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Concepts of Expert Systems, Fuzzy Mathematics and Pattern Recognition Techniques in Mining Geomechanics

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1 INTRODUCTION

Performance often belies prediction in rock engineering because of geologic uncertainties involved in the design process. Over the decades,consistent efforts have been made for developing and improving geomechanic prediction models. With the advent of high speed,large memory and low cost digital computers,sophisticated 3-D finite element techniques are now being increasingly used as decision tools in rock engineering design. Another entirely different approach to tackle the problems of design in rocks has come into vogue with the popularisation of Bieniawski's RMR (Bieniawski,1976) and Barton's Q (Barton et.al.,1974) systems of rock mass classification. In the last one and half decades,scores of classification models for different geo-technical situations including mining applications have been developed and used for decision purposes(Ghose and Raju,1981;Unal,1983;Brook and Dharmaratne,1985;Venkateswarlu,1986). This signifies that today's specialists of rock engineering design fall into two relatively exclusive schools that can be termed as the behavioural school and the classificatory school.Depending on knowledge acquisition and its organisation,these two schools independently describe a real and complex geologic environment to a reasonable degree. As the approach of each school to the description of real world objects is structured so differently from the other,each school has problems in communicating with the other (Fairhurst and Lin,1985).

The classificatory school generalises knowledge by statistical analysis of historical realities to develop prediction models. Like a perfectly scientific method that iteratively searches for the most plausible explanation of natural phenomena through the formation of hypotheses,the verification of the trial explanations through the experiment and their subsequent improvement to take into account what these tests indicate,classificatory school can home in on optimal solutions by learning from historical realities and,over time,from the effects of implementing the model under development. Design process in rock engineering is essentially a learning process. In this search for the best solution,as in the search for the scientific truth,preliminary schemes must be revised in the light of new insights obtained either as analysis proceeds or implementation takes place.

Since the design in rock involves subjective information,contradictory concepts,integrated knowledge derived from different fields,conflicts of opinion etc. it provides enticing opportunities to use some of the developments of Artificial Intelligence (AI),fuzzy mathematics and pattern recognition techniques in a unified way for the development of rock mass classification models.

2 ARTIFICIAL INTELLIGENCE (AI) AND EXPERT SYSTEMS

An expert system is an intelligent computer program that uses knowledge and information procedures to solve problems that are difficult enough to require significant human expertise for their solution (Jackson,1986;Winston,1984). The Expert System is a computer based consultation service that improves its interpretation techniques with the incorporation of more and more knowledge and can also handle subtle variations in the problem addressed,like human experts. An Expert System starts with a prototype to arrive at a decision through a highly interactive computer program of some hard and fast rules and contending hypotheses. Knowledge of the prototype is continuously enhanced by incorporating experts' knowledge from respective fields through the techniques of machine learning. Thus,the development of an Expert System is a two fold task--developing sophisticated computer software and acquisition of experts' private knowledge from respective fields. Knowledge can also be extracted by assimilating information from a text book or by case history analysis with the consultation of an expert from the concerned field.

Mechanistic computer algorithms can sort,select,compare and combine data and perform calculations and with the help of a computer,this can be done at speed which people can never emulate. But computers can not understand the data they process. They cannot take initiatives,nor can they make sense of vague,incomplete and contradictory information. They cannot cope with information in a natural language,and although they can produce spectacular graphic displays,they cannot interpret information in a visual form.

As conventional data processing is based on information,AI is based on knowledge and it aims at processing knowledge. As management information system (MIS) is based on information processing,futuristic decision support system will be based on AI. Expert systems are the product of the application of techniques of AI to specific fields. All Expert Systems operate on a knowledge base and have sets of rules. They have control techniques for applying the rules to the knowledge base in order to solve the problems posed to them. The particular set of characteristics associated with intelligent human behavior that Expert Systems are to exhibit includes learning, representing, reasoning about, problem solving and advice giving with regard to some knowledge rich domain (Jackson,1986).

The earliest Expert Systems were confined to domains in which the knowledge is well-structured according to the following criteria : a small search space,a consistent knowledge base with no contradiction, and reliable static data provided by the user during interactions with the Expert Systems (Alty and Coombs,1984). Later systems have been able to relax these constraints to an increasing extent,allowing Expert Systems to be constructed in fields of increasing complexity. Perhaps,fifth generation computers will allow them to be relaxed almost entirely,making it possible to design an Expert System for use where the knowledge base is very large,the knowledge is vague,incomplete and contradictory (Moto-Oka,1981).

Today,designers in rock excavation projects like construction and maintenance of underground caverns,tunnels and exploitation of minerals etc. require special knowledge in geology,rock mechanics,mining or civil technologies,mathematics etc. if they are to handle sheer volume of geologic and other information required for decision making. Experts in rock mechanics can no longer comprehend and integrate the breadth of knowledge in the fields that contribute to rock mechanics (Fairhurst and Lin,1985). Moreover,for making best interpretation of frequently ambiguous,ill-defined geologic information,heuristic knowledge of expert practiceners and research scientists is also needed. In this context,AI involving natural language processing and intelligent knowledge based systems opens new vistas to the specialists of classificatory school.

2.1 An Expert System Prototype for Assessing Caving Characteristics of Longwall Roof Rocks

By analysing case histories of caved longwall faces of India,authors have developed an Expert System prototype by formulating more than hundred rules concerning caving behaviour of longwall roof rocks . Longwall roof rocks are divided into three zones whose individual thickness depends on the extraction height. Caving nature of each zone is assessed by the Expert System by interacting with the user in the form of asking questions about the nature and number of individual beds in a zone,thickest bed in each zone and compressive strength and average core size of each zone. With the user-supplied fact to the closed ended queries,this Expert System tries to infer the caving characteristics of the entire roof by applying the facts to the set of rules. Some typical rules in the knowledge base of the system read as:

IF
  Parting plane in 1st zone does not exist
THEN
  parting plane characteristics of 1st zone is strong.

IF
  Parting plane characteristics of 1st zone is strong AND average core size of 1st zone is 0-5 cm.
THEN
  Bulking ability of 1st zone is good.

Besides assessing the caving characteristics of roof rocks,the system also advises for choosing appropriate support parameters. A typical output of consultation with the system is as follows :

Extremely difficult caving roof AND
overhangs upto 20 m AND
Requires heavy capacity shields AND
support resistance required is 60 te/sqr. m.

It is interesting to note that the rules in the knowledge base of the Expert System involves vague and imprecise concepts like "strong","good" etc. that are inherent to natural language. In this context,fuzzy mathematics can be applied to develop Fuzzy Expert System.

3. FUZZY ENVIRONMENT IN ROCK ENGINEERING DESIGN

Decision making in a system can be done by deterministic techniques or by probabilistic techniques when the inherent randomness of the system is considered. These type of approaches can be considered classical quantitative techniques. Some aspect of real world always escape the precise mathematical models of emperical phenomena constructed in hard science like engineering,physics or chemistry etc. to make predictions while in soft sciences like sociology,psychology etc.,there is an elusive inexactness,a readjustment of structure or an effect of observation over the original model.

A central idea in platonic philosophy is that ,in the real world, elements are perturbed by imperfection.Perfect notions or exact concepts corrospond to the sort of things envisaged in pure mathematics,while inexact structures are rampant in real life.It is a belief that inexact structures are rich enough in operations and properties to be of genuine use in constructing models for a wide variety of situation, and further that these mathematical properties will provide practical guide for both philosophical and technical reasoning.

A unifying point of view to the notion of inexactness is based on the theory of fuzzy sets introduced by Zadeh in 1965 (Zadeh,1965).Goguen (1968) has given the reason supporting the representation of inexact concepts by fuzzy sets and his representation theorem says that any system satisfying certain axioms are intutively plausible for the system of all inexact concepts, the theorem allows us to conclude that inexact concepts can be represented by fuzzy sets.Since certain aspects of reality always escape the models, strictly classical quantitative techniques to the treatment of physical phenomena are not always adequate to describe systems in the real world and the attribute of the system variable often emerge from an elusive fuzziness, a readjustment to context, or an effect of human imprecision. Even if the model is precise, fuzziness may be concomitant of complex system in the real world. According to Zadeh's principle of incompatibility (Zadeh,1969) our ability to make precise as well as significant statement diminishes as the complexity of the system increases until a threshold limit is reached, beyond which precision and significant relevance become exclusive characteristics due to some inherent vagueness, variability or fuzziness of the system. Often in real life problems, all the numerical data are not precise and the nature of uncertainty is possibilistic rather than probabilistic when we term the data as fuzzy (Zadeh,1976).

Fuzzy set theory is the generalisation of our concept of classical crisp set theory that uses two-valued logic i.e. an object belongs to the set or it does not belong. In mathematical parlance,the classical set theory is defined by the binary function whose values are either zero or one. In contrast, a fuzzy set theory is defined by a membership function whose value ranges from zero to one. Fuzzy set theory always include the abstract "crisp" set theory as a special case: definitions,theorems,proofs and so on of fuzzy set theory always hold for nonfuzzy sets. Because of this generalisation, fuzzy set theory has a wider scope of applicability than abstract crisp set theory in solving problems that involve to some degree, subjective evaluation.

Much of the expert's knowledge in rock engineering is vague and it is true that facts and rules are neither totally certain nor totally consistent. Rock with its geologic environment becomes a complex system behaving independently of any analytical divisions made to it for the sake of human and academic convenience. Neither construction of rigorous behavioural models leads to a correct decision, nor the application of classical quantitative techniques yield a true solution in rock engineering design. The actual situation in which a system analysis approach is to be applied for taking decision in rock engineering is that of a vague and ill-structured geological and managerial environment with combinations of quantitative data and qualitative information discontinuties and missing observation, conflicts of opinion amongst the problem solver etc (Fairhurst and Lin,1985). Impreciseness and subjectivity rule large in the realm of geomechnics (Nguyen,1985). Subjectivity arises due to the use of adjectives like "good" "poor" etc. in describing rock or its features and some degree of impreciseness creeps into the determination of physico-mechanical properties of rock due to wide dispersion of their values and inaccurate test results (Ghose and Dutta,1986). This fuzzy environment requires its own methodologies for decision making based on fuzzy set theories as enunciated by Zadeh (Zadeh,1965,Zadeh,1966) and others (Gupta and Sanchez,1982; Mamdani and Gaines,1981).

3.1 A Fuzzy Algorithm for Cavability Classification Model

A fuzzy algorithm was suggested by Ghose and Dutta (Ghose and Dutta,1986) for determining a total rating for longwall roof rock assessment. The algorithm makes use of logic, fuzzy mathematics and liguistic variables (Zadeh,1985) and starts with the assumption of three statements concerning rock mass strength as :

s1 = " High mechanical strength " is indicative of high rock mass strength.
s2 = " Good structure " increases rock mass strength.
s3 = "Low stresses" can not induce fracture in the roof rocks and, thus, contribute to rock mass strength.

The three phrases "high mechanical strength", "good structure" and "low stresses" can be modelled as three linguistic variables. Let R {1,2,...,100} be a space of points and the three linguistic variables be represented by three fuzzy sets - S1 , S2 , S3 - in R{1,2,...100}.

The proposition obtained by the conjunction of s1, s2, and s3 can be stated as :

s = "High rock mass strength" results due to "high mechanical strength", "good structure" and "low stresses".

Boolean variable associated with s will be true only when s1, s2 and s3 are true.

Now it can be easily be deduced that the fuzzy set S obtained by the intersection of S1 and S2 and S3 represent the linguistic variable "high rock mass strength" in R {1,2,...100}.

Let V be the fuzzy set representing the linguistic variable "massive strata" and the statement v reads as :

"Massive strata" makes roof difficult to cave.

The logical sentences s and v are conjuncted to get a proposition c where,

c = "High rock mass strength and "massive strata" result in "difficult" caving roof or "low cavability".

If the phrase "low cavability" is modelled by the linguistic variable C then C = S$\cap$V. Hence,

$$S=\{[r,\min(\mu_{S1}(r)^{\omega 1},\mu_{S2}(r)^{\omega 2},\mu_{S3}(r)^{\omega 3})]\}$$

$$C=\{[r,\min(\mu_{S}(r)^{\omega'},\mu_{V}(r)^{\omega})]\}$$

where μ's are membership grades of respective fuzzy sets, w's are weighting assigned to the respective fuzzy sets (Dubois and Prade,1980) and r is the generic element of R.

The decision rating or cavability value is $r \in R$ which is associated with the highest membership grades of C or $r \rightarrow \max [\mu_{C}(r)]$.

By applying factor analysis techniques to 32 case history data of caved longwall faces, four features - thickness of bed, uniaxial compressive strength, average core size and depth were selected (De,1987). Each feature is reduced to a set R {1,2,...100} by evaluating a membership function at the measured value of the feature. Pattern boundaries are fixed in R {1,2,...100} by employing a training set--a collection of samples obtained by engineering judgement and these samples represent pattern that would have been

TABLE I CAVABILITY CLASSIFICATION OF ROOF STRATA

Class	Cavability	Cavability decision rating	Caving behaviour and tentative support guidelines
I	Extremely high	0-30	Extremely weak and easy caving strata. Caving is controlled by bulking factor. Prompt support is required close to face. Shield or chock shield is necessary to prevent goaf waste flushing.
II	High	31-45	Easy caving strata. Caving is controlled by bulking factor. Props can be used for heights upto 2.5 m.
III	Moderate	46-60	Moderately caving strata. caving is poor and in big blocks. Periodic weightings may occur due to overhang. Preferably,powered support should be used.
IV	Low	61-70	Difficult caving roof that overhangs for considerable length. At higher cavability values violent weightings may result. Goaf blasting may be required before first weighting. High capacity shields are required
V	Extremely difficult	71-100	Extremely difficult caving roof. Large overhang and violent weightings. High capacity shields with rapid yield valve systems,if warranted.

obtained by large collection of samples. Table-I shows the classification of cavability pattern obtained by putting fixed boundaries in the set R {1,2,...100}. The model has been tested against case studies (Ghose and Dutta,1986).

3 PATTERN RECOGNITION TECHNIQUES

Pattern recognition process and machine learning presently form a major area of research and development activities simulated by the concept of fifth generation computing systems. The science of automatic computer recognition of patterns and the development of theories and techniques for designing a software which can perform these recognition can be put under Patterns Recognition. Pattern recognition process can be viewed as a two fold task - developing decision rule based on previous knowledge called learning and using the decision rule for taking decision regarding an unknown pattern called classification.

Classification system like RMR and Q are basically pattern recognition algorithm when applied to an object (rock) yields certain deterministic decision to be taken regarding the nature of rock and its support requirement when excavation is made for tunelling in the same rock. It signifies that opportunities exist for the use of pattern recognition techniques in rock mechanics.

4.1 Operating stages in Pattern Recognition System

Fig. 1 outlines the operating stages in developing and implementing the decision rule in pattern recognition system.

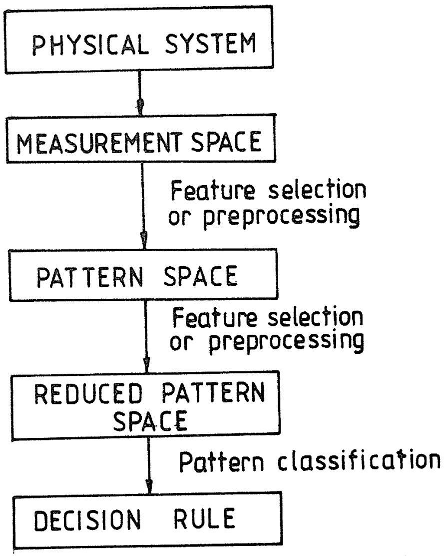

Fig. I Stages in the derivation of decision rule

For the purpose of recognition,rock is represented by the physical system having some physical embodiments which can be represented numerically by some set of measurements in a Q dimensional measurement space Ω_Y. Thus,the measurement space can be viewed as a set of finite number of measurements of physico-mechanical properties of rock. Feature space is obtained by selecting a map of the form $X=f(Y)$ by which a sample $Y\ (y1,y2,\ldots,yQ)$ in Ω_Y is transformed into a point $X\ (x1,x2,\ldots,xN)$ in N ($<Q$) dimensional feature space Ω_N. In the RMR system five features (uniaxial compressive strength,RQD,joint spacing,joint conditions and water inflow rate) are to be known to recognize the pattern of a given rock. The process of deriving a decision rule on the basis of finite set of labelled or known classification samples for classifying a point in the feature space corresponding to an unlabelled sample and its implementation is called pattern classification. By feature selection and extraction,a pattern is transformed to a vector X in Ω_X. Thus,$X=(x1,x2,\ldots,xN)$,where $x1,x2,\ldots,xN$ are measurement values on the object (rock). There is a finite number of unknown pattern classes $C1,C2,\ldots,Cm$ into which points of Ω_X is to be classified. Let

$$Xj(1),\ Xj(2),\ldots,Xj(l),\ldots,Xj(h) \in Cj$$

$$l=1,2,\ldots,hj$$

$$j=1,2,\ldots,m$$

be a set of hj labelled samples of class Cj,where each $Xj(l)=[\ (\ Xj1(l),Xj2(l),\ldots,XjN(l)\ )\ ]$ is a point in Ω_X. With the finite number of labelled samples of each class,each point in Ω_X is assigned to one of the unknown classes by a mapping from feature space to decision space on the basis of a characterising function or decision function. This decision function is the discriminant function in the context of deterministic classification technique,probability density function in the case of statistical decision theory and membership function in the fuzzy set theory.

5 CONCLUSION

we have introduced the concepts of Expert System,fuzzy set theory and pattern recognition techniques vis-a-vis rock engineering design. It is envisaged that these emerging techniques can be used to develop efficient design tools for narrowing the gap between prediction and performance in rock engineering. Many classes of problems in mining geomechanics involving complex environment,ill-defined variables and concepts,personal bias,subjectiveness and natural language processing can be identified and can sufficiently be modelled by using AI and fuzzy pattern recognition techniques.

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