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Applications of Knowledge Based Systems in Mining Engineering

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Managers need quality information for effective decision making. This demand, at the present time, is being fulfilled by the increased use of computers via information systems, decision support systems and management information systems. The idea of incorporating intelligence into computers to aid decision-makers has been evolving for over two decades. In recent years, significant progress is reported on applications to business and sciences. In engineering functions, the Artificial Intelligence approach that seems to have great potential is the application of Knowledge Based Systems.

The primary objective of this paper is to identify domains in mining engineering where application of knowledge based systems could be beneficial. Incorporation of the expertise required during the analysis and interpretation stages of an engineering design problem through knowledge based systems is recognized as an area of significant benefit. To this end, the components of knowledge based systems for mine ventilation and strata control design are described. The potential applications and limitations of knowledge based systems are outlined.

Introduction

Correct decisions are the key to success in any enterprise. Scope of decisions varies with the echelons of management hierarchy. The decisions of top management are strategic, relating to the long-term future of the organization. In a mineral organization, these deal with such issues as the acquisition of a new mineral property or the diversification of the business to exploit additional markets. At the operational level, a manager is concerned with decisions pertaining to day-to-day eventualities related to production activities and other short-term needs. In either case, the prerequisite is the timely availability and use of information. The difficulty involved in decision-making depends on the situational aspect. In many cases, the decisions to be made under given conditions are fairly straight-forward and standard. This may be due to experience gained from decision-making in similar situations in the past. In fact, many decisions in operations management are either repetitive or routine.

However, there are several situations, particularly at the higher management levels, in which the decision-making procedure does not fit a standard mold, the available information is uncertain or there are no clear guidelines as to how to make the decisions. These semistructured and unstructured decision problems, defined hereafter as complex problems, require the incorporation of judgement and experience in the decision-making process. Several problems in engineering design can fall in the latter category.

Mine engineering design is a complex problem involving subproblems which can be structured, semistructured or unstructured. Structured design problems can be handled with standard algorithmic approaches. The solution of semi- and unstructured problems, however, has posed great difficulties, in some cases, in defining the problem itself. From the early sixties, the use of computers and mathematical logic to aid managers in decision-making has taken several algorithmic and heuristic approaches. The earliest information systems (IS) were concerned with producing historical reports with little information pertaining to current and/or future operations. Most of these IS were accounting and payroll systems. These were followed by rudimentary management information systems (MIS) which focused on summarizing data from past operations and providing limited decision-oriented information to managers. Over time, the role of MIS has increased to a point where today there are systems for providing managers with the latest information. Developments in data base technology, particularly data base management systems (DBMS) and relational data base schemes, and decision support systems (DSS) have been key in the continual evolution of MIS.

In recent years, advancements in the field of Artificial Intelligence (AI), particularly Knowledge Based Systems (KBS), have made significant contributions in bringing novel computer-oriented approaches to the solution of complex problems. KBS can incorporate aspects of reasoning under uncertainty in situations where information is incomplete or unreliable. KBS have incorporated formalized approaches such as fuzzy logic and Bayesian probability schemes to quantify incomplete 'artistic/soft' knowledge. The KBS approach has permitted the knowledge of 'experts' to be captured in computer oriented symbolic programs and bear upon the problems of users in many diverse ill-structured domains. Examples of highly publicized areas of applications of KBS include medicine (MYCIN),[1] mineral exploration (PROSPECTOR),[2] chemical structure identification (DENDRAL)[3] and structural engineering (SACON).[4]

The flow of information in a typical IS and MIS framework with an expert system interface is shown in Figure 1. The data collected from the system and via sensors are first sifted to filter out unwanted 'noise.' The filtered data are stored in data bases and is also available online. In structured decision situations, the data are fed to algorithmic models, the output from which is made available to the decision-maker in the form of information reports. In case of semi- and unstructured decision problems which defy a programmed approach, the expert system can provide the

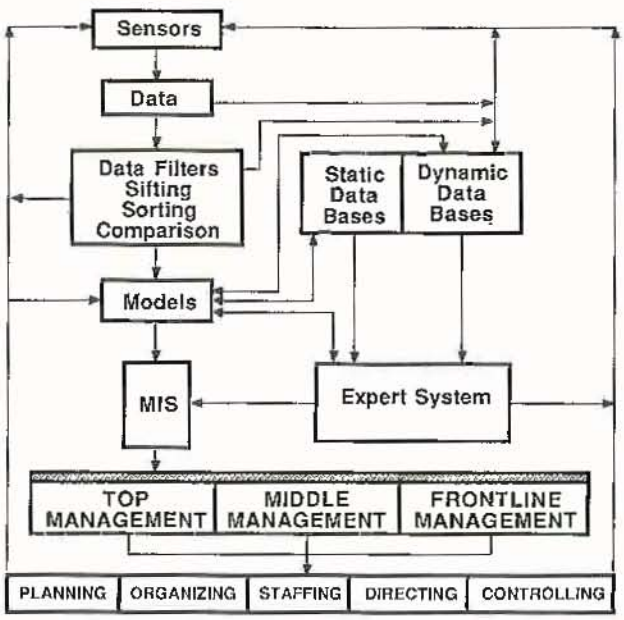

FIGURE 1. Flow of information in a management information system (MIS) with an expert system interface

experiential and judgemental knowledge required. As shown in Figure 1, the expert system functions in close interaction with classical MIS and as such it is an integrated part of MIS - a broad epithet encompassing all systems aiding management in decision-making.[5]

The objective of this paper is to present the principles of the knowledge based paradigm and to outline its usefulness as a decision support aid for solving mineral engineering design problems. This discussion will also focus on two functionally important areas of mine engineering design: mine ventilation system design and mine strata control design.

Knowledge based systems

Knowledge based systems are sophisticated, interactive computer programs which use high quality, specialized knowledge in some narrow problem domain to solve complex problems in that domain. KBS have been referred to with a variety of names such as expert systems, intelligent assistants, epistemological systems and design and analysis systems. The two terms most popular in common usage, often used synonymously, are KBS and expert systems.

This is unfortunate because some systems which are advanced as expert systems do not have the essential elements to be considered as such. Strictly speaking, the term expert system implies that a predominant part of the knowledge in the system has been acquired from expert practitioner(s) in the chosen field. As a result of their unique experiences, experts solve complex problems in reasonable (minimal) time using creative approaches and rules of thumb. As such, a strict or straight-forward mathematical algorithm cannot be an expert system. Further, with KBS, there is no implication of the presence of expert knowledge. The knowledge could be gathered from disparate sources in the public domain. Expert knowledge can be viewed as a particular instance of total knowledge (both expert and other). Expert systems, therefore, are a special breed of KBS where an expert(s)'s knowledge takes prominence over the public domain knowledge. The more encompassing term KBS will be used in this paper.

KBS features

There are four important aspects of KBS which need to be emphasized: (i) they are knowledge intensive, i.e. it is the fundamental hypothesis in Artificial Intelligence, the parent field of KBS, that the problem solving power of a program comes from the quality and quantity of knowledge it possesses relevant to the problem; (ii) the inference or reasoning mechanisms are human-like, i.e. the reasoning strategies adopted by the program reflect the reasoning style of the humans; (iii) the domain of application is narrow; this requirement is a consequence of the high levels of performance expected of the program; expertise is deemed to come with great depth of knowledge in some specialized area rather than general knowledge of several different fields; (iv) KBS are able to explain their line of reasoning to the user, i.e. they can give justifications as to 'why' a particular line of reasoning was or is being pursued over another and explanations as to how it arrived at a certain conclusion. Clearly, problems requiring significant infusion of common sense and general knowledge for solution are not suitable for KBS applications.

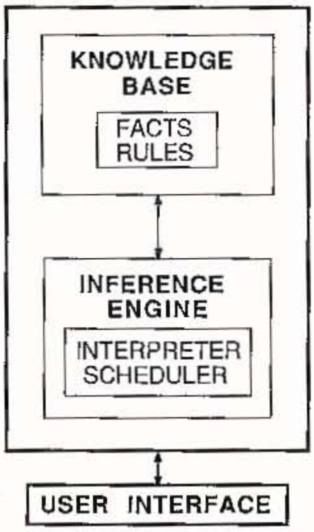

FIGURE 2. Anatomy of a knowledge based system

KBS components

There are two main parts to any KBS - the knowledge base and the inference engine (Figure 2). In addition, there are peripheral features designed to facilitate interaction with end-users (user interface), explanation of a line of reasoning (justifier), etc. The knowledge base consists of two different kinds of domain specific knowledge: (i) declarative knowledge which includes facts related to the domain and the specific problem, and (ii) procedural knowledge which contains rules (or procedures) and heuristics which generate alternate paths of reasoning. The facts and rules constitute a body of information that is widely shared, publicly available and generally agreed upon by practitioners in the field. The heuristics, on the other hand, are private, experientially gained rules of thumb (rules of plausible reasoning, rules of good guessing, etc.). The primary role of heuristics is to aid in limiting the search for solutions to a problem. This is probably the most powerful feature of KBS.

Knowledge representation

The predominant means of representing the vast amount of problem specific knowledge in KBS has been by production rules. Production rules are of the form 'situation >> action', i.e. they are syllogisms of the form 'IF a certain situation holds THEN take a particular action'. The IF portion of the rule is called the antecedent and the THEN portion, the consequent of the rule. The reasoning mechanism of KBS (Inference Engine) uses these IF...THEN rules to arrive at a conclusion, establish the validity of a fact, etc.

Because of the inherently uncertain nature of the system knowledge, in many instances the rules may not imply strict logical implication. That is, each rule is not deemed to be categorically true or false but rather a qualified statement having a certain amount of 'strength' associated with it. The strength value could have a probability interpretation as in PROSPECTOR, or could be an ad hoc 'certainty factor' (-1 to +1, certainly false to completely true) measure, as in MYCIN.

Inference engine

The inference engine is made up of two parts: (i) an interpreter which decides on how to apply rules to infer new knowledge, and (ii) the scheduler which decides on the order in which the rules should be applied. Generally, the interpreter validates the relevant conditions of rules and performs the tasks which the rule prescribes. The scheduler maintains control of an agenda and determines which pending action should be executed next. There are two major ways in which inference engines apply reasoning strategies to arrive at plausible conclusions:

(i) Data driven reasoning/forward chaining: To illustrate this type of reasoning, consider the following three rules:

RULE1: IF A THEN B

RULE2: IF B THEN C

RULE3: IF C THEN D

when it is known that A is true at a particular instance. The system starts drawing inferences on this newly asserted fact. The new fact asserted satisfies the antecedent of RULE1. This establishes fact B. Since the truth of B satisfies the antecedent of RULE2, C is established and so on.

(ii) Goal directed reasoning/backward chaining: Consider the following set of rules in the knowledge base.

RULE1: IF (A and B) THEN C

RULE2: IF (D and E) THEN A

RULE3: IF (F and G) THEN B

The problem to solve may be to find out if C is true. To establish C (the consequent of RULE1), the inference engine tests if the antecedent is true. The antecedent involves the establishment of the truth of A and B. Two subgoal problems are now set up: (i) prove truth of A and (ii) prove truth of B. Only when A and B are proven true, C is true. But proof of A and B themselves involve two more conjunctive sub-goal problems - proof of D and E, and F and G. Therefore, the truth of the facts D, E, F and G are checked in the knowledge base. If they explicitly exist in the knowledge base, then C is established, otherwise the inference engine has two options: (i) report that it does not have sufficient information to establish the truth of C, or (ii) query the user for any information regarding the truth of D, E, F and G. This is a very common reasoning process used in medical diagnosis, or any system diagnosis for that matter, when it is desired to establish if a patient has a certain disease, i.e. check if the patient has the symptoms endemic to the disease.

MYCIN (an expert system, developed at Stanford University, for providing physicians with advice on diagnosing bacterial infections) uses backward chaining for its reasoning process. The advantages over forward chaining are very apparent in this instance. If the inference mechanism had started out to establish C by looking into the knowledge base trying to find an antecedent which is true and initiating forward chaining on the fact, it could be led into blind alleys and may never realize the goal of establishing C. In a knowledge base with hundreds of rules, this could mean an inefficient and unintelligent search procedure, even if C were to be established.

This is not to imply that backward chaining would always yield better results. There are problems in which the current system knowledge is used to infer more interesting knowledge which leads the system closer to the goal. Forward chaining is ideally suited for such problems. There are also situations where even a combination of forward and backward chaining might be necessary. The choice, however, is critical.

Strict delineation between the knowledge base and inference engine is a desirable feature. If the two are intermixed, domain knowledge gets spread out through the inference engine and it becomes less clear what ought to be changed to improve the system at a later date. The result is an inflexible system. If all the task specific knowledge has been kept in the knowledge base, then it is possible to remove the current knowledge base and 'plug in' another. The explicit division thus offers a degree of domain independence. It does not mean, however, that the knowledge base and inference engine are totally independent. Knowledge base content is strongly influenced by the control paradigm used in the inference engine.

User interface

The user interface is basically a language processor which permits the end-user to communicate with the KBS in a problem/task jargon, usually some restricted variant of English. Typically, the user interface parses and interprets user questions, commands and volunteered information. Conversely, the interface formats information generated by KBS, including answers to questions, explanations and justifications for its behavior and requests for information.[6]

KBS versus conventional programs

The utility of KBS and its superiority over conventional computer programs are not obvious. A frequently asked question is: What is the difference between a KBS and a normal program? Consider the IF...THEN statements versus the IF...THEN rules. The difference is analogous to the difference between sequential and direct access of information from disks (as far as program execution is concerned). In conventional computer programs, the IF...THEN statements are executed in a preset sequence and the execution is entirely control flow dependent. In KBS, on the other hand, it is the state of the system's current knowledge which determines its future course of execution. The system's current knowledge accesses the relevant IF...THEN rules and chooses from them the most appropriate one. Therefore, in KBS, the execution is totally knowledge dependent. A further difference emanating from the above argument is that in a KBS the control of execution is in the hands of the user, i.e. what question will be asked next, or what piece of information will be necessary next is entirely dependent on what response is given to the present question. Moreover, explanations and justifications can be requested of the system at any time. These explanations and justifications are more powerful and context dependent than information obtained by invoking HELP menus in conventional computer programs.

The knowledge base in a KBS is organized in a way that separates the knowledge about the problem domain from the system's other knowledge, viz. general knowledge about how to solve problems in the domain - the inference engine. This aspect highlights one more important difference between KBS and conventional computer programs, viz. additional knowledge in the form of IF...THEN rules can be added to the knowledge base of a KBS without any adverse side effects in terms of system functioning. Adding an additional piece of code to a conventional computer program might prompt a major restructuring of the program.

Developments of knowledge based systems in widely different fields have shown that the same inference engine can be used in different application areas (e.g. EMYCIN). The popularity of the rule based knowledge representation approach has also contributed to the development of 'canned' reasoning strategies. Therefore, a gradual shift towards a formalized means of developing these inference engines has evolved. These inference engines interfaced with other peripheral components are being marketed under the name of 'expert system shells'. The inferencing scheme in these shells is built by assuming a certain knowledge representation scheme. Therefore, one can conclude that some of the aspects of KBS development are being algorithmized. However, development of the domain dependent knowledge base remains the key activity involving the most time and effort.

KBS for engineering design

Hitherto the dominant application area of KBS has been in diagnostic fields, i.e. weighing and classifying complex patterns of evidence to evaluate a situation that is either abnormal (as in diseases and faults) or developable in new ways (as in mineral prospecting). But diagnosis is just one of the tasks that requires expertise. There are other tasks which are equally demanding of expertise.[7] These include:

(i) INTERPRETATION: analysis of data to determine its meaning and implications. Diagnosis can be considered as a major component of interpretation. But use of the term diagnosis has been reserved exclusively for evaluating maladies/abnormalities from available symptomatic data.

(ii) PLANNING: creating programs of action to achieve goals.

(iii) DESIGN: constructing or creating a system or object that satisfies certain stipulated requirements.

(iv) PREDICTION: forecasting the future from a model of the present or past (or both); forecasting the values at locations where there is no data from data at known locations.

In engineering disciplines, the role of design is important. The view of design here is different from that stated above. In an engineering design problem, there are strong underpinnings of both planning and interpretation. Diagnosis also plays an important part in the design process but it is not the objective per se. The overall design process can be viewed as consisting of the following three major components:

(i) ANALYSIS COMPONENT: this includes the planning and interpretation tasks and involves the idealization of the given problem situation to make it amenable to engineering analysis.

(ii) SOLUTION COMPONENT: this involves the use of major algorithmic programs to operate on the idealized model and provide results.

(iii) INTERPRETATION COMPONENT: this involves diagnosis and interpretation of the model results to check the validity of the idealized model and hypothesize refinements (if needed) before going back to the analysis step for another iteration, if necessary.

The solution component is a structured problem and its computerization and automation in mining engineering have reached a high level of maturity. Excellent computer programs are available for the solution of, for example, finite element models of mine structures, network models of mine ventilation systems and influence function models for subsidence prediction. The complexity of these programs has grown to such an extent that, user's manuals notwithstanding, it takes months to use the program options. Even if one learns how to run the program, the user is ill-prepared for the tasks of analyzing a physical problem in terms of the model and interpreting the model output in terms of the overall design objectives and constraints. This is because the analysis and interpretation components are not structured and require experience and expertise. At the same time, there are recognized 'experts' (albeit few in number) who perform the analysis and interpretation tasks with relative ease and with great competence.

Advances in computer hardware and software have been incorporated in recent computer application packages to alleviate some of these problems. Programs have been made interactive and user-friendly. Interfaces with graphics devices have been established to aid interpretation of data and results. These approaches, however, have not addressed the real problem. The 'experts' perform better than others largely because of their greater knowledge acquired through exposure to different kinds of problem scenarios and experience gained therefrom. The requirement is to transfer the accumulated analysis and interpretation expertise of experienced people to other, less experienced users.

For example, geostatistical techniques have been used for years in ore reserve estimation. Much of the methodology has been formalized and programmed in the last two decades. The first step in any geostatistical study is the determination of the form of the spatial variability function (the variogram). The choice of the form of this function is highly judgemental and depends heavily on the knowledge of the geology of the area. Similarly, the interpretation of the results from a geostatistical investigation is also dependent on experience gained with the applications of this and other techniques in specific deposits. Without this expert analysis and interpretation, the geostatistical exercise may not provide valid information to decision makers. The tapping of this expertise and its incorporation in the knowledge base are crucial. To achieve this goal, the KBS approach seems viable.

Incorporation of expertise in programs via KBS is not new. As mentioned earlier, there has been great success in such efforts in fields such as medical diagnosis. But a significant limitation of such KBS is that they tend to be based solely on rules of experience gleaned from 'experts'. Since the solution component is a major stage in engineering design, in addition to experiential knowledge, the capability to model the behavior of the system under consideration is also necessary. This kind of system would take advantage of the synergistic efficiency afforded by using expert rules of experience and algorithmic programs (to provide information needed by a rule, e.g. pressure drop in a particular branch of a ventilation network). The integration of algorithmic programs with expert systems for analysis and interpretation would, therefore, represent a major step in enhancing design capability. A generic knowledge based system anatomy is illustrated in Figure 3.

A mining knowledge based system must have as a minimum the following features which also permit identification of programs which are not legitimate KBS.

(i) A knowledge representation formalism and a knowledge base. The knowledge should not be mere

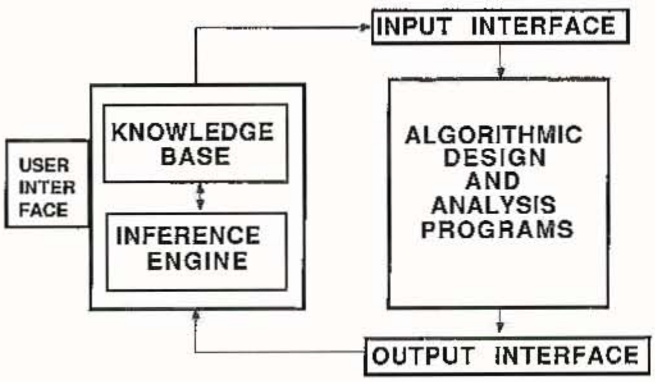

FIGURE 3. Anatomy of a knowledge based system for engineering design

numeric data but must include symbolic data as well.

(ii) An inference engine which manipulates the knowledge to arrive at conclusions. The inference should not be an algorithm. If the problem has an algorithmic solution it is not necessary to build a KBS for it.

(iii) An explanation facility capable of providing explanations (in terms of the system knowledge) as to how the system arrived at a certain conclusion or result and justifications as to 'why' a certain piece of information is being requested.

(iv) A user interface that facilitates communication between the user and the KBS in a subset of English.

(v) Input and output interfaces between design and analysis programs and the KBS.

Mine ventilation system design

Although the importance of mine ventilation has been recognized from the earliest days of mineral extraction, ventilation planning is, even today, more commonly considered an art rather than a science.

Ventilation system design is an engineering design problem whose solution requires the steps of perception, idealization, modeling, interpretation, feedback and control.[8] During the analysis phase, since ventilation system design is a part of the overall mine design, consideration must be given to the interrelationships which exist between the mine infrastructure and mine ventilation system. The adequacy of the input data and their reliabilities are also of paramount importance. In the interpretation phase, an objective analysis of the output is necessary. This step may identify weak areas in the definition of the problem in which case redefinition of the problem may be in order. The solution may have undesirable elements or maybe infeasible to implement, leading to questions on the design or the data. Also, the solutions, when properly analyzed and interpreted, can lead to a better definition of the problem, or superior alternatives to the problem. The design process can be visualized as an iterative process leading to improved perception, idealization, definition and solution of the problem.

The application of digital computers to solve the pressure quantity problem associated with mine ventilation systems began to make an impact only two decades ago. It is important to stress that the solution of the pressure quantity problem is only one step in the total planning process outlined before. There are important analysis steps prior to this 'solution' stage and even more important interpretation steps after the 'solution' stage. Considerable experience and expertise are needed in mine ventilation systems and mining engineering to arrive at good ventilation designs. Many benefits of computer-aided analysis are not realized in practice as this expertise is not readily available. Therefore, integration of KBS reasoning with mathematical models seems desirable. The essential elements of such a system are shown in Figure 4.

There are three major elements in the integrated system: (i) the KBS and its input-output interfaces to the design and analysis programs (DAP); (ii) the design and analysis programs, consisting of a ventilation data base and ventilation programs, and (iii) the actual mine system which is operated on by natural (mine location, seam characteristics, methane,

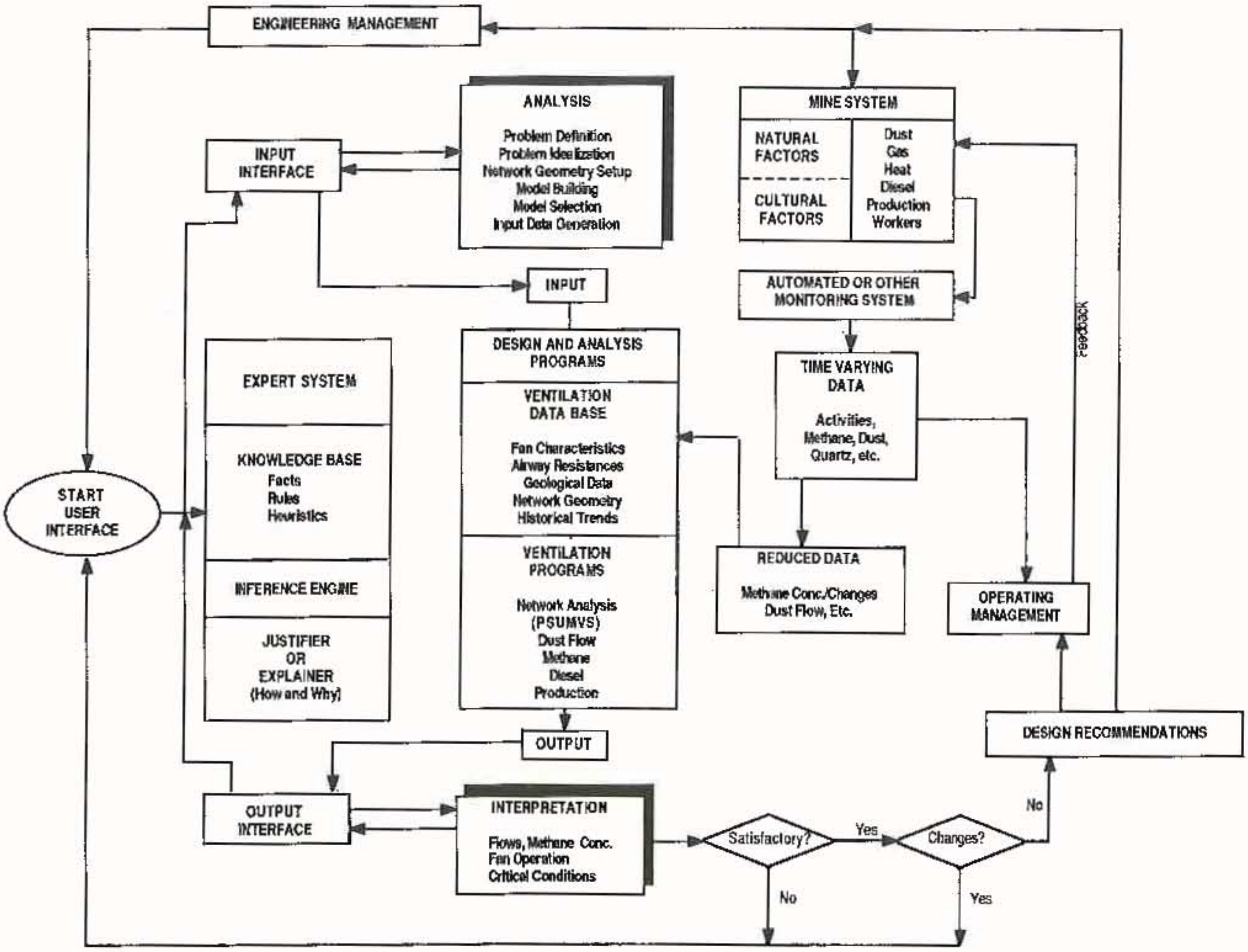

FIGURE 4. A logic flow diagram of a knowledge based system for planning mine ventilation systems

etc.) and cultural factors (equipment characteristics, fan operation, etc.) resulting in dust, gas, heat and humidity, etc. and from which data can be collected on a real time basis. The KBS element is the prime mover of the whole system.

In the analysis step, decisions have to be made regarding some of the following factors:

(i) What is the problem to be addressed? Is it dust generation? Is it lack of requisite air quantities? Is it the excessive liberation of methane? Is it a combination of the above?

(ii) Interrelationships of the problem with other mine design aspects, e.g. ground control, mining method and extraction, hydrology, regulations, etc. have to be identified.

(iii) Since an engineering problem is rarely amenable to engineering analysis as is, the problem has to be idealized with simplifying assumptions. A major decision has to be made regarding the relevant assumptions to make so as not to sacrifice the purpose of the analysis. An appropriate model will have to be hypothesized.

(iv) An appropriate design and analysis program will have to be selected commensurate with the availability and quality of the input data and desired accuracy of results. The data necessary for the model have to be developed.

Following the analysis step, the selected DAP is executed and after this solution stage, interpretation of the output follows. In the interpretation stage the model results have to be interpreted and any discrepancies diagnosed in terms of the overall design objectives. Among the questions arising at this stage are the following:

(i) Are the model results realistic? Is the hypothesized model a valid idealization of the problem situation?

(ii) What do the flow directions, air quantity, dust and methane concentration values mean and imply? What are the fan operating conditions? Are they realistic?

(iii) How sensitive is the solution? Are the conditions critical in any branch of the network? If so, what could be the possible reasons?

(iv) What are the refinements which can be made to the current analysis? What other model alternatives can we choose from?

(v) Which one of the available options should be chosen?

Most of the knowledge involved in answering these questions and making these decisions is experience dependent. This knowledge can be acquired from public domain sources and from experienced mine ventilation practitioners, and incorporated in the KBS for ventilation systems. An integration of KBS and traditional algorithmic programs yields a superior decision support system for mine ventilation system design. Development of such a system is possible with the current state of system technology.[5]

Mine strata control design

Mine strata control design is another important area where an integrated approach seems to hold promise. An outline of a typical strata control design approach is shown in Figure 5. As can be seen, the overall design philosophy is still the same, i.e. it fits the standard 'analysis -- solution -- interpretation' mold.

The objective in a strata control design program is usually the selection of the location and subsequent design (construction) of access and service openings and structures. To achieve this objective, three types of information are essential: (i) knowledge of the material properties of the different rock strata in the area -- these include the compressive, tensile and shear strengths, RQD, RMR, etc., (ii) knowledge of the in-situ stress regime in the area, and (iii) knowledge of the location and frequency of major geological features like folds, faults, etc. in the area. Most of this data is collected during the exploration stage from cored boreholes and geophysical measurements.

The above information is often not adequate to characterize the behavior of the various rock strata completely. An appropriate material behavior has to be hypothesized. Moreover, once some form of material behavior is assumed, an appropriate analysis tool has to be selected. These two aspects form the core of the ANALYSIS stage in strata control design. In this stage questions such as the following must be answered: (i) Should the design be based on empirical formulae or should a more rigorous analysis (such as Finite Element Method - FEM) be adopted? (ii) How should the material behavior be characterized? What failure criterion is most appropriate? What are the loading and

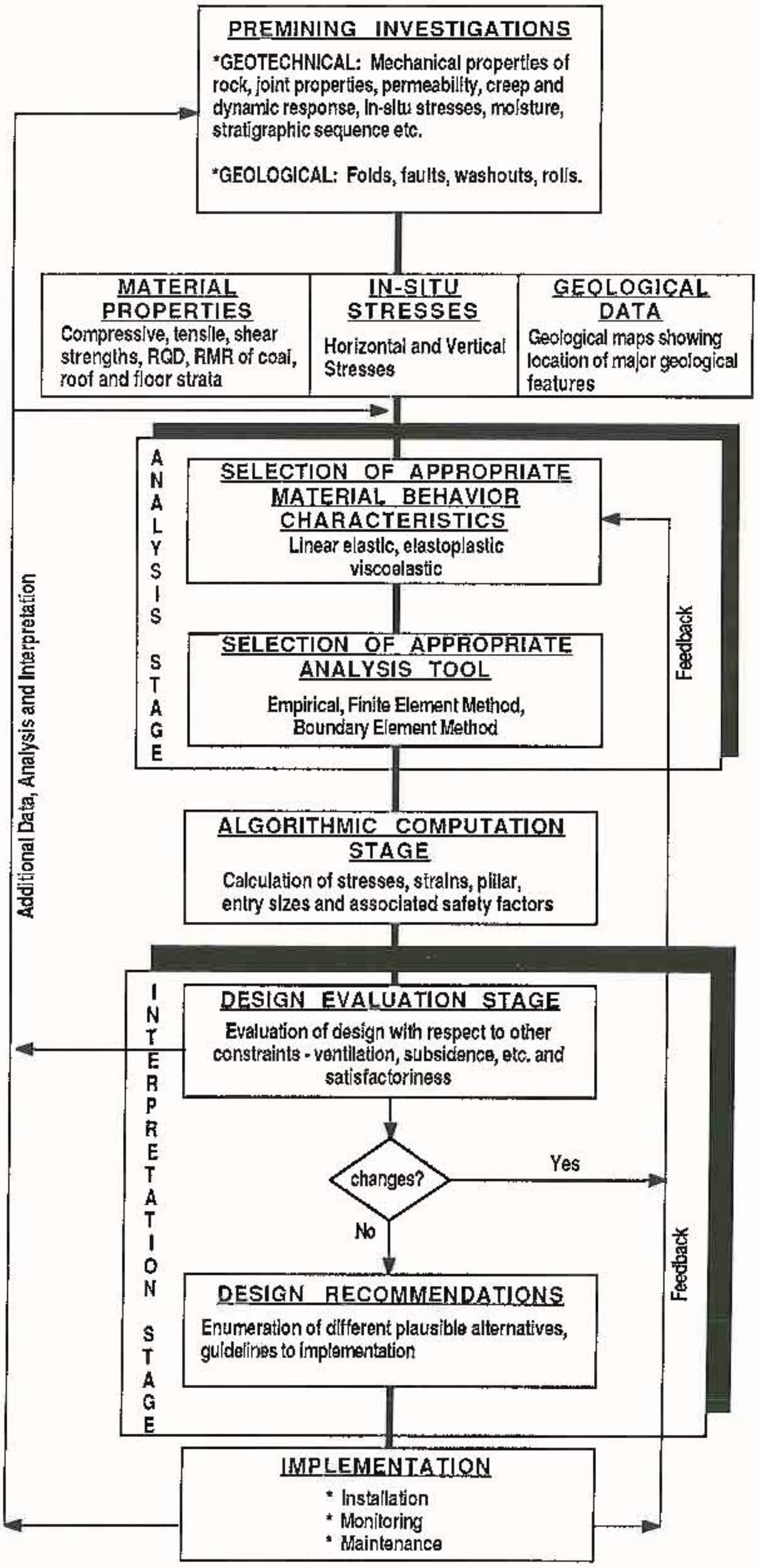

FIGURE 5. An outline of the design approach for strata control in mines

boundary conditions? What will be the granularity of the analysis? (iii) From the quantity and quality of the input data available, which design and analysis program would be most suitable? Most of the reasoning in this stage is nonalgorithmic and requires considerable experience and expertise.

The solution stage, as shown in Figure 5, can be purely algorithmic, the input to which is generated in the analysis stage. Here use is made of algorithmic design and analysis programs such as a finite element analysis program for an idealized coal pillar model. The number of programs available to the user at this stage is numerous. In the mining domain, for example, one could use ADINA/BM or BMINES etc. These programs generate reams of output, usually the stresses and strain in each element of the model.

The interpretation of the output generated by the solution stage again requires considerable expertise. What do the stress and strain values in the different elements imply? Is there local failure in a certain portion of the mine? If so, what can be said of overall stability and the type of analysis procedure chosen in the analysis stage? Was it adequate? Was it representative? Is the design satisfactory with respect to the design in other areas such as the ventilation system? If there is some experimental data available, how does the model output compare with the real world scenario? Are the discrepancies due to poor material behavior idealization? If so what changes should be tried out? In this stage too, judgemental knowledge is necessary to identify the overall adequate design.

Other application areas

In addition to the two applications discussed above, there are several other areas in mining engineering which can benefit from the KBS approach. The potential for the development of a KBS for geostatistical studies was already mentioned. KBS use in the analysis of investment and risk also falls in the same category. Other major design elements in mining engineering such as electrical, drainage and haulage systems, and surface mining reclamation schemes can also benefit from KBS applications. There also are promising applications in the area of diagnosis, viz. troubleshooting and maintenance of mining machines and equipment via goal directed KBS. Development of these systems will also be of value in computer assisted training and instruction.

Conclusion

This paper has highlighted the importance of incorporating experiential and judgemental knowledge in engineering design problems. This issue, as it relates to mine ventilation and mine strata control systems, has been outlined. It is imperative that efforts be made to formalize this 'artistic' information via knowledge engineering so that it is widely available. Nonavailability or difficulty in accessibility of expert opinion and input has severely throttled design efforts in the past. In light of this paucity, the advantages of mathematical models for design have not been fully realized. The benefits accruing from the proposed approach are:

(i) Permanent availability of timely, high quality and diverse expertise for analysis and interpretation.

(ii) Assistance in characterization of

the problem situation and proper consideration of relevant (and critical) factors.

(iii) Avoidance of misinterpretation of program outputs and assistance in faster convergence of the iterative design process towards the goal.

(iv) Ability to solve problems where incomplete or uncertain data only are available.

(v) Enhanced training of new engineers and analysts.

(vi) Increased productivity and better designs.

It is important to evaluate the suitability of the problem for solution through a KBS approach. A common pitfall has been the recasting of algorithmically solvable problems in the KBS mold. In looking for appropriate problems for KBS development instead of seeking problems which require expertise to solve, a common error has been to look for experts whose knowledge can be captured. A better approach is to look for engineering design problems which are demanding of knowledge and expertise. Moreover, in any problem being considered, it is essential to filter out the algorithmic portions and attempt to use the KBS approach for the judgemental and experiential portions only. KBS technology is successful only when applied in narrow, specialized domains. Extending the problem domain to such areas as overall mine design will involve large commitment of funds and efforts without any guarantee of success.

References

1. BUCHANAN, B. C. and SHORTLIFFE, E. H. Rule Based Expert Systems - The MYCIN Experiments of the Stanford Heuristic Programming Project. Addison-Wesley, Reading, MA, 1984.

2. GASCHING, J. PROSPECTOR: an expert system for mineral exploration. In: Introductory Readings in Expert Systems, Michie, D. Gordon and Breach Science Publ., New York, NY, 1982.

3. FEIGENBAUM, E. A., BUCHANAN, B. G. and LEDERBERG, J. On generality and problem solving: a case study using the DENDRAL program. Machine Intelligence 6. Edinburgh University Press, 1971.

4. BENNETT, J., CREARY, L., ENGLEMORE, R. and MELOSH, R. SACON: A knowledge-based consultant for structural analysis. Technical Report STAN-CS-78-699, Stanford University, 1978.

5. KOHLER, J. L., RAMANI, R. V., KOHARCHIK, G. J. and BHASKAR, R. A conceptual investigation of a management information system for coal mines. Final Report to U.S. Bureau of Mines. Contract #J0348005, August 1986.

6. HAYES-ROTH, F., WATERMAN, D. A. and LENAT, D. B. eds. Building Expert Systems. Addison-Wesley, Reading, MA, 1983.

7. STEFIK, M., AIKINS, J. BALZER, R., BENOIT, J., BIRNBAUM, L., HAYES-ROTH, F. and SACERDOTI, E. The organization of expert systems - a tutorial. Artificial Intelligence, 18, 1982, pp. 135-173.

8. LUXBACHER, G. W. and RAMANI, R. V. The interrelationship between coal mine plant and ventilation system design. Proc. 2nd. International Mine Ventilation Congress. Society of Mining Engineers of AIME, New York, NY, 1979, pp. 73-82.