Ore-age: a hybrid system for assisting and teaching mining method selection

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Abstract

Mining method selection is among the most critical and problematic points in mining engineering profession. Choosing a suitable method for a given ore-body is very important for the economics, safety and the productivity of the mining work. In the past studies there are attempts to build up a systematic approach to help the engineers to make this selection. But, these approaches work based on static databases and fail in inserting the intuitive feelings and engineering judgments of experienced engineers to the selection process. In this study, a system based on 13 different expert systems and one interface agent is developed, to make mining method selection for the given ore-bodies. The agent Ore-Age, to follow his goal of supplying the maximum assistance to engineers in selecting the most suitable method for a specific ore-body, tries to learn the experiences of the experts he has faced. After this learning process the knowledge base is evolved to include these experiences, making the system more efficient and intuitive in mining method selection work. To realize the above goal, the system’s tutoring procedure is executed by the agent, in case an inexperienced user enters the system, to complete his/her missing knowledge about mining method selection.

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1. Introduction

Mining methods are the systematic approaches defining how to carry out the production in a mine. Among the several methods available, choosing the right method is of utmost importance for the economics, safety and the productivity of the mining work, therefore they are usually named as the core of the mining engineering subject. The decision by a mining engineer about mining methods should provide healthy working conditions for the workers, a protective working process for the environment, a profitable job for the company and a productive mine for the welfare of the country. However, unfortunately, in addition to the importance of the selection, the procedure of making the selection is rather confusing and difficult. The difficulty of the selection arises from some basic facts. One of them is the absence of a specific formulation for selecting a mining method, in spite of the studies performed by Boshkov and Wright (1973), Brady and Brown (1985), Hamrin (1982), Laubscher (1977,1981), Morrison (1976), Nicholas (1981), and Tymshore (1981) to obtain such a methodology. These studies were neither enough nor complete, as it is not possible to design a methodology that will automatically choose a mining method for the ore-body studied. Each ore-body is unique with its own properties and engineering judgement has a great effect on the decisions in such a versatile work like mining. Therefore, it seems clear that only an experienced engineer who has improved his experience by working in several mines and gaining skills in different methods can give logical decisions about mining method selection.

In this paper, a mining method selection assisting and tutoring system is described. Only underground mining methods are included in this selection process. So, it is assumed that the decision for underground mining is given before using this system. The system acts as an assistant tool for senior mining engineers during the selection process for a mining method. Moreover, the system can act as a tutoring tool for junior engineers or mining engineering students, who are learning the mining method selection procedure with the execution of the tutoring mode. Our system has also the ability of...
reflecting the intuitive feelings of the expert engineers to the mining method selection process by the help of its learning mode. The system in this study is composed of three main parts. The first part is composed of thirteen virtual experts that evaluate the mining methods by a quantitative (numerical) approach, based on the Takagi–Sugeno–Kang (TSK) (Takagi & Sugeno, 1985) model of the fuzzy theory. The second part is an interface agent called ‘Ore-Age’ working as a mediator between the users and the virtual experts. In Ore-Age, ore stands for the abbreviation of ore-body and ‘age’ stands for the abbreviation of agent. Ore-Age decides on the mining methods that will be recommended to the user. This decision is based on the evaluations of the virtual experts. The last part is composed of users. Therefore, the system can be identified as a hybrid system based on agent theory and neuro-fuzzy learning architecture. When mining method selection scheme is discussed, it is observed that the ore-body characteristics are usually introduced and used in terms like hard, strong, thick, etc. For example, if an ore-body’s thickness is higher than a certain threshold, this ore-body is considered in the ‘thick’ category during the evaluation process without thinking on how thick it is. Therefore, in some cases there is the danger of behaving two ore-bodies, which are considerably different in thickness from each other, as if they possess the same thickness when classical set theory is used in this process. After the identification of this issue, the introduction of fuzzy logic to the developed system becomes a very important requirement for a safe and effective execution of the system. The fuzzified ore characteristics defined by Gaussian membership functions, are taken as inputs to the TSK model of evaluation and real valued outputs are handled. These outputs symbolize the suitability of a given ore-body to the method the virtual expert is working on. It can be stated that this model of evaluation can also be identified as a two-layered neural network, because of its functional structure. The learning theory works based on this neuro-fuzzy system. The objective of the study, is to design an hybrid system that can be used as an assistant and tutoring tool for mining method selection, inserting the intuition of the expert engineers systematically to the selection criteria by the help of its learning abilities.

In the literature, some decision support systems are proposed to assist, especially the inexperienced engineers, in selecting mining methods; however, they may not lead completely to an efficient and correct selection. Bandophadyay and Venkatasubramanian (1987) developed on of the first studies on the application of expert system in the area of mining method selection. It is developed to help the mining engineers in selecting mining methods for coal deposits mineable by underground methods. For the initial system, several geotechnical factors such as rock strength, groundwater, floor condition that influence the selection of a mining method were chosen. Values for the certainty factor in each production rule was obtained from the expert opinion. Camm and Smith (1992) developed another study on the application of expert systems in the area of mining method selection. A mining and milling method selection expert is described using a knowledge base that is composed of alternative methods, experience, intuition, deposit types (that are studied beforehand based on geologic data and expert knowledge), mine plans and engineering studies. Another expert system is developed by Gershon, Bandopadhyay, and Panchanadam (1995) based on Nicholas’ methodology (1981). By using ‘Multi-Attribute Utility Theory’ which provides a convenient way of handling preference and attitudes in decision-making, the system’s choices are based on the users’ objectives that are having priorities like safety. In the study performed by Tatiya (1998), a mining method is selected among three stipping methods namely sublevel, down the hole and cut and fill based on a detailed economic analysis. Basu then developed a similar expert system in 1999 (Basu, 1999) by improving practically and technically the system of Gershon et al. (1995). However, all of these are static systems lacking the capability of giving interactive decisions to increase the selection efficiency. In addition, they are not capable of embedding the intuition and the judgement simulating the experienced engineers in the selection process. There are two major contributions of this study to the literature; first of all the databases of the virtual experts evaluating the methods continuously evolve based on a neuro-fuzzy training algorithm. Therefore, if a selection made by an expert user on a case study differs from that of the system, the selection of the expert user is learned by the system. This choice will be offered as an alternative choice if a similar case study is activated in the system. In this way, the intuitive knowledge and the judgement capability of the expert users or in other words ‘experienced engineers’ can be directly added to the databases of the virtual experts (Guray, Celebi, Atalay, & Pasamehmetoglu, 2002). This addition can be made in a dynamic and systematic way, because creative expert ideas about new case studies will be continuously added to the database, for every execution of the system by an appreciated expert. The second contribution is related to the system’s interactive tutoring ability, which is activated for inexperienced users. In the case when an unacceptable answer is received from the user, our system, by concentrating the user one by one on the ore-characteristics, which are utmost importance for the selection work, finds the point where the user makes mistakes. The system also keeps an error database to be aware of the common errors. If the user’s possible area of error is faced before, the system will change its strategy to concentrate the user directly to the area of the possible error. It can be said, that this system will determine its strategies to find the most efficient and fast way to complete the missing knowledge of the inexperienced users.
In this paper, in Section 2 an overview about the mining method selection process is given. System architecture and the theoretical background of the system execution are described in Section 3. Consecutively, the procedures and modes that are used in the system are given in detail. In Section 5, a case study that is processed in the system is given as an example to demonstrate the learning capabilities of the system. The results of the performance evaluation of neuro-fuzzy learning are presented in the next section. Finally, conclusions and recommendations are given in Section 7.

2. Overview of the mining method selection process

There are mainly four stages for a mining application: prospecting, exploration, development and exploitation (Hartman, 1992). During prospecting, the presence of a mineral deposit is sought in certain places by means of visual examination, aerial photography, topographic and structural maps, geophysical and geochemical methods. Consecutively, by means of exploration, the possible size and the value of the deposit found by prospecting is determined by more refined techniques like X-ray, spectrographic or radiometric analysis, trenching, tunneling and drilling. By this way, the amount of mineral in the deposit and its possible value is estimated. The financial worth of the ore-body is compared with the estimated cost of mining to give the decision of extracting or abandoning the deposit. If it is decided to extract the deposit, then come the development and exploitation stages. In development, the mineral deposit is opened for exploitation, which cover the actual recovery of the mineral from the earth. Mining methods are the systematic approaches defining how to carry out the production in a mine, therefore development and exploitation stages of mining are performed based on the mining method selected for the ore-body.

The techniques for evaluating mining methods reflect the previous experiences and intuition of the miners. The ultimate goals of mining method selection are to maximize company profits, maximize recovery of the mineral, and provide a safe environment for the miners by selecting the method with least problems among the feasible alternatives. The underground mining methods that are considered in this study can be stated as follows: Undercut and fill, Longwall, sublevel stoping, block caving, sublevel caving, room and pillar, cut and fill, top slicing, square set, shrinkage stoping, longitudinal sublevel stoping, longitudinal sublevel caving and longitudinal block caving. In order to determine which method is the most suitable one, the input variables of the mining costs, mining rate, labor availability and environmental regulations should be considered in detail (Karabeyoğlu, 1986). Among several studies of designing a methodology for mining method selection, Nicholas’ (1981) work has an important characteristic of collecting and systemizing all criteria which have been put forward by the other authors and the ideas he proposed in a single methodology. Because of this reason and because of the algorithmic structure of his system, our study concentrates more on his work and uses certain parts of this system as the background knowledge base. According to Nicholas, two important factors that have a great impact on the selection of a mining method are as follows.

1. Geometry and grade (amount of valuable mineral found in unit weight of deposit, e.g. g/t distribution of the deposit).
2. Rock mass strength for the ore zone, the hangingwall (the rock above the ore-body), and the footwall (the rock below the ore-body).

The geometry of the deposit (ore-body) is defined in terms of the general shape (with subtopics of massive, platy-tabular and irregular), ore thickness (with subtopics of narrow, intermediate, thick, very thick), plunge (with subtopics of flat, intermediate and steep) and depth below surface. On the other hand, grade distribution of the ore-body is defined being as uniform, gradational or erratic. According to Nicholas, the rock mechanics characteristics of the ore-body that can be considered as critical during mining method selection can be identified by the topics of rock substance strength (having weak, moderate and strong categories), fracture spacing (having very close, close, wide, very wide categories) and fracture strength (having weak, moderate and strong characteristics). As the most important step in the selection process of Nicholas’ methodology, after the characteristics of the ore-body is learned, the applicability of each of the mining methods for this ore-body is evaluated by assigning certain points (weights) to the mining methods. The points assigned to the methods increase or decrease proportionally according to the suitability of the ore-body characteristics to the method. For this purpose, ore characteristics starting from ore geometry to boundary shape are investigated and evaluated for each of the mining methods. If the investigated ore characteristic makes the mining method more applicable for the given ore-body a higher point is given to the method or vice versa. Therefore, if the characteristic is preferred for the mining method, 3–4 points are assigned. If the mining method can be used with the given characteristic without any problem 1–2 points are assigned. If it is unlikely that the mining method would be applied by the given characteristic, but the method is not completely ruled out, 0 point is given. If the characteristic completely rules out the method −49 points are given. Therefore, following this logic, the suitability of the ore-body to each method is evaluated and the feasible ones can be chosen after a numerical ranking process based on the total points collected by each method.

The system which can also be called using the name of the interface agent Ore-Age described in this paper uses the general logic and most of the numerical evaluation values in...
the database of the Nicholas’ methodology (1981). However, during the design of the system, some other minor criteria are added to this methodology, to be able to have a more detailed evaluation platform. These are capital cost factor, operating cost factor, productivity factor, boundary condition factor, ore-grade factor, surface subsidence factor, spontaneous combustion factor, and lake presence factor. The detailed application of these factors cannot be faced in Nicholas’ methodology, but their absence can lead to the failures in the selection procedure. In addition to this, some of the Nicholas’ information in the database is updated after the entrance of new mining methods in our methodology (Pasamehmetoglu, 2001).

Therefore, with the above additions to the Nicholas’ methodology, a mining method selection procedure based on a similar numerical evaluation approach is embedded in our system.

The mining method selection procedure embedded in our system follows this flow of operations:

1. The required characteristics of the ore-body for the evaluation are determined.
2. The values of these characteristics for the given ore-body are asked as either numeric or verbal inputs from the user.
3. For each mining method the points taken for each criteria are added up for the evaluation of all the characteristics with respect to all of the mining methods. Then all the methods are ranked according to the amount of points they have collected. The methods with higher ranks seem suitable for the given ore-body. If the user requests, these methods are further ranked considering the effect of the productivity and operating costs of these methods.
4. The three methods determined to be most applicable are then recommended to the user by assigning priorities based on the points they have acquired.

This system is operated by the use of interface agent Ore-Age. Ore-Age asks for the necessary information from the users and transfers this information to the virtual experts who will make the evaluations. After taking the separate evaluation results from each of the experts, he decides on the three methods that will be recommended to the users.

3. System architecture

This hybrid system is composed of three main elements (Fig. 1):

- users,
- virtual experts giving decisions about the suitability of the mining methods according to the characteristics of the given ore-bodies,
- agent Ore-Age acting as an interface between these two elements.

In the system, users both enter the necessary inputs regarding to the ore characteristics and receive the system responses about the selections. The users may either be taught by the system or the system can acquire some knowledge from the users if they have an expertise level of knowledge on mining method selection. The virtual experts are in fact expert systems that have a necessary background knowledge and evaluation capacity on the mining methods embedded in this system. The virtual experts numerically analyze the suitability of the mining methods they are dealing with to the given ore characteristics and send the results to Ore-Age.

Ore-Age is an interface agent between these two media. He receives the inputs from the users and sends them to the virtual experts; consecutively he receives the results coming from the experts and gives the final decision about the selection process. Ore-Age also judges about the expertises of the users and it either puts them in the tutoring session to teach them or in the learning session to acquire knowledge from them, according to their expertise levels. The decisions of the Ore-Age about the expertise levels of the users control the mode to be executed. So, if he is convinced that the user is an expert the system is switched to the learning mode to acquire knowledge from the user and if he decides that the user is an inexperienced one, the tutoring mode is executed to give the user a qualified education.

This system works based on the evaluations of 13 different expert systems for 13 different mining methods. Their work is to evaluate the given ore-body according to the mining method they are dealing with and submit a certain amount of point to their mining method to reflect its suitability for using on the given ore-body.

The goal of the agent Ore-Age, is to make the mining method selection as efficiently as possible and to make
the users make this selection as efficiently as possible too while giving them a remarkable education on mining method selection. To fulfill these goals Ore-Age should have the ability of communication with the virtual experts to make a selection, learning capacity to extend his information and tutoring capacity to educate the users.

The agent Ore-Age carries out three courses of action to realize his goal

(a) Method selection based on the ideas of the 13 virtual experts.
(b) User evaluation to decide on the execution of either tutoring or the learning algorithm.
(c) Execution of the tutoring or the learning algorithm.

The general flow of the system including Ore-Age is given in Fig. 2.

The execution of the system starts with acquiring the necessary inputs about the ore characteristics from the users. Ore-Age handles these data and passes them to the virtual experts for evaluation. Thirteen virtual experts make their evaluations for the methods separately and remind Ore-Age about their numerical results reflecting the suitability of the ore-body to the methods they are dealing with. Ore-Age then chooses the three most suitable methods after a numerical ranking process. These choices can also be called first, second and third degree of choices. After that, Ore-Age evaluates the expertise level of the user based on his/her performance on a previously determined set of case studies. If the user is decided to be an expert, the learning mode is executed by Ore-Age. First, the three alternatives chosen by Ore-Age are given to the user, and his/her choice is asked. If the user has a different choice, this choice is learned by the system to be an alternative choice for the similar cases to be faced. This learning process is performed by a degree of reliability changing proportionally by the expertise level of the user determined by Ore-Age. The higher the level of expertise of the user is, the higher the reliability of the information achieved from him/her. If it is decided that the user is a new learner, the tutoring mode is executed, to give educate him/her.

There are six important modules in the agent Ore-Age as can be observed in Fig. 3. These are perception, control-decision, user evaluation, learning, tutoring and communication modules. The perception module gets the necessary input from the outside environment and the virtual experts. User evaluation module, decides whether the user is an expert or not, based on his/her performance on the given cases. The control-decision module depends on the decision of the user evaluation module to execute either the learning or the tutoring module. Tutoring module has the mission of teaching to inexperienced users, whereas the learning module updates the database of the virtual experts according to the experiences of wise engineers whom can be classified as experts. The tutoring module works in coordination with the error database to model the common errors of the users in case to change its teaching strategy to a more effective one. All the reactions to the outside objects are reflected by the use of the communication module.

The evaluation part of our system composed of virtual experts, should be able to take fuzzy inputs, since the inputs to the system are all fuzzy (ore grade, ore shape, etc.) or are fuzzified (ore thickness, etc.). In other words, an input of ‘massive’ for ore-shape is already fuzzy, but an
ore thickness input of ‘50 m’ should be somehow fuzzified to be placed to some point among the membership categories of ore thickness as the numerical evaluation criteria works based on these membership categories (thick, very thick, etc.)

Another requirement for our system is about the outputs of the virtual experts: the learning procedure requires accurate numeric data for the success of the neural network in the learning procedure. Besides, Ore-Age also needs accurate numerical outputs from the virtual experts to decide on the suitable mining methods to be used. Therefore, the functions the virtual experts are working on should be able to give accurate numeric results as outputs in order to result in clear conclusions and achieve a successful learning procedure during a possible training work to make up for the missing knowledge and intuition for the system. The TSK model of fuzzy theory seems very suitable for such an approach. Takagi and Sugeno introduced TSK model in 1984 (Takagi & Sugeno, 1985). The main motivation for developing this model is to reduce the number of rules required by other models, especially for complex and high-dimensional problems. In general, rules in TSK model have the form

If \( x_1 \) is \( A_{1i} \) and \( x_r \) is \( A_{ri} \), then

\[
y = f_i(I_1, I_2, \ldots, I_s) = b_{0i} + b_{1i}I_1 + \cdots + b_{si}I_s
\]

where \( f_i \) is the linear model, and \( b_{ij} \) are real-valued parameters and \( A_{ij} \)'s are the fuzzy membership functions. It may be seen that although the inputs are not fuzzy, they are re-defined by using the membership functions (Yen & Langari, 1999). TSK model resembles the general logic of the evaluation part of our system based on virtual experts where after the inputs are handled the outputs of the fuzzy membership functions are multiplied by constant weights in the knowledge base to find the result, which is defining the suitability of the specific method the virtual expert is dealing with for the given ore-body characteristics. It can be stated that this whole model of the evaluation part of the system for each mining method can also be identified as a two-layered neural network without a hidden layer using TSK model to give its outputs, where \( A_i \) indicate the membership function and \( W_i \) denote the weight (Fig. 4). As seen in the figure, input values are put in a suitable format for the execution in this fuzzy system by the use of membership functions (ore characteristics). After that, these inputs are directly transferred to the output nodes by achieving the effect of some pre-defined weights. In these output nodes they will be transformed to a total number of points reflecting the suitability of the mining method according to the inputs of ore characteristics. This transformation work is performed by the use of a ‘summing’ function embedded in the output node. As seen the model carries out all the characteristics to consider it as a neural network.

Experimental results show that the two-layer configuration is sufficient to classify the space, which seems to be linearly separable. This model is used for the design of each expert system in the model. Therefore, it can also be stated that this system carries a neuro-fuzzy architecture, which will supply the designers a highly effective base for the training or learning procedure.

All the membership functions in the model for the ore-body characteristics are defined by Gaussian type functions, which will also simplify the work in the training procedure. The functions are designed after a detailed literature survey on the mining literature and it is seen that Gaussian functions are very efficient in describing these characteristics. A Gaussian membership function is specified by two parameters \( \mu \) and \( \sigma \) as follows

\[
G(I : \mu, \sigma) = \exp \left[ \frac{-(I - \mu)^2}{\sigma^2} \right]
\]

where \( m \) and \( \sigma \) are the mean and standard deviation of the function which also denote the center and width of the function, respectively. \( I \) is the input value.

The weights that are used to evaluate the mining methods in the neural network model and the membership functions to classify the ore characteristics used to define the ore-body are kept as information in the databases of the 13 virtual experts. Therefore, for an ore-body, whose characteristics are given as inputs to these virtual experts, they can make an evaluation and achieve the result symbolizing the suitability of the characteristics of the given ore-body to the mining method as an exact number. This can be done by means of the iterative procedure described as

\[
x_i = x_{i-1} + W_j \exp \left[ \frac{(I_j - \mu_j)^2}{\sigma_j^2} \right]
\]

where \( i \) denotes the ore characteristics where \( i = 1, \ldots, s \), \( x_i \) is the total points collected for characteristic \( i \), \( j \) denotes the membership functions classifying the characteristics where \( j = 1, \ldots, p \), \( W_j \) denotes \( j \)th membership function (ore characteristics) for characteristic \( i \), \( I_j \) denotes the input about \( j \)th ore characteristic, \( \mu_{ij} \) indicates the center coefficient of Gaussian function in \( j \)th membership function

![Fig. 4. Neural network configuration for the virtual experts in the evaluation part of the system (\( A_i \)'s are the membership functions).](image-url)
for characteristic $i$, $\sigma_j$ is the width coefficient of Gaussian function in $j$th membership function for characteristic $i$.

4. Procedures of the system

There are three main procedures the agent Ore-Age is working on. User evaluation procedure embedded in user evaluation module, decides on the expertise level of the user. Based on this decision, Ore-Age either chooses to execute ‘tutoring procedure’ which will give educational effort for the new users, or ‘learning procedure’ which will try to put the intuitive decision capability, knowledge and experience of the expert engineers to the database of the system. These two procedures are embedded in the learning and tutoring modules of the system.

4.1. User evaluation procedure

Once the results about mining method selection from the virtual experts are obtained by the perception module of the system, a decision should be given by the control decision module of the system to execute the learning or tutoring module. The learning procedure is used for making the system’s database richer by acquiring knowledge from real experts using the system. The tutoring procedure is used for giving education to inexperienced engineers or engineering students. Therefore, before making this decision, the system should rate the level of expertise of the users. In user evaluation procedure, the users are given case studies at different difficulty levels so that their levels of expertise can be identified. After this process, the agent decides whether to activate learning procedure or the tutoring procedure, which is an example of the partial autonomy of the system.

4.2. Decision and the learning procedure

The most critical part of the system is the interface agent that is constructing the communication network both between the virtual experts and between the users and the system. One of the goals of this agent is to make the optimal choice of mining method for a given ore-body with respect to the background knowledge, intuition and the engineering judgement.

The first work of the agent, which is being named as ‘Ore-Age’ afterwards, is to ask virtual experts their results one by one by the help of its communication module. Once, it obtains these numerical values by the help of its perception module, it compares them and the method achieving the highest numeric result will be defined as the choice of the system.

If the incoming user is an expert, which can be identified by the performance of him/her in using the system Ore-Age, will be willing to acquire the knowledge and judgment capability of this expert to its knowledge base, to be more successful in mining method selection and to be more helpful to the new users. In a specific problem, Ore-Age by keeping in mind the system’s choice of mining method, asks for the expert’s choice for the same case. If these two choices match, then there is no problem and no need for learning or training session. However, if these two choices do not match, the virtual expert of the method in expert’s choice will be considered in learning session and its parameters should be updated until it supplies enough points to make the expert’s choice an equally alternative solution in the system (Guray et al., 2002).

As the system is a neuro-fuzzy one, back-propagation algorithm, which can be fast and effectively applied to such systems, is the employed tool for the learning process. Especially back-propagation can be more easily and efficiently be applied, to TSK models, which have Gaussian type membership functions.

The parameters to be updated are the parameters of the membership functions and the weights assigned to the method according to ore-body characteristics. The learning procedure should occur such that if the system faces the same problem again, it will give two choices with the highest priority to the user; one is the choice of the system before training and the other is the method that the expert has chosen before training. To reach this aim the virtual expert dealing with the method in the expert’s choice should be trained to give an equal numeric result to the system’s choice. Therefore, the error function in the learning procedure will be taken as the square error of the difference between the points achieved by the system’s choice ($y_i$) and the points collected by the expert’s choice ($y_i'$) by using the below formula

$$J^k = \frac{1}{2}(y_i' - y_i)^2$$

(4)

The parameters of the gaussian membership functions and the weights in the system can be trained iteratively as follows (Laubscher, 1981)

$$w_{ij}^k = w_{ij}^{k-1} - \eta_1 \frac{\partial J^k}{\partial w_{ij}} \bigg|_{w_{ij}=w_{ij}^{k-1}} i = 1, 2, \ldots M$$

(5)

$$\mu_{ij}^k = \mu_{ij}^{k-1} - \eta_2 \frac{\partial J^k}{\partial \mu_{ij}} \bigg|_{\mu_{ij}=\mu_{ij}^{k-1}} i = 1, 2, \ldots M$$

(6)

$$\sigma_{ij}^k = \sigma_{ij}^{k-1} - \eta_3 \frac{\partial J^k}{\partial \sigma_{ij}} \bigg|_{\sigma_{ij}=\sigma_{ij}^{k-1}} i = 1, 2, \ldots M$$

(7)

where $w_{ij}$ are the weights, $u_{ij}$ and $\sigma_{ij}$ are the parameters of the gaussian membership function, $\eta_1$, $\eta_2$, $\eta_3$ are the learning rate parameters. $K$ symbolizes the iteration number, $i$ symbolizes the ore characteristics and $j$ symbolizes the membership functions of the ore-characteristics in our system.

The derivatives of $\partial J/\partial w_{ij}$, $\partial J/\partial \mu_{ij}$, $\partial J/\partial \sigma_{ij}$ can be easily derived when gaussian membership functions are used and the remaining three iterative formulas can be used to
perform the training procedure for the membership function coefficients and weights. The formulas that can be seen below are directly embedded in the algorithm to execute the learning procedure:

\[ w^j_k = w^1_j + 0.5EJ^k \]

\[ \mu^j_k = \mu^1_j + 0.5EJ^k \left( w^k_j - \left( \sum_{i=1}^s AV^k_i V^k_i \right) \right) \]

\[ \sigma^1_j = \sigma^1_j + 0.5EJ^{k-1} \left( w^k_j - \left( \sum_{i=1}^s AV^k_i V^k_i \right) \right) \]

where

\[ V_j = \prod_{j=1}^p \exp \left( \frac{(\mu_j - \mu^1_j)^2}{\sigma^1_j} \right) \]

\[ AV_i = \left( \sum_{j=1}^p w_j \right) / p \]

\[ E \] indicates the difference between the best result (chosen among the results of the virtual experts by Ore-Age) and the current result.

Therefore, after this learning procedure is introduced, this system can behave like this expert in his later decisions for the new problems it will face, reflecting his/her judgement capability and knowledge background to the solution of these problems.

4.3. Tutoring procedure

If the user is understood to be an inexperienced engineer or a student, he/she may be in need of acquiring extra knowledge about the selection scheme. If this is the case after the execution of the user evaluation algorithm, tutoring procedure is executed. Till this time, the problem input would have been entered by the user and agent’s response to this problem would have been computed by the activation of perception, control decision and communication modules. The tutoring procedure is given in Algorithm 1.

In the tutoring procedure, by comparing the weights of ore characteristics, agent tries to find the point where the user makes mistakes. If one of these differences is higher than a certain threshold in one of the ore characteristics then the user may have the possibility of making an erroneous selection based on this characteristic. Then he warns the users about their possibility of knowing something wrong about this characteristic’s effect to the selection criteria. The strength of the warning sentence changes in direct proportion with the difference of weights (Algorithm 2). If the difference is higher than a threshold of \( t_{low} \), the system’s warning sentence is ‘there can be better choices than your choice’, if it is higher than a threshold of \( t_{high} \), the warning sentence is a stronger one like ‘your choice is not mostly used’. These threshold values are determined experimentally by the contributions of an expert (Pasamehmetoglu, 2001).

While checking the ore characteristics one by one to find the point of error, the agent has the chance of copying the points of errors to his error database (Algorithm 1). The agent continuously controls this error database to find the common errors occurring frequently (Algorithm 3). If some errors occurring more than a certain threshold are determined, these errors are passed to the common error database. When an inexperienced user makes a mistake, before executing the time consuming algorithm of searching for the point of error, this error database is checked to quickly direct the user to his/her possible point of error.

In Algorithm 3, during the latter parts of this error modeling process, if Ore-Age detects a user having potential problems in one of the areas where common errors occur, he

\[ found = false \]

\[ \text{While( not processed all ore characteristics) and (not found) } \]

\[ \text{compare the weights in agent’s choice and the user’s choice; } \]

\[ \text{if their difference is more than } t_{high} \]

\[ \text{then indicate that his/her choice is not mostly used } \]

\[ \text{if their difference is more than } t_{low} \]

\[ \text{then indicate that there can be better choices than his/her choice } \]

\[ \text{ask again the choice; } \]

\[ \text{if two matches found=true; } \]

Algorithm 2. Searching for the point of error.
will directly change his strategy from checking the characteristics one by one, to directly concentrating his and user’s attention to the point of potential error. This can be considered as an example of the proactiveness of the agent and the system.

5. A case study

The performance of the system is tested by means of a case study. During the execution of this case study, \( \tau_{\text{low}} \) is used to be 1 and \( \tau_{\text{high}} \) is used to be 3, which are determined experimentally.

The case study is about a tabular ore-body, which has a thickness of 5 m, a plunge of 65°. The hangingwall, the ore-body and the footwall are strong in means of rock strength. Ore-body is moderate in grade. After the above input is entered (Fig. 5), agent makes an initial selection of the mining method (Fig. 6). Decision of the user is asked and for this case the user appears to be an expert after the evaluation phase.

In the selection process of the agent, sublevel stoping method acquired a point of 19.6168 and became the choice having the highest priority. Cut and fill method was the second with a point of 17.4649. Undercut and fill method was the third. However, according to the expert (Pasamehmetoglu, 2001) as the grade of the ore increases, cut and fill method, which can value rich minerals effectively by its selective capability can be chosen too, instead of sublevel stoping method. Therefore, he enters cut and fill method as his choice. The important question here is ‘how valuable the ore is?’ If the ore is valuable enough to afford cut and fill which is an expensive method when compared to sublevel stoping, it can be used to valuate ore more efficiently. Therefore, the work of the agent here is to introduce cut and fill method as an alternative solution having the same priority as sublevel stoping to the new users, to make them discuss this alternative too. So, the training algorithm is executed with a square error of 2.15, which is the result of the subtraction of, 19.6168 – 17.4649, and the parameters \( w, \mu \) and \( \sigma \) are updated in 18 iterations (Fig. 7).
If a new user activates the same case study again, he/she will face with a result such as in Fig. 8.

6. Performance evaluation

To test the learning capability of the system ‘Jacknife’ method of estimation for classification accuracy is used (Duda, Hart, & Stork, 2001). The accuracy of a given algorithm is estimated by training the classifier \( n \) separate times; each time using the training set \( D \) from which a different single training point is deleted. Each resulting classifier is tested on the single deleted point, and the jackknife estimate of the accuracy is then simply the mean of these leave-one-out accuracies. In this case a training set of 40 cases was used. On the test cases, a success rate of 1 is assigned to the point if the most suitable choice of the mining method is given in the first degree choice, whereas a success rate of 0.67 is assigned if the most suitable choice is found in the second degree choice, a success rate of 0.33 is assigned if the most suitable choice is given in the third degree choice and finally a success rate of 0 is given if the most suitable method cannot be found in any of the alternative choices offered by the system. When the results are searched it is observed that in 33 cases the most suitable method is found in the first-degree choice, in six cases the most suitable method is found in the second-degree choice and in one case the most suitable method is found in the third-degree choice. So, the success rate, which is found by taking the mean of the success rates of the separate cases, is 93.38%. This rate seems to be sufficient to identify that the learning module of the system works successfully.

7. Conclusion

This study describes, a hybrid system composed of 13 experts and one agent, which is used as a semi-automated, and user assisted system in order to cope with the mining method selection problem of the mining discipline. This problem is handled both by the help of a rich database about mining method selection procedure, acquired from past experiences systemized by Nicholas (1981) and by a long term study experience about mining method selection work with the directives of outstanding mining experts (Pasamehmetoglu, 2001). Besides, first time in the mining literature, the intuitive feelings of the experienced engineers, which are very important in the selection work, are systematically inserted in the database of a selection system. An efficient learning algorithm embedded in the system taking the advantage of its neuro-fuzzy structure can perform this work.

The objective of the study, is to design a hybrid system that can be used as an assistant and tutoring tool for mining method selection, inserting the intuition of the expert engineers systematically to the selection criteria by the help of its learning abilities. An agent Ore-Age stands at the core of the system as an interface and decision media. Ore-Age has two main goals, the first one is to make mining method selection work as efficient as possible and the second is to make the users to make the selection of mining methods as efficient as possible by supplying them a qualified education. Therefore, a continuously evolving selection database by the help of these mining experts will result in a very efficient media for mining method selection work for Ore-Age to realize his first goal. To realize his second goal he is offering the tutoring procedure by the help of which a fast and productive education session on mining method selection is given to the users. The interactivity of this procedure is creating a suitable platform for the inexperienced users to find their errors by themselves. By, this way tutoring can be more efficient. The system or the agent Ore-Age can be stated as proactive by its ability to change the teaching strategy based on the search for common errors and semi-autonomous by its user evaluation algorithm deciding on the procedure to be executed according to the expertise level of the user without any outside effect. The performance of the learning of the system is tested by the Jacknife method for classification accuracy (Duda et al., 2001). A success rate of 93.38% found which is sufficient to remark that the learning module of the system work successfully. As, the future work the tutoring module can be improved in a pedagogic base. Besides, more effort can be put in especially about user evaluation and learning algorithms to achieve more autonomy in system execution so that the system can behave more similarly to a real mining expert. The system will soon be available on the web for common use.

References


