrix dimension determines the number of the eigenvalues and eigenvectors. This means that the matrix dimension is the same as the number of eigenvalues and the eigenvectors of the criteria matrix. The eigenvector that corresponds to the maximum eigenvalue is obtained. The eigenvector corresponds to the weights to be associated with the memberships of each attribute/criteria/feature/goal. Thus, the eigenvector is used as the exponential weighting for each criterion, which are selected for alternative systems. The value corresponded to the minimum criteria is taken for each system alternative in determining the decision vector (Equation [1]). The optimum system alternative that corresponds to the maximum value is obtained from the optimum decision vector (Equation [2]).

The EQS software carries out this selection by using the fuzzy logic algorithm in a numerical manner and calculates the optimum system alternative. As a consequence, the user can easily obtain the result that corresponds to the optimum system alternative.

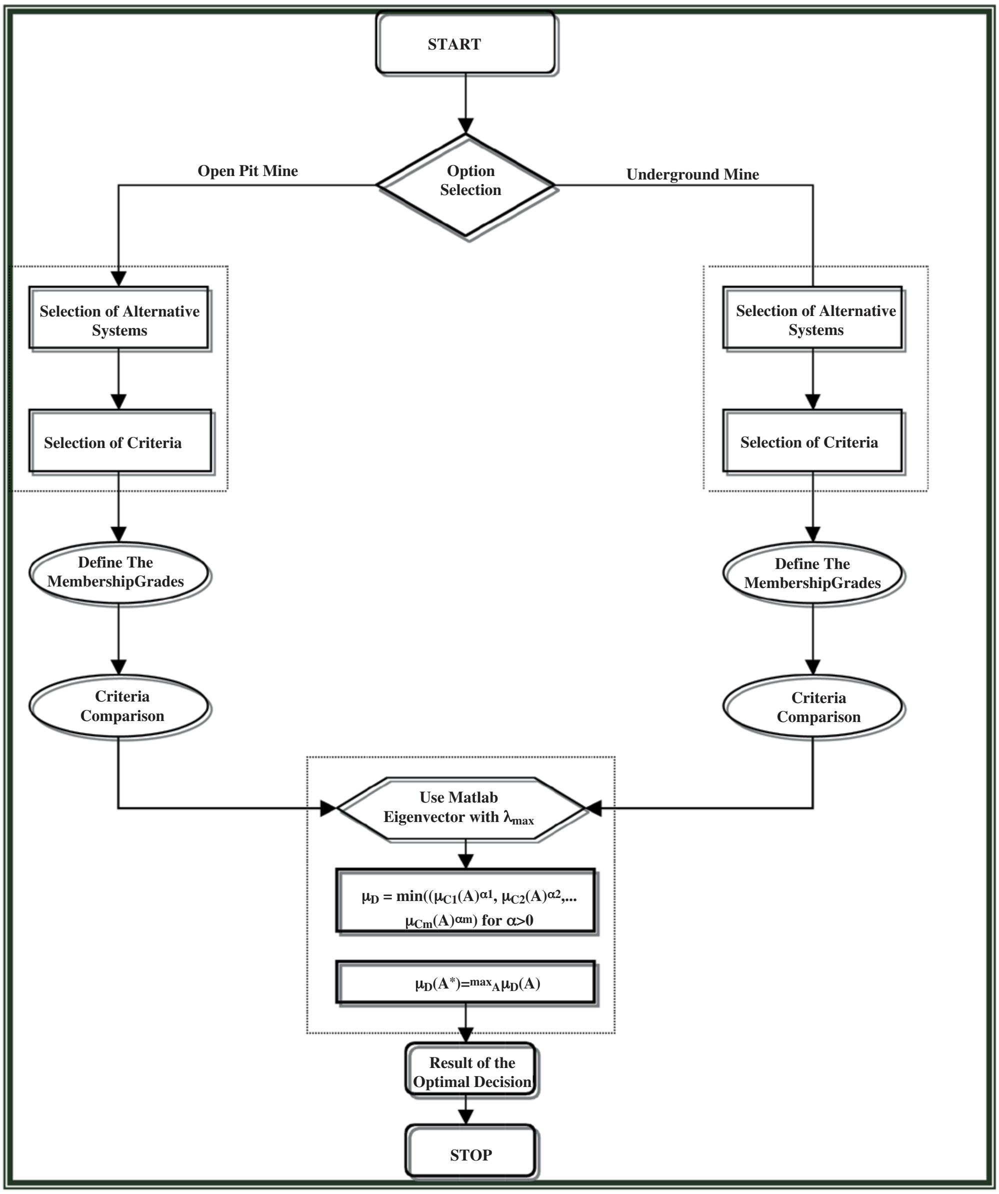

Figure 2—General flow chart of EQS program

Case study

Case study for underground mining method selection

This study is done for searching the optimum underground mining method selection based on the brown coal (lignite) mine situated in Black Sea coast north-west of Arnavutkoy, Istanbul, Turkey[24]. Because of the existance of a summer resort area in the Black Sea, open-pit mining may be restricted in the future. Therefore, the application of one of the underground mining methods is unavoidable for producing coal.

The necessary physical parameters such as the geologic and geotechnical properties of ore, hanging-and footwall, economic effects, environmental impacts, which are established with field and laboratory tests, together with other uncertain variables were determined. The generated parameters for the method selection are given briefly in Table I together with related criterion.

The initial analysis of the method selection system suggests the following alternatives: longwall with filling (direction of inclination rising) (A_1), longwall with filling (direction of inclination decline) (A_2), longwall with filling (progressed) (A_3), longwall with filling (returned) (A_4), or room and pillar with filling (A_5) systems. Some of the linguistic results produced are as follows:

- According to dimension, A_3 is the best method
- Seam thickness is an average 2.1 metres, therefore A_3 can be chosen
- A_5 is suitable in terms of seam inclination
- A_5 is safer according to the soundness degree of the hangingwall
- From the viewpoint of safety of groundwater, A_1 would be the best choice.

Before the underground mining method selection procedure, the following eighteen criteria of each operation are considered in the decision-making (Table II).

At the end of the evaluations (determining the membership grade of each criterion and building m x m matrix, obtaining the maximum eigenvalue of the reciprocal matrix and finally exponential weighting), the following results are obtained[24].

$$\mu_D(A) = \begin{Bmatrix} 0.81/A_1, 0.79/A_2, 0.89/A_3, \\ 0.87/A_4, 0.92/A_5 \end{Bmatrix}$$

And the optimal solution is,

$$\mu_D(A^*) = 0.92 / A_5.$$

In conclusion, the room and pillar method with filling (A5) resulted in a more suitable method, with 0.92 membership degree, than the others.

Case study using EQS for underground mining method selection

In this section, we apply our EQS program to the case study mentioned above. Our aim is to prove our program's reliability and demonstrate its application procedures.

After the selection of the mine type, the system alternatives and criteria can be taken from the related files for our case study. The membership grades of the alternative systems for each criterion can be loaded from the program. However, these values can also be entered manually into the program by using the program window. For the comparison of the criteria with each other, a default data window is selected and then a squared-matrix form is taken automatically. After these processes are completed, the matlab algorithm is executed to obtain the eigenvalue and the eigenvector of the criteria matrix. Finally, the optimum final decision, which is a room and pillar method, shown in Figure 3, is obtained.

The other important application for open-pit mining method selection is given in Appendix II.

Table I

Geometric shape of the lignite deposit	Plate state (layered)
Thickness of the lignite seam	2.1 m (average)
Seam inclination	7°
Ore depth	50 m (average)
Soundness degree of the lignite	Low strength
Contact state of hanging and foot wall	Not clear
Hanging wall	Clay, low strength (compressive strength: 2.2 kg/cm^2)
Foot wall	Clay, low strength (compressive strength: 2.2 kg/cm^2)
Subsidence effect	Risky (seam is close to surface)
Roof support	Necessary
Settlement area	Exist over the coal seam
Combustion	Combustible coal properties
Ground water	Exist because of the sea

Conclusions

The development of computer technology and programming of colloquial language with expert systems have considerably reduced decision-makers' burden. Considering this fact, we have developed a computer software called EQS that automates decision making in a fuzzy environment for solving multiple attribute problems of optimum equipment selection in surface mining and optimum underground mining method selection. The EQS program makes decisions about the optimal equipment selection by applying the fuzzy set theory to the multiple attribute problem. The EQS software has been explained and the case studies for open-pit and underground mine types by using the EQS are presented.

Mining methods obtained from our case studies have been applied in these mines. These results show the applicability of the decision-making method based on fuzzy logic. The method is very sensitive to the subjective criteria values and membership degree of alternatives.

Although the EQS program is in its initial stage and may require to be modified depending on mining applications and programming structure, it is faster, more practical, and more cost-efficient than conventional approaches. Thus we think that the EQS software has a great potential to become a helper tool in various mining applications.

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Table II

Criterion	Operation	Criterion	Operation
C1	Geometric shape of the deposit	C10	Roof support
C2	Coal thickness	C11	Settlement area
C3	Seam inclination	C12	Combustion
C4	Ore depth	C13	Methane existence
C5	Soundness degree of the lignite	C14	Ground water
C6	Contact state of the lignite seam	C15	Mining cost
C7	Soundness degree of the hanging wall	C16	Capital cost
C8	Soundness degree of the foot wall	C17	Production ratio
C9	Subsidence effect	C18	Labour cost

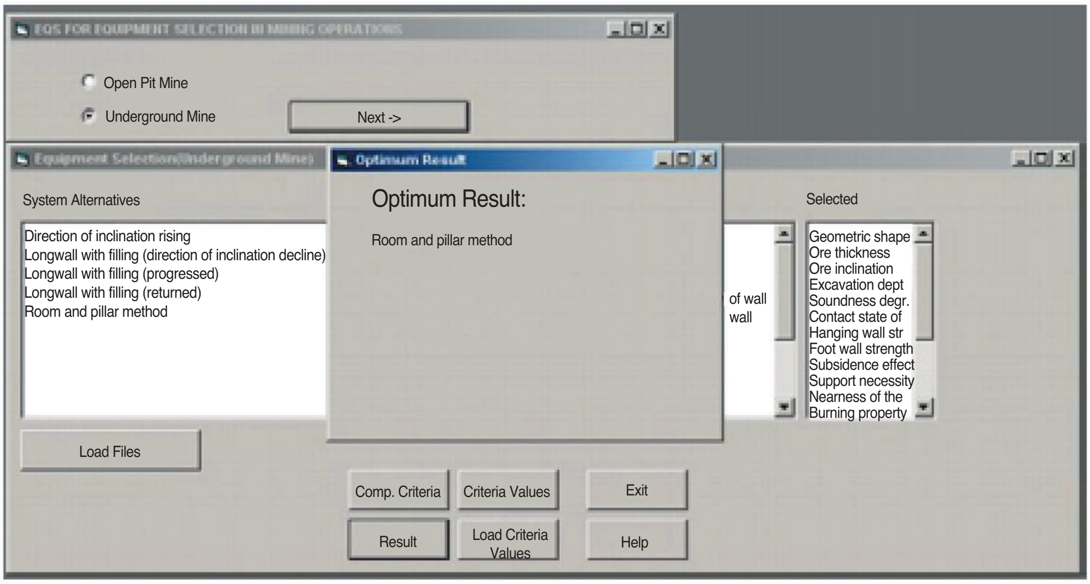

Figure 3—The window shows the result of the optimum method selection

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Appendix I

Matlab code for EQS fuzzy process

```
load ozd.txt
[V,D]=eig(ozd)
n=length(V)
m=D(1,1)
indis=1
for i=2:n
  if D(i,i)>m
    indis=i
    m=D(i,i)
  end
end
VS=V(:,indis)
load kk.txt
[nn,mm]=size(kk)
for i=1:nn
  for j=1:mm
    kk(i,j)=kk(i,j)^VS(i,indis)
  end
end
for j=1:mm
  kkk(1,j)=min(kk(:,j))
end
mks=kkk(1,1)
ind=1
for j=2:mm
  if kkk(1,j)>mks
    mks=kkk(1,j)
    ind=j
  end
end
save ds.txt ind -ascii
```

Appendix II

Case study for open-pit mining method selection

This case study is done for searching the optimum open-pit mining method selection[15]; it is carried out on loading-hauling systems to transport coal to the power plant (2x150MW capacity) that will be constructed 5 kilometres from Çan lignite mined by TKI (Turkish Coal Enterprises). The coalmine is situated about 79 kilometers north of the town of Çan in southeastern Çanakkale located west of Turkey. The mine has been in continuous operation since 1975.

The initial analysis of the transportation system suggests the following alternatives: shovel-truck (A_1), shovel-truck-in-pit crusher-belt conveyor (A_2), or shovel-in-pit crusher-belt conveyor (A_3) systems. The characteristic of the mine site and the equipment specifications are given in Table I.

The following are some of the given linguistic results produced from various solution methods (linear programming, expert systems, etc.) and therefore presented by the experts to questions posed (what if...? or if..?, etc.) Each system shows its own advantages. In this case, it does not appear that an easy solution to the problem can be obtained. From the solution point of view, the application of the fuzzy set theory would be a proper choice, and is therefore also used in this case study.

- The road conditions differ from season to season. Thus, the value of rolling resistance gives rather low (2%) in dry season while it reaches a high (5%) in winter

Table I
Technical parameters calculated for each system

Reserve	Possible: 97 236, 350 ton, available: 78 122 206 ton
Coal production	1 800, 000 ton/year (for power plant), daily: 6 006 ton/day
Active workday	3 shift/day, 300 days/year, 6000 h/year
Coal	Lignite, intermediate: clay, tufa, slica
Coal density	1.5 ton/m^3
Average coal thickness	19.3 m
Coal size	Max. 50 cm (run-of-mine), 10 cm (belt conveyor)
Coal analysis	Moisture: 22.5%, Ash: 25%, Low calorific value: 2 878 kcal/kg, Sulfide: 4.2%
Swell factor (coal)	1.2 (conveying)
Blasting	Exist
Haulage distance	5 km (A_1), 3 km belt conveying - 0.3 km truck haulage (A_2), 3.3 km (A_3)
Average grade resistance	3%
Average rolling resistance	3%
Max. inverse grade	+ 2%
Dump level	Front shovel: 7.5 m Truck (Loading height: 3.78 m)
Bucket capacity	Hydraulic excavator: 4.6 m^3
Bucket fill factor	90%
Operating weight	Front shovel: 83 800 kg, Truck: 40 188kg
Useful life	Front shovel: 25 000 h, Loader: 20 000h, Truck: 15 000 h, Conveyor: 24 000 h
Loading time	Hydraulic excavator: 25 s
Cycle time	26.3 min for 5 km (A1), 6.2 min for 0.3 km (truck-conveyor)
Belt conveyor	2 m/sec, 900 mm width, 3 km length (out of pit) 0.3 km (in-pit)
In-pit crusher	350 ton/h
Capital cost	Truck: $400,000, Crusher: $700,000, Conveyor: $3,000,000 (3 km long), Conveyor: 3,200,000 (3.3 km)
Operating cost	A_1=$5.67/ton, A2=$3.75/ton, A_3=$3.42/ton

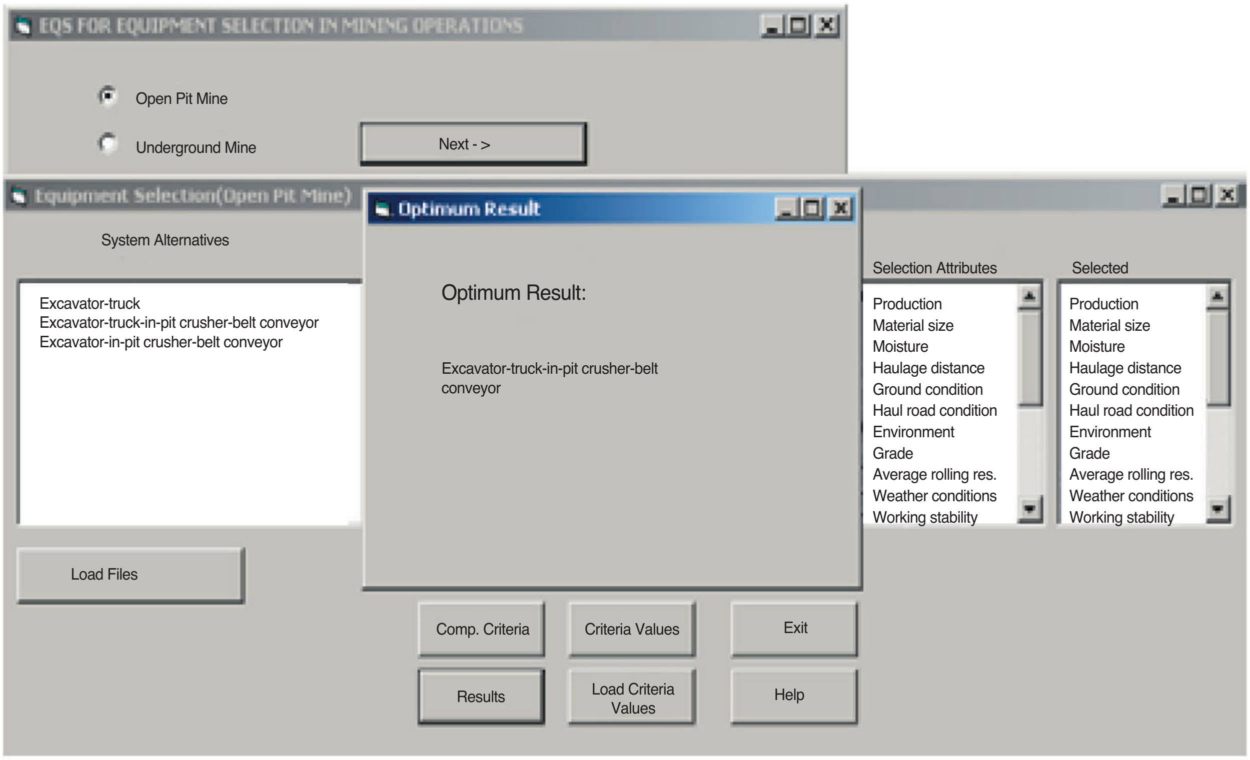

Figure 4—The window shows the result of the optimum equipment selection

Table II

Criteria of each operation

Criterion	Operation	Criterion	Operation
C1	Production	C12	Useful Life
C2	Material Size	C13	Flexibility
C3	Moisture	C14	Availability
C4	Haulage Distance	C15	Utilization
C5	The Ground Condition	C16	Mobility
C6	Haul Road Condition	C17	Continuous
C7	Environment (dust, noisy, etc)	C18	Support
C8	Grade	C19	Net to Tare Ratio
C9	Average Rolling Resistance	C20	Capital Cost
C10	Weather Conditions	C21	Operating Cost
C11	Working Stability		

- Maximum material size is about 0.5 metres, in case, truck haulage has an advantage from the loading point of view
- A_1 and A_2 are the best alternatives when mobility and flexibility in the system are considered
- A_2 is the better system in terms of the working stability.

Before the loading-hauling method selection procedure, the following twenty-one criteria of each operation are considered in decision making (Table II).

At the end of the evaluations (determining the membership grade of each criterion and building m x m matrix, obtaining the maximum eigenvalue of the reciprocal matrix and finally exponential weighting) the following results are obtained[15].

$$\mu_D(A) = \{0.86 / A_1, 0.93 / A_2, 0.70 / A_3\}$$

and the optimal solution is,

$$\mu_D(A^*) = 0.93 / A_2.$$

In conclusion, shovel-truck-in-pit crusher-belt conveyor (A_2) resulted in a more suitable method with 0.93 membership degree than the others.

Case study using EQS for open-pit mining method selection

In this section, we apply our EQS program to the case study mentioned in Section 5.3. After the selection of the mine type, the alternative systems and criterions can be taken from the related files for our case study. The similar steps explained in the section: Case study using EQS for underground mining method selection (p. 5). should be followed to obtain the optimum final decision which is shovel-truck-in-pit crusher-belt conveyor method as shown in Figure 4. ◆