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Department of Mining Engineering

SURFACE MINE DESIGN USING INTELLIGENT COMPUTER TECHNIQUES

by

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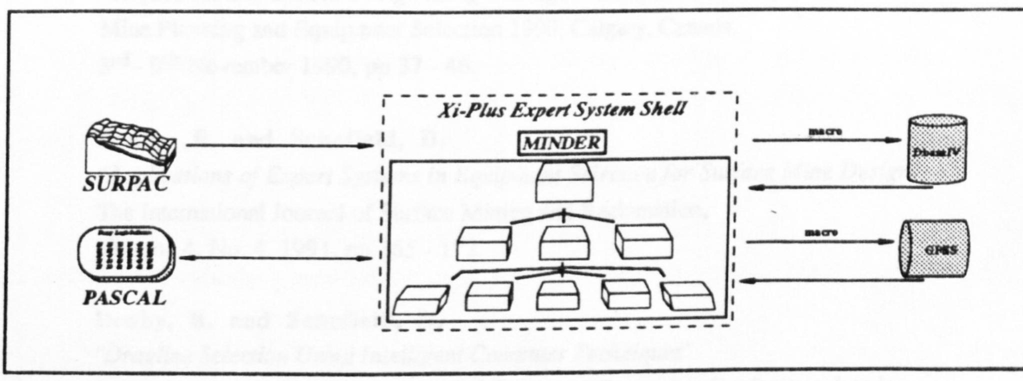
'Never Apologise. Never Explain.'

The Sandman
Neil Gaiman, 1990

Abstract

Surface mine planning involves the results of algorithmic numerical calculations being used by engineers to make informed decisions relating to the design. The Department of Mining Engineering at the University of Nottingham has in the past been involved in developing modular algorithmic packages. The emphasis of the computer research has now altered. Smaller specialised systems are now being developed to cover individual aspects of the design process. Artificial intelligence techniques are being introduced into the mining environment to solve the planning problems often associated with the large amounts of uncertain information needed by the engineer. This thesis is concerned with the development of MINDER, a decision support system capable of assisting the mine planner in the complex task of optimum surface mining equipment selection. An expert system shell has been used to create a series of individual application modules, each containing a multi-level knowledge base structure. An information handling system has been developed which is capable of storing consultation information and transfering it between knowledge bases and between application modules. Once an effective method of information handling had been achieved the flow of control between the system knowledge bases was rapid and followed complex inferencing routes.

Most of the commercially available packages mathematically model a deposit, calculate volumes and simulate operations. One of the aims of the MINDER system was to integrate with other software, for example MINDER is capable of reading volumetric and material information from Surpac mine planning software.



Geological data and manufacturer's equipment specifications are stored in DbaseIV databases. The expert system is capable of writing macros based on the consultation and performing complex relational operations involved in the elimination and ranking of equipment. In a similar manner macros are written to control the simulation package GPSS, which used to simulate operations using the selected equipment. A range of 'in-house' Pascal software is used for numerical calculations and matrix manipulation, an example of this is the fuzzy logic software used to handle uncertain information.

Another aspect of the project is an investigation into the use of machine learning techniques in the field of equipment selection. Knowledge induction software has been used to induce new rules and check those produced in the MINDER system. Various experiments have been carried out using neural network software to produce equipment selection models. Training data taken from the mining industry was used on both these systems, and the results were tested against MINDER consultation results.

Affirmation

The following papers have been published based on the work presented in this thesis :

Schofield, D. and Denby, B.
"CAD/Expert System Interface in Mine Design"
Surface Mining Future Concepts, East Midlands Conference Centre, Nottingham,
18th - 20th April 1989, pp 97 - 102.

Denby, B., Clarke, M. P. and Schofield, D.
"Decision Making Tools for Surface Mine Equipment Selection"
Mining Science and Technology, Volume 10, 1990, pp 323 - 335.

Schofield, D. and Denby, B.
"MINDER - A Multi-Level Intelligent CAD System for Surface Coal Mine Design"
22nd APCOM Conference, ICC, Berlin, Germany.
17th - 21st September 1990, Book II, pp 155 - 166.

Schofield, D. and Denby, B.
"Surface Mining System Design using Intelligent Computer Techniques"
Mine Planning and Equipment Selection 1990, Calgary, Canada.
3rd - 9th November 1990, pp 37 - 46.

Denby, B. and Schofield, D.
"Applications of Expert Systems in Equipment Selection for Surface Mine Design"
The International Journal of Surface Mining and Reclamation,
Volume 4, No. 4, 1991, pp 165 - 172.

Denby, B. and Schofield, D.
"Dragline Selection Using Intelligent Computer Techniques"
Proceedings of Computer Solutions in Mining and Processing Conference, Leeds,
23rd - 24th September 1991.

Denby, B., Schofield, D. and Bradford, S.
"Neural Networks Applications in Mining Engineering"
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Chapter 1

Introduction

1.1 Surface Mine Planning

Over time the world wide mining industry has moved towards policies of mechanisation and automation, increasing efficiency by implementing new production and planning techniques. Management needs to be able to assess the future of any mining operation, and complex information and planning systems are needed to justify future investments.

The overall effect of the gradual depletion of high quality, easily extractable reserves and increasing environmental pressures has directed the focus of the mining engineer's attention to the development and production of innovative solutions (Pratt 1989).

The routine use of personal computer systems at all stages of the mine planning operation has greatly enhanced the decision making capabilities of the engineer. Specific decisions need to be made at set points throughout the design process. One of the most important and difficult decisions to be made is the choice of mining method and equipment to be used. Substantial economic losses can arise from the selection of the wrong piece of equipment. Decisions are based on collated information on the deposit, engineering knowledge and a large amount of subjective judgement.

1.2 Computer-Aided Mine Planning

Mine planning is a complex process due the individual nature of each deposit and the high interdependence of the decisions required. Present mine planning software tends to provide algorithmic support to the decision making process, in the form of geological models and numerical results. The mine planner often has to be conversant with a range of computer languages and application packages.

From the initial stages of a modern mining project, computers are used to store, analyse and sort borehole data. Large modelling packages record the geological structure and build three-dimensional models of the geology, this permits classification and reserve estimation to be carried out. Databases are used throughout the design for the storage of many types of data. Specialist software covering such topics as optimum pit design and equipment simulation help to develop the planned method of working. Financial appraisal is usually carried out using spreadsheet based software.

Large amounts of mine planning software is now available, the usefulness of such software is often be limited by the difficulties of data transfer and restructuring. Individual mine design and planning software packages often lack the flexibility to handle a wide range of real data, and are generally application specific. Some vendors develop programs in their strongest areas of expertise and use other commercial software to provide a comprehensive package (Gibbs 1990). The compatibility of the various mine design and planning components across system boundaries requires radical re-appraisal of the manner in which data is used by planning software.

1.3 Intelligent Mine Planning Applications

A large amount of heuristic decisions are involved in the planning of a surface mine and the use of knowledge based systems as decision aids has introduced a new level of sophistication to the available software. Development has moved away from large expert systems and knowledge based software is being integrated with conventional programs. Using these intelligent front ends to link and control external software allows a mine designer's software capabilities to be extended. These techniques of storing and distributing the resource of human knowledge augments the abilities of the engineer and allows the dissemination of expertise.

The MINDER (MINe Design using Expert Reasoning) system discussed in this thesis is an attempt to select an optimum item of equipment for a particular mining scenario. The expert system uses information from mine design packages such as Surpac and Datamine, accesses a commercial database (DbaseIV) and utilises simulation software (GPSS). Pascal software has been written to perform the algorithmic functions required by the expert system, and DOS text files are used for data handling.

The inherent complexity and the large amounts of information, often of an uncertain nature, indicate that intelligent computer techniques should be applied. Most planning and engineering problems require that data be constantly updated to take account of on-going changes in the design. The future will see the introduction of software that can learn from experience, these are collectively known as machine learning systems.

1.4 Project Objectives

The aim of the MINDER system is to act as a decision support tool for equipment selection, and suggest starting points for a further detailed analysis. The general objectives being :

- That the knowledge based system should minimise the need for the user to refer to other sources of information.
- The system should provide information on any aspects of the mining operation - queried by the user.
- The system should be capable of making decision based upon uncertain information.
- The system should reduce the requirement for the user to have any specialist programming expertise.
- The system should provide an explanation to any conclusions or recommendations made.
- To evaluate the use of knowledge induction systems to automatically generate knowledge.
- To evaluate the use of neural networks as decision support aids to the mine planner.
- To apply the systems developed to a range of practical problem and validate their operation.

1.5 Thesis Overview

Chapter 2 : discusses the computer software available to the mine planner and illustrates some of the problems encountered when using this software.

Chapter 3 : introduces the concept of knowledge based and machine learning systems and describes their main features and applications.

Chapter 4 : discusses the techniques and software used to develop the MINDER system, it also provides information on the integration and control of external software.

Chapter 5 : details the individual MINDER system application modules and describes their function.

Chapter 6 : contains a selection of case studies, providing a validation for an equipment selection, decision support system.

Chapter 7 : provides the conclusions reached during the project and suggests some recommendations for further work in this field.

Chapter 2

Mine Planning Using Computer Techniques

2.1 Introduction

The objective of mine planning is to maximise the return on the investment while optimising the recovery of the mineral inventory. Mining an exploitable mineral reserve as a profitable venture is a complex task requiring a selection of specialist skills. The planning of the mine determines its viability, as the mine's efficiency depends upon a good mine plan.

The planning of a mine involves three major activities (Singhal 1989), each stage based on the results of the preceding step:

- Economic and technical feasibility studies.
- Design, procurement and construction.
- Mining and reclamation.

The technical design aspects of the surface mine planning process can be further broken down into the following topics:

- Geological data processing.
- Geological modelling.
- Pit design.
- Scheduling and simulation.
- Economic evaluation.

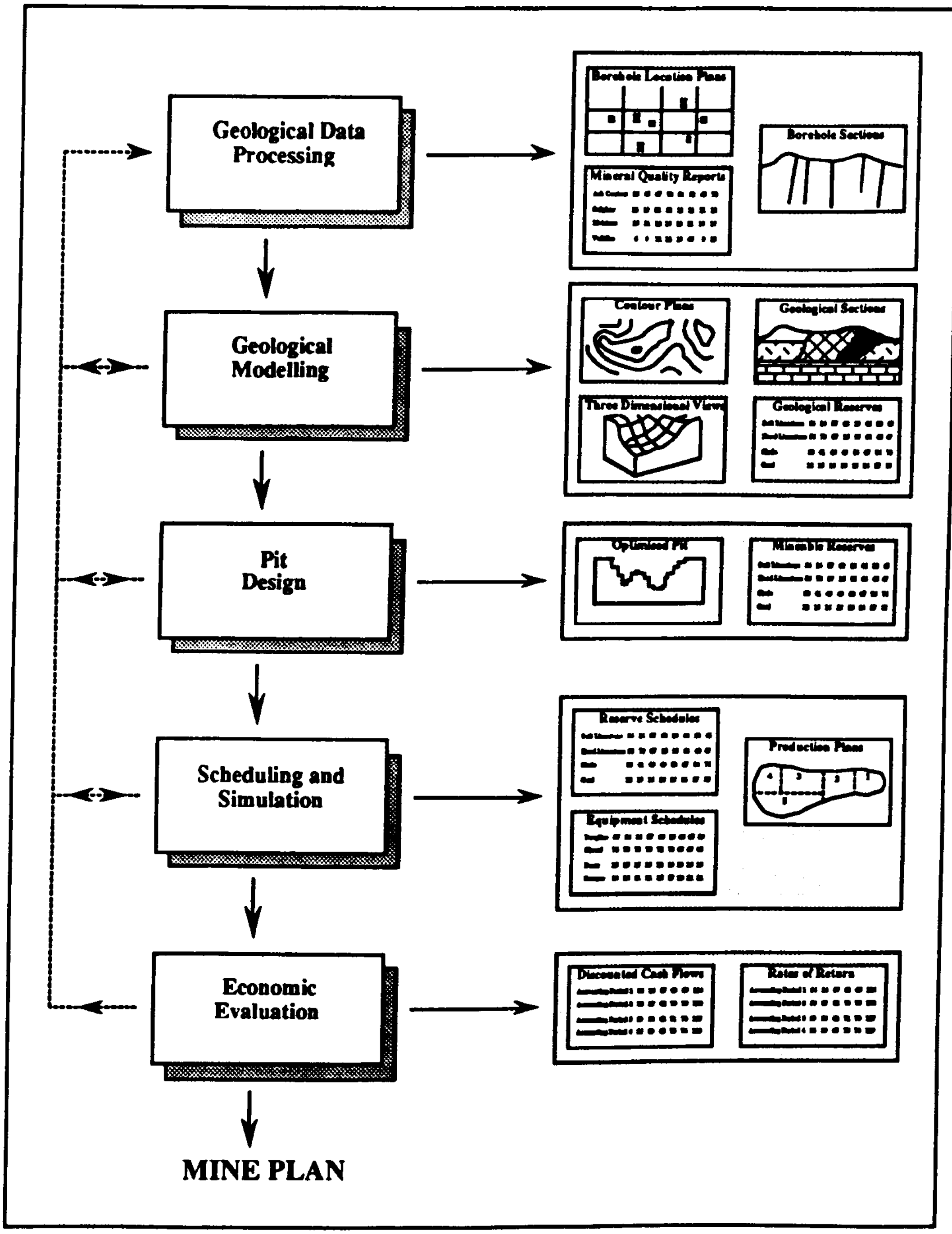


Figure 2.1. Components of a Surface Mine Planning Operation

These procedures are generally undertaken in logical order iterating back to obtain information, for example the scheduling of the production units may show limitations in the selected pit design. Figure 2.1 shows the elements involved in surface mine planning and the information obtained from each stage of the design.

This chapter will discuss the use of computers in mine planning and consider their application to each of the elements listed above. It is not intended as an exhaustive list of available software, and concentrates mainly on surface mining.

2.2 The Use of Computer Techniques

Mining is very capital intensive, and risks are implicit in all mining ventures. The depletion of high quality and readily accessible deposits means that the exploitation of less favourable, geologically complex, remote deposits has become standard in the industry. Moreover, low profit yield exploitation increases the importance of effective design tools.

Surface mine planning requires the optimum use of surface and mineral information in a combination of numerical computation and information processing, together with significant input in the form of the planning engineers knowledge and experience (Clarke 1989).

Surface mine design is often characterised by:

- **Data :** Large unwieldy numerical data sets.
- **Data Manipulation :** Data is often produced, modified and reproduced.
- **Calculations :** A considerable number of repetitive calculations.
- **Result Analysis :** Determination of conclusions from tabulated results.
- **Graphical Output :** A large number of plans and sections are required.

The volume and complexity of this information may cause the performance of the engineer to decline. The introduction of computers has added a new dimension to mine planning. The speed and accuracy of the algorithmic elements of the process eliminate the need for time consuming, repetitive, manual calculations.

These programs are particularly useful in optimising the mine plan. Computers can rapidly consider numerous alternatives and critically perform sensitivity analyses to determine the plan which best suits the design objectives.

2.3 Computer Applications in the Mining Industry.

The application of computers has traditionally been slower in the mining industry than in many other engineering disciplines due to the industry's reluctance to accept this new technology, however this developing science has caused significant changes.

Most large modern mines rely on the use of computers at some stage of the planning process. Computers are used in both the long and short term planning of a mine.

Mine planning used to be limited to costly and inflexible mainframe computers. Advances in computer technology have increased the power of the desktop computer, and have consequently led to a greater use of computer aided mine planning.

Mining software has changed radically in the last ten years, and programs are now available covering all facets of the design process. The quantity of software available has increased and programs available five years ago have matured and been enhanced by the advances in hardware. Over 600 commercial programs for all types of applications are available ranging from simple spreadsheets to comprehensive pit design packages. Several directories of mining software are available [1].

Mine planning software is often categorised by the development method (Denby 1987) :

Off-the-shelf : "Software produced by a software house or mining consultant covering a whole range of planning tasks." In the field of mineral evaluation, software is actively marketed by many companies. These are the largest and most widely used programs which vary in the modelling techniques and mine planning methods used. These packages have evolved over time and there is usually a significant cost associated with the acquisition of mineral evaluation software. A degree of complexity is often built into this software requiring a training period ranging from days to weeks (Hrebar 1985).

In-house : "Software developed by a mining company computer department or individual staff." A few larger mining operations have had in-house computer based reserve estimation for many years, such as Kidd's Creek in Canada, Nchanga in Zambia and Palabora in South Africa. Palabora performs short and medium term planning on computers based on the mine, long term planning is carried out at the head office in Johannesburg (Kear 1990). Rössing uranium mine has developed a cost modelling system to improve the data available for the mine planner (Knowles 1990). Other recent systems developed have included Outokumpu Oy's Minenet software system, developed on a Vax Mainframe computer, at the Enonkoski mine, Finland (Pulkkinen et al. 1990). Computerised planning has also been recently introduced to the

[1] Gibbs Associates produce a computer listing of over 600 programs for all categories of mining applications (Gibbs 1987).

Neves-Corvo copper mine, Portugal, installed on a network of workstations and IBM personal computers. This system is used for underground development planning and creates three dimensional images of the underground workings and mineral orebody (Teixeira and Caupers 1990).

Combination : "Software bought-in and modified to improve the efficiency or applicability of the system." The unique nature of a reserve may require that existing ore-reserve and mine planning software be customised. Boliden Engineering in Sweden provide a mine planning package called BOLIS based on Microstation 3D-CAD, Ashton Tate's DbaseIII and Microsoft Excel. The system is controlled by support routines which use a combination of macros and the C language (Renström and Andersson 1990). The Boron mine, California uses three individual programs, a reserve estimator, a scheduling system and a spreadsheet for simulating costs (Maddocks 1990). The RTZ general open-pit programs have been modified and tailored to suit the mine planning requirements of Minas de Rio Tinto in southern Spain (Preller and Rich 1990).

The major mining software houses are moving towards a modular approach to software design, where a basic system can be purchased and supplementary modules are available. Minex are an example of a company who market software in this form, a list of their modules is given in Table 2.1 (Exploration Computer Services 1987).

Major Modules

BDS	Borehole Database System
GMS	Geologic Modelling System
MRS	Mine Reserve System
MSS	Mine Scheduling System

Supplementary Modules

DRG	Dragline Simulation
TRK	Vehicle Haulage Simulation
MRS/S	Spoil Design
MSS/S	Spoil Scheduling

Table 2.1 An Example of a Modular Mine Planning System

Development work undertaken in the past in the Department of Mining Engineering, University of Nottingham was aimed at producing a comprehensive system called NU-

MINE, figure 2.2. The system was not targeted at any particular type of deposit and had individual modules linked via a central database (Atkinson et al. 1987). This was one of the first attempts at modularisation of the computer aided mine planning process, and included important central elements such as databases, utility software, and a graphical user interface.

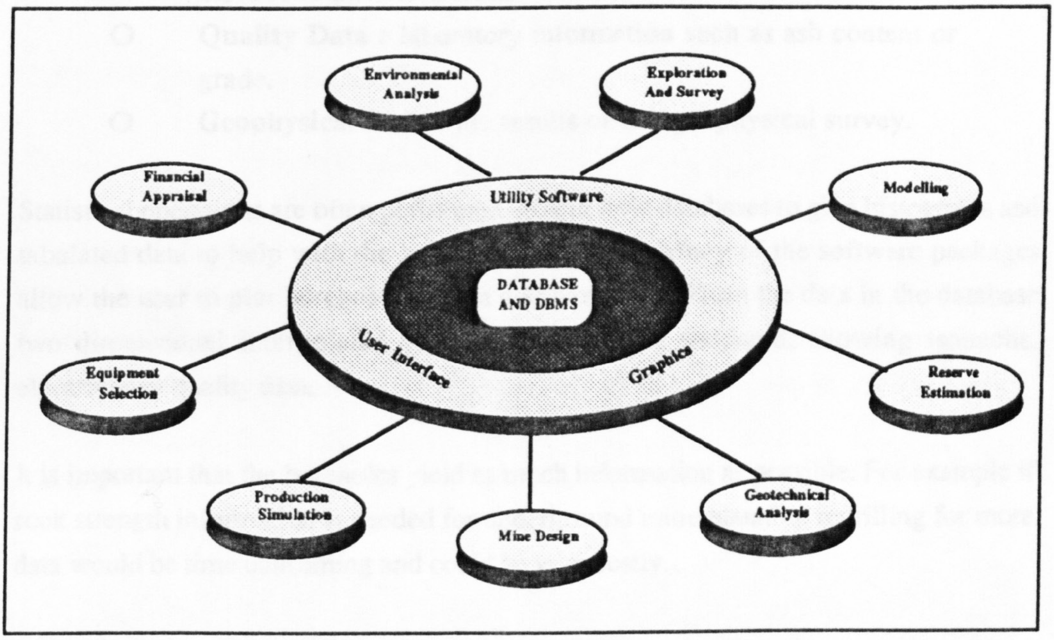


Figure 2.2 Initial NU-MINE Conceptual Design

Computer Aided Design has become synonymous with computer graphics, many mine design packages allow the mine planner to create and display solids and surfaces encountered in the design. These graphical techniques combine accuracy with a flexibility of display, but the complex properties of mine design still strain present software capabilities (Mill 1989).

2.4 Geological Data Processing

It is important that decisions made during the planning process are based on the most accurate information possible. Much of the initial data upon which a mine plan is based comes from the information entered into a drill hole database. Most commercial or in-house mine planning software has a component capable of managing and interpreting drill hole data as a standard feature.

Information stored in any borehole database usually includes:

- **Project Data** : such as site information, borehole identifiers and borehole location.
- **Lithological Data** : including collar elevations, mineral elevations and thicknesses.
- **Quality Data** : laboratory information such as ash content or grade.
- **Geophysical Data** : the results of any geophysical survey.

Statistical operations are often performed on drill hole databases to give histograms and tabulated data to help with the borehole correlation. Many of the software packages allow the user to plot boreholes in plan and in section. From the data in the database two dimensional interpolated contour maps can be prepared, showing isopachs, elevations or quality data.

It is important that the boreholes yield as much information as possible. For example if rock strength information is needed for underground mine planning redrilling for more data would be time consuming and could be very costly.

2.5 Geological Modelling

The primary objective of any modelling system is to define a mineral deposit or orebody with respect to its size, shape, boundary or other physical parameters. Thus, in this context, a model can be defined as 'an organised representation of reality' (Croghan 1989). Geological models are built by projecting known data to approximate 'true' outlines of underground surfaces in three dimensional space. There is a need to match quality information with the lithological horizons determined in the model. The model should be able to mitigate the problems caused by data with fundamentally heterogeneous characteristics (Rendu 1984, Voortman 1987).

Software companies have developed a variety of techniques to define and generate geological models. The modelling techniques developed reflect the type of deposit worked with and there are differing philosophies about how best to represent three dimensional deposit models. The modelling method chosen for a deposit should define the volume contained within a geological outline from known data, as well as the quality or grade values of the model segments.

A substantial review of the modelling software available and individual capabilities is given by Gibbs (1990). Integrated software packages for geological modelling usually include more than one type of modelling. With models costing anything from US$ 5,000 to US$ 75,000 the purchasing of mine design software can represent a major investment. The model geometries presently offered include those discussed in the next sections.

2.5.1 Regular and Grid Block Models

These are by far the most common method used, and most packages have this type of modelling available. The three dimensional block model, shown in figure 2.3a, was originally developed for massive open pit deposits, and the two dimensional grid model may be used for seam deposits. From a programming stand-point this is the simplest model to code and manipulate, but the technique is very rigid and does not allow for modelling of local detail (Davie 1984). Most packages have this modelling capability.

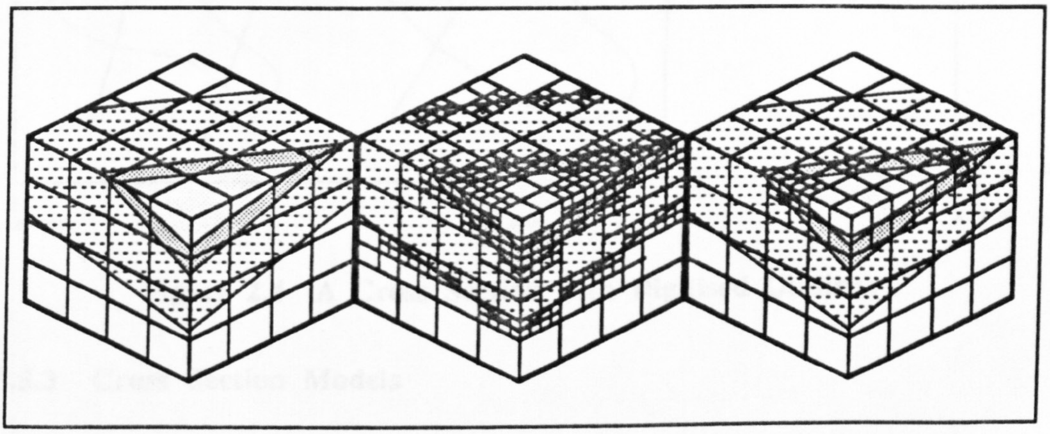


Figure 2.3a **Regular Model** | **Figure 2.3b** **Irregular Model** | **Figure 2.3c** **Enhanced Octree Model**

2.5.2 Irregular Block Models

These consist of blocks of different sizes within the same model. The model is initiated with the same size blocks and then as geological definition is applied, "sub-blocks" are created along the boundaries which provide a closer approximation to detail. Techniques developed to control the splitting of the blocks include quadtree and octree modelling, an example of a pure octree model is shown in figure 2.3b. The quadtree and octree methods of cellular decomposition break the cube into either four or eight segments of equal area or volume respectively (Mill 1989).

The Department of Mining Engineering, University of Nottingham was involved in the development of new modelling techniques known as enhanced quadtree and enhanced octree. These methods are similar to the pure quadtree and octree in that homogeneous adjacent blocks are grouped together, but it also allows a block to contain a single line without being split down further (Croghan 1988). An example of an enhanced octree model is shown in figure 2.3c.

Packages using irregular block models include: MINEX, MINEX 3-D and DATAMINE.

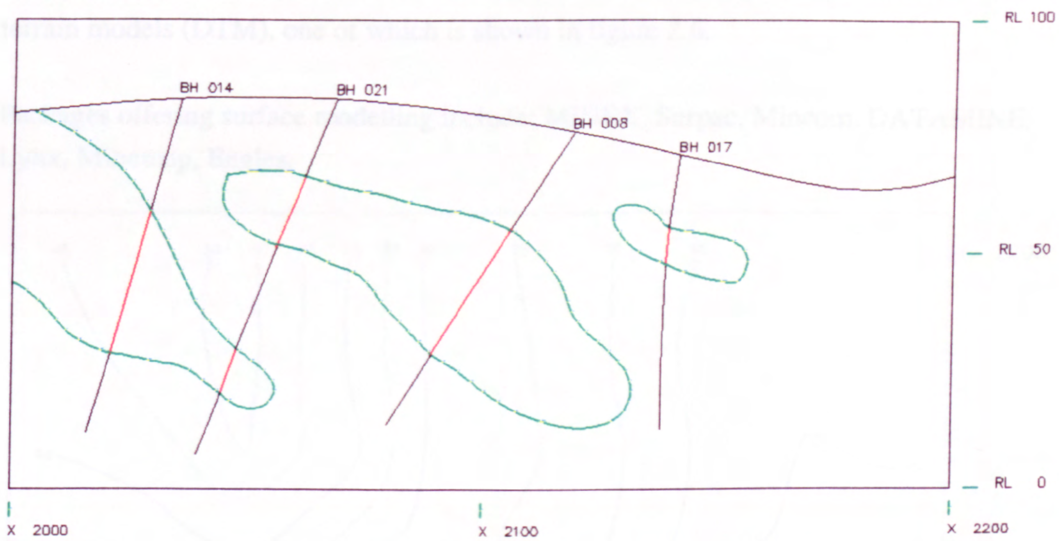


Figure 2.4 A Cross Section with Digitised Outlines

2.5.3 Cross Section Models

These are models developed by digitising geological outlines on cross sections produced by the modelling package, as shown in figure 2.4. These outlines can be transferred to a block or wireframe model depending on the package being used.

Packages offering cross sectional modelling include: MINEX 3D, Surpac, Mintec, GEOMODEL, Geomath, Geostat Systems, Lynx, Micromine, Eagles.

2.5.4 String Models

A string is a group of three dimensional points in space represented by XYZ coordinates. Strings model programs use techniques of defining limits and boundaries. Volumes are usually calculated using string polygon boundaries on cross sections, figure 2.5 shows a Surpac series of strings used as topographical contours.

Packages offering string modelling include: Surpac, Lynx, Micromine, Minemap.

2.5.5 Surface Models

These models can be visualised as a surface laid over a series of data points, this surface can take the form of a grid, with values estimated at each node or of a triangulated network (Howard 1988). Surface models are sometimes called digital terrain models (DTM), one of which is shown in figure 2.6.

Packages offering surface modelling include: MINEX, Surpac, Mincom, DATAMINE, Lynx, Minemap, Eagles.

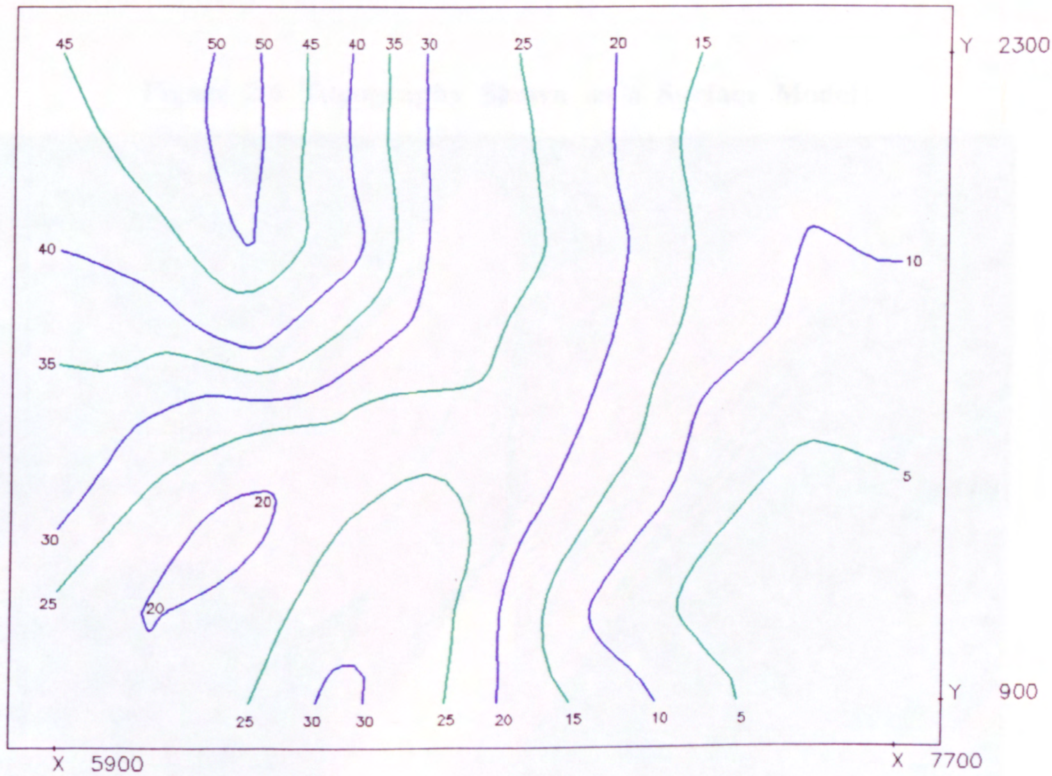


Figure 2.5 Polygon Strings used as Contours

2.5.6 Solid Models

These models also known as wireframe models are generated by digitising boundaries onto sections. These outlines are then connected to form a three dimensional shape.

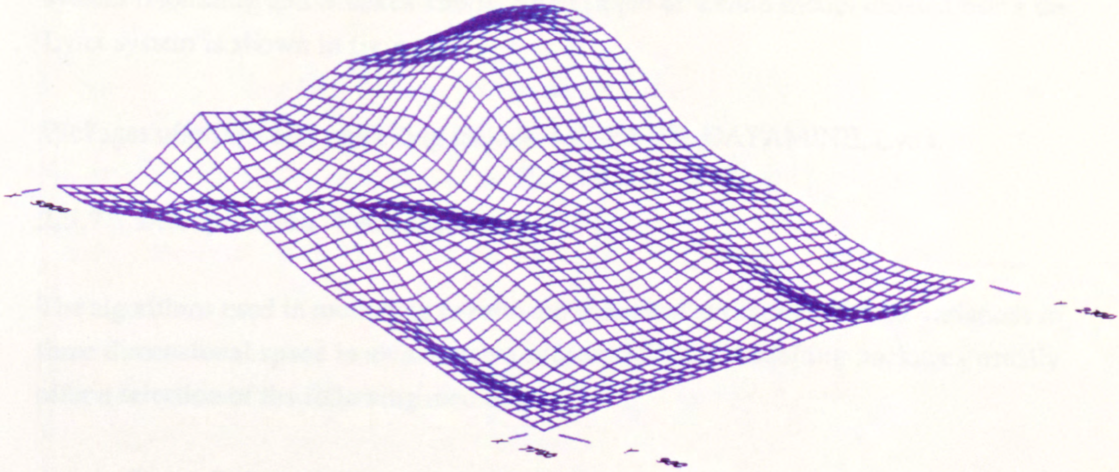


Figure 2.6 Topography Shown as a Surface Model

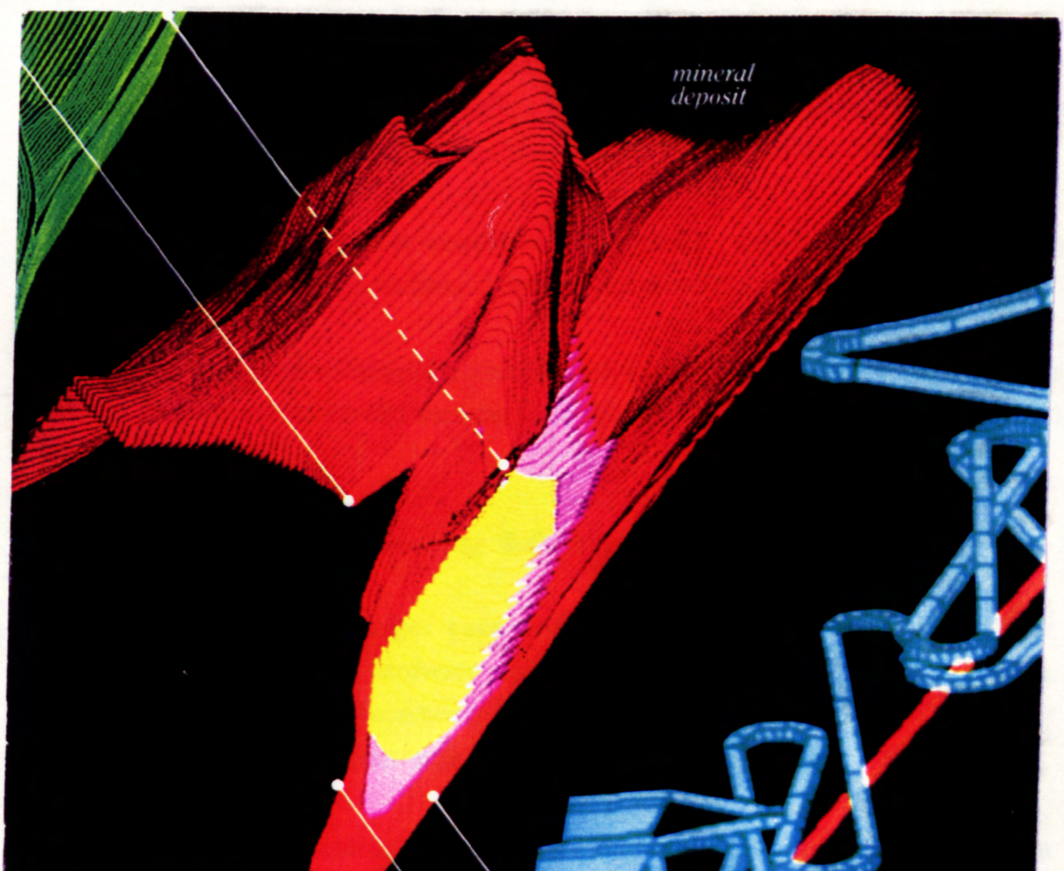


Figure 2.7 Orebody Solid Model (Lynx Geosystems Inc. 1990)

This shape can then be defined mathematically, based on the theory of solids of integration, as in the three dimensional component modelling system used by the Lynx system (Houlding and Stoakes 1990). An example of a solid model created using the Lynx system is shown in figure 2.7.

Packages offering solid modelling include: MINEX 3D, DATAMINE, Lynx.

2.5.7 Interpolation Techniques

The algorithms used in modelling to estimate numerical attributes and their variations in three dimensional space is an extensive subject. Modern modelling packages usually offer a selection of the following methods:

- **Triangulation** : A triangle represents the slope differential between the three corner data points. Several methods are available. Mainly used for surface or wireframe modelling.

- **Inverse Power of Distance** : A distance orientated algorithm is used to assign weightings to particular value locations. Generally used to set grade values in a block model.

- **Polygon** : This technique is provided by most modelling software, it relies on the traditional polygonal method of calculating reserves.

Other techniques used within mine planning software include geostatistical techniques such as kriging, use of a trend surface, least squares algorithms, Fourier analysis and minimum curvature.

2.5.8 The Future of Modelling Software

Geological modelling packages have evolved to maintain compatibility with the enhancements provided by hardware development (Cameron 1990). One of the main developments has been the increase in processing power available allowing geological models without size limitations to be produced.

Another major development is the use of graphics in mine planning software, both as a method of display and as an interactive method of control. Computerised modelling involves the production of both two and three dimensional views of the deposit. This capability goes beyond viewing the deposit, computers provide a three dimensional descriptions of reality. Some state-of-the-art commercial software provides colouring and shading, resultant images taking on the aspects of a photograph (Gibbs 1990).

Recent work at Imperial College has shown the use of new data structures in the modelling and presentation of geological information (Mill 1989) which exploit powerful spatial searching techniques. These searches will allow an optimum pattern and schedule for the extraction of ore to be developed.

As computerised mine planning techniques advance mine planners need to be able to control large amounts of detail in the geological models. The application of intelligent computer systems to this area of expertise is being investigated, these techniques will be discussed in more detail in the next chapter.

2.6 Pit Design

After modelling the geology the mine planner considers the appropriate parameters and goes on to design the pit limits. These limits may be geological, property lease limits or a combination of cost factors giving an economic limit (Jardine and Evans 1988). To identify an optimum resource area and maximise earnings from an open pit mine, significant variables such as yield, energy value and depth must be considered (Jeffreys and Hoare 1985). The exploitation of the identified area should be optimised prior to detailed scheduling costing and conventional financial analysis.

Many general mine planning programs have pit optimisation options as standard, others contain interfaces to link with currently available pit optimisation software. The optimisation programs tend to use block model information to determine the ideal pit limits. The most popular optimisation packages are Whittle Programming's Three-D and Four-D software, which can be used alongside many generalised mining packages (Whittle 1988).

Optimum pits can be generated using a moving cone algorithm, repeatedly searching for incremental pits consisting of combinations of blocks which are worth mining. It is thought that the moving cone algorithm is inefficient and does not always find the optimum pit (Whittle 1989). The Whittle software uses the Lerchs-Grossman method which takes a different approach to the problem but always finds the optimal pit.

The other method common in mine design software is to define a pit bottom polygon, and then generate a pit with selected slope angles. This may not take into account haul roads and minimum mining widths but these problems can be overcome by adjusting the slope angles to the averages required.

Rio Tinto Management Services have developed an optimised pit design (OPD) program which is used for the long term planning of surface mines such as Palabora (Kear 1990). The Borax and Chemical corporation have detailed their use of pit optimisation software at the Boron mine, California, here it is used in the short term planning of each new mining advance (Maddocks 1990).

For every pit shape considered mining reserves are produced, taking into account the slope configuration, pit limits and quality characteristics. When the pit limit which yields the highest cash flow has been identified it is scheduled in such a way to best utilise any selected equipment. An example of a simple pit design model is shown in figure 2.8.

As part of the Nottingham University NU-MINE system (see section 2.3), a pit optimisation technique was developed using a 3D DP Algorithm, employing a dynamic programming principle. This method avoids some of the rigid constraints placed upon rigourous design methods (Kordestani 1988).

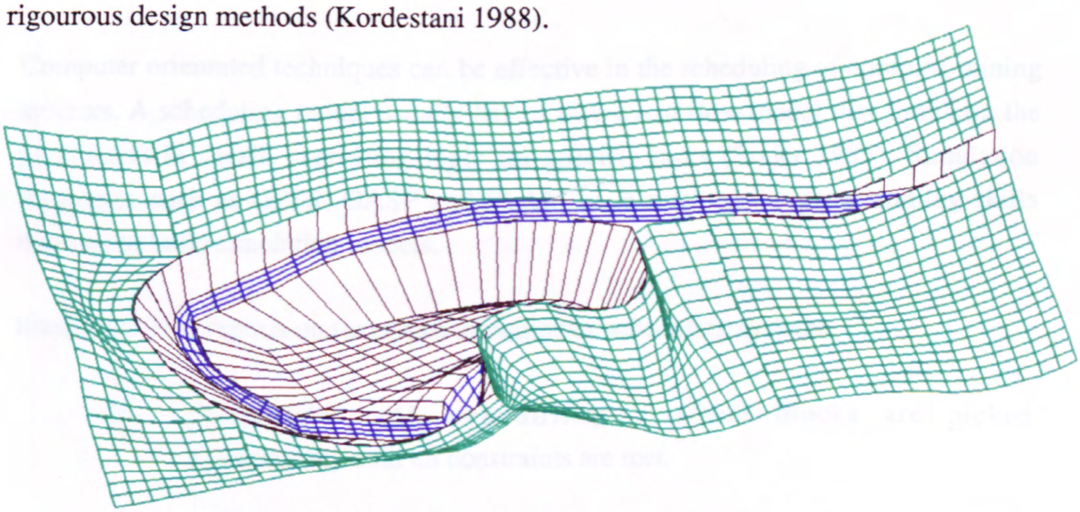


Figure 2.8 Design Model of an Opencast Mine

Considering the many computer techniques used to determine the 'optimum' pit limits Kim (1979) has pointed out that "there is no harm striving for the optimum pit limit as long as one does not lose sight of the fact that one is optimising the 'model' and not 'reality'.

The reserves and optimum pit design are dependent upon the result of other aspects of a modular planning process, such as slope stability and equipment selection. These parts of the design process are often performed by the planning engineer using the results of the previous stages.

2.7 Scheduling and Simulation

Simulation continues to be popular in the operational side of mining, one reason for this is the need to solve the many waiting line and storage problems in the industry (Manula et al. 1975). Scheduling requires tonnages from the design stage, equipment details and information from the modelling system. In the field of mine planning a scheduling system would require the following features (Singhal 1989) :

- Annual and life-of-mine sequencing.
- Multiple pit scheduling.
- Annual and life-of-mine quality predictions.
- Resource optimisation.
- Mine production reporting and forecasting.
- Fleet sizing, equipment simulation.
- Capacity for cost analysis.

Computer orientated techniques can be effective in the scheduling of complex mining systems. A scheduling model usually has its own event flow model that simulates the parameters in detail, exercising logic for specific tasks (Srajer 1985). Simulation languages such as GPSS, GASP and SLAM have reduced the programming skills required to build simulation models.

Franklin (1985) reports on two types of computer scheduling systems.

- **'Computerised' scheduling** : where blocks are picked automatically until all constraints are met.

- **'Computer-aided' scheduling** : where control remains in the hands of the engineer, who uses the speed of the computer to manipulate mining increments and evaluate them.

Many of the major commercial mine design packages contain scheduling modules, for example the MINEX software contains a mineral scheduling package, a waste scheduling package and an overall mine scheduling package (Exploration Computer Services 1987). Many specialised packages have been developed to simulate specific mining activities.

2.8 Economic Analysis

Recently, increased operating costs and low product revenues have highlighted the importance of selecting the most profitable project design. In the final analysis, the rate of return on investment is the prime consideration in project evaluation. Many evaluation techniques are available, almost all rely on predicting the cash flow profile over the life of the mine.

The investment worth of the mineral deposit can be realistically evaluated in relation to specific engineering design criteria. Selecting the best design parameter will ensure an optimum investment performance.
The economic analysis is an on-going iterative process throughout the mine design, this was shown in figure 2.1. Economic criteria are applied as constraints to the pit optimisation and during the production scheduling.

It is possible to create micro-models simulating the economics of a single item of equipment, which act as subroutines to production macro-model for the whole mine.

2.9 Conclusions

As mining projects become progressively more marginal from a financial stand-point, it is essential to obtain the best possible deposit model for reserves assessment. In Britain as the Environmental planning bill is brought into force there will be a need for software to encompass all aspects faced by the mine planner, such as estate management, environmental assessment, reclamation planning and requirements for planning enquiries (Cameron 1990).

Reductions in the costs of hardware have led to the routine use of personal computer systems at all stages of the mine planning operation. Some packages which run within the constraints of these desktop computers assume a particular processing sequence. These sequences build rigidity into the design method, modular systems and enhanced user interfaces may eliminate this problem (Stokes and Henley 1990). Individual modules may provide recommendations allowing the planner to meet the environmental requirements required by current and future legislation.

While there are numerous mine planning packages on the market today, there is no shortage of disillusioned and frustrated mining engineers trying to use these to solve real problems (Jardine and Evans 1988). These problems include the representation of the unique properties of each deposit within a computer. Often inappropriate sets of technical applications software are used for the specific problem. Kear (1990) suggests a possible solution, engineers should develop their own software rather than 'program' a programmer who does not understand what the engineer really wants.

It is important that all planning work is based as far as possible on 'real-time' data, so that people involved with different aspects of the design process can be confident of having updated information to work with. A method of throwing all the data into a computer and expecting it to come up with a full mine design is still an unrealistic approach (Brien et al. 1985).

In opposition to the view expressed above the commercial modelling software companies believe the accuracy of their models is limited only by the reliability and density of the data and the degree of detail required by the user (Houlding and Stoakes 1990). This is partly due to many packages offering a variety of modelling options within a single consistent framework.

Many mining engineers are wary of large modelling packages due to their mathematical content and lack of flexibility. Computer graphics have, to some extent, helped overcome this problem. These systems provide a new degree of 'user-friendliness' as two and three dimensional graphic controls can be introduced in the form of menu's and mouse controlled systems. Mining companies have recently discovered the advantages of linking their software to AutoCad, utilising the high quality presentation features of this software as a relatively cheap software extension.

This decade has seen considerable software development. Most of this work has been on a modular basis although systems to integrate the various facets of these modules still require development. This favours the development of software which can easily adapt to meet changing project requirements.

As nearly all mining projects rely on computer techniques at some stage of the design process, it is the intelligent use of the application, irrespective of the source of the software, that ensures success. Brien et al. (1985) believe that a computer can not replace an engineer because of the judgement required during the planning stages of a mine design. The author believes that while not replacing an engineer, new computer techniques are becoming available which will be able to assist the planner in specific design domains, acting as a second opinion and design guide.

The computer based research within the Department of Mining Engineering at Nottingham University has progressed into specialised areas of mine design, such as environmental assessment, spontaneous combustion risk, slope stability and equipment selection. These individual modular programs link to commercial software providing valuable aids to the mine planner. Research has moved away from conventional approaches into the application of intelligent computer techniques in the mine design process. The application of artificial intelligence techniques to the field of mine design has resulted in both stand alone knowledge based systems and larger integrated systems capable of linking to and controlling conventional software.

Chapter 3

Intelligent Systems

3.1 Introduction

In recent years a new inter-disciplinary subfield of computer science known as Artificial Intelligence (AI) has emerged. Researchers in this field are concerned with developing computer systems that perform functions normally associated with human intelligence. Many of the uncertainties concerning the nature of artificial intelligence arise because it does not conform with other categories of science, it is often associated with cognitive and behavioural psychology but this association neglects the mathematical and engineering aspects of the subject (Campbell 1986).

Artificial intelligence can be divided into three relatively independent research areas :

- **Natural Language Processing** : techniques which allow computer systems to accept inputs and produce outputs in a conventional language like English. Several expert systems incorporate a primitive form of natural language in their user interface.

- **Robotics** : the development of visual and tactile programs to allow robots to 'see' and 'manipulate' objects in a dynamic environment. Artificial intelligence is concerned with the heuristic techniques which allow robots to function in these changing environments.

- **Knowledge Based Systems** : are concerned with the acquisition, representation and manipulation of human knowledge in symbolic form. Human knowledge consists of reasoning as well as facts or data.

The majority of artificial intelligence research is concerned with abstract problem solving. Knowledge based systems tend to focus on replicating the behaviour of a specific expert in a narrowly defined problem area (figure 3.1). An expert system is a caricature of the real expert who is said to know more and more about less and less (Forsyth 1989). Expert systems technology offers an opportunity to build applications that replicate intelligence. Knowledge is the fundamental concept. Harnessing, distributing and amplifying this resource is the goal of expert systems (Goodall 1989).

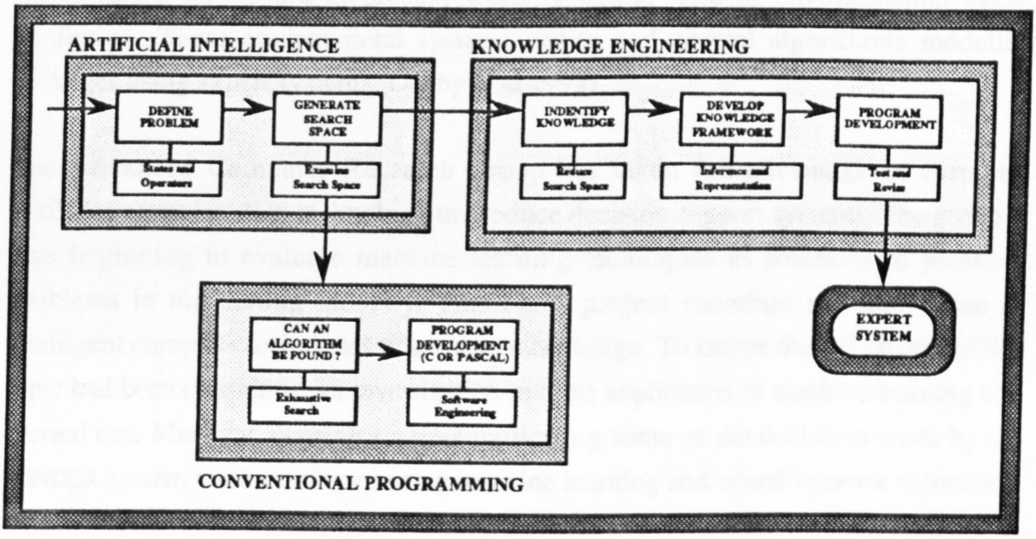


Figure 3.1 The Different Concerns of A.I. and Knowledge Engineering

There are many successful applications where an expert system can surpass a human, these tend to be in restricted domains with well defined parameters (see section 3.11). One reference source, the CRI Directory of Expert Systems (CRI 1986) lists over 600 systems at the end of 1985, at present there are well over 1000 commercial systems available.

It is difficult to determine how much money is being invested in artificial intelligence research, or expert systems in particular. There is a rapid commercialisation of the technology. The introduction of several IBM-PC based building tools has expanded the number of companies who can begin to experiment with these systems. Artificial intelligence and expert systems are likely to remain a major growth area in the 1990's.

A variety of expert systems are currently under development within the Advanced Computer Applications Group at Nottingham University. The equipment selection system project, which is the topic of this thesis, has been on-going for three years. It is capable of providing advice on a range of surface mining excavating and haulage equipment. A slope stability expert system (ESDS) has been in development for six years. From an original Prolog system it has been updated to a shell system capable of reading graphical information and using it to predict and explain possible slope failures (Kizil 1990). A spontaneous combustion expert system (ESSH) has been created to predict the occurrence of coal heatings in surface mines, underground workings and during shipment (Ren 1991). Three researchers within the Advanced Computer Applications Group are at present working in the field of environmental hazard prediction. These environmetal systems utilise and control algorithmic modelling packages using expert systems (Denby et al 1992).

The Advanced Computer Research Group has taken full advantage of currently available expert system technology to produce decision support systems. The group is also beginning to evaluate machine learning techniques as solutions to planning problems in the mining industry. This Ph.D. project examines the application of intelligent computer techniques to surface mine design. To ensure that all aspects of this topic had been considered an investigation into the application of machine learning was carried out. Machine learning systems replicating some of the decisions made by the MINDER system were developed using machine learning and neural network software.

3.2 Expert Systems

Knowledge based or expert systems are perhaps the most developed of the three aspects of artificial intelligence. Figure 3.2 shows how computing techniques have developed to solve more complex problems. The area on the left of the figure consists of structured problems which can be analysed by means of an exhaustive search, these problems are solved using conventional programming techniques.

The area in the centre of figure 3.2 represents ill-structured problems which existing symbolic programming techniques can help to solve. The heuristic and knowledge representational techniques used to prune problem spaces and provide workable answers to problems of this type will be discussed in this chapter.

The area to the right of figure 3.2 represents problems which are only just beginning to be represented by conventional or commercially available artificial intelligence software. The problem of manipulating substantial amounts of knowledge is being solved by parallel processing systems which are capable of rapidly processing the knowledge.

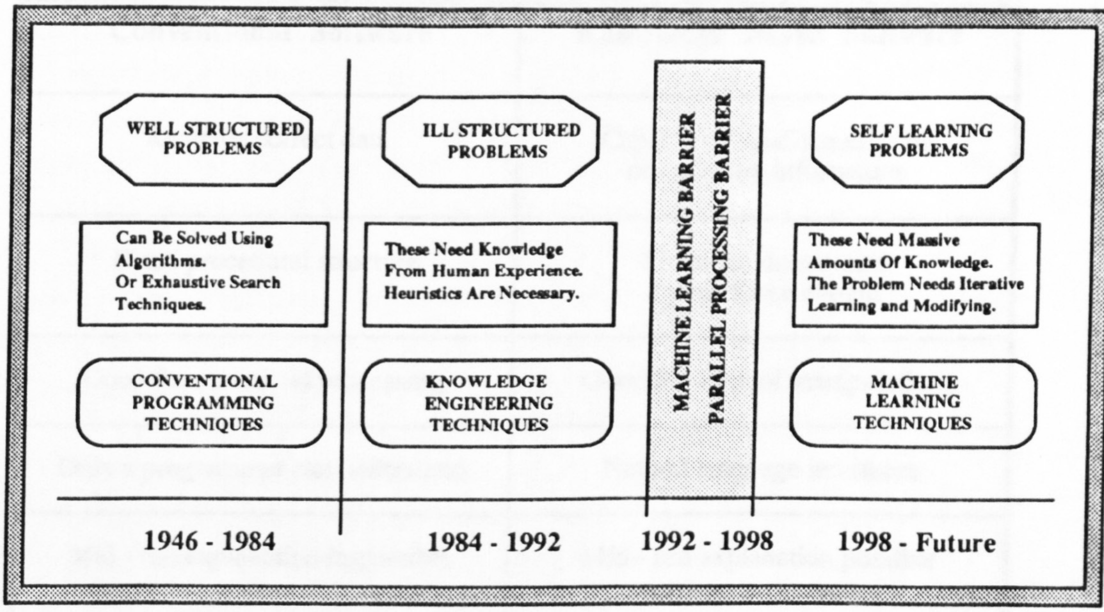


Figure 3.2 Problem Domains of Knowledge Engineering Techniques
(Modified from Harmon and King 1985)

Machine learning techniques such as knowledge induction and neural networks are being used to solve problems where the systems must learn from experience. The use of these new techniques will be discussed later in this chapter.

Expert systems are knowledge intensive computer systems. They contain large amounts of expertise, i.e. knowledge about a particular domain. There are many expert system definitions available (Gashnig 1981, Brachman 1983 and Jackson 1986), although most are similar. Professor E. Feigenbaum (Barr and Feigenbaum 1981) of Stanford University has defined an expert system as :

'...an intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution. Knowledge necessary to perform at such a level, plus the inference procedures used, can be thought of as a model of the expertise of the best practitioners of the field.'

Expert systems differ from conventional programs in an number of fundamental ways, as is shown in table 3.1. It can be seen that conventional programs are ideal for batch algorithmic processing of numeric data. Unfortunately, few real world problems fall into this category.

Conventional Software	Knowledge Based Software
Requires correct data	Capable of handling missing or uncertain information
Fixed procedural structure	Sequence determined by inference engine
Good for numerical processing	Good for symbol manipulation
Only a programmer can understand	Natural language interfaces
Mid - run explanation impossible	Mid - run explanation possible
Structure Program = Algorithm + Data	**Structure** Expert System = Control + Problem + Data

Table 3.1 Conventional and Knowledge Based Systems

Expert systems work using knowledge rather than algorithms. 'Data' can be converted to 'knowledge' by analysing, selecting, sorting, summarising or organising the data. Knowledge is more valuable than data (Stonier 1989). Digital computers therefore know nothing, they merely store and manipulate information. Thus the term 'knowledge base' is, strictly speaking, a misnomer.

Once the knowledge is stored within an expert system, a reasoning or inferencing strategy must be selected. Inferencing is to knowledge as processing is to data. Inferencing introduces causality into an expert system, transforming perceptions into conclusions.

Expert systems need to be thoroughly tested, the best way to accomplish this is to have a set of test cases. An expert system should be tested for all cases of uncertain or missing information and any failure mechanisms should be noted. Expert systems are notorious for degrading very ungracefully, that is a small error in the reasoning can lead to major error in a conclusion.

Knowledge engineers are now realising that small useful systems can be built which are not modelled on human experts. This is not revolutionary at all, it is simply an extension of basic computer principles to new levels of sophistication. Barr and Feigenbaum (1981) point out that most problems can be represented either by a search for points in a state space, by reduction to simpler sub-problems or by decision trees.

Expert systems offer a view of the future of computing, but there are areas in which further development is needed before the full benefits of artificial intelligence in commercial software is realised (Partridge 1986). These problems are listed below :

- The problem of knowledge representation.
- The problem of knowledge acquisition.
- The problem of the human-machine interface.
- The problem of approximate reasoning.

Some of the techniques used in overcoming these problems are discussed in this chapter.

3.3 Knowledge Representation

The knowledge representation problem concerns the mismatch between human and computer 'memory' - i.e. how to encode knowledge so that it is a faithful reflection of the expert's knowledge and can be manipulated by a computer. Psychological research suggests that we do not exhibit the kinds of reasoning behaviour that we associate with deductive or 'theorem-proving' systems (Hart 1985). Humans reason from situations to actions, using logical consequences.

Knowledge engineers, or epistemologists, have defined several dimensions to knowledge, such as: scope, granularity, uncertainty, completeness, consistency and modularity. These dimensions will affect the techniques used to represent knowledge. At present the system builder's best option is to use whatever formalism is available which suits the task at hand. The most widely used representation techniques are briefly listed below :

Semantic Networks : These consists of a collection of objects (or nodes) for the representation of physical entities, situations or events, connected by descriptors (or links) characterising their interrelationship. One of their main properties is class inheritance.

Frames (or scripts) : These are a collection of semantic network nodes and links (called slots) that together describe a single object, act or event. A frame is similar to a form with a title and number of slots which accept predetermined data types.

Predicate Logic : The assigning of an object to a certain class, for example an object being described by an attribute is the definition of a predicate (Carrol 1958). Predicate logic allows the derivation of the consequences of facts. Predicate logic clauses with only one conclusion atom (Horn Clauses) have led to the development of logic languages such as Prolog (Clocksin and Mellish 1981).

Production Rules : Propositional logic leads to rule-based systems containing rules called productions and these have formed the basis of several well known expert systems. The rules can be simple or complex, composed of single or multiple IF and THEN clauses. The format may also be extended by use of AND or OR logical operators to provide alternative values and express alternative clauses. The general form of the rules is :

```
IF     [ (antecedent  1)......(antecedent  n) ]
THEN [ (conclusion  1)......(conclusion  m) ]
```

Production rules are a natural way of expressing knowledge. They are easy to understand both by programmers and by users and, being modular, new rules (knowledge) may be added or deleted independently of other rules (Rosenman and Gero, 1985).

The knowledge representation techniques above have been discussed in detail elsewhere (Jackson 1986, Shadbolt 1989, Clarke 1990). The use of the term 'deep' knowledge based systems is now being used to describe systems which allow more sophisticated representations of knowledge. Steels (1986) uses the term 'second generation' expert systems to denote those that combine heuristic reasoning based on rules with deep reasoning based on causal models of problem domains.

3.4 Knowledge Acquisition

Modern knowledge based systems are confined to well-circumscribed tasks, applying relatively simple reasoning mechanisms to some very specific area of expertise. Specialist knowledge is narrow but deep; the jocular definition of a specialist being someone who knows ultimately 'everything about nothing'. Common sense is the tool of the generalist, who knows 'nothing about everything', this knowledge is broad but shallow (Goodall 1989).

Expert systems do not learn and thus are limited to using the specific facts and heuristics which were set by a human expert. Their lack of common sense means that expert systems cannot reason by analogy, and their performance deteriorates rapidly when problems extend beyond the narrow tasks they were designed to perform.

Knowledge acquisition has been defined as 'the transfer and transformation of potential problem-solving expertise from some knowledge source into a program' (Buchanon 1983). The knowledge acquisition process usually involves the following stages :

- Identify the knowledge domain.
- Examine the proposed system goals.
- Locate the sources of domain knowledge.
- Define domain boundaries.
- Elicitate the knowledge.
- Review and analyse the acquired knowledge.

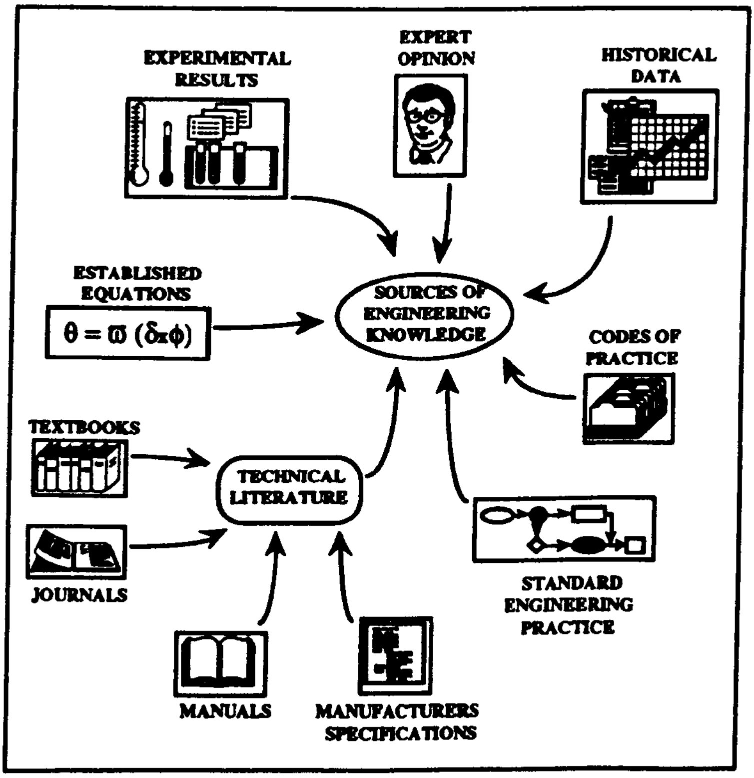


Figure 3.3 Sources of Engineering Knowledge

Knowledge consists of facts, procedures and judgemental rules and is widely disseminated. Most expert systems rely on the intuitive knowledge of the human expert, although other knowledge sources in addition to the human expert may be consulted. Figure 3.3 summarises the various sources of engineering information (after Clarke 1990).

Experts are notoriously bad at introspection, when it comes to describing their reasoning processes they tend to tell stories (Forsyth 1989). Obtaining the knowledge may be difficult for three main reasons :

- Deliberate resistance of the expert.
- Inarticulacy of the expert.
- Cognitive mismatch between knowledge and rules.

Several knowledge elicitation techniques exist (Boose 1986 and Adeli 1988), including interrogation, experimentation, observation, questionnaires and literature examination. Most elicitation techniques tend to be highly interactive, involving frequent meetings with the expert. Often a small prototype is developed, which is modified by consultation with the expert. The expert becomes involved in the development and often becomes an active member of the development team.

The well-known difficulties in knowledge acquisition has led to the development of machine learning systems (Hart 1985). Software induction tools have been developed which allow computers to generate rules from pre-classified examples. Knowledge induction techniques are discussed in more detail later in this thesis.

A knowledge engineer must become familiar with the knowledge domain under examination, which is not always easily achieved. Expert systems are now being developed by engineers as artificial intelligence techniques become more widespread and user friendly.

3.5 Development Tools for Expert Systems

A number of activities precede the development of an expert system, these include identifying the problem domain, finding the expertise and selecting the development tool. There are essentially four main types of development tool available for expert systems, which are listed below in order of increasing sophistication :

- **Algorithmic languages.** (such as 'C', Pascal, Basic)
- **Symbolic languages.** (such as Prolog, LISP)
- **Development Environments.** (such as Art, KEE, LOOPS)
- **Expert System Shells.** (such as Crystal, Leonardo, Xi-Plus)

3.5.1 Algorithmic Languages

Conventional languages are procedural in nature and designed to work on an algorithmic basis. In the field of expert system development they often act as implementation languages for production systems. An expert system is developed using an artificial intelligence language, shell or tool and translated into a conventional language when it performs satisfactorily. The designer needs to be well aware of the internal workings of the inference engine although object orientated languages (such as 'C^{++}') have made it easier to develop inference structures using conventional programming languages. It is possible, using these languages, to design software tools which enable engineers to develop their own systems (Mutagwaba et al 1991).

Only a few individuals have insisted on applying conventional languages to tasks for which they were not designed, almost all expert system development has taken place using other development mediums (Bramer 1989).

3.5.2 Symbolic Languages

Human knowledge is a dynamic concept and any attempt to represent it must involve extensible knowledge structures. This was recognised in the development of artificial intelligence languages which tend to be based around list structures which can be extended, truncated and combined as desired.

Using a 'raw' artificial intelligence language allows an implementer more flexibility but requires more effort to be spent on facilities such as the user interface for which the language may not be particularly well suited. Symbolic languages such as LISP and Prolog are the most common :

> **LISP (LISt Processor)** : This language contains a set of primitive operators that enable it to carry out several kinds of deductions with lists containing arbitrary strings of characters representing predicates and their arguments (Charniak and McDermott 1985).

Prolog : Prolog is a higher level language than LISP in that it has deductive and search capability already built in. Prolog is a vehicle for declarative programming : by providing a Prolog program with a set of statements or axioms describing some system, it deduces desired additional facts.

3.5.3 Development Environments

Development environments, or toolkits, are usually based on hardware optimised for a symbol manipulation language such as LISP or Prolog. These symbolic languages are embellished with context sensitive editors and graphics and often contain a built-in inference method.

Typical development environments are KnowledgeCraft, Art and KEE (Jackson 1986) which offer a variety of methods for representation and control of the reasoning process. They provide some partially-working modules in a number of libraries which can be linked by the programmer to develop applications. Programmers can also add their own tools into the environment.

Many large scale applications in the USA have been built using these development environments (Bramer 1989). Unfortunately these are generally large items of software, which often require specialised hardware and are correspondingly expensive.

3.5.4 Expert System Shells

Expert system shells contain knowledge representation facilities and inferencing mechanisms. A shell can be thought of as an expert system with all the domain specific knowledge removed and a facility for entering a new knowledge base provided.

In Britain the principal development vehicles for expert systems in business and industry have been relatively unsophisticated rule-based shells. A large number of expert systems have been constructed in this manner, and are being used on a regular basis (CRI 1986). Ready-made applications are now available, these allow solutions to problems in specific domains and are mainly available in fields such as fault diagnosis and legislative advice.

During the development of a major expert system many organisations purchase an inexpensive shell for prototyping purposes. This allows small demonstration systems to be built and problems recognised before the large scale development work begins.

Inference methods vary significantly from one domain to another and expert system shells have developed to allow the designer more flexibility during the building of the expert system. Some of the expert system shells currently available are listed below :

- EMYCIN (Empty MYCIN)
- ESIE (Expert System Inference Engine)
- Savoir
- Leonardo
- Crystal
- KnowledgePro
- COMDALE
- Guru
- Xi Plus

3.5.5 Development Tool Selected

When work began on an equipment selection expert system the choice of a shell was determined by the characteristics of the problem. The Xi Plus expert system shell was selected to reduce programming effort and allow more time to be devoted to the building of the knowledge bases. The development of the expert system using Xi Plus took place on an IBM PS2, Model 70 running under MS-DOS, the configuration of which is shown in figure 3.4.

The Xi Plus software is written in 'C', but both the end user and knowledge engineer work with a simple English grammar. Knowledge representation is in the form of production rules, following a simple IF-THEN format. Xi Plus provides knowledge engineering facilities allowing a knowledge engineer to create, modify and explore knowledge bases. Extensive interfacing facilities are also provided, these link Xi Plus to external software such as Dbase IV and programs written in Pascal, C, or Assembler (Expertech 1988).

The MINDER equipment selection system, developed using Xi Plus, uses information from Mine Design packages such as Surpac and Datamine, accesses a commercial database (Dbase IV) and utilises simulation software (GPSS). Pascal software has been written to perform the algorithmic functions required by the expert system, and DOS text files are used for data handling. Rules induced from machine learning software have been imported into the expert system (see section 3.10 of this chapter). Figure 3.5 illustrates the major external software links to the expert system.

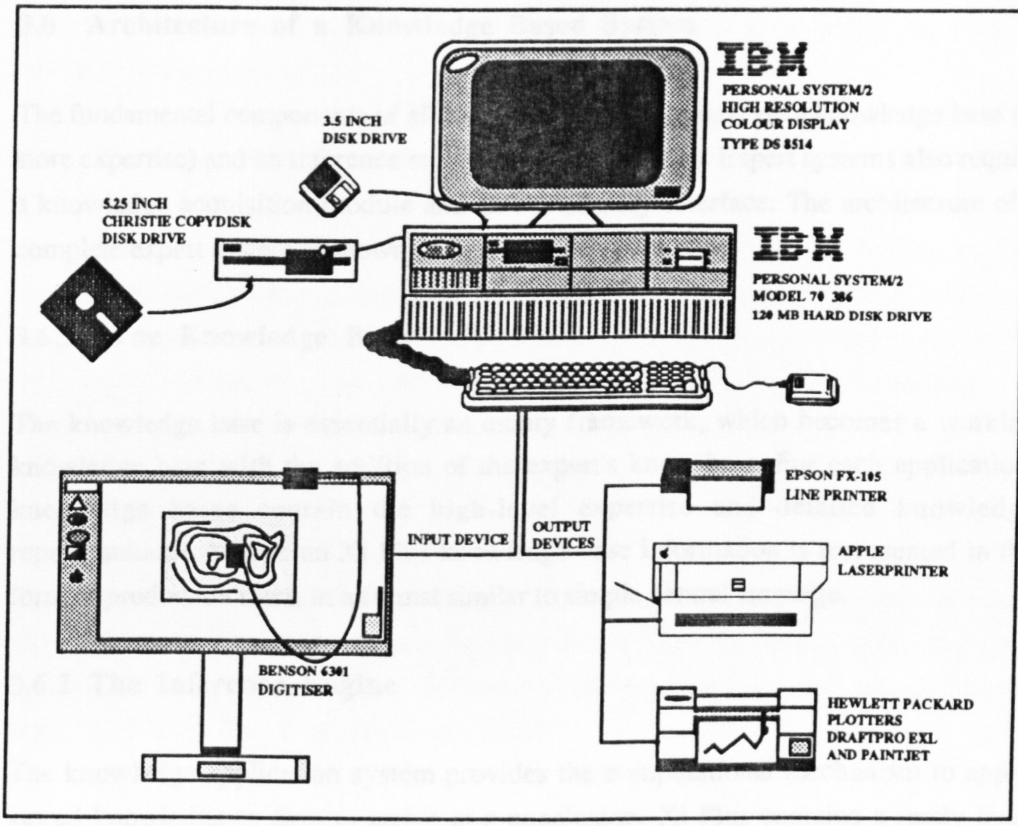


Figure 3.4 Hardware Configuration Used for Development

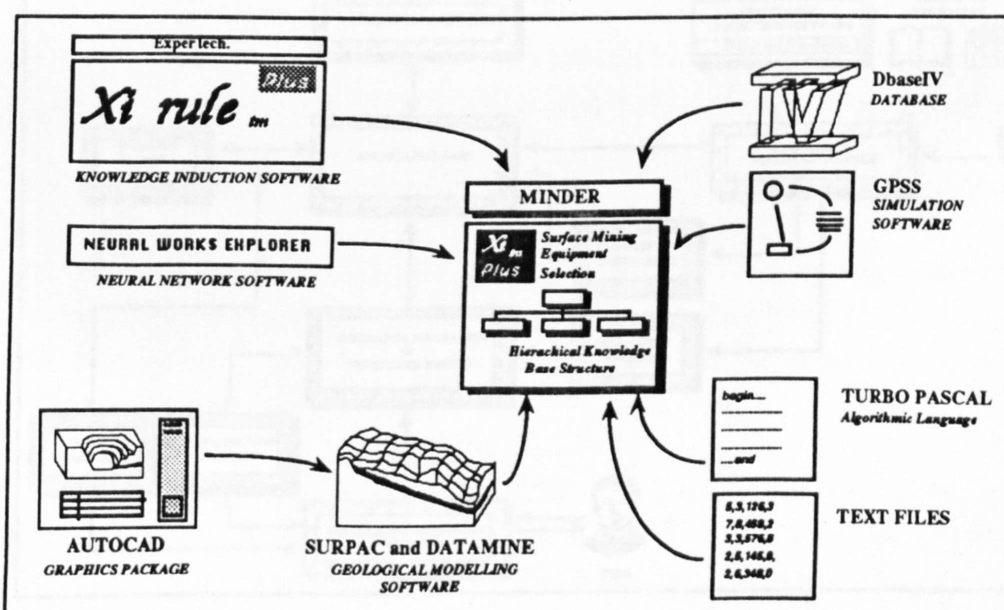


Figure 3.5 Software Configuration Used for Development

3.6 Architecture of a Knowledge Based System

The fundamental components of all knowledge based systems are a knowledge base (to store expertise) and an inference engine (to put it to work). Expert systems also require a knowledge acquisition module and an explanatory interface. The architecture of a complete expert system is shown in figure 3.6.

3.6.1 The Knowledge Base

The knowledge base is essentially an empty framework, which becomes a working knowledge base with the addition of the expert's know how. For each application, knowledge bases contain the high-level expertise and detailed knowledge representations. Within an Xi Plus knowledge base information is represented in the form of production rules, in a format similar to simple natural language.

3.6.2 The Inference Engine

The knowledge application system provides the computational mechanism to apply stored knowledge to data to arrive at a conclusion. Xi Plus contains a ready built inference engine, which is essentially a set of routines, which operate in conjunction

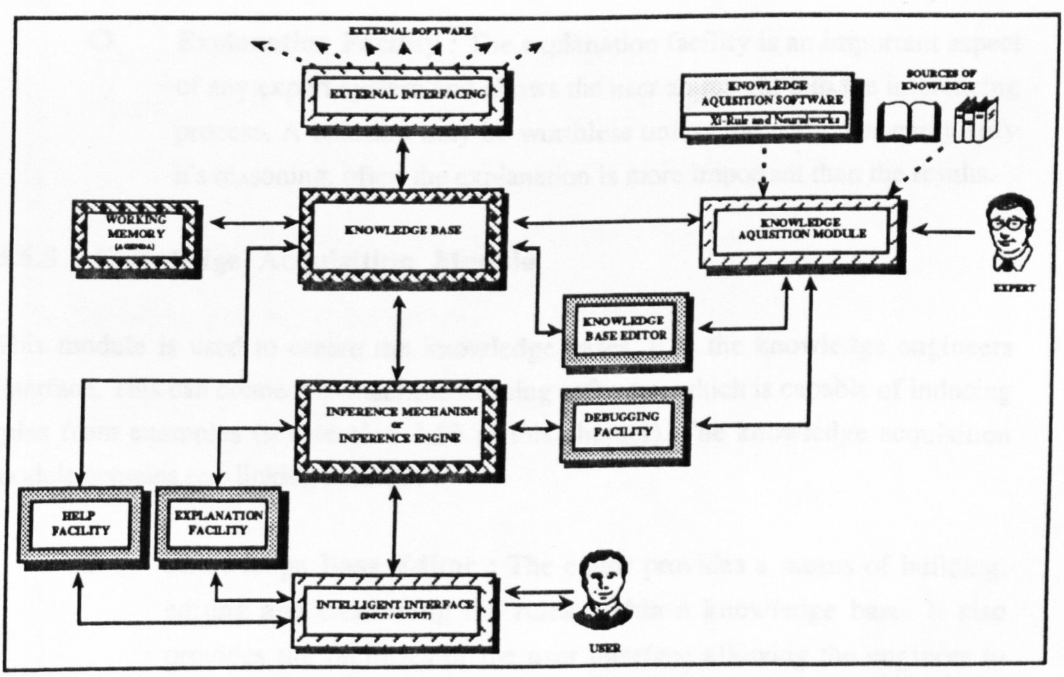


Figure 3.6 Architecture of an Expert System

with the internal database (working memory), to carry out inferencing and control strategies (see section 3.8).

3.6.3 Working Memory (Internal Database)

The working memory acts as a working store, a 'notepad' which the inference engine uses to hold data on the current status of a problem. The expert system's internal database is equivalent to a table in the computer's memory. The database works with the agenda (or inference register) which contains the information controlling the inference process when running a query.

3.6.4 User Interface

The user interface is provided to handle the dialogue between the operator and the inference engine. An intelligent user interface should allow the user to make enquiries of the expert system, to volunteer data and inform the user of any conclusions. Expert system interfaces often contain two other facilities:

- **Help Facility :** The user interface should provide additional explanations to questions and supplements the users understanding.

- **Explanation Facility :** The explanation facility is an important aspect of any expert system and allows the user an insight into the inferencing process. A solution may be worthless unless the computer can justify it's reasoning, often the explanation is more important than the results.

3.6.5 Knowledge Acquisition Module

This module is used to create the knowledge bases, it is the knowledge engineers interface. This can connect to machine learning software, which is capable of inducing rules from examples (see section 3.10 of this chapter). The knowledge acquisition module contains two linking facilities :

- **Knowledge Base Editor :** The editor provides a means of building, editing and examining the rules within a knowledge base. It also provides the facilities of the user interface allowing the engineer to consult the expert system.

- **Diagnostic Facility** : This facility allows the knowledge engineer to log the dialogue and trace the reasoning by displaying the chains of rules fired.

3.6.6 External Interfacing

The capabilities of most expert systems can be extended by making use of external interfacing. This permits a knowledge base to make use of functions that are best written in a conventional programming language. Packages such as AutoCad, Spreadsheets and Dbase IV can be called and controlled from the Xi Plus expert system shell. The external interfaces used by the MINDER system will be discussed in more detail in Chapter 4.

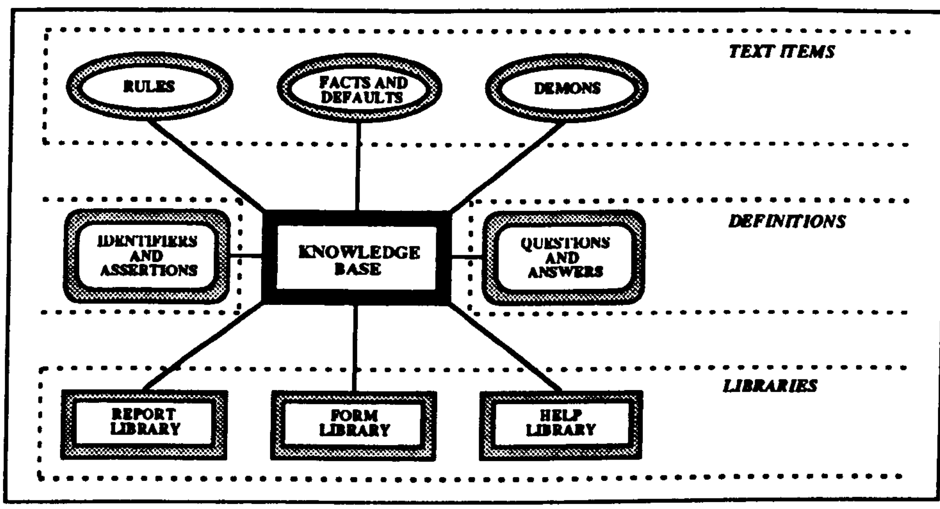


Figure 3.7 Knowledge Base Components

3.7 Knowledge Base Components

The basic units of an Xi Plus knowledge base are shown in figure 3.7. A knowledge base can have just a few rules, or thousands, depending on its scope and application domain.

3.7.1 Text Items

Within an Xi Plus knowledge base, identifiers can represent any item that can be expressed in words. They are used with relations and values to form clauses analogous to a spoken phrase :

Spoken Phrase:	Subject	Verb	Object
Xi Plus:	*(Identifier)*	*(Relation)*	*(Value)*
Example:	**ground**	**is**	**hard**

Identifiers are used in different ways within the knowledge base, an example of each of these text items can be found in figure 3.8 which shows text items in a simple Xi Plus knowledge base.

- **Assertions** : An assertion is a special type of identifier, the complete phrase is either 'true' or 'false' and does not contain a separate relation and value.

- **Rules** : Rules express the essential heuristics or knowledge of the domain. The normal form of a rule is the basic IF-THEN format. This format may be extended by the use of OR to provide alternative values and express alternative clauses.

- **Demons** : A demon is a priority rule which fires immediately its conditions become true. Demons share exactly the same format as normal rules except that **when** is used instead of the **if** keyword. Demons provide the forward chaining mechanism within Xi Plus (see section 3.8).

- **Facts** : A fact is an assignment or unconditional rule, which is treated as true in all circumstances.

- **Defaults** : A default is used within a knowledge base to establish a value for an identifier, when all other means have been exhausted.

- **Comments** : Comments are used to annotate knowledge items, to help in the understanding and maintenance of the knowledge base.

3.7.2 Arithmetic

In any numeric condition both a relation and value can be replaced by an arithmetic expression, for example *'if temperature > 30'*. When using arithmetic representation there is an obvious contradiction between making the expression readable and keeping it in the normal terse format.

comment	comment MUD Knowledge Base	
rule 1	if it rained yesterday then ground is wet	- *assertion* - *identifier -relation-value*
rule 2	if excavation material is earth and ground is wet then ground condition is muddy	
demon	when ground condition is Anything then do report ground condition	- *local variable* - *call to the report library*
default	default excavation material is earth	- *used if material unknown*
fact	fact it rained yesterday	- *assertion is true*

Figure 3.8 Example of an Xi Plus Knowledge Base

3.7.3 Definitions and Libraries

The knowledge base may use definitions made at the application level, these are available to all knowledge bases within the application.

- **Questions** : Questions are used to specify the screen presentation of a single user question.

- **Queries** : Queries are used to specify the screen presentation of the query to the knowledge base.

- **Identifiers** : Identifiers specify attributes for an identifier concerning the way it is used within the knowledge base.

- **Assertions** : Assertions refer to a complete condition or consequence of a rule. It is treated as a statement which is either true or false.

Three types of libraries are supported within any Xi Plus application :

- **Form Library** : The form library contains form definitions. A form definition is used to specify a screen display that is produced from a knowledge base during a consultation.

- **Report Library** : The report library contains report files. A report file is used to display information from the knowledge base during a consultation. It can contain pre-defined text plus information entered dynamically at the time of display.

- **Help Library :** The help library contains help files. A help display is produced, when help is requested, from an application or knowledge base list, and from a form or question display during a consultation.

3.8 Inferencing Mechanisms

A knowledge based system is an essentially declarative system and as such should not be dependent on the order in which the rules are entered, stored or processed, unless there is some good reason for forcing modularity on the rules. This means that there are two primary problems facing the inference engine (Harmon and King 1985) :

- A knowledge system must have a way to decide where to start. Rules and facts reside in a static knowledge base. There must be a way for the reasoning process to begin.

- The inference engine must resolve conflicts that occur when alternative lines of reasoning emerge. It could be, for example, that the system reaches a point at which four or more rules are ready to fire. The inference engine must choose which rule to examine next.

3.8.1 Reasoning Systems

Considering the reasoning systems used by conventional expert systems, a clear distinction is seen between monotonic and nonmonotonic reasoning. In a monotonic reasoning system, all values concluded for an attribute remain true for the duration of the consultation session. Facts that become true remain true, and the amount of true information grows steadily. In a nonmonotonic reasoning system, facts that are true may be retracted.

Design and planning are good examples of problems demanding nonmonotonic reasoning. In the early stages of a mine planning problem, it may make sense to assume certain values, later as more information becomes available, these values may change.

Changing the value of a single attribute is not difficult, current software allows identifiers to be reset or to have new values forced into them. Tracking down all the implications based upon a particular fact is difficult. Most knowledge based systems marketed today allow only carefully controlled nonmonotonic reasoning. Xi Plus provides a 'what-if' facility allowing identifiers to be altered, although the forcing of new values into established identifiers during a consultation must be monitored carefully.

It is clearly desirable for a facility to be available to ensure that no piece of knowledge is inserted which directly contradicts knowledge already in the knowledge base. These systems are often known as knowledge base management systems and are similar to database management systems (Bramer 1989). Xi Plus provides such a system in the form of a powerful knowledge base debugger which checks knowledge for circular reasoning, logical contradictions and unused consequences.

3.8.2 Modus Ponens

Before examining the complex inferencing strategies found in expert systems, the basic simple inference (as found in Aristotelian logic) will be described (Carrol 1958). This logical rule is known as modus ponens and sanctions inferences of the form :

When A is known to be true,
and if a rule states "If A, then B",
it is valid to conclude that B is true.

Stated differently, when the premises of a rule are true, this allows a degree of belief in the conclusions. This infers the truth value of one proposition from another using a rule of inference in one step. During a knowledge base consultation inferences (or proofs) will involve long chains of reasoning using the rules of inference and some initial suppositions (or axioms). These chains of reasoning are controlled using two basic inferencing methods, forward and backward chaining (Gervarter 1985).

3.8.3 Forward Chaining

In forward chaining, (also known as data driven or event driven reasoning) the user provides initial data and the inferences made are those which follow from the data. The premises of the rules in the knowledge base are compared to the contents of the working memory. When a rule succeeds, its conclusion(s) are placed in the working memory.

Reasoning in a forward chaining system is described as a 'recognise-act' cycle. First, the rules that can succeed are recognised, then one rule is selected and the conclusion (or action) is asserted into working memory. The system then uses this conclusion as initial data and proceeds to the next cycle. The inferences made are always consistent with the supplied data and knowledge items, but they may be irrelevant because the user may not be interested in the conclusions that result.

Data driven processing employs what have become known as 'demons'. A demon is the procedure that is attached to a data object, whenever the condition relating to that data becomes true the demon performs the appropriate processing function.

Figure 3.9 shows an example of a forward chaining procedure through a simple knowledge base, the knowledge has been taken from the example shown in figure 3.8. Rule 1 and rule 2 are presented in figure 3.9 as demon 1 and demon 2 respectively (a demon being distinguished by the 'when' keyword). Two pieces of initial information are provided :

- **'it rained yesterday'**
- **'excavation material is earth'**

From the assertion *'it rained yesterday'* the inference engine fires demon 1 and infers the conclusion *'the ground is wet'*. This is used in conjunction with the second piece of initial information to fire demon 2 and infer that the *'ground condition is muddy'*. The inference engine then reports these two conclusions to the user.

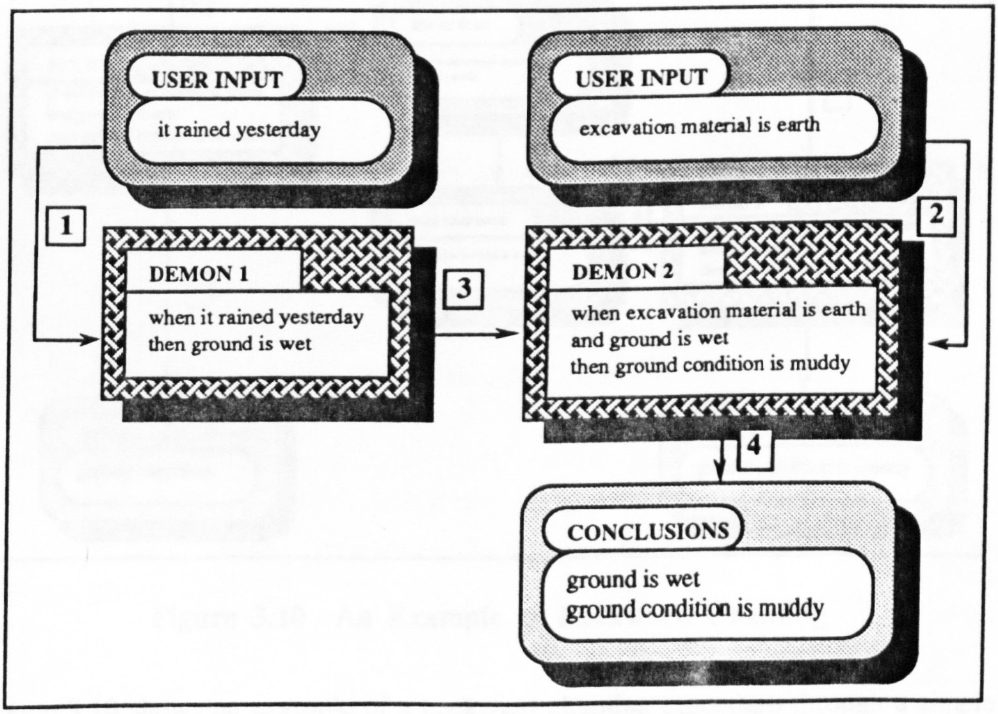


Figure 3.9 An Example of Forward Chaining

It is assumed that the rules are applied 'in parallel' which is to say that every rule fires on the basis of the initial data. This strategy is particularly appropriate in situations where data is limited and expensive to collect (Graham 1989). Typical domains are financial planning, process control, the configuration of complex systems and system tuning.

3.8.4 Backward Chaining

Most existing expert systems use a backward chaining (or goal driven) reasoning strategy. In backward chaining the inference engine starts at the goal and works 'backward' through subgoals in an effort to select an answer. It therefore reasons backwards from conclusions to the conditions that establish them, data and information only being supplied as required. If the number of possible outcomes (i.e. the values of the goal attribute) are known, and if they are reasonably small in number, then backward chaining is very efficient.

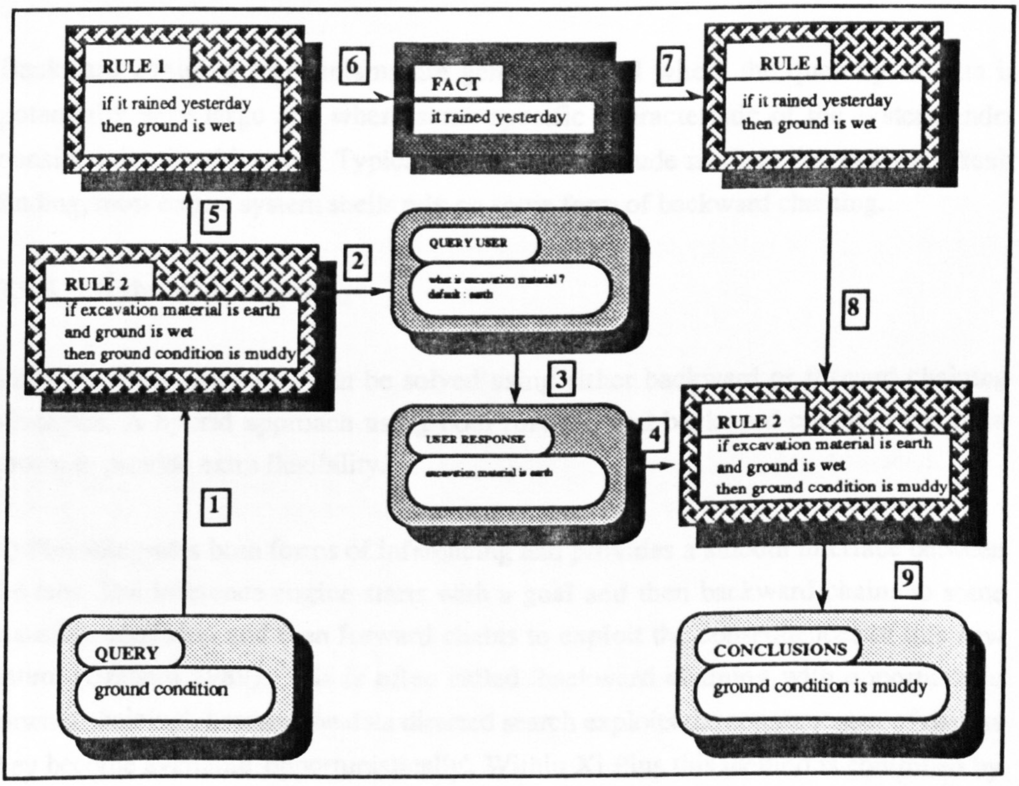


Figure 3.10 An Example of Backward Chaining

Figure 3.10 shows an example of a backward chaining procedure through a simple knowledge base, the knowledge has again been taken from the example shown in figure 3.8. The inference engine begins with the goal *'ground condition is ?'*, initially the system retrieves all the rules which make a conclusion about the goal. In the simplified example in figure 3.10 rule 2 is selected.

Each condition in the antecedent part of the rule is then evaluated to see if the rule can be fired. The system queries the user, who responds that the *'excavation material is earth'*. If the user had responded *'unknown'*, the system would have taken the default value which has been specified as *'earth'*.

The conditions are evaluated in turn and the next condition of rule 2 *'ground is wet'* results in the inference engine chaining into the conclusion of rule 1. The antecent part of rule 1 which is the assertion *'it rained yesterday'* is proved to be true by a knowledge base fact.

The inference engine then uses this information to back track through the rules firing them in sequence, as shown on the right hand side of figure 3.10. This results in the system providing an answer of *'ground condition is muddy'*.

Backward chaining mechanisms are generally used where the quantity of data is potentially very large and where some specific characteristic of the system under consideration is of interest. Typical applications include medical diagnosis and fault finding, most expert system shells rely on some form of backward chaining.

3.8.5 Hybrid Systems

Many problem categories can be solved using either backward or forward chaining strategies. A hybrid approach using both forward and backward chaining has been shown to provide extra flexibility.

Xi Plus integrates both forms of inferencing and provides a smooth interface between the two. The inference engine starts with a goal and then backward chains to some plausible condition and then forward chains to exploit the consequences of this new datum (Graham 1989). This is often called 'backward chaining with opportunistic forward chaining', because the data directed search exploits the consequences of data as they become available 'opportunistically'. Within Xi Plus this method is controlled by the use of demons.

3.9 Uncertainty

Bertrand Russell noted in 1923 that :

'All traditional logic habitually assumes that precise symbols are being employed. It is therefore not applicable to this terrestrial life, but only to an imagined celestial existence.'

One feature of expert systems is their ability to overcome the restraints of conventional logic and continue reasoning in the face of uncertain or missing information. The concept of 'uncertainty' which arises in an expert system can be described as being derived from the following sources (Jones 1989) :

- Lack of data.
- Inconsistency of data.
- Imprecision in measurement.
- Imprecision in concept.
- Lack of theory.

In practice a frequent problem is that knowledge is not available to an expert system (or of dubious reliability), but it is nevertheless essential to the systems inferencing process. There is no clear-cut and completely satisfactory way of dealing with this problem of missing knowledge.

Many models of inexact reasoning have been developed, but none has been selected as an optimum technique. The methods developed include : Bayes's theorem, certainty factors, fuzzy logic, possibility theory, belief theory and the use of non-standard logics. Another common technique is the use of formal definitions of linguistic concepts of certainty, such as *'X is likely'* or *'X is suspected'*. This technique is often used in conjunction with other uncertainty methods.

It is important not to be carried away with quasi-mathematical formulations which look impressive but do not actually correspond with real evidence. Experience with human experts has shown that experts do not use information in a way compatible with standard statistical methods (Negoita 1985). The following sections will consider a selection of relevant uncertainty handling methods.

3.9.1 Bayes's Theorem

The Reverend Bayes was an 18^{th} century English vicar who spent his life studying statistics. Essentially, the theories he developed rely on the belief that for everything, no matter how unlikely, there is a prior probability that it could be true (Naylor 1989). It may be a low probability, in fact it may be zero. This does not prevent the calculation from proceeding as if a probability existed. Given relevant evidence this prior probability can be modified to produce a posterior probability of the same hypothesis. Bayes's rule can be encapsulated in the following expression.

$$P(H:E) = P(E:H) \times \frac{P(H)}{P(E)}$$

This states that the probability of a hypothesis (**H**) given some evidence (**E**) is the probability of the evidence given the hypothesis times the probability of the hypothesis divided by the probability of the evidence. Bayes's theorem has been used as the thread to tie together chains of uncertain inference in many commercial expert systems, such as PROSPECTOR (Gashnig et al 1981).

3.9.2 Certainty Factors

One of the simplest methods of coping with uncertain information is to assign numerical certainty factors to rules. These numerical values indicate the level of doubt, uncertainty or level of belief (Brown 1988 and Shortliffe 1976). Certainty factors have values between -1 and +1 and are commonly determined from the representation shown in figure 3.11.

There are three ways that degrees of certainty can be managed within an expert system :

- Facts may be concluded by more than one rule. A combining function blends the certainty factors.

- Compound premises (clauses joined by AND or OR) may test uncertain facts. An uncertain premise leads to an uncertain conclusion.

- Rules themselves may be less than definite.

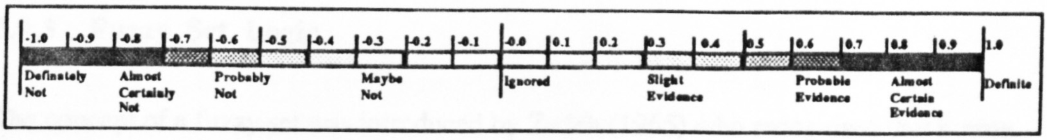


Figure 3.11 Certainty Factor Representation (The Impact Ruler)

Two certainty factors (CF_1 and CF_2) may be added to give a final measure of belief (CF) using the following simple equations. The formula to be used depends on whether the individual certainty factors are positive or negative. The combining function for more than two certainty factors is applied incrementally (Giarratano and Riley 1989).

$$CF = \begin{cases} CF_1 + (CF_2 \times (1 - CF_1)) & \text{if both } CF_1 \ \& \ CF_2 > 0 \\ \dfrac{CF_1 + CF_2}{1 - \min(|CF_1|, |CF_2|)} & \text{if either } CF_1 \text{ or } CF_2 < 0 \\ CF_1 + (CF_2 \times (1 + CF_1)) & \text{if both } CF_1 \ \& \ CF_2 < 0 \end{cases}$$

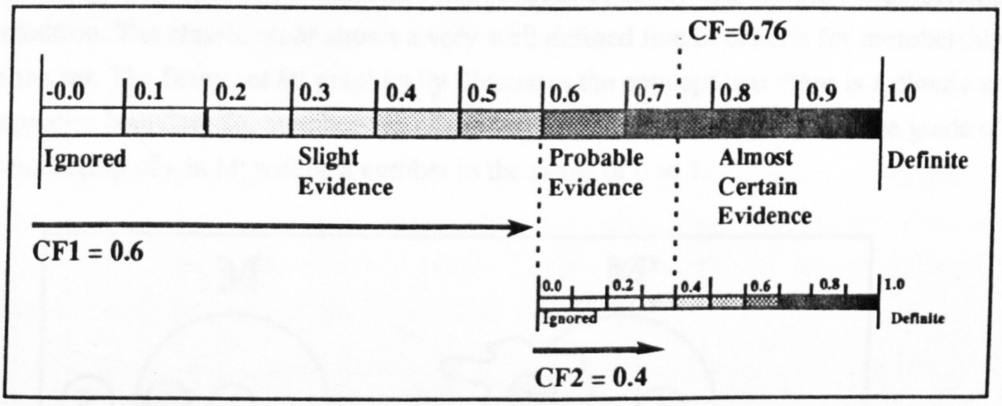


Figure 3.12 Certainty Factor Combination

An example of certainty factor combination is shown in figure 3.12. The first conclusion is 0.6 certain and the second conclusion is 0.4 certain, which pushes the total certainty 40 percent closer to total certainty. The final certainty factor is 0.76 certain. The calculation is shown below :

$$CF = 0.6 + (0.4 \times (1 - 0.6)) = 0.76$$

It can be seen that as more positive information emerges then the confidence in a conclusion rises. Indefinite information will never accumulate to yield a definite conclusion.

3.9.3 Fuzzy Set Logic

The concept of a fuzzy set was introduced by Zadeh (1965) who recognised that human problems were not amenable to standard control systems. Zadeh's principle of incompatibility states that :

'As the complexity of a system increases, our ability to make precise and yet significant statements about its behaviour diminishes until a threshold is reached beyond which precision and significance (or relevance) become almost mutually exclusive characteristics.'

Set theory and formal logic are dual representations of the same information. The law of the excluded middle states that for any 'thing' it is either true or untrue that it possesses any given property. Fuzzy sets and fuzzy logic repeal this law. Any object may be a member of a set 'to some degree'; and a logical proposition may hold true 'to some degree'. Figure 3.13 illustrates the concept of fuzzy sets by their membership definition. The classic set **M** shows a very well defined line of criteria for membership of the set. The fuzzy set **M'** graphically illustrates the concept that there is a cloudy or imprecise boundary for membership of the set. In the case of the fuzzy set, the grade of membership of **x** in **M'** will be a number in the range of 0 to 1.

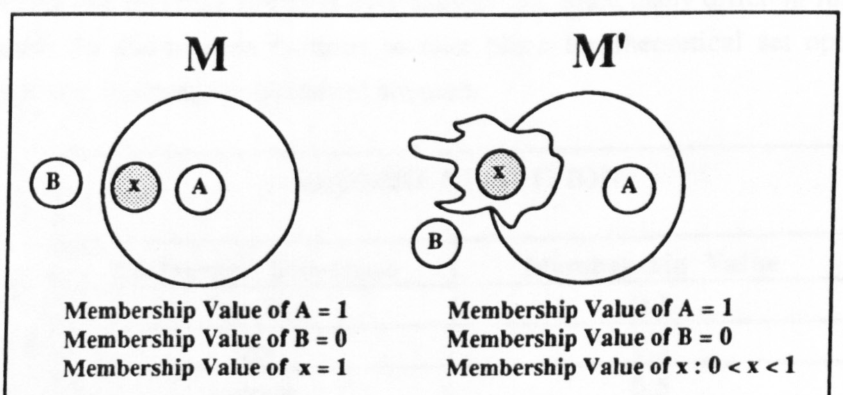


Figure 3.13 The Concept of Crisp and Fuzzy Sets (after King 1986)

A fuzzy set can be regarded as a label applied to a linguistic concept which has no precise boundary; and such concepts, with all their associated vagueness, are how humans mediate and exchange ideas (Fairhurst and Lin 1985). Figure 3.14 shows how fuzzy sets can be represented numerically. The chart to left of the figure is a truth table selecting numbers between 4 and 9. The chart on the right shows numbers which are near 7. This is a fuzzy set, each particular number along the x-axis has a degree of membership of the set (normally represented as $\mu(x)$). The y-axis is scaled from 0 (meaning false) to 1 (meaning true).

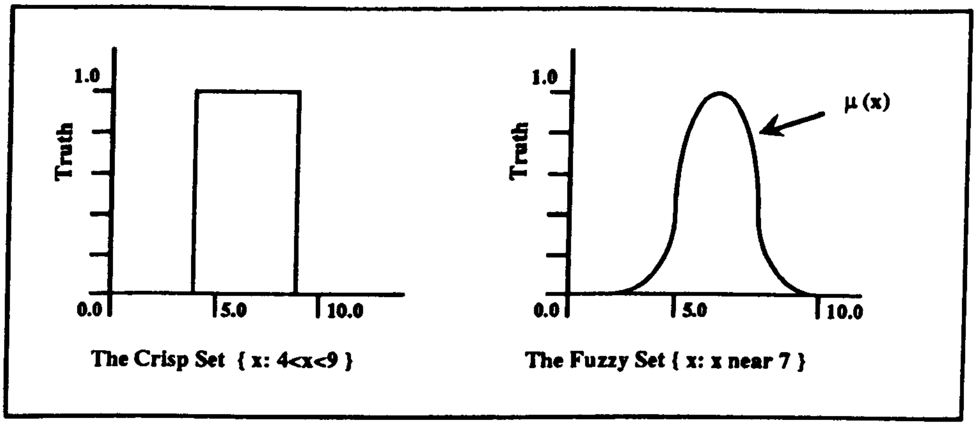


Figure 3.14 The Difference Between a Crisp Set and a Fuzzy Set

Often a weak point in the application of fuzzy logic is the mapping or membership function of the set. Someone has to decide the shape of the fuzzy set graph such as the one shown in figure 3.14 (Bellman and Zadeh 1970). There are no strong grounds for prefering one mapping function over another and often many different functions are applied. To allow these fuctions to take place the theoretical set operations of intersection, union and complement are used.

GROUND CONDITION	
Preference Structure	**Membership Value**
Very Dry	0.1
Dry	0.3
Average	0.5
Wet	0.7
Very Wet	0.9
Impact Ruler (Similar to Certainty Factor) 1 : Very Wet ——— 0.5 : Average ——— 0 : Very Dry	

Table 3.2 The Transformation of Ground Condition

Linguistic variables from within a knowledge base need to be converted into manipulative numerical values, (qualitative to quantitive). The linguistic preference structure is assigned membership values of a set between 0 and 1 (Guo and Clibbery 1990). Table 3.2 illustrates this principle applied to the factor ground condition.

This linguistic preference structure allows fuzzy set membership values to be manipulated in the form of matrices. Computer representations of fuzzy sets often take the form of two dimensional arrays, stored as individual files in the computer memory (Bandopadhyay 1987 and Clarke 1990). Within these knowledge matrices each column represents an alternative within a particular domain, each row represents factor or features relating to those alternatives and each cell in the matrix is the relative merit of a factor for a particular alternative.

A simple example of a complete knowledge matrix is shown in figure 3.15. From this knowledge matrix an evaluation matrix is built by extracting relevant information for the problem. The example shown in figure 3.15 is an equipment selection example, the alternatives are shown along the top of the knowledge matrix, and all factors are shown at the side of the knowledge matrix.

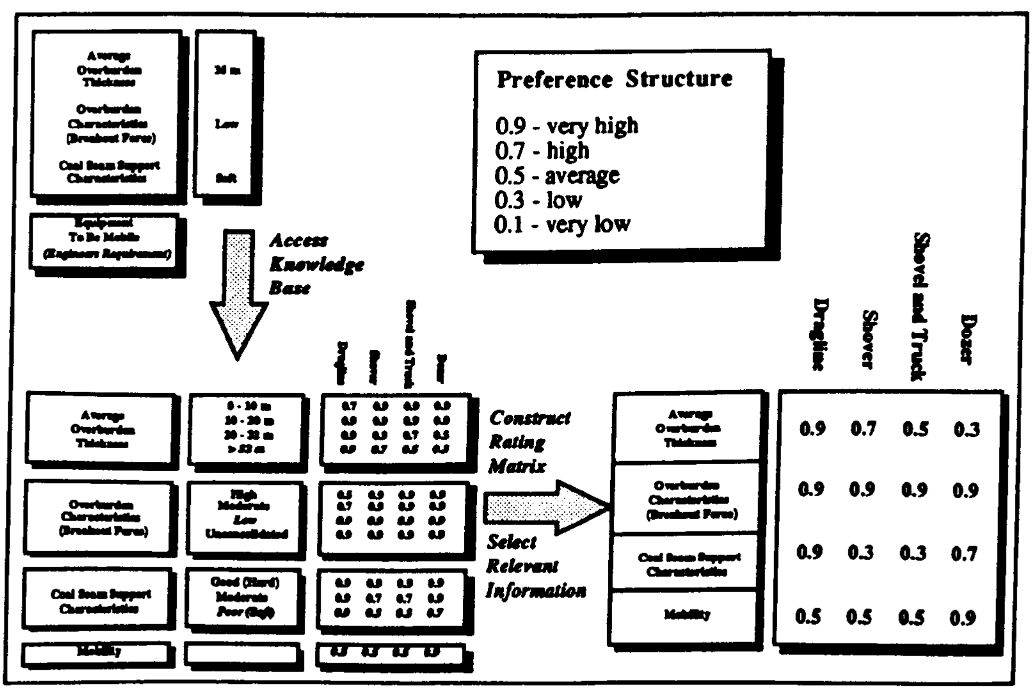


Figure 3.15 Construction of a Simple Evaluation Matrix

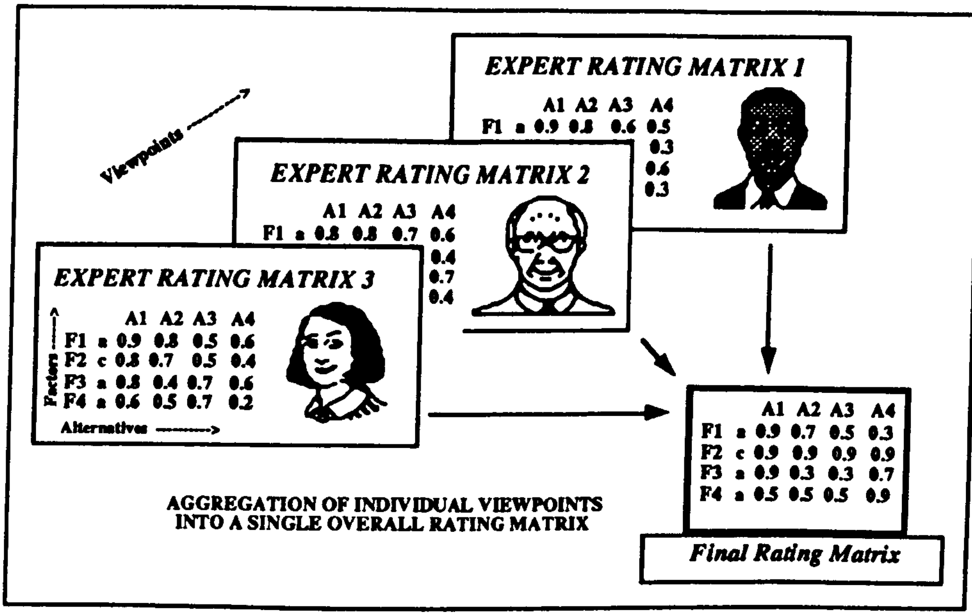


Figure 3.16 Combination of Knowledge Matrices

A variety of knowledge matrices may be considered, each representing knowledge from different sources, possibly the opinions of a different experts, see figure 3.16. These matrices may be aggregated together using a variety of techniques (Hippel 1982) such as :

- Pessimistic Aggregation.
- Optimistic Aggregation.
- Mean Aggregation.
- Modified Pessimistic Aggregation.

There are two main algorithms used to rank fuzzy alternatives these are the dominance algorithm and the similarity algorithm (Bandopadhyay 1987 and Bellman and Zadeh 1970).

3.9.3.1 Multi-Criteria Dominance Algorithm

This algorithm ranks alternatives depending upon the domination of one alternative over another. Within the evaluation matrix an alternative is said to dominate another if its membership value for a given feature is greater than any other alternative (Clarke 1990). The imprecision or fuzzy nature of the attributes is accounted for by the application of an equivalence limit (Alley 1979).

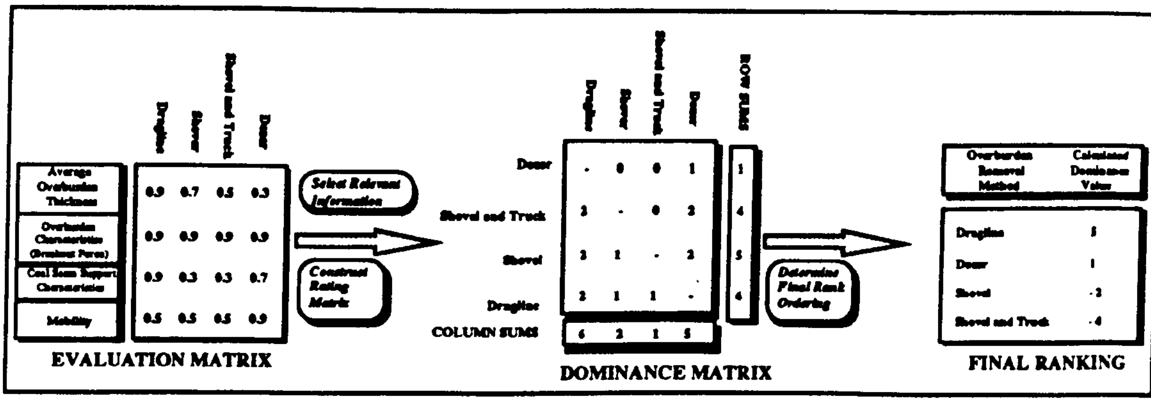


Figure 3.17 Multi-Criteria Dominance Algorithm

Figure 3.17 shows an example of a decision using a dominance algorithm, the evaluation matrix is a fuzzy set of equipment selection alternatives taken from the knowledge matrix shown in figure 3.15. A dominance matrix is created from the evaluation matrix. Each d_{ij} element within the dominance matrix indicates the number of factors for which the value of alternative j dominates alternative i. For example the dragline dominates the shovel twice (d_{12}) and the shovel dominates the shovel and truck once (d_{23}). The columns are summed to give the number of dominances over other alternatives, the rows are summed to give the number of dominations by other alternatives. The final ranking is achieved by a subtraction of the two values for each alternative (Bandopadhyay 1987). Weightings are often applied to the factors within the matrix to give a more realistic opinion.

3.9.3.2 Multi-Criteria Similarity Algorithm

The concept of fuzzy similarity was introduced by Yun and Huang (1987). Similarity is defined by the concept of Hamming distance (Kaufman 1975 and Znotinas and Hippel 1979) which is a relative measure of difference between set members. For fuzzy sets, Hamming distance can be defined as follows :

$$d(\underset{\sim}{A},\underset{\sim}{B}) = \sum_{i=1}^{i=n} \left| \mu(\underset{\sim}{A}(x_i)) - \mu(\underset{\sim}{B}(x_i)) \right|$$

where $d(\underset{\sim}{A},\underset{\sim}{B})$ is the Hamming Distance between fuzzy sets $\underset{\sim}{A}$ and $\underset{\sim}{B}$
and $\mu(\underset{\sim}{A}(x_i))$ is the membership value of the fuzzy set.

A simple example of a similarity ranking of mining equipment is shown in figure 3.18, where the evaluation matrix from figure 3.15 is taken as the fixed model which represents the actual mining conditions encountered. The aim is to select the item of plant closest to the ideal values which are stored in an ideal matrix. The Hamming distances are calculated by subtracting the matrix cells for each alternative from their respective ideal value. Relational matrices are then developed using Hamming distance ratios of the format :

$$\text{ratio of cell } r_{12} = D1 \ / \ (D1+D2)$$

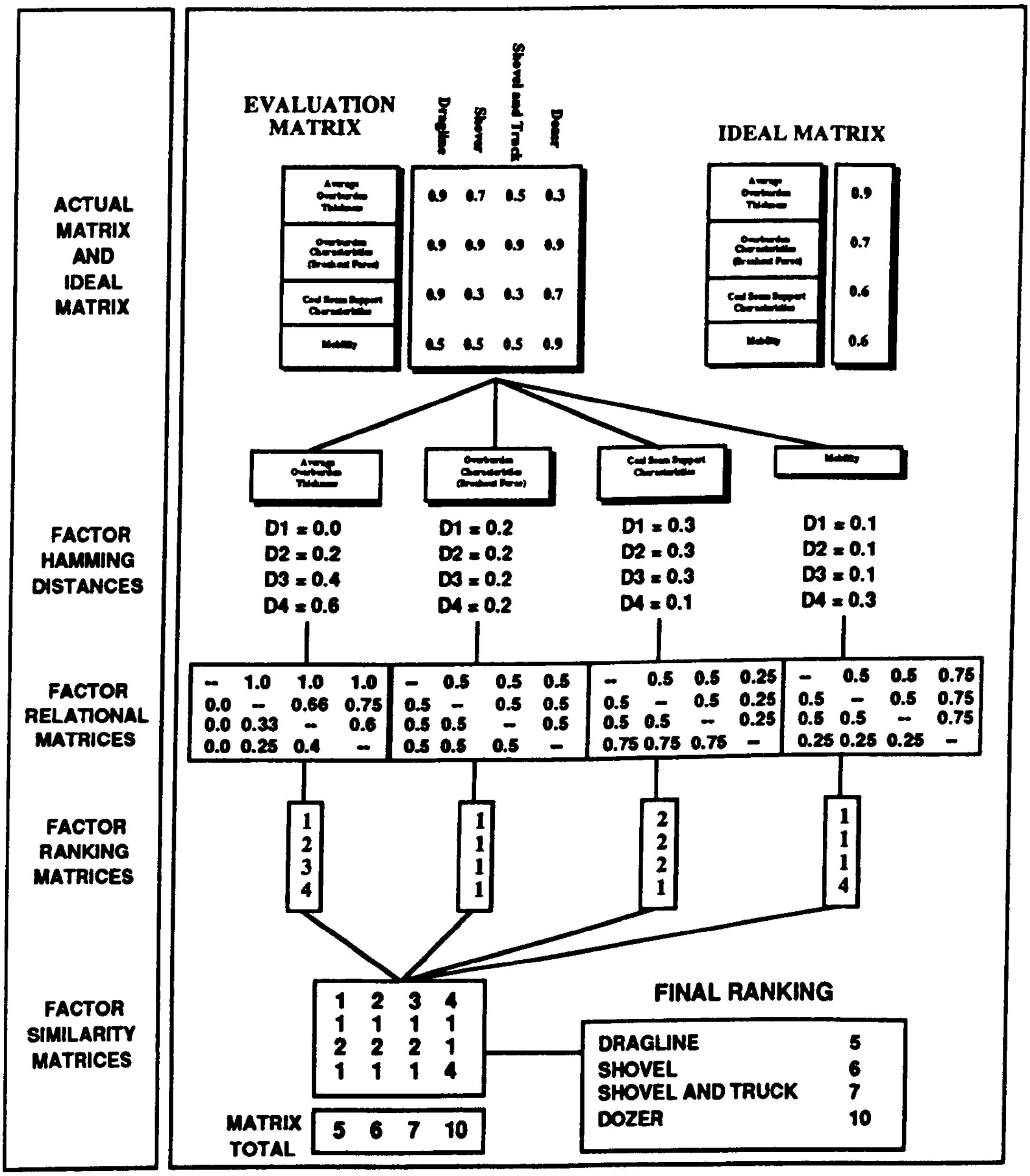


Figure 3.18 Multi-Criteria Similarity Algorithm

Each element in the fuzzy relational matrix is then compared to a variable value. This value is initially set at 1 and gradually reduced. If an element within the relational matrix is greater than this value the element is changed to 1. This procedure is repeated until all the rows consist of integers, and the order in which the rows fill with integers is placed in the factor matrices. Each column of the factor matrices are transferred as rows into a final factor matrix and the alternative columns are summed. The lower the total, the more similar the alternative to the ideal matrix. The example shown in figure 3.18 selects the dragline. Weightings are often applied to the factors within the matrix to give a more realistic opinion.

Fuzzy set logic has been successfully applied to many engineering problems such as :

- Seismic risk evaluation. (Dong et al 1986)
- Tender evaluation. (Nguyen 1986)
- land use. (Nijkamp and Vos 1977)
- Tunnel support design. (Fairhurst and Lin 1985)
- Rock mass classification. (Nguyen and Ashworth 1985)

3.10 Machine Learning

In the past, computer solutions have provided analytical solutions to structured problems, these utilise conventional programming techniques. In solving ill-structured problems symbolic programming techniques are applied. Heuristic and knowledge representational techniques, such as expert systems, are used to prune problem spaces and provide workable answer (Harmon and King 1985).

Many planning and engineering problems require that the data be constantly re-evaluated to take on-going changes into account. This may involve the application of nonmonotonic reasoning systems. In the early stages of a planning problem, it may make good sense to assume certain values. Later as more information becomes available, initial values may change.

If knowledge systems are to handle such problems, the systems will have to be able to learn from their own experience and constantly update their knowledge (Buchanon 1976). These various approaches to building systems that can learn from experience are normally spoken of as machine learning. Self learning systems are only just beginning to be represented by conventional or commercially available AI techniques.

Expert Systems	Neural Networks
Rule Based	Example Based
Domain Specific	Domain Free
Needs Rules	Finds Rules
Much Programming	Little Programming
Difficult to Maintain	Easy to Maintain
Not Fault Tolerant	Fault Tolerant
Needs a Human Expert	Needs a Database
Rigid Logic	Fuzzy Logic
Requires Reprogramming	Adaptive System

Table 3.3 Comparing Expert Systems and Neural Networks

Computers are currently becoming available which involve 'machine learning' and use 'parallel processing systems' allowing the rapid processing of self-learning reasoning. Techniques such as knowledge induction and neural networks are now being used along with parallel processing systems to overcome the nonmonotonic reasoning barrier. Table 3.3 shows the differences between expert systems and neural networks. If a rule based expert system is designed to model a process, and the process is modified, then the expert system may need to be rebuilt. Whereas, with a neural network based system, all one would have to do is retrain the network.

3.10.1 Knowledge Induction

Induction is defined as the automatic creation of a hypothesis by analysis of initial data. The aim of induction is to alleviate the 'expert system bottle-neck' of knowledge acquisition. Knowledge induction is important since the power of an expert system lies in it's specialist knowledge.

Experts are subjective, forgetful, they omit details and may be inconsistent. Experts find it easier to quote examples then to describe processes. If a set of decisions are provided which consist of the outcome and the factors contributing to this outcome then a knowledge induction system can induce rules based on this data.

The relevance of a training set of data, from which the system learns, is important as the system cannot induce what is not there (Hart 1985). This data set can take the form of a truth table covering all results or it may be a set of noisy real data containing many repetitions and irregular values.

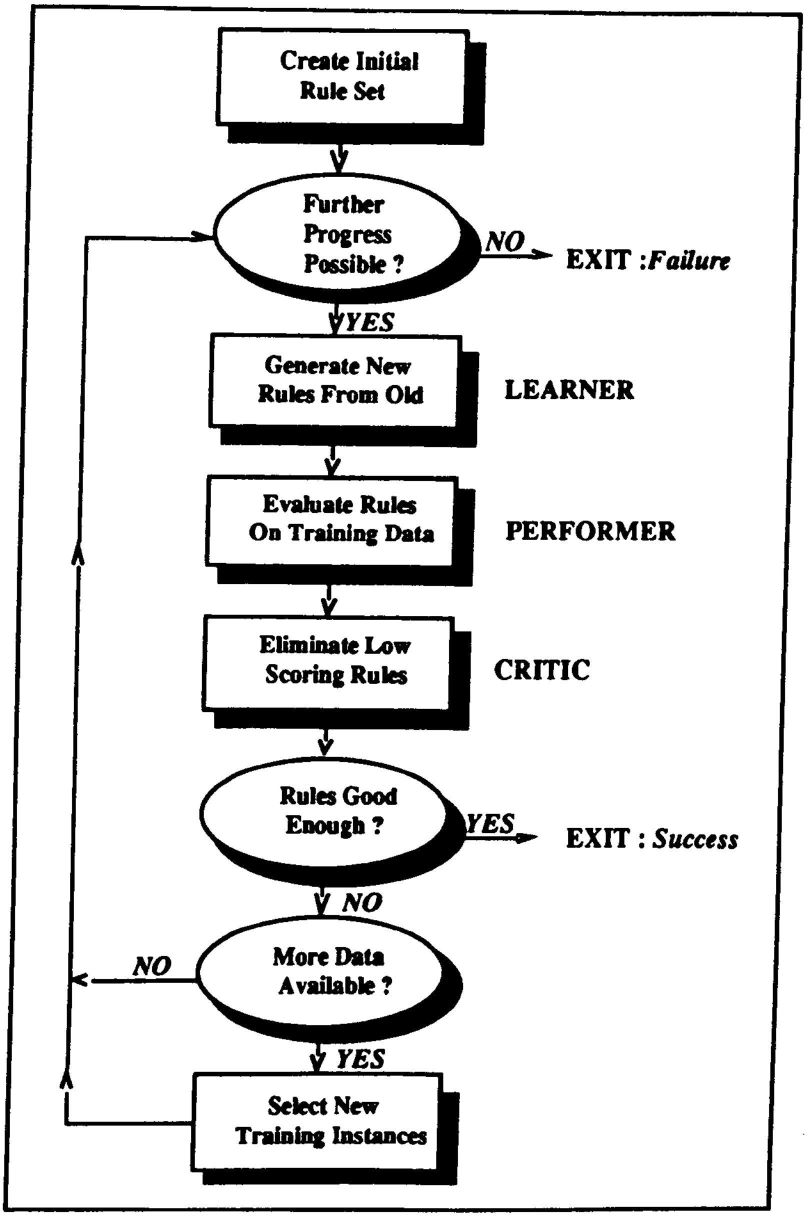


Figure 3.19 General Rule Induction Flowchart

The accuracy of the results is uncertain, often the quality of the results depends upon the learning algorithm selected. Most algorithms involve the generation of a search tree, in which the nodes of the tree make up decision rules, successive rules are generated from these. The general method of rule generation is shown in figure 3.19. Most techniques of knowledge induction can be split into three parts (the learner, performer and critic) capable of generating new rules, using these rules and then evaluating them repectively.

3.10.1.1 Induction Techniques

Statistical analysis, although often useful in pattern recognition, is often not applicable to knowledge induction. Heuristic methods are needed to guide this search and develop low level rules into generic high quality rules. The search space often takes on the aspect of a network, which may be optimised using many techniques including:

- **Mitchell's Technique** : Mitchell's 'Binary Chop' Technique lists all possible descriptions of a set of data and the eliminates those that do not apply (Mitchell 1982).

- **Quinlan's ID3** : Interactive Dichotomizer 3, this creates a discrimination tree from a subset of the data and verifies this against the remaining information (Quinlan 1982). This has recently been developed into the Quinlan C4 algorithm which involves the use of probability on the decision tree.

- **AQ11** : This is an incremental technique, appending conjunctive terms to give new evidence, (Forsyth 1989).

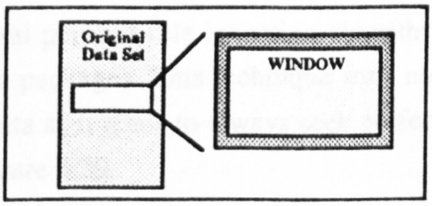
- **META-DENDRAL** : This uses a crude search to generate low level rules and takes only the positive results to generate offspring from these. It handles uncertainty well (Buchanan 1976).

- **BACON 4** : This mathematical learning program searches for algorithmic relations and claims to have 'rediscovered' almost all 19^{th} century chemistry (Langley 1981).

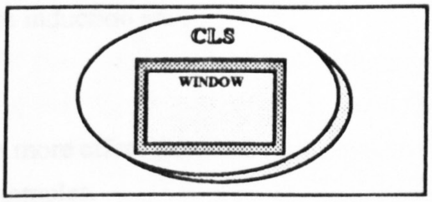
- **UNIMEM** : This is a database which organises itself, generalising similar examples, allowing more efficient retrieval of information (Lebowitz 1986).

The number of plausible structures for any set of data varies depending on the technique used. Many items of commercial software utilising these techniques are available. The Mining Department at Nottingham University uses Xi Rule, a companion program to Xi Plus, also marketed by Expertech. This software uses a modified form of Quinlan's ID3.

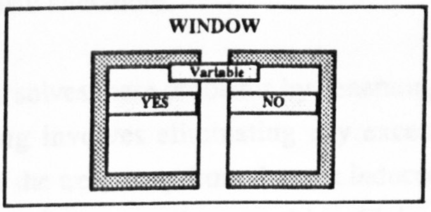
From the training set of data a subset is selected this is refered to as the 'window'.



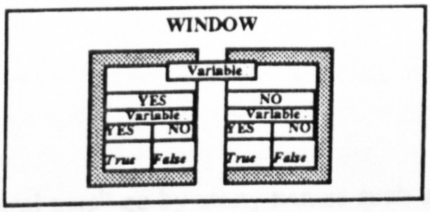
To this window the CLS algorithm is applied. The Concept Learning Algorithm (CLS) was developed by psychologists based on human learning methods.



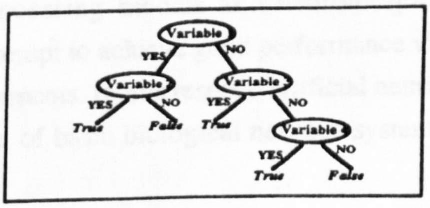
The CLS algorithm finds the variable which is most discriminatory and partitions the data with respect to that variable.



Having divided the data into two subsets, each subset is partitioned in a similar way until it contains products of only one kind.



The end product is a discrimination tree, a knowledge representation format which is easy to understand and use.



This tree is then tested against the original data and refined to generate a set of 'true' rules based on the decision tree.

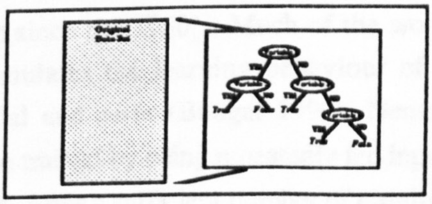


Figure 3.20 Quinlan's ID3 Algorithm

3.10.1.2 Quinlan's ID3

Quinlan's Interactive Dichotomizer 3 is a general purpose rule induction algorithm which is incorporated into many rule induction packages. This technique may not produce accurate rules when faced with noisy data as it tends to always seek perfect rules. The program works in manner shown in figure 3.20.

The main problems with this method of knowledge induction are :

- The rules are not probabilistic.
- Several identical examples have no more effect than one.
- It cannot deal with contradicting examples.
- The results are over-sensitive to small alterations.

The modified ID3 algorithm is known as C4, this solves these problems by generating decision trees capable of being pruned. Pruning involves eliminating any excess branching or empty outcomes at the leaf nodes of the tree, away from the root induced knowledge. This reduces the effects of noise, insufficient attributes and insufficient examples.

3.10.2 Neural Networks

Artificial neural network models or simply "neural nets" go by many names such as connectionist models, parallel distributed processing models and neuromorphic systems. Whatever the name, all these models attempt to achieve good performance via dense interconnection of single computational elements. In this respect, artificial neural network structure is based on our understanding of basic biological nervous systems (Widrow 1990).

Neural networks have been under development since the 1950's. Much of the work done has been in generating software that simulates the learning behaviour of a hypothetical brain. Humans often learn by trial and error (Bhagat 1990). Neural networks operate analogously. A network must be trained by being repeatedly fed input data together with corresponding target outcomes. After a sufficient number of training iterations, the network learns to recognise patterns in the data and, in effect, creates an internal model of the process governing the data. The network can then use this internal model to make predictions for new input conditions.

The neuron is the fundamental cellular unit of the nervous system which includes the brain. Each neuron is a simple processing unit which receives and combines signals from many other neurons. The brain consists of tens of billions of neurons densely inter-connected. The axon (output path) of a neuron splits up and connects to dendrites (input paths) of other neurons through a junction refered to as a synapse. The synaptic efficiency (or strength) combined with neuron processing forms the basic memory mechanism of the brain (NeuralWare Inc. 1990).

In an artificial neural network, the unit analogous to the biological neuron is referred to as a "processing element". An artificial neuron, or processing element, emulates the axons and dendrites of its biological counterpart with wires and emulates the synapses by using resistors with weighted values (Decker 1986).

Biological systems are generally not very efficient at analysing logic or detailed numeric processing. Living creatures are far better than our present computer systems at pattern recognition and a host of other tasks necessary for the survival of an organism in a dynamic and hostile environment. Neural network computer systems provide a kind of self programming based on experience.

This does not mean that neural network development attempts to exactly copy the mechanisms of the brain. The primary parallel between biological nervous systems and artificial neural networks is that each typically consists of a large number of simple elements that learn and are able to collectively solve complicated and ambiguous problems.

3.10.2.1 Neural Network Structure

All the processing in an artificial neural network is carried out by nodes (or processing units) - there is no 'executive' or 'overseer'. Networks are trained on data for which the 'right answer' is known, after which they should be able to generalise what they know, responding correctly to novel data (Lippman 1987).

Computational elements or nodes used in neural net models are nonlinear, typically analog and may be slow compared to modern digital circuitry. The simplest nodes or processing elements sums a number (N) of weighted inputs and passes the result through a nonlinearity as shown in figure 3.21.

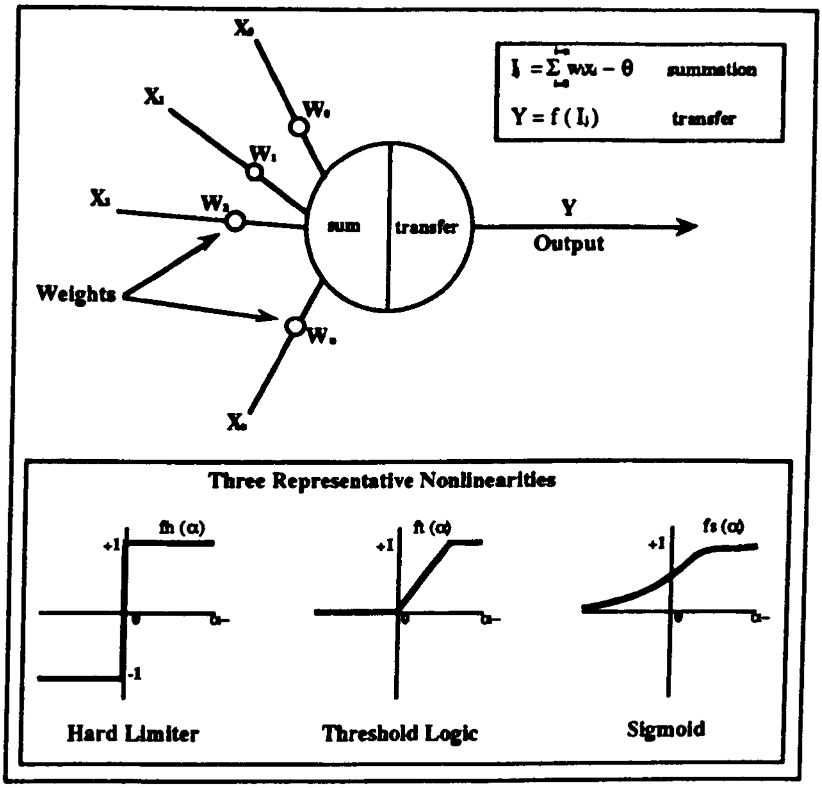


Figure 3.21 A Neural Network Computational Element or Node.

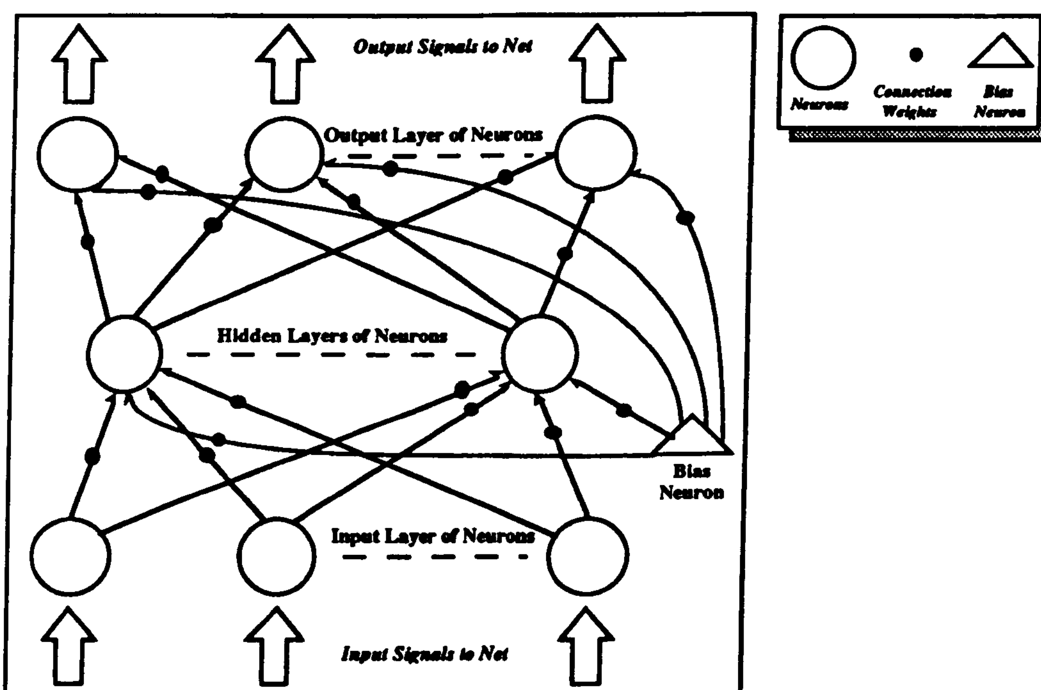


Figure 3.22 A Schematic of a Typical Neural Network Structure

The result is an internal activity level for the processing element. The combined input is then modified by a transfer function. This transfer function can be a threshold function which only passes information if the combined activity level reaches a certain level, or it can be a continuous function of the combined input. The internal threshold or offset (θ) characterises the node. Figure 3.21 illustrates three common types of nonlinearities; hard limiters, threshold logic elements, and sigmoidal nonlinearity. More complex nodes may include temporal integration or other types of time dependencies and more complex mathematical operations than summation.

The output path of a processing element can be connected to input paths of other processing elements through connection weights which correspond to the synaptic strength of neural connections. Since each connection has a corresponding weight, the signals on the input lines to a processing element are modified by these weights prior to being summed. Thus, the summation function is a weighted summation. In itself, this simplified model of a neuron is not very interesting; the interesting effects result from the ways the neurons are connected.

The structure of a neural network forms the basis for information storage and governs the network's learning process. Neural networks (see figure 3.22) comprise of interconnected simulated neurons. The processing elements are usually grouped into linear arrays called layers or slabs. Most neural networks consist of three to five layers, namely the input layer, the middle or hidden layer (s) and the output layer. Data is presented to the network in the input layer and the response of the network to a given output is in the output layer.

The input vector, applied to the input layer, is multiplied by the weight matrix of that layer while interlayer connections transfer the new information to the middle layer. The steps are repeated, in turn, in the middle and output layers to ultimately generate the output vector. A network where data flows through the network from one layer to the next is called a feedforward network. Transferring output from a later layer into an earlier one is referred to as a feedback or resonant network.

Neural networks of the feedback type have the ability to learn from their own experience without being explicitly programmed for each new input. These not only detect patterns or significant relationships in data, but also remember the patterns by associating them with the weights assigned during the training phase.

Among a variety of available learning algorithms, perhaps the most popular is the back propagation algorithm. This method allows errors to be propagated backwards from the outer layer to the middle layer(s) and on to the input layer.

The multi-layer, hierarchical networks are more powerful because they can generate their own internal representations in the hidden layers. These hierarchical networks are used for the better known applications, such as speech and character recognition (Arbib and Sun-ichi-Amari 1988).

When analysing a network, two kinds of hidden unit representations need to be studied. First, to understand what the weights mean. Second, to look at the patterns of activation of units in the hidden layer in response to particular inputs. Introducing a layer of hidden units increases the power of the network, since each hidden unit can partition the input space in a different way. The output unit then computes a linear combination of these partitionings to solve the problem.

If the number of processing elements in the middle layer is too great, it will replicate the elements from the input layer, causing problems similar to those encountered in a single layer network. If the number of processing elements in the middle layer is too small, the network will require many iterations to train, and recall accuracy will suffer.

3.10.2.2 Neural Network Paradigms

There are many types of neural network structures. This section introduces standard network examples, each showing different perspectives of this wide field. A selection of paradigms are briefly described below (Grossberg 1988).

Perceptron Networks : In the mid 1950's Frank Rosenblatt devised a computational model for the retina which he named the 'perceptron'. The perceptron was designed to model and explain the pattern recognition capabilities of the visual system. This is basically a three layer, strictly feedforward network without any feedback, cross-talk between processing elements, or randomness about the operation of the network.

Adaline and Madaline Paradigms : Widrow's earliest contribution to neural computing was the Adaline (ADAptive LInear NEuron). This was a threshold logic device which used outputs of -1,+1, the input to the unit was also bi-state -1,+1. Like the Perceptron, the Adaline is capable of classifying linearly separable patterns. However, certain multi-layer extensions to the adaline paradigm provide a much richer technique for separating the input space. One of the earliest approaches to solving the linear separability problem was the Multiple Adaline or Madaline. The Adaline elements in a Madaline network evolve as detectors for specific input features.

Brain-State-in-a-Box : Anderson's brain-state-in-a-box is essentially a linear associative network combined with a nonlinear post-processing algorithm which is used to clean up spurious responses. There are two learning rules associated with linear networks, Hebbian learning and Widrow-Hoff (delta rule) learning. These two rules give rise to networks with different characteristics. The potential applications of the brain-state-in-a-box come from the experiments which have been done to create associative memories and simulate human cognitive processes.

Hopfield Networks : In 1978 John Hopfield developed a new type of neural network based on research into the neuro-physiology of garden slugs. The nature of Hopfield networks lend themselves to analog and optical implementations. Using very fine-line processes, the researchers have been able to put millions of connections on a single chip. The high fault tolerance of partially damaged systems lend this technique for use in robotic and control applications.

Back-Propagation : Complex non-linearly separable classes can be separated with a multi-layer network. Back-propagation assumes that all processing elements and connections are somewhat to blame for an erroneous response. Responsibility for the error is affixed by propagating the output error backward through the connections to the previous layer. This process is repeated until the input layer is reached. The name 'back-propagation' derives from this method of distributing the blame for errors.

Counter-Propagation : Counter-propagation was invented by Robert Hecht-Nielson. It selects from a set of exemplars by allowing them to compete amongst each other. Normalised inputs and competition between exemplars selects the nearest neighbour. This provides a method of constructing an adaptive pattern classifier. If the input classes are reasonably well separated, the network can learn the categories and how to separate them.

A whole range of minor network paradigms also exist, many are modified forms of those described above. Indeed, the major problem of building a neural network is to select and configure the correct paradigm for the problem requiring solution.

3.11 Applications of Expert Systems

The last decade has seen an increased interest in AI, improvements in computer power and advanced software products has moved AI from the laboratory into industry. Many expert systems have been developed for worthy applications.

Recent studies suggest that to improve productivity large corporations will need to improve the overall coordination of their production, scheduling and management systems. Knowledge based systems can be used to monitor and control complex equipment, replacing or assisting the expert operator or engineer. By acting as 'front-ends' to large conventional computer packages, they allow the user to communicate with these packages in a natural language format (Harmon and King 1985).

The 'deskilling' of expert tasks may enable decisions to be made by those with considerably less expertise. This may be highly beneficial as the skills of leading experts could be made available in an expert system form to the remotest (or poorest) parts of the world. On the other hand this transference of skills could foster an increasing reliance on relatively junior members of staff, providing an excuse to dispense with the experts (Bramer 1989).

3.11.1 General Applications

It is very difficult to fully assess the expert systems currently functioning or under development. The following list gives some idea of the areas where knowledge based systems can be applied with examples of existing applications (Denby and Schofield 1991).

Control : Expert systems can be integrated into the control and monitoring of complex equipment. Current applications include nuclear reactor control, steel mill control (Intelligent Applications Ltd. 1990), and chemical plant control from COMDALE technologies.

Diagnosis : The replacement of procedure manuals by small expert systems allows an engineer to find the reason behind faults from a consultation with the system. These have been widely used in medicine, MYCIN diagnoses bacterial infections of the blood (Shortliffe 1976). DENDRAL (Feigenbaum et al 1971) analyses chemical spectrograms and AMETHYST is a widely used machine vibration monitor.

Design and Planning : Design involves a combination of numerical computation and information processing, together with a significant expertise from the planning engineer. Computer Aided Design systems have often lacked flexibility, expert systems integrated into existing systems can now aid the planning engineer. Architects use intelligent systems to help in the structural design of new buildings (Maher 1985) and a system known as XROUTE is able to solve vehicle routing problems (Kadaba et al). DEC use the R1 expert system to configure VAX computer systems to customer orders, resulting in a saving of approximately $20 million per year.

Interpretation : Expert Systems may be used as intelligent front ends to conventional software, providing an intelligent mediator between the user's 'ordinary' language and complex software commands. SHRDLU was one of the first natural language processors (Lightwave Consultants 1985), INTELLECT a modern language processor allows the user to communicate with a database in English (Partridge 1986).

3.11.2 Mining Applications

In the late 1970's the PROSPECTOR was developed for the mining industry, which was one of the first working expert systems. The success of this initial system resulted in a variety of expert systems being developed, but the mining industry has not (in many cases) committed the resources necessary for the development and application of knowledge engineering techniques.

3.11.2.1 Geological Applications

Expert systems have been developed in a diverse range of geological fields from exploration to classification to reserve modelling. The topic of mineral prospecting is a common application area for expert systems.

PROSPECTOR : This is a large scale expert system designed to interpret mineral data and predict the location of mineral deposits. Inference networks are used to express both judgemental and static knowledge, and Bayes's theory is used to handle uncertain information. PROSPECTOR discovered a previously unknown $100 million molybdenum deposit in Washington state (Gashnig et al 1981).

muPROSPECTOR : This expert system, patterned after PROSPECTOR also aids the geologist in evaluating unknown mineral deposits. This system has been developed on an IBM-PC allows new models to be built (McCammon 1986).

UP : The Uranium Prospector is a small expert system developed to analyses the reasoning processes in exploring for uranium deposits in sandstone. The system runs on an IBM-PC and used weighted probability factors to give a final value of probability of uranium endowment (Chhipa and Sengupta 1987).

Miller (1987) discusses the possible future uses of expert systems in the evaluation of energy resources, to counteract the loss of valuable staff during down turns in the energy and mineral industries. King (1986) explains the use of expert reasoning models applied to mine geologic data and the application of imprecise and fuzzy logic to mining situations. Applications of these reasoning models in expert systems have included :

GEOSTAT1 : GEOSTAT1 decides upon the values of parameters allowing variograms to be drawn. The expert system also determines homogeneous areas within a large deposit (David et al 1987).

muPETROL : muPETROL provides the means for classifying the sedimentary basins of the world as the first step to acquiring a regional geological background for estimating undiscovered petroleum reserves (Miller 1986).

A natural development of the use of these expert reasoning models is their application to geological modelling. One of the benefits to emerge from the use of new data structures has been the opportunity to exploit powerful spatial searching techniques. Combined with a rule base, these searches allow complex modelling problems to be attempted.

GEOCAD : GEOCAD is a computer based system which is designed to assist the geologist and the production or planing engineer. The software uses an information management system and small expert system modules to integrate the exploitation context and the engineers knowledge (Cheimanoff et al 1989).

Krupp Polysius : An expert system is integrated into the existing software environment of the deposit modelling program. The ultimate objective is to develop an optimum strategy for the exploitation of a mineral deposit using quarrying techniques (Streckhardt and Kade 1990).

EXPLORE : This Greek geological modelling system is used to model large lignite deposits. The software is being developed to understand statements such as 'hill', 'river' and 'valley' and apply these statements to the model (Galitis and Doganis 1986).

3.11.2.2 Fault Diagnosis Applications

Automatic interaction with the real world has been a major element in the development of mining expert systems. Fault diagnosis expert systems are used extensively in the mining industry.

CATS-1 : This is General Electric's expert system for diagnosing diesel locomotive malfunctions. It is used by repair personnel and is integrated with a videodisk and a video terminal to provide visual explanations (Harmon and King 1985).

DELTA : This is the Diesel-Electric Locomotive 'Trouble-shooting' Aid, developed by General Electric as a companion program to CATS-1. It is used by maintenance teams and has been applied to underground locomotives (Harmon and King 1986).

Trolex : Trolex are developing expert system applications for monitoring, diagnosis and interpretation of machinery faults. This is achieved using the spectral interpretation of vibration 'finger prints' (Billington 1990).

Longwall Shield Supports : The failure of longwall shield supports has been modelled in an Prolog based expert system knowledge base. The system uses a process of symptom interpretation, as most failures can be identified as a manifestation of some well understood failure mechanism (Bandopadhyay and Venkatasubramanian 1990)

3.11.2.3 Underground Mining Applications

In spite of its success in other areas, applications of expert systems in both the surface and deep mining industry has been fairly limited. In the area of underground environment, a variety of systems have been developed.

METHPRO : The U.S. Bureau of Mines has reported a PC based system to aid in the selection of methane drainage techniques for underground coal mining situations. The user provides the system with mine information, the computer analyses the mines problems and recommends control strategies (King 1986).

DUSTPRO : A companion program to METHPRO from the U.S. Bureau of Mines. This piece of software gives advice on dust problems in underground coal mines.

HEATDIAG : This expert system has been developed to handle the problem of heat and humidity in coal mines. HEATDIAG identifies the existence of heat and humidity problems in a mine and suggests a solution when a problem arises.

MECS : The Methane Explosion Consultation System diagnoses and assesses the possibility of a methane explosion based upon coal characteristics, geological and production conditions (Guo and Xin 1990).

AITEMIN : This expert system, developed by AITEMIN, evaluates the methane explosion risk in coal mines using fault trees. The system is used as a decision support aid for mining safety personnel (Alarcon and Silva 1990).

ESSH : The Expert System for Spontaneous Heating has been developed by the Advanced Computer Applications Group in the Department of Mining Engineering, Nottingham University. A large knowledge based system contains the information, engineering judgement and experience to perform a risk assessment on a coal seam in an underground environment (Atkins et al 1990).

The use of expert systems for design and planning applications has meant the development of decision support systems to aid the underground mine planner.

Tunnel Support Design : By classifying the rock around a proposed tunnel using fuzzy logic techniques this program is able to advise a mine planner on tunnel size and support characteristics (Fairhurst and Lin 1985).

Mine Ventilation Planning : This expert system controls an algorithmic network analysis program, and examines the input and output with regard to legal stipulations and ventilation principles. The system then analyses the network output in terms of the critical parameters in the context of the given problem (Ramani et al).

PSSS : The Powered Support Selection System is an expert system designed to select the proper roof supports based upon seam and roof characteristics. It provides a subjective assessment of the roof stability and a supports suitability to the mine roof (Guo and Xin 1990).

RESCUE : This expert system was developed for underground mine fire emergency situations. The atmosphere in the vicinity of the fire is monitored to determine the response of the fire to fire-fighting techniques (Osei-Tutu and Baafi 1990).

3.11.2.4 Surface Mining Applications

Expert systems have been applied to various aspects of surface mine planning including slope stability assessment.

SSA : The Slope Stability Analyser is a Prolog based expert system running on a VAX Mainframe computer. This system guides the user through various failure scenarios and suggest failure types. The system is very simple and is capable of directing a student of slope stability in the right direction (Sinha and Sengupta 1989).

ESDS : The Expert System Slope Design System was originally built in Prolog in the Department of Mining Engineering, University of Nottingham (Brown 1988). This early expert system has now been altered to run using compiled high level languages and a shell system. Based upon several Ph.D. thesis the system automatically identifies potential slope instabilities (Kizil 1990).

Blast Design : This expert system which designs and evaluates opencast mining blasts includes a fragmentation prediction function and an algorithm to select blasting detonator delays. The program is written in LISP and runs on an IBM PC (Scheck 1988).

Expert systems capable of selecting equipment and advising on equipment use have been developed. These systems handle the uncertain information and heuristic knowledge needed for such a decision, the optimum item of equipment is often not readily apparent.

ASTURLABOR-hulla : This Spanish expert system selects mining methods and equipment primarily based on the characteristics of the coal seam to be worked. The ASTURLABOR-hulla expert system is specific in as much as it selects a suitable mining method for the geologically disturbed bituminous coal region of Central Asturia in Spain (Cortina 1989).

MINDER : The topic of this thesis is the MINDER, (MINe Design using Expert Reasoning) system developed in the Advanced Computer Application Group. The system is designed to select optimum items of surface mining equipment and will be discussed in detail in subsequent chapters.

Truck Dispatching : The Canadian organisation CANMET have written a Prolog dispatching algorithm which has been integrated into a real time simulation program. It is claimed that information expressed as logical clauses simulates the commands issued by a dispatching foreman (Stuart et al 1988).

3.12 Machine Learning Applications

The state of machine learning technology is such that the prototype inducted and neural network decision systems have been developed using low-cost software on widely available hardware. These systems have many applications in a variety of industries making the knowledge of the engineer more widely available and providing new methods of storing and generating knowledge.

Knowledge induction systems are used in conjunction with expert system shells as rule generators, hence their applications are inseparable from the expert system applications. Knowledge induction systems have been used to generate knowledge for insurance firms, medical consultancy, crime detection and mineral exploration (Attar Software 1990).

The major independent application of knowledge induction is the analysis of data. It is possible to obtain better performance using these techniques to analyse data then by consultation with an expert. Recent applications have included data driven modelling of the financial markets (Ricketts 1990) and consumer credit card information (Attar Software 1990). The accuracy of customer credit worthiness prediction using knowledge inducted from examples is claimed to be approximately 20% more accurate than an expert opinion.

The applications benefiting most from neural networks are those that require the understanding and recognition of patterns, where many hypotheses are pursued in parallel and where high computational rates are required. Neural networks have mainly been developed in certain application areas and distinctive features of these applications can be identified.

Pattern Recognition : Neural networks have been used in sonar target classification, radar signal analysis, speech synthesis, handwriting recognition and electrocardiogram interpretation.

Data Compression : Neural networks can compress images for transmission down a communication channel with limited band width, and then reconstruct them with minimum error.

Chaotic systems : Dynamic systems that are theoretically deterministic but unpredictable in practice - are commonplace. Many such systems are treated as random, but if the underlying dynamics can be gleaned, better predictions might follow than statistical methods would suggest. Neural nets are sometimes able to extract the underlying dynamics, and make effective predictions.

Forecasting : Neural networks are claimed by some to be a better technique for economic forecasting than any other method currently used. This claim should be viewed with some reservation, since much depends on the reliability of the data as an indicator, and the way a chaotic system is sampled over time.

Although there are few current examples of neural computing in the field of mining engineering it is worth speculating on the possible applications of this technology in the future. The following examples represent possible areas which could be exploited by neural network technology (Denby, Schofield and Bradford 1991).

Reserve Estimation : In the past the assessment of mining reserves has moved towards the use of mathematically complex geostatistical techniques. A neural processing approach utilising the same input data would replace the semi-variogram fitting phase with a network training phase. Surrounding samples would be related to individual samples on a repeated basis, until the spatial relationship becomes encoded into the network. The network could then be used to estimate unknown grades at other positions. Such an approach would remove the need to understand a number of abstract concepts and mathematical details of the geostatistical method (Burnett 1992).

Image Analysis : In the field of mining engineering, image analysis techniques have been widely applied to the fields of blast fragmentation, particulate analysis and remote control of mining machinery. The pattern recognition proficiency of neural networks add a new dimension to the capabilities of visual and aural information processing systems.

Data Compression : In an underground mine a large amount of information is sent along data channels from transducers monitoring the underground environment. Large amounts of data are continually registered and a method of optimising the information transmission could increase the frequency and reliability of data flow within a mine. In addition, there is often a requirement to archive large amounts of mine data in an efficient form for later retrieval.

Automated Rock Loading : Semi-automatic rock loading equipment, utilising radio remote control and video systems are already in use in underground mines (Laurila and Aalto 1990). The video images of the rock pile being loaded could be correlated with equipment information read from transducers to generate a neural model of the loading operation. This system would be designed to 'try out' various strategies based on what has been taught to see if the loading technique could be improved.

Decision Support Systems : Neural networks could be applied to the complex planning decisions made in the initial stages of a mine design. The large amounts of uncertain or missing data associated with these decisions supports the use of intelligent computer techniques. For a number of years the work within the Advanced Computing Research Group at the Department of Mining Engineering has centred on developing expert systems for the mining industry. The emphasis of the research group is now moving to encompass aspects of machine learning technology, applying neural networks to the problems of geological hazard assessment (Kizil 1992) and equipment selection (Denby and Schofield 1991).

3.13 Conclusions

Knowledge engineering still has strong roots in academia, but many commercial expert systems are now available. A few years ago there was a small number of languages and shells. Today there are at least twenty versions of Prolog, at least ten versions of LISP and over thirty shells. The power of these tools has increased enormously.

Even with this increased power, computers still do not encompass the richness and depth of human reasoning, and won't for the foreseeable future. It is easy to imagine that an expert system is knowledgeable, but the system only understands the meanings assigned to the symbol names and as much of the structure as the syntax allows.

An expert system's conclusions may differ from those of an expert. Experts unavoidably make mistakes and frequently disagree amongst themselves. A demand for absolute correctness is likely to prove fruitless. An expert system recently embarrassed the Pentagon by winning the annual naval war game several times. On one occasion it did so by destroying it's own crippled ships and steaming on to victory. The rules had to be subsequently changed to disallow this rather bloodthirsty option (Graham 1989). At this point in time expert systems are no more than idiot-savants. As our ingenuity in manipulating computer systems grows expert systems will become more savant and less idiot (Stonier 1989).

It is clear that if expert systems can come to terms with the technical problems that exist, the potential payoffs could be enormous. By way of summary, at least six kinds of use can be identified (Bramer 1989).

- To increase expert productivity.
- To augment expert capability.
- To spread expertise more widely.
- To provide expert training aids.
- To preserve expertise.
- To provide heuristic solutions.

The loss of professional expertise in geology, geophysics, engineering and geochemistry may prove to be the most serious outcome of the cyclic nature of the energy and mining industry (Gregg 1986). The first trials of expert systems in the mining industry have proved the economic benefits of these systems by resolving problems which conventional programs are incapable of solving due to the complex symbolic manipulation involved.

The field of mine design provides an opportunity for the introduction of machine learning systems. The inherent complexity and the large amounts of information, often of an uncertain nature, all indicate that these techniques should be utilised. Expert systems offer a method of interfacing and controlling the various types of machine learning software.

Neural networks won't replace database and knowledge based processing because they are inefficient when presented with imprecise data. In the next few years, it is likely that the first practical neuron based circuits will appear in silicon, and a neural network may be used as a co-processor controlled by a host digital computer. The combination of traditional computers and the unique power of neural networks could unravel problems that otherwise would remain unsolved.

The MINDER system discussed in this thesis is an attempt to select an optimum item of equipment for a particular mining scenario. In view of the difficulties in selecting equipment and the substantial economic losses arising from the selection of the wrong piece of excavation equipment, it is certain that this kind of system provides a valuable decision aid to a surface mine planner.

Chapter 4

System Architecture

4.1 Introduction

Mine planning, as detailed in Chapter 2, is a complex process due to the site specific nature and the high inter-dependence of the decisions required. The general approach to mine planning is one of progressive plan refinement as alternatives are evaluated. Figure 4.1 depicts some of the broad inter-relationships that exist.

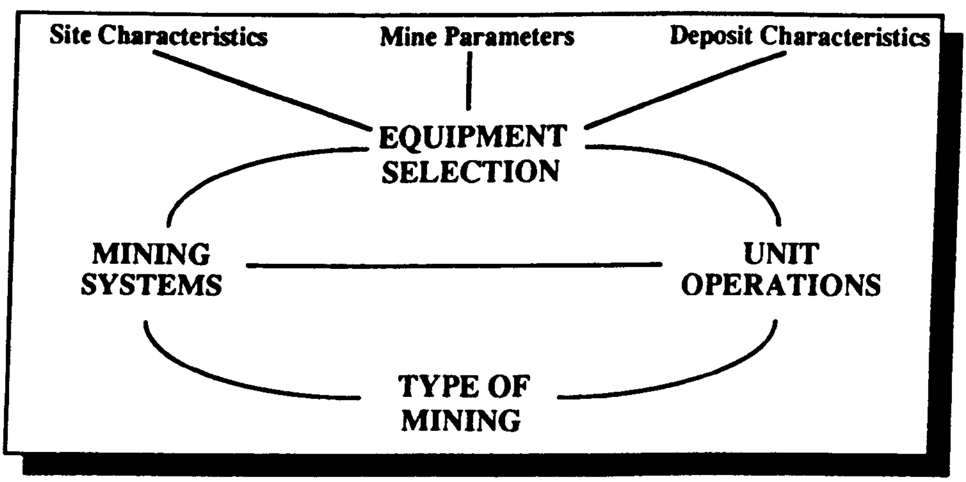


Figure 4.1 The Inter-Relationships Involved in Equipment Selection

The equipment selection process begins with the conception of mine development. Detailed analysis starts after the exploration has located a deposit and preliminary analysis has established that development is feasible and financially justified. Three sets of constraints are identified which define the input criteria for selecting the mining equipment to be utilised.

- **Site Characteristics** : Such as terrain, labour availability, rainfall and temperature.

- **Mine Parameters** : Such as production rate, production requirement, property limits and product quality.

- **Deposit Characteristics** : Such as depth of deposit, deposit size, deposit thickness, nature of overburden and material properties.

Deciding the relative effectiveness of equipment systems involves both qualitative and quantitive analysis. Direct numerical estimates can be determined to match production requirements, these are often based on a broad variety of assumptions with respect to actual site conditions, formation characteristics, machine performance, operator and management skills. The model is related to 'average' or 'typical' conditions which, of course, rarely occur (Martin Consultants Inc. 1982).

The standard computer tools used in mine design include databases, spreadsheets, simulation and algorithmic software. The linking of conventional mine planning tools is not a new concept (Renström and Anderson 1990). The application of expert systems to control these software packages, however, provides an innovative approach to mine design. MINDER (MINe Design using Expert Reasoning) is an expert system developed to select surface mining equipment for a particular mine scenario. The MINDER system interfaces to, and is capable of controlling, the following conventional software.

- **Pascal** : Pascal software is run to perform algorithmic calculations.
- **DbaseIV** : Databases of equipment and geological information.
- **GPSS** : To simulate certain surface mine truck operations.
- **Excel** : The system results are reported to a spreadsheet for scheduling.

By making the system compatible with this external software interaction the user is not required to have knowledge of each of the software packages involved. For example the expert system can interrogate a DbaseIV database to obtain information without the user being aware that a database has been accessed. Interaction with the user is reduced by the singular input of data, and the use of inferencing procedures to determine relevant information.

The MINDER system is also capable of making a decision when information is uncertain or missing. A variety of uncertainty techniques are used, including linguistic variables, certainty factors and fuzzy logic techniques.

Parallel to the principal MINDER expert system development an expert system module relying upon induced knowledge has been created using the Xi Rule knowledge induction software. A series of experimental neural networks have also been created using the Neural Works Explorer software package. These machine learning applications replicate certain MINDER decisions and are used as validation models.

4.2 System Knowledge Modules

During the development of the MINDER system the structure of the knowledge modules has changed drastically. The initial architecture of the envisaged system is represented in figure 4.2.

This structure follows a general rule for large applications where knowledge bases are broken down into a number of knowledge modules. These knowledge modules incorporate different types of knowledge; textbook knowledge, heuristic (surface) knowledge and deep knowledge. These may be defined in a hierarchy of three levels.

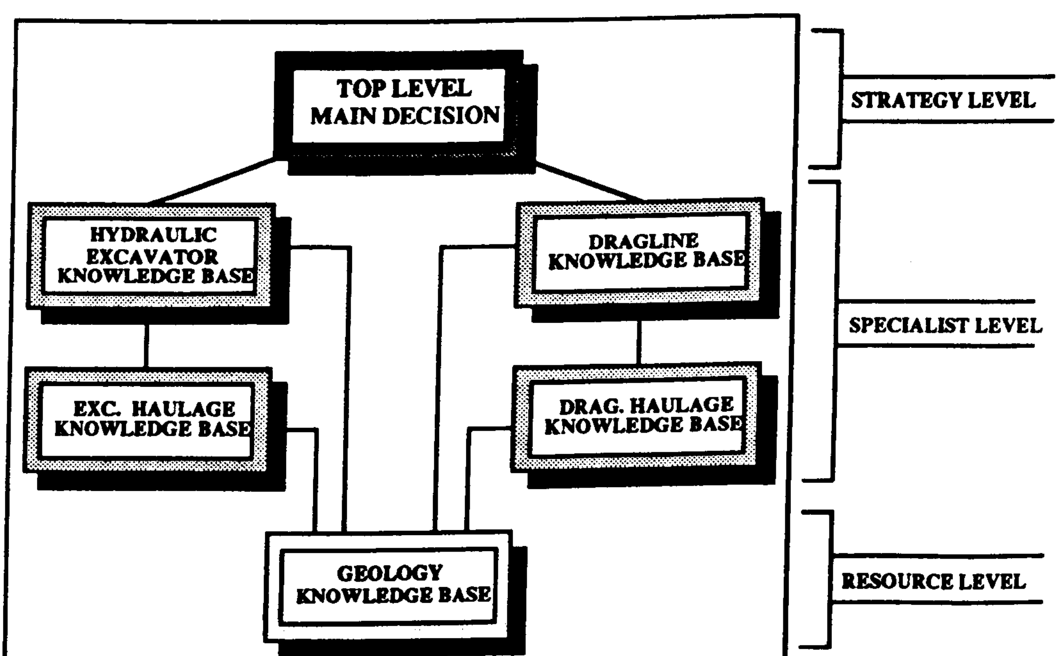


Figure 4.2 Initial MINDER System Structure

- **Strategy level** : Analyse state of the solution to decide upon the next course of action. This knowledge module is used to control the execution of the specialist knowledge modules.

- **Specialist level** : These expert knowledge modules control the engineering heuristics, they evaluate the best design and make decisions based on the information from the resources level knowledge modules.

- **Resources level** : These modules contain the analytical knowledge and reference information required for analysis and design. The resource level modules also tend to control database management systems and information acquisition.

Figure 4.2 shows the original MINDER knowledge modules split into these three levels. The top level main decision controls the execution of the specialist equipment knowledge modules. These specialist knowledge modules draw on information from the application packages and the geology resource module rules to suggest design factors. The geology resource module covered a wide range of resource factors. A set of control rules were incorporated into the geology knowledge base to allow different queries to be fired as required.

The impracticality of this approach soon became apparent. One of the first problems was the transfer of information between the various levels. If all the data in the working memory was used this rapidly led to memory shortages. As knowledge acquisition techniques were applied to each knowledge domain, the amount of knowledge began to increase beyond a reasonable number of rules necessitating a new structure for the MINDER system. To achieve this each level of action within the initial architecture was split into an independent application. These individual application modules contain a hierarchical structure of knowledge bases. A simplified example of an application module is shown in figure 4.3, which illustrates the present dragline module architecture.

Each individual application remains divided into the same three levels. The information from the geology knowledge base of figure 4.2, however, has been distributed into a series of smaller domain specific knowledge bases as shown in figure 4.3. Typical dragline resource knowledge bases include ; discontinuity spacing, blasting and digging resistance. Each of these individual modules will be discussed in greater detail in the next chapter.

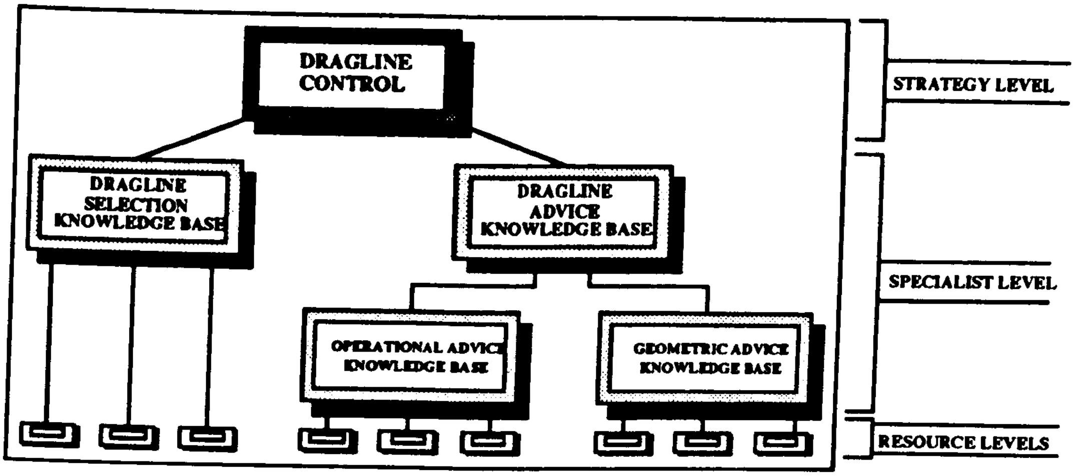


Figure 4.3 Dragline Module Structure

To retain continuity the files belonging to each application were created to the same specifications. The directory structure was the same for each application, an example of the directory structure is shown in figure 4.4.

```
D:-----|
       |--Applic.------|
                       |--- Expert   (Xi Plus knowledge bases and applications)
                       |--- Dbase    (DbaseIV databases and indexes)
                       |--- Pascal   (Executable 'in-house' algorithmic software)
                       |--- Fuzzy    (Xi Plus knowledge bases and applications)
                       |--- Data     (Information handling files and final results)
```

Figure 4.4 Typical Directory Structure

It is still important that information can be passed from one application to another. For example, if the hydraulic excavator knowledge base has been consulted, and the haulage application is then queried, information from the excavator consultation should be used during the haulage selection process. The solution to this problem is detailed in the next section.

4.3 Information Handling

A large knowledge based system needs the ability to transfer data between the knowledge modules through a common communication medium. An inheritance mechanism can be used to control the manner in which attributes and values are connected to sub knowledge modules via relational links. Communication between the different sections of a large expert system involves three functions :

- Linkage of Knowledge Bases.
- Transfer of Data Between Knowledge Bases.
- Transfer of Data Between Applications.

4.3.1 Linkage of Knowledge Bases

Within Xi Plus, the facility for one knowledge base to call another as a subroutine uses the following form of call :

```
if / when .....
then do kb (kb name)
```

This provides a convenient means of linking knowledge bases. When such a call is invoked, the expert system automatically saves the current state of the consultation in the top level knowledge base before loading and running a sub-knowledge module.

Upon completion of the sub-knowledge module query, the call '**command return**' returns control to the top level knowledge base. Xi Plus then restores the previous state of the top level consultation.

4.3.2 Transfer of Data Between Knowledge Bases

There are three main methods of transferring information between knowledge bases, all have been tried within the MINDER system, with varying degrees of success. The three methods are as follows :

- The Subroutine Call.
- The Save and Load Command.
- Using a Comma Delimited File.

4.3.2.1 The Subroutine Call

The knowledge base subroutine call facility '**do kb**' allows '**using**' and '**giving**' lists which provide a simple and effective way of transferring data across knowledge bases. The call takes the following format.

```
if / when .....
then do kb (kb name) using (input list) giving (output list)
```

The *(input list)* represents a list of one or more parameters, separated by commas, from the calling knowledge base. If omitted, no input parameters will be passed to the called knowledge base. The *(output list)* represents a list of identifiers or assertions, separated by commas, which will be assigned the values returned by the called knowledge base as it's output parameters.

An **entry** parameter in the called knowledge base, usually placed at the start, accepts the information into identifiers from the **do kb** input parameter list. The format to return an output list of parameters to the top level is :

> **if / when .....**
> **then command return** *(output list)*

This approach is only suitable for knowledge bases in which it is anticipated that only a few items of data will need to be transferred. It is not an efficient method when a large amount of data is to be manipulated.

The MINDER system initially relied upon this transfer technique. Problems arose, however, in knowing which information was needed at a particular time and in which knowledge base. An attempt to transfer all the information that may possibly be used resulted in unwieldy commands and system failures when data was unavailable. Attempts to send only useful information led to an overly complex sequence of data transfer rules. A better transfer method was needed.

4.3.2.2 The Save and Load Command

To transfer the full set of consultation data between two knowledge bases, the values given and inferred from the top level consultation are retained in a file using the following command.

> **command save data** *'file specification'* (e.g. d:\minder\data\temp)

This saves the whole of the consultation working memory to a file within the MINDER directory structure (in this case temp.dbc). This file can then be loaded into a second knowledge base using the following command :

> **command load data** *'file specification'* (e.g. d:\minder\data\temp)

This technique was used briefly during the early stages of MINDER development and soon abandoned. If one value from a particular knowledge base is needed, the whole of the working memory has to be loaded. The system often failed as the memory was filled with irrelevant data.

4.3.2.3 Using Comma Delineated Format (CDF) Files

The Xi Plus 'report to file' facility allows any ASCII text string to be output into a text file during a consultation. Any identifiers that are contained in square brackets in the report text will be substituted for their respective values as the report is output. This preserves the values of identifiers that may subsequently be reset. This facility is used to build Comma Delineated Format (CDF) files which can act as data output files from a knowledge base.

These files contain a sequence of fields, separated by commas, and organised into records. A record corresponds to a row in a spreadsheet with the fields being cells in that row. The CDF data file interface program (defined as the 'read cdf' procedure) is called to read these cells. This Xi Plus call requires the file name and the location of the cells within that file to be defined. The data read from the file cells are placed into expert system identifiers. Figure 4.5 shows how an identifier can be passed between two knowledge bases using a CDF file (temp.dat).

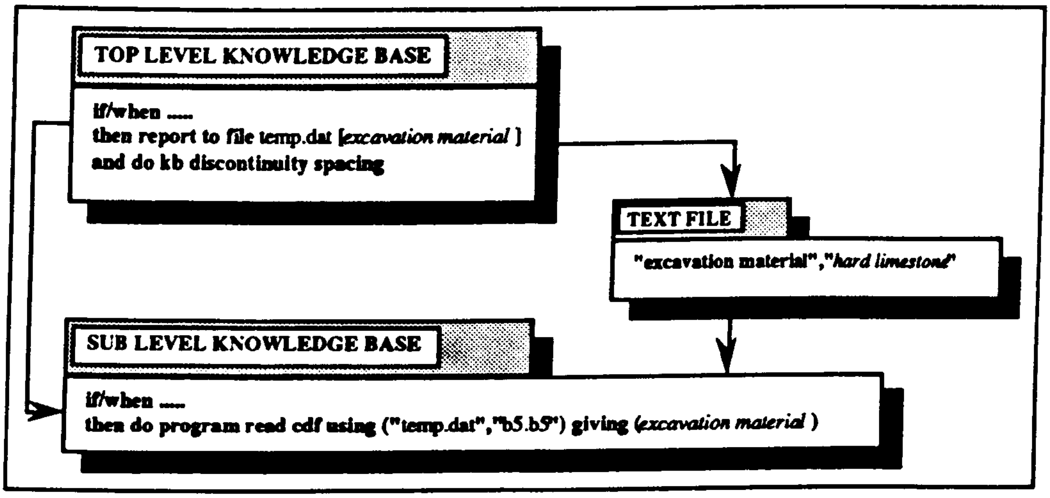


Figure 4.5 Information Handling Using Text Files

The complexity of the MINDER system meant that this file reading technique had to be modified to allow any identifier to be checked for a previous value at any time. This was achieved using global data files known within the system as 'cerebral' files. Figure 4.6 shows an example of part of a dragline cerebral file. Each module of the MINDER system has a cerebral file in the application's data directory. At the beginning of each consultation the cerebral file is reset with blank or zero values, this effectively clears the working memory.

```
                    HAULAGE  DATABASE

        *******     Cerebral.dat      *******

**      Excavation Machine      **

"excavation machine","blank"

**     Material Size     **

"excavation material","blank"
"gravel","blank"
"surpac file existence","blank"
"material type","blank"

"blasting used","blank"
"fragmentation","blank"
```

Figure 4.6. An Example of a Cerebral File.

Each time a value is required the MINDER system checks the application's cerebral file. If a blank value is returned the the system calls either a knowledge base, which will infer a value for the identifier, or a form, which will allow the user to select a value for the identifier. Once an identifier has been given a value, the value is written into the cerebral file, ready for future use. Control rules interrupt the backward chaining reasoning process using forward chaining demons, these obtain and reset the current value of an identifier. An example of a set of control rules for the identifier excavation material are shown below.

```
if check excavation material
then do program read cdf using ("cerebral.dat","b7.b7") giving (excavation material)

when excavation material is blank
then command reset excavation material
and do form excavation material
and excavation material needs changing

when excavation material needs changing
then report to file reprtcdf.dat 7
and report to file reprtcdf.dat [excavation material]
and report to file reprtcdf.dat str
and do form processing
and do program reprtcdf
and command reset excavation material needs changing
```

The first rule is fired during the normal backward chaining inferencing process, reading a value from the application cerebral file. If any value other than 'blank' is read then the system continues to backward chain through the knowledge base.

When the excavation material is blank a forward chaining demon interrupts, and a form, or screen menu is called. This allows the user to select a value for excavation material. An alternative to the form call would be a knowledge base call of the following format :

and do kb excavation material **giving** (excavation material)

After returning control from the called knowledge base, this would place a value in the identifier excavation material.

The excavation material value now needs to be written to the cerebral data file. The third rule/demon does this by again interrupting the backward chaining to send the file row number and value to a temporary text file. A form called 'processing' informs the user that 'processing is in progress' while a simple Pascal program, 'reprtcdf', writes these values from the temporary file to the appropriate row in the cerebral file. This information storage procedure may increase the consultation time.

4.3.3 Transfer of Data Between Applications

Information needs to be transferred between different application modules. For example, if the top level application is run and the MINDER system selects a dragline as the ideal type of equipment, the dragline module would then be used and should be able to access any information from the top level module. The data to be transferred is all contained within the application cerebral files. There are three methods of transferring cerebral file information used within the MINDER system.

- **Copy 'cerebral' file :** The cerebral file from the data directory of one application is copied into the directory structure of a different application. Thus the values of all identifiers from the previous consultation are copied with the file.

- **Copy certain identifiers :** When the system realises that a previous application has been consulted a block of relevant identifiers are read from the previous cerebral file and written to the current cerebral file.

- **Checking other file :** During the normal backward chaining process, the system checks the previous application's cerebral file instead of the current cerebral file. Any values obtained are written to the current cerebral file.

4.4 Recursion Between Knowledge Bases

Once an effective method of information handling had been achieved the flow of control between the system knowledge bases was rapid and often followed complex inferencing routes. The use of cerebral files meant that a query initiated in any knowledge base would call any sub (or higher level) knowledge bases needed to complete that query. One surprising factor of this free flow of information was recursion between smaller knowledge bases. An example of the recursive process between knowledge bases is shown in figure 4.7.

Recursion is the process of repeatedly evaluating the same rules at different levels of a consultation. Recursive descent in the rules of the MINDER system was well controlled. Standard backward chaining inferencing within the MINDER system never used more than two layers of recursive descent.

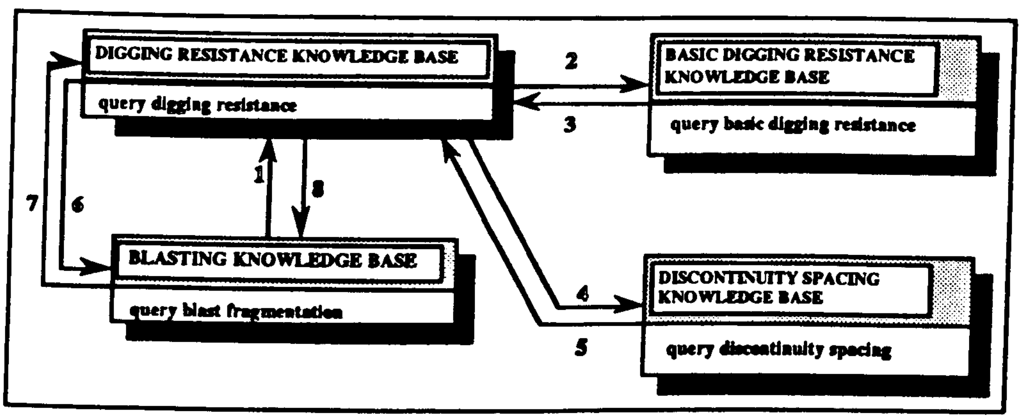


Figure 4.7 Example of Recursion Between Knowledge Bases

In the example shown in figure 4.7, the consultation begins in the blasting knowledge base. To advise on whether blasting is needed for a particular scenario, the system needs an approximate value of the digging resistance of the excavation material (1). To obtain this value the MINDER system combines three factors to give a value for digging resistance.

- **Basic digging resistance :** Based on material, water and ground conditions.
- **Discontinuity spacing :** Information on bedding and fracture spacing.
- **Blasting :** The blast fragmentation characteristics of the material.

The basic digging resistance knowledge base is consulted (2) and returns a numerical value to the digging resistance knowledge base (3). This basic digging resistance value is modified by the description of the discontinuity spacing (4 & 5).

The blasting knowledge base is then reopened as a sub knowledge base by the digging resistance knowledge base (6), this is equivalent to the start of a new blasting query. When this query starts the blasting knowledge base again needs an approximate value for the digging resistance of the excavation material. The basic digging resistance, modified by the discontinuity spacing, has been reported to the cerebral file. The blasting knowledge base reads this data from the cerebral file and advises the user on potential explosives use based upon this value.

The blasting information provided is then returned to the digging resistance knowledge base (7), where the basic digging resistance is modified by the fragmentation description to give a final value of digging resistance.

The final digging resistance is passed into the blasting knowledge base (8), to satisfy the initial digging resistance knowledge base call. The system finds that a blast description exists and ends the consultation.

4.5 Linking to Geological Models

Information to enable the expert system to draw conclusions is also drawn from geological and design models. These models are created using commercially available modelling packages allowing the user to interpret the geology from borehole data and to obtain reserves, quality data and other planning information. Pit shapes can then be superimposed on the geology allowing in-pit volumes, bench positions, and other scheduling information to be obtained (Schofield and Denby 1989). Figure 4.8 shows an example of a pit design superimposed upon the geology taken from the Surpac Mining System.

The Department of Mining Engineering at Nottingham University uses two of the widely available commercial mine design packages to model a variety of deposits.

- **Datamine** : Developed by Mineral Industries Computing Limited.

- **Surpac** : Developed by Surpac Mining Systems.

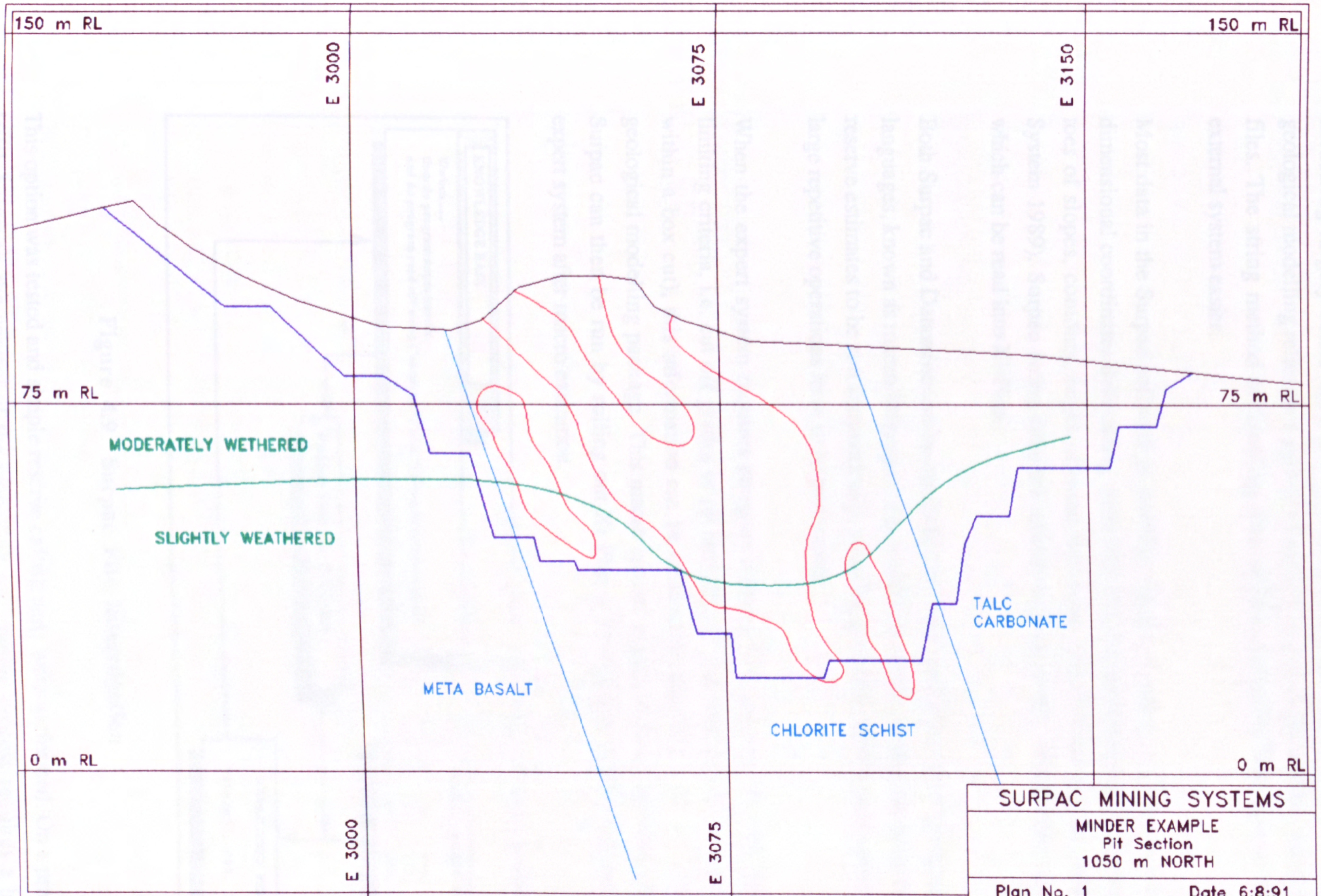


Figure 4.8 An Example of a Pit Section

The geological modelling part of the Datamine software although capable of terrain modelling largely relies upon a block modelling technique, whereas the Surpac geological modelling relies on a system of string files and digital terrain model (DTM) files. The string method of handling data makes interfacing with Surpac from an external system easier.

Most data in the Surpac software is stored as strings. A string is a sequence of three dimensional coordinates delineating some physical feature. Strings include crests and toes of slopes, contours, edges of roads and many other elements (Surpac Mining System 1989). Surpac string files are stored as readable and changeable text files, which can be read into Xi-Plus.

Both Surpac and Datamine can be controlled by their own independent programming languages, known as macro languages. These macro's enable geological modelling and reserve estimates to be run automatically, allowing greater flexibility and speed where large repetitive operations have to be performed.

When the expert system requires complex information, such as reserves based on limiting criteria, i.e. cut off grades or pit boundaries (e.g. reserves of a certain seam within a box cut), this information can be obtained by running a macro within the geological modelling package. This macro can be written from Xi Plus to a text file. Surpac can then be run by rolling out Xi Plus onto disk and control returns to the expert system after macro execution.

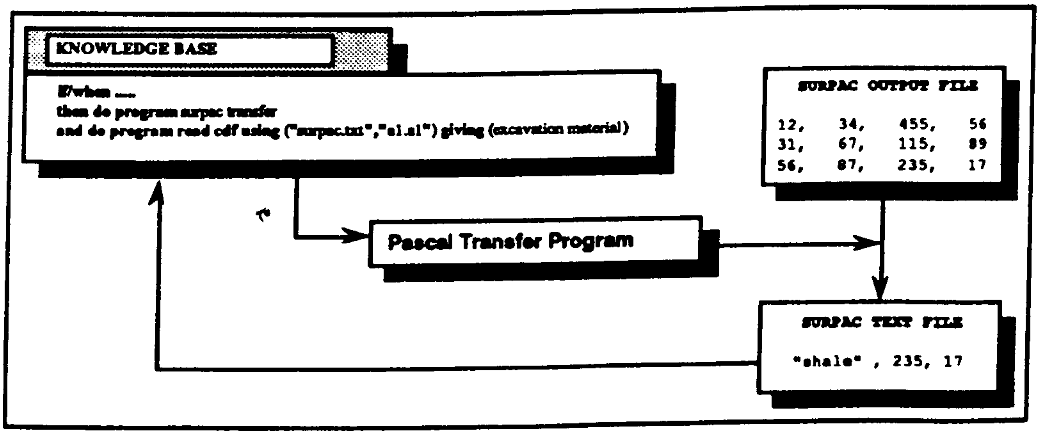


Figure 4.9 Surpac File Interrogation

This option was tested and simple reserve calculations were performed. On a practical level, however, the control of the modelling and reserve process requires a highly complex knowledge base covering geological and scheduling aspects. Hence, the MINDER system relies upon a manual execution of the geological modelling software, but is capable of reformatting and interrogating the Surpac results files.

A simple Pascal file manipulation program is used to reformat the Surpac output files and the Xi Plus read cdf procedure is used to read simple information such as material types, densities and volumes from the text file produced. Figure 4.9 shows an example of a simple Surpac file interrogation.

Rendered pit images have been produced by linking Surpac to AutoCad software. Surpac contour files are converted into a DXF file format and read into an AutoCad drawing as a series of three dimensional vectors, producing a line drawing. This wire frame model can be used to generate three dimensional gridded surfaces, which are superimposed on the line drawing allowing the user to create a series of high quality plans sections and three dimensional views, as shown in figure 4.10.

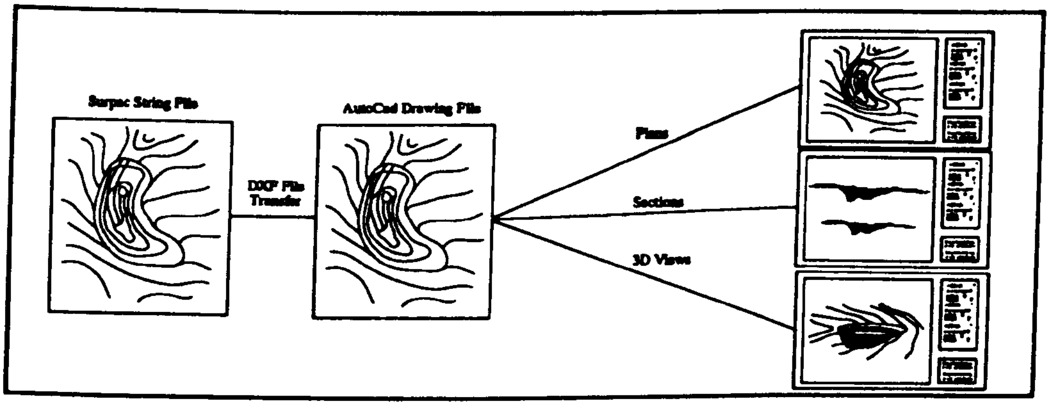


Figure 4.10 Converting Surpac Models into AutoCad Drawings

This wire frame model can then be shaded (using AutoShade software) and these shaded models can be animated (using AutoFlix software). Shading changes a wire frame model into a rendered picture that shows perspective, surface shading, and specular reflection (Autodesk 1990). These pictures are very useful in applications for planning permission for a new surface mine. These computer images will be used as the 'artists impressions' of the future, a rendered pit design is shown in figure 4.11.

The wire frame and the shaded models can be animated using AutoFlix software. The animation techniques used on a personal computer equipped with mass market graphics boards involves some compromises, however, this technique can bring a design to life and provide an excellent perception of reality.

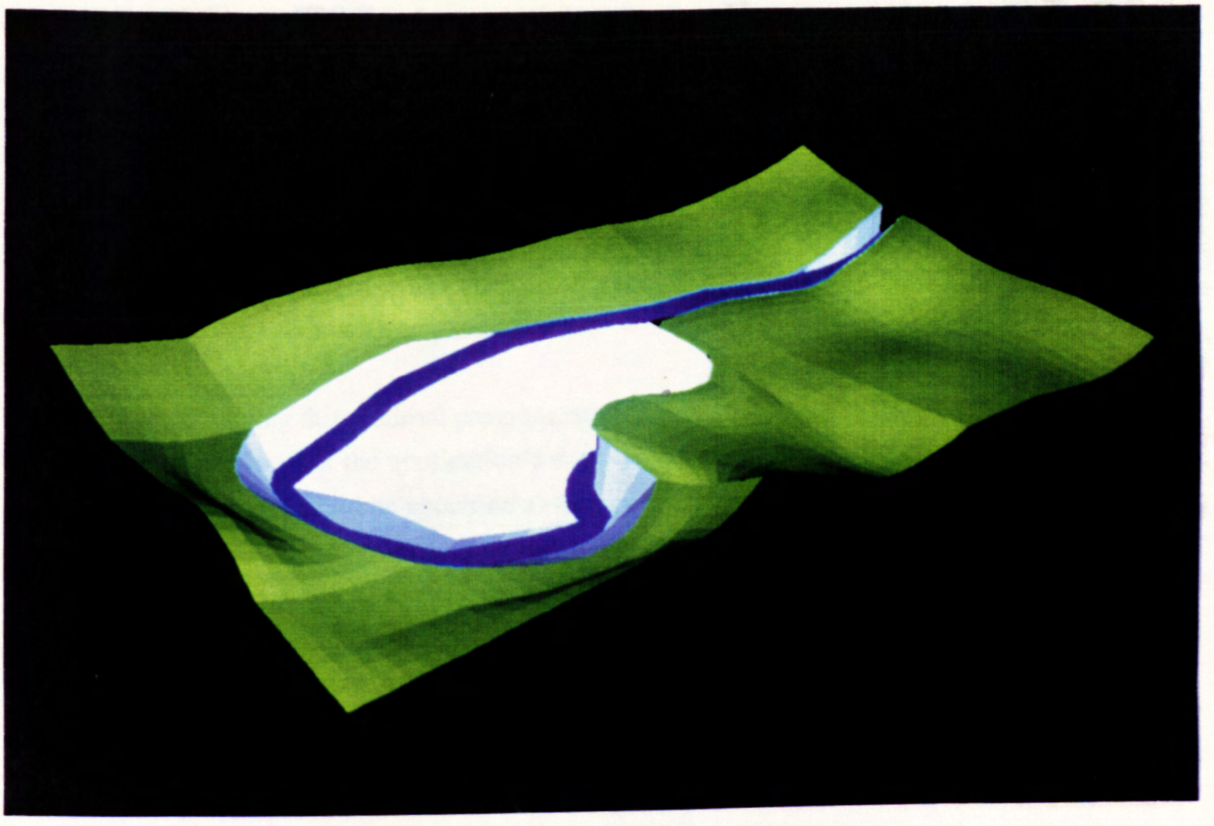


Figure 4.11 A Rendered Pit Design

4.6 Linking to a Database

Xi Plus provides high level interface programs which allow large programs, and most software products, to be called directly from the knowledge base. It is possible to roll out some or all of the Xi Plus system to disk to make space for a called program to reside in memory. Once the called program has completed execution, control returns to the Xi Plus knowledge base. There are two different interface programs which run high level external programs :

- **Load Program :** will load the called program into memory alongside Xi Plus and pass control to the called program. Once the called program has completed execution, it will return control to the calling knowledge base. This is the fastest method of calling another software program but it requires the called program to be small enough to fit into the available memory together with Xi Plus and the current application.

- **Roll Program** : performs the same function as Load Program. It rolls out some or all of the Xi Plus system to disk to make space for the called program to reside in memory. This is useful for programs that are too large to run together with Xi Plus in memory, such as AutoCad and DbaseIV. It requires available disk space to hold the rolled out program and a small time delay to perform the disk operations. Once the called program has completed execution, control is returned to the calling knowledge base.

Before running this external program, an interface (for example Dbase access) must be pre-defined within the application's external interfaces library. Within this definition, Roll Program should be specified as the required language interface, to provide space for DbaseIV to reside in memory. The interface used is a general purpose interface, which means it has no understanding of the program it calls and is therefore unable to pass back any results or values. The results from the database are therefore transferred to a text file, where they are read using the CDF data file interface.

4.6.1 Use of DbaseIV

If all the data can be stored internally within the MINDER system, why use a commercial database ? The database is not used for storing expert system knowledge, it is mainly used for storing long lists of manufacturer's data and specifications. Such information can be obtained from text books and manufacturers information. The database acts a source of information for the expert system consultation. Most prototype expert systems applications are restricted to limited amounts of data and have no facility for sophisticated data management, by integrating an expert system with a database a realistic data management system can be achieved (Renhak and Howard 1985 and Schofield and Denby 1990).

A large quantity of information is needed to select an optimum item of equipment which suits the design constraints of a particular mine. The task for the planner is to match design information from a geological model and site investigations, with known equipment specifications. During the conceptualisation of the MINDER system it was decided to store the excavating and haulage equipment data in a commercially available database. DbaseIV, developed by Ashton-Tate was chosen since it is an extensively used, large capacity, database capable of being controlled by a macro language. Four large database structures pertaining to this problem domain have been developed :

- **A materials database** : containing a wide range of rock types, densities, swell factors and compressive strengths.

- **A truck database** : containing information on truck sizes, weights, payloads and other relevant information.

- **A dragline database** : containing information on bucket sizes, operating radii, clearance and other relevant information.

- **A hydraulic excavator database** : created as a multi-level database, the structure of which is shown in figure 4.12. This database division is due to the structure of the data, i.e. hydraulic excavators can be split into frontend and backhoes. The hierarchical structure is also useful when performing relational operations. Each DbaseIV file contains tagged fields which link the files together, for example in figure 4.12, the field MODEL is used to link the hydraulic excavator file with the frontend data file.

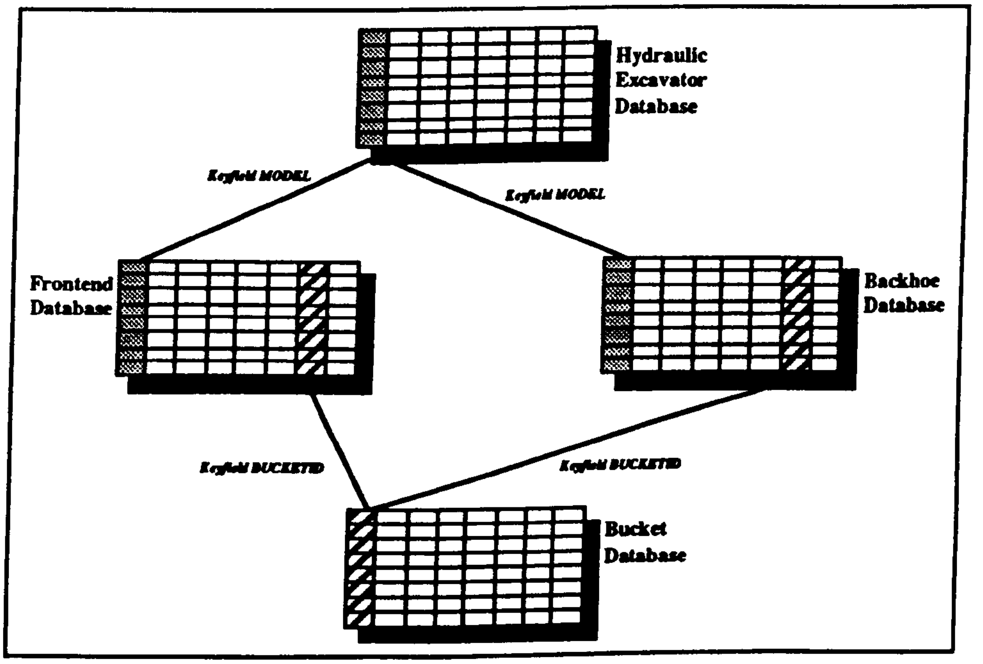


Figure 4.12 Hydraulic Excavator Database Structure

Xi Plus can link very easily into these DbaseIV databases and the interface between the expert system and the database is used to perform the following operations :

- To extract information from DbaseIV databases.
- To sort or rank records in a database to provide the record with the highest (or lowest) value in a particular field.
- To eliminate values in a particular database using a relational operation : for example deleting all records with height > 20 m.

The user of the system should not be required to perform any programming in order for the appropriate database actions to occur. The Xi Plus expert system accesses the DbaseIV databases by creating program files, which are of a text format. The advantage of this method of control is that all program files once created and used can be deleted, remaining totally invisible to the user who may not even realise that an external program has been accessed. From a programming point of view, all corrections and changes to Dbase and Xi Plus can be done in the same Xi Plus editor.

4.6.2 Controlling DbaseIV

The DbaseIV software is controlled from the expert system using macros, these enable complex tasks to be carried out by the database running under the control of these programs. The expert system creates DbaseIV program files, which are of a text format and incorporate variables relevant to the particular scenario. Figure 4.13 shows a simple representation of the MINDER system controlling a Dbase operation.

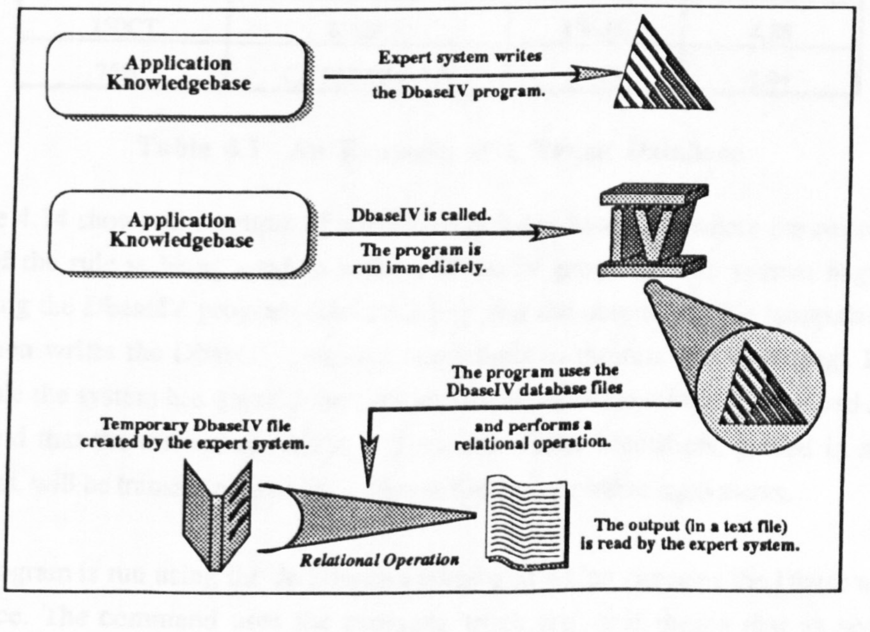


Figure 4.13 Simple DbaseIV Relational Operation

The writing of the program to the text file is integrated into the knowledge base rules and fired during the normal chaining process of the inference engine. A major factor in any of these operations is the transfer of information for the relational operation, from Xi Plus into a DbaseIV program. The Xi Plus 'report to file' facility allows any program lines to be sent to a text file as an ASCII text string, whilst automatic substitution of identifier values enables expert system variables to be included. With repeated reporting, successive lines can be built up to produce a complete program file. The identifier values, now in a DbaseIV macro, are then used in subsequent information retrieval or relational operations.

4.6.3 DbaseIV Example

In a simple example of a truck database the database will consist of only four fields : Truck Model, Manufacturer, Payload and Height and seven records. This database is shown below in table 4.1. The actual MINDER truck database has seventeen fields and over 150 trucks.

MODEL	MANUFACTURER	PAYLOAD	HEIGHT
R-170	EUCLID	257.41	5.69
33-03b	TEREX	19.96	3.58
D400	CATERPILLAR	36.29	3.45
785	CATERPILLAR	115.94	5.57
HD325-2	KOMATSU	32.00	4.05
150CT	WABCO	136.08	4.88
769C	CATERPILLAR	31.75	3.94

Table 4.1 An Example of a Truck Database

Figure 4.14 shows an example of a truck knowledge base rule, where the consequent part of the rule is being used to write a DbaseIV program. The system begins by resetting the DbaseIV program file 'truck.prg' and the output text file 'temp.dat'. The rule then writes the DbaseIV program commands to the text file 'truck.prg'. In this example the system has queried the user and knows that the minimum payload is 100 tons and that the maximum height is 5 meters. These identifiers, placed in square brackets, will be transferred into the program file as their value equivalents.

The program is run using the do program command which executes the Dbase access interface. The command uses the program 'truck.prg', this means that as soon as DbaseIV is called this program is executed.

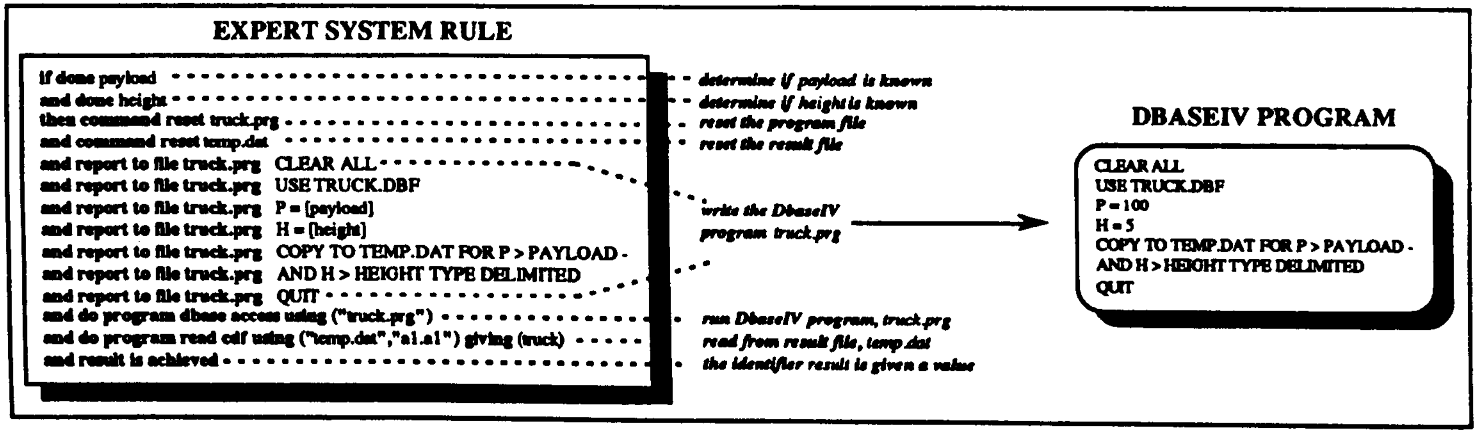


Figure 4.14 Truck Example : Expert System Rule

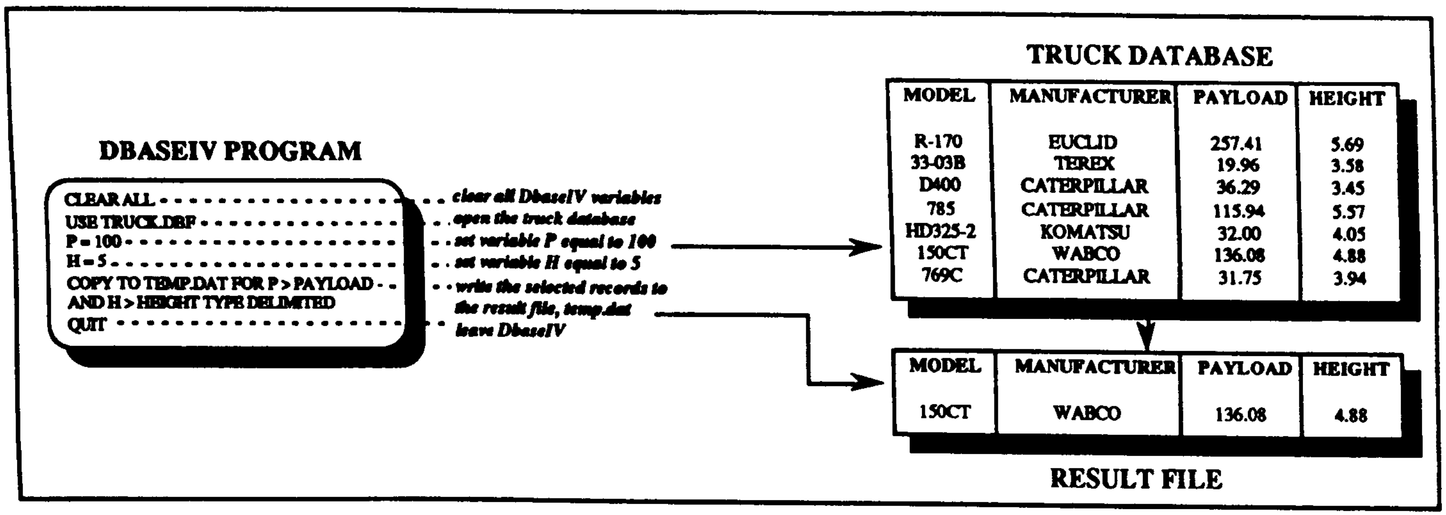


Figure 4.15 Truck Example : DbaseIV Program

The diagram in figure 4.14 showed the DbaseIV program being written to the program file. Figure 4.15 shows the running of this DbaseIV macro. The program first clears all variables and references the database to be used, which in this case is the truck database. The program then sets the variable P = 100, and the variable H = 5, these values were transferred from the expert system. A relational operation is then performed and the items of equipment which suit these Dbase conditions are transferred to the result file 'temp.dat'. Control then quits the external application and returns to the expert system to continue the consultation.

The read cdf interface reads the result from the text file and places the value read from the first location into the identifier 'truck'. In this simple example, the only truck with a payload of over 100 tons and a height below five metres is the Wabco 150CT.

4.7 Linking to Simulation Software

Computer simulation is widely used as a decision-making tool in business and industry. One definition of simulation is the construction of a mathematical model of a physical system (Minuteman Software 1988). The basic requirement for this model is that it should 'behave' like the physical system it is supposed to be modelling. For example, it is proposed to upgrade an item of production equipment, such changes involve considerable expenditure and the advantage of the mathematical model is to estimate in advance the effect these changes will have. The only expense involved is that of building and running the simulation model. Due to the speed of the computer simulation, it is feasible to study a variety of proposed options in turn and identify the configuration for optimum performance of the system (Strugul 1988). In the mining industry simulation software is often used for the basic queueing model of a single server (or excavator), large population (number of trucks) and random service (variable loading time).

To perform a discrete-event simulation on a computer a program must describe the sequence of events that occur, incorporating time assumptions and all possible options. Several programming languages have been invented specifically for writing simulation programs. Of these, GPSS (General Purpose Simulation System) is the most widely used for discrete-event simulation (O'Donovan 1979). GPSS is a powerful, non-procedural, language capable of simulating complex systems using relatively short programs.

The MINDER system uses GPSS in a manner similar to DbaseIV, programs are written to text files, when run, GPSS automatically calls these program files. The user needs no knowledge of simulation software and is not required to perform any programming in order for the appropriate model to be used. The simulation model is created using values passed from the expert system consultation into the program text file.

Knowledge base rules, fired during the normal chaining process of the inference engine, control the reporting of lines of text to the program files in a similar way to DbaseIV macro creation. The simulation model is created using values passed from the expert system consultation into the text file. These identifier values are then used as variables in subsequent simulation operations. Figure 4.16 shows how GPSS runs the program to simulate the operations and produces a results file, a second piece of software GPSS - REPT formats the results to allow them to be read back into the expert system.

4.8 Handling Uncertainty

The proper handling of uncertainty has a radical impact upon the ultimate reliability of an expert system. The techniques of dealing with uncertainty have been discussed in Chapter 3. The certainty factor method can be included directly within the rule structure of a knowledge base. In the MINDER knowledge bases certainty factors are only used, in conjunction with linguistic concepts of certainty, in the dragline module to suggest values for pit width and dig out length. The way the certainty factors are applied to these calculations will be discussed in the next chapter.

As the MINDER system uses uncertain information and forms inferences based upon missing data an internal software counter is to determine the overall uncertainty on which any equipment decision is based. This statistic is reported to the user at the end of a consultation with the MINDER system in the form shown in figure 4.17.

Fuzzy set logic often needs extensive matrix algebra. The fuzzy set algebra is performed by external software which is linked to and controlled by the expert system. Almost every equipment decision made within the MINDER system relies, to some extent upon one, or more, fuzzy logic rankings. A set of fuzzy logic Pascal software was written in the Department of Mining Engineering at Nottingham University by Clarke (1990). This software adapts the basic fuzzy logic techniques to manipulate imprecise and fuzzy information, enabling complex problems to be analysed.

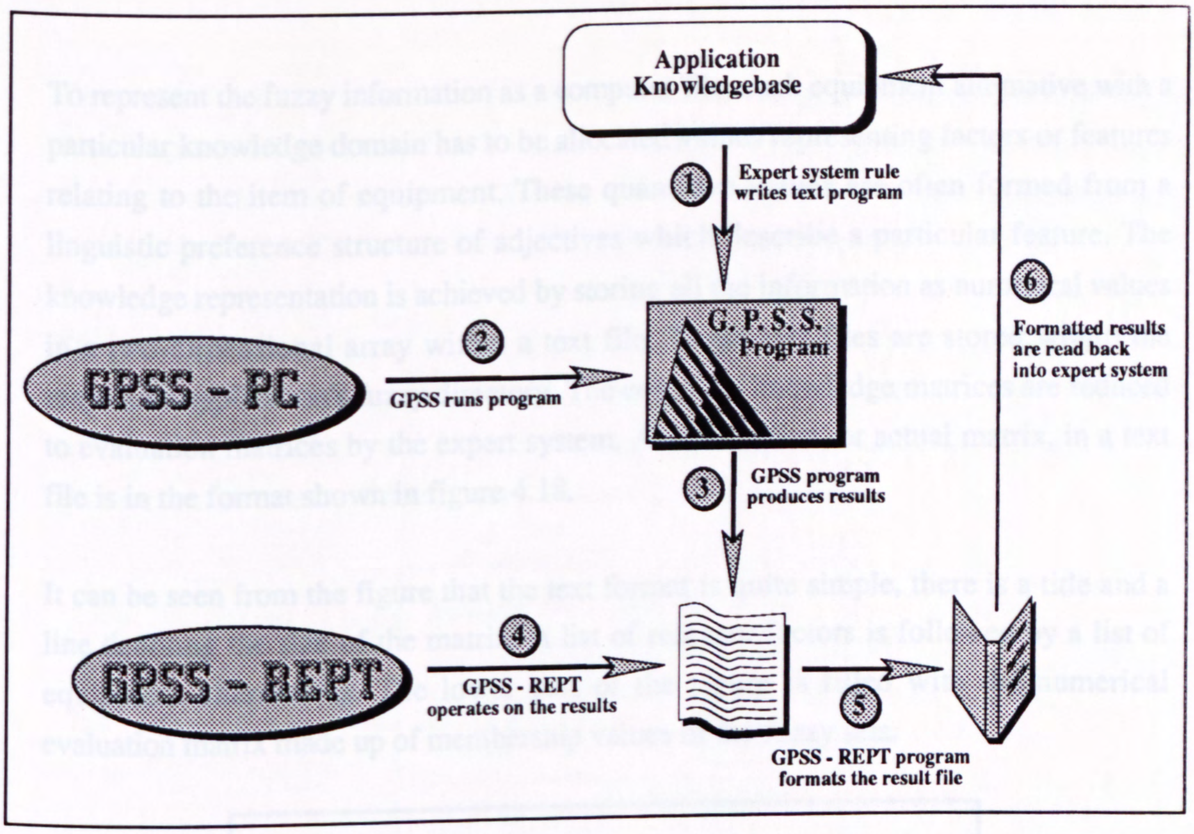


Figure 4.16 An Example of a GPSS Operation

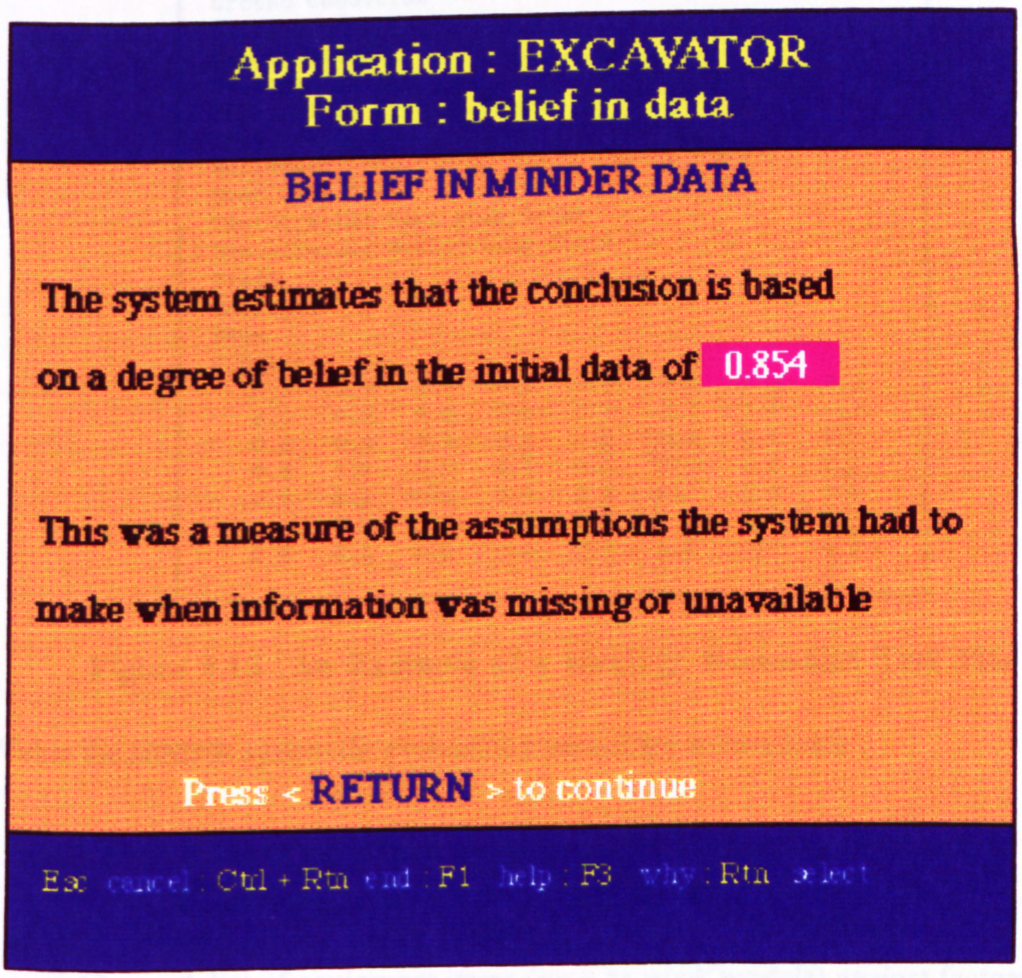


Figure 4.17 Reporting Belief in Data to the User

To represent the fuzzy information as a computer file, each equipment alternative with a particular knowledge domain has to be allocated values representing factors or features relating to the item of equipment. These quantitive values are often formed from a linguistic preference structure of adjectives which describe a particular feature. The knowledge representation is achieved by storing all the information as numerical values in a two-dimensional array within a text file. These text files are stored within the respective application's fuzzy directory. The complete knowledge matrices are reduced to evaluation matrices by the expert system. An evaluation, or actual matrix, in a text file is in the format shown in figure 4.18.

It can be seen from the figure that the text format is quite simple, there is a title and a line denoting the size of the matrix. A list of relevant factors is followed by a list of equipment alternatives. The lower part of the figure is filled with the numerical evaluation matrix made up of membership values of the fuzzy sets.

```
Haulage Actual Matrix
             7              8
Material Size
Ground Condition
Daily Production
Length of Haul
Maximum Adverse Grade
Flexibility of Conditions
Total Tonnage
Bulldozer
Rear Dump Truck
Semi-trailer Rear Dump Truck
Semi-trailer Bottom Dump Truck
Train
Conveyor
Skip
Pipeline
   0.8   0.8   0.8   0.6   0.8   0.4   0.8   0.0
   0.0   0.8   0.8   0.8   0.0   0.4   0.2   0.2
   0.8   0.8   0.8   0.8   0.8   0.8   0.8   0.2
   0.8   0.8   0.0   0.0   0.0   0.8   0.6   0.2
   0.8   0.8   0.8   0.0   0.8   0.2   0.8   0.0
   0.0   0.8   0.8   0.8   0.0   0.2   0.2   0.2
   0.8   0.8   0.8   0.8   0.8   0.8   0.8   0.2
```

Figure 4.18 An Example of a Haulage Evaluation Text File

Within the MINDER system the evaluation matrices are in two forms :

- A list of equipment alternatives (such as haulage type) against factors based upon expert opinions (such as overburden depth).

- A list of equipment items (such as truck models) against factors based on manufacturers specifications (such as bucket size).

To create the actual evaluation matrix from a knowledge matrix, or database file, a transfer process may be needed. This usually takes the form of Pascal file manipulation software called from the MINDER system. This reads the relevant information and reports this data, in the correct format, into an actual matrix text file.

The ideal matrix is a fixed model of actual or preferred data. For example, the ideal matrix for the haulage selection evaluation matrix in figure 4.18 would represent the actual mining conditions to be encountered with the appropriate ratings for each factor. An example of a haulage ideal matrix is shown in figure 4.19.

```
Haulage Ideal Matrix
        7              1
Material Size
Ground Condition
Daily Production
Length of Haul
Maximum Adverse Grade
Flexibility of Conditions
Total Tonnage
Ideal
   0.8
   1.0
   0.8
   0.6
   0.6
   1.0
   0.8
```

Figure 4.19 An Example of a Haulage Ideal Text File

A feature of the fuzzy algorithms presented in Chapter 3 is that they do not consider the relative importance of the factors being considered, each factor is considered of equal importance. In an attempt to place more emphasis during the evaluation on those factors believed to be of greater importance the evaluation matrix is weighted (Alley et al 1979). This involves the construction of a weight vector for each evaluation matrix, each factor within the matrix is assigned an exponent which is the corresponding weight. The evaluation matrix is combined with the weight vectors to form a weighted evaluation matrix using a matrix multiplication procedure.

For each MINDER fuzzy logic decision three independent weighting matrices are used, these allow the user a broader spectrum of results on which to base a decision. For example, when selecting a dragline from an evaluation matrix of available models the user is presented with three dragline rankings :

- Based on an equal weighting.
- Based on weighted operating radius and bucket size.
- Based on a weighted MUF (maximum usefulness factor).

The weight matrices are each contained in an individual text file similar to that of the ideal matrices, an example is shown in figure 4.20.

```
Haulage Weighting Matrix
          7                  1
Material Size
Ground Condition
Daily Production
Length of Haul
Maximum Adverse Grade
Flexibility of Conditions
Total Tonnage
Weighting
   2.0
   1.0
   1.0
   2.0
   1.0
   1.0
   1.0
```

Figure 4.20 An Example of a Haulage Weighting Text File

4.8.1 Fuzzy Logic Pascal Software

The fuzzy logic software within the Department of Mining Engineering was designed as part of the Strip Mine Modelling System (SMMS) (Clarke 1990). This system was designed to advise on dragline use in a strip mining operation.

The fuzzy logic software consisted of one large Pascal program designed to procedurally perform matrix algebra, including :

- Dominance ranking of alternatives.
- Similarity ranking of alternatives.
- Aggregation of evaluation matrices.
- Weighting of evaluation matrices.

For integration into the MINDER system this program was rewritten to act as a unit of procedures to a controlling Pascal program. Each application module has it's own variation of the control program calling the appropriate matrices from the apropos text files, and performing pertinent actions to achieve a required ranking.

The program is compiled to disk, in the Pascal directory of the application, and called from an expert system rule using the 'roll program' external interface. An example of the use of this software is shown in figure 4.21, the process shown in the figure is usually iterated three times, once for each weighting to give three independent rankings.

4.9 Intelligent User Interface

An expert system intelligent front end performs many functions, one of the most important being the simplification of the user interface. The expert system can ensure that as much information as possible is taken from external software. In controlling the external software, the expert system may be required to write programs in the language of the application software. This would enable the computer package to execute in a set order, ensuring that the results are reported to the correct data files. Given certain data and a selection of rules the inference engine would be able to deduce certain other information to minimise user input (Ahmad et al 1985).

Any interaction between the computer and the user should be in the form of questions with suggested answers. The use of mouse driven 'pop-up' menus on most modern application programs has led to a more widespread use of mining software, overcoming the keyboard shyness of certain professional engineers. An intelligent interface should ideally utilise as many user friendly options as possible.

Psychological barriers to the acceptance of expert systems are high. In this context it should be remembered that one of the most important parts of a mine design expert system is it's explanation facility. Often the conclusions reached are not as important as the reasons for the conclusion, and any expert system must be able not only to advise, but to give full explanations for any advice it may give (Schofield and Denby 1989).

One of the concepts introduced by the classic expert systems such as MYCIN and Prospector is the idea that a decision support system should be able to justify it's conclusions on request. Obviously when profit-and-loss decisions are being made with the help of a computer it is essential for the system to explain it's own reasoning.

The MINDER system utilises the Xi Plus 'form' facility to provide a menu driven user interface, an on line help facility and full explanations. A form is defined as a formatted screen display that can contain questions and reports, and provide full control over the screen layout and colours used (Expertech 1988). In particular, a form may contain multiple questions, to provide a more efficient way of entering data than a single item per screen. Form definitions are held in the application form library.

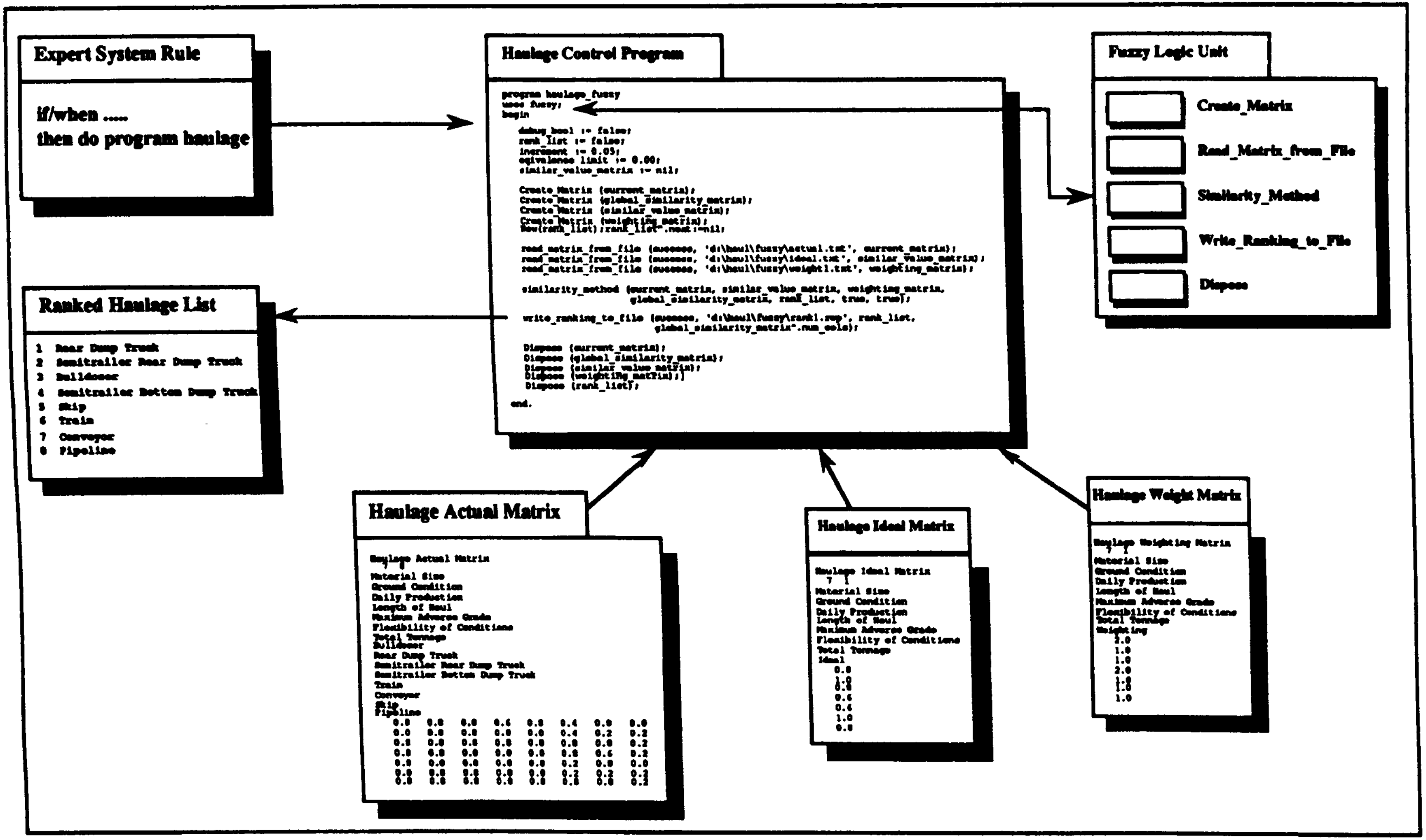


Figure 4.21 Use of Pascal Fuzzy Logic Software

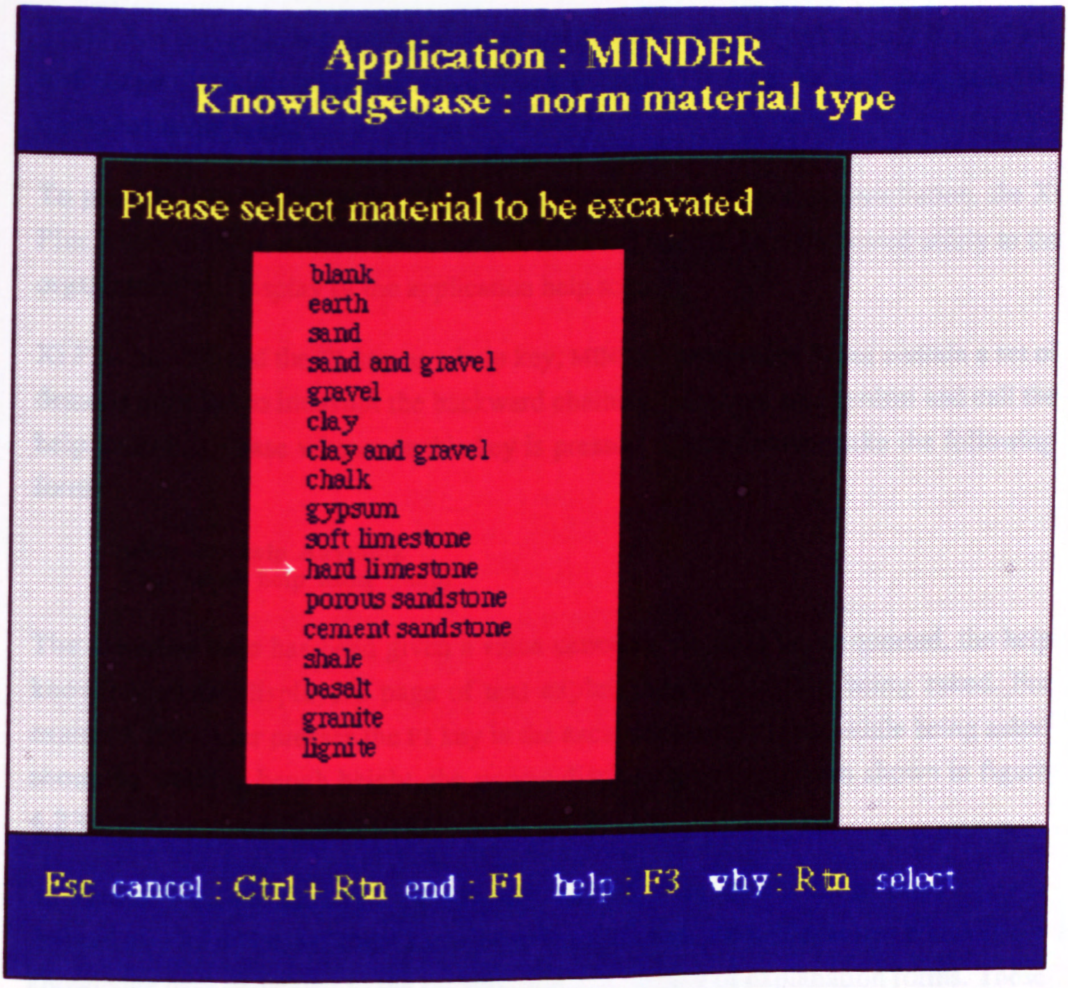


Figure 4.22 The Excavation Material Question Form

A form has a background, on which text is entered using text editing facilities. Fields are defined within the form, these are used to hold text input, user question menus, current values of identifiers and text report output from the knowledge base. Many fields may be included in any form, provided they don't overlap. Each form and field has an associated set of parameters, these are known as attributes and control how the form and its contents are displayed and used.

A form can be automatically displayed during a typical backward chaining consultation if it contains an identifier whose value is required and that form is marked to be used in the chaining process. An example of a form asking for excavation material is shown in figure 4.22. The arrow scrolls of the bottom of the field to reveal a continuing list of excavation material options.

These Xi Plus forms are generated using ASCII characters and can include text, blocks and simple lines. Simple diagrams can be constructed to help the user understand the questions being asked.

To provide help information to the user during the progress of a consultation, the Xi Plus help facility is utilised. Each module has a knowledge base dedicated solely to the organisation and display of the application help screens.

Xi Plus has defined the F1 key as a help key, MINDER knowledge bases contain a set of demons intended to interrupt the backward chaining inference mechanism and call the help knowledge base whenever this key is pressed. These demons take the following form :

```
when key help Anything
then do kb help using (help)
```

The identifier **help** has been given a value denoting the form being queried, the help knowledge base displays a page of text explaining the question being asked. For example, if the user presses the F1 key in the excavation application, while being asked about the working bench height, the system displays the screen form shown in figure 4.23.

Xi Plus defines the F3 key as a why key, in much the same way as the F1 key is defined as a help key. MINDER knowledge bases contain a set of demons which call a knowledge base dedicated to the organisation and display of explanation forms. These demons take the following form :

```
when key why Anything
then do kb why using (why)
```

The identifier **why**, similar to a help value, denotes the form being queried. The why knowledge base is used to link the current form to the overall consultation and explain the reason for the question. For example, if the user presses the F3 key in the excavation application, while being asked for the working bench height the system displays the screen form shown in figure 4.24.

The integrated use of demons, dedicated knowledge base rules and forms within MINDER provide the user with a comprehensive explanatory interface. This interface allows the user to interrogate the system, by posing 'help' and 'why' questions. Help questions ask the system to explain the question (What do you mean by that ?). Why questions ask it to explain why it requires some piece of information (Why are you asking me that ?). Both facilities help make the system more usable but human-machine interaction is still one of the weakest links in expert systems technology.

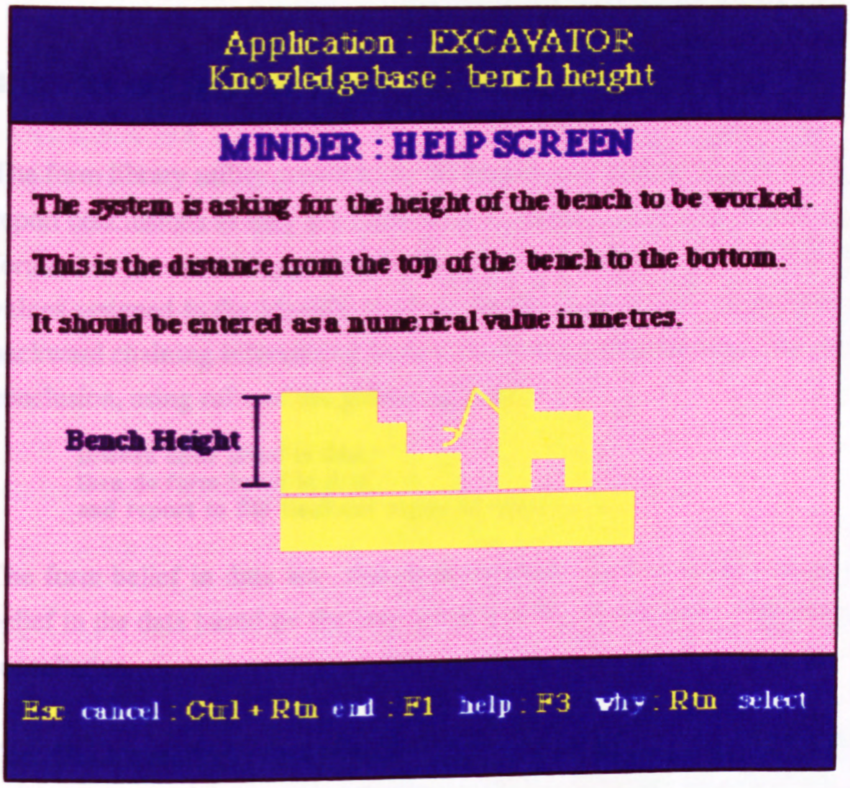


Figure 4.23 The Bench Height Help Form

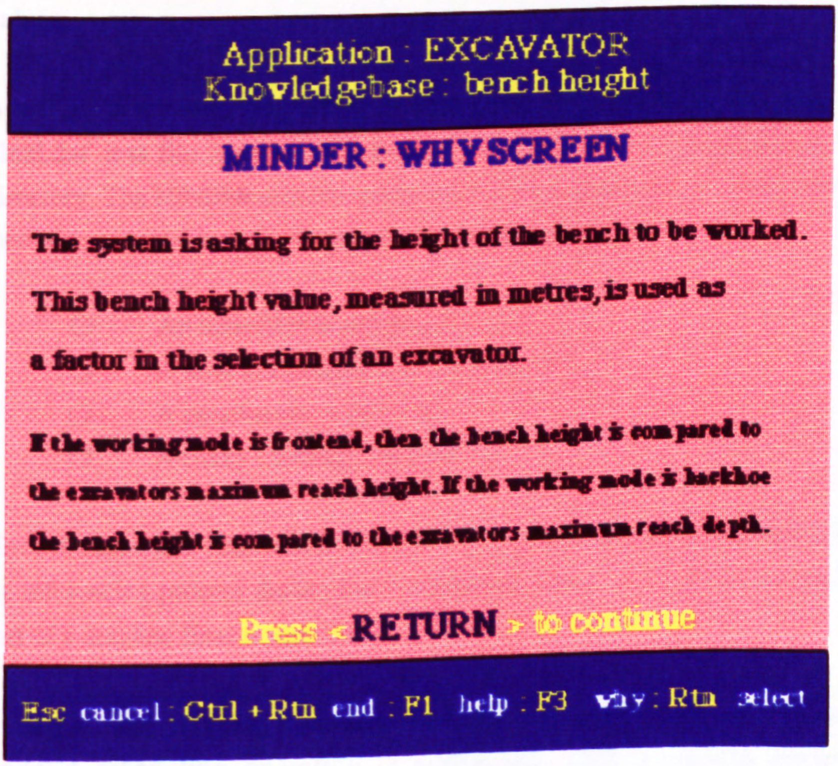


Figure 4.24 The Bench Height Why Form

4.10 Reporting of Results

The form library utility provided by Xi Plus is also used within the MINDER system to report conclusions as they are inferred. These forms are similar to the user questioning forms, but the menu input fields are replaced with text output fields displaying the values assigned to the identifiers. These forms are not displayed as part of the normal backward chaining inferencing process, they are displayed when the system reaches a conclusion, using rules of the following form :

if/when done belief in data
then do form belief in data
and report to file final.dat degree of belief

The form belief in data was shown in figure 4.17. This form reports the degree of belief in the data based on the amount of missing or uncertain information during the consultation.

Text files are routinely used in both expert systems and algorithmic applications, often for the storage of temporary information. This facility is often used by the MINDER system to store consultation information. At the end of a consultation, the cerebral file can be accessed to give a list of identifiers used in the consultation and their assigned values.

A text file result reporting facility has also been installed within the MINDER system. A 'final.dat' text file is created during a consultation in the application module's data directory. The MINDER system resets this file at the beginning of any consultation, and then reports to the text file when any of the following events occur.

- An identifier is assigned a value.
- A new knowledge base is accessed.
- A conclusion is inferred.
- A fuzzy ranking is produced.

Since the final text file results are reported in order, this gives a realistic impression of the inferencing process during the consultation. Figure 4.25 shows a simple example of part of a dragline final report file.

During a mine planning operation, after the equipment selection decision has been made, a scheduling operation is performed. This is usually undertaken using spreadsheet software, such as Excel or Lotus 1-2-3. In an attempt to bridge the gap between these disparate elements of a mine planning project, the results of a MINDER consultation are reported to Excel, a commercially available spreadsheet. The information is presented in a time based worksheet format allowing a rapid and accurate assessment of the equipment performance to be obtained.

Linkage to Excel is achieved using a combination of expert system knowledge bases and Pascal software. The expert system gathers and organises the necessary information from the various application modules accessed during the consultation. The Pascal program then performs numerical and string handling procedures to arrange the data into a spreadsheet compatible file with the spreadsheet.

```
          Dragline Selection And Advice System
          -------- --------- --- ------ ------

                    Damian Schofield 1991

Dragline Selection System

  Knowledge Base : Dragline Bucket Size


          Sub-Knowledge Base : Volume Per Hour


          Yearly volume = 1510000
          Volume per week = 30804
          Volume per day = 6160.9

          The required volume per hour = 616.1 m3



 Sub Knowledge Base : Fuzzy Operations

 Results of Fuzzy Operations on Dragline Database
 ------------------------------------------------


 Equal                Operating Radius and              MUF
 Weighting            and Bucket Size Weighted          Weighted


 1. be 1260 W              1. be 1260 W              1. be 1300 W
 2. be 1300 W              2. be 1300 W              2. be 1260 W
 3. be 1370 W              3. be 1370 W              3. be 1370 W
 4. be 680 W               4. be 2750 W              4. be 680 W
 5. be 1380 W              5. be 680 W               5. be 1380 W


The dragline selected is model be 1260 W
```

Figure 4.25 A Final Report File

Spreadsheet of Tonnages for Layer 1

Block	Excavator	Model	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Month 9	Month 10
1	Dragline	be 1370 W	183278	183278	33444							
2	Dragline	be 1370 W			149834	183278	66888					
3	Dragline	be 1370 W					116390	183278	100332			
4	Dragline	be 1260 W							52604	147396		
5	Dragline	be 1260 W								5540	152936	41524

Figure 4.26 An Example of a Scheduling Worksheet

An example of a scheduling worksheet is shown in figure 4.26, which illustrates a schedule for the extraction of three blocks of 400,000 tonnes and two blocks of 200,000 tonnes. Two draglines have been selected, the 'be 1370 W' dragline is capable of extracting 183,278 tonnes per month under the given conditions. The 'be 1260 W' can remove 152,936 tonnes per month.

An advantage of using spreadsheets to display scheduling results is the ability to produce a range of graphical representations of the information. Figure 4.27 shows a chart of monthly production against time. This illustrates the drop in production in month seven due to the use of the smaller dragline.

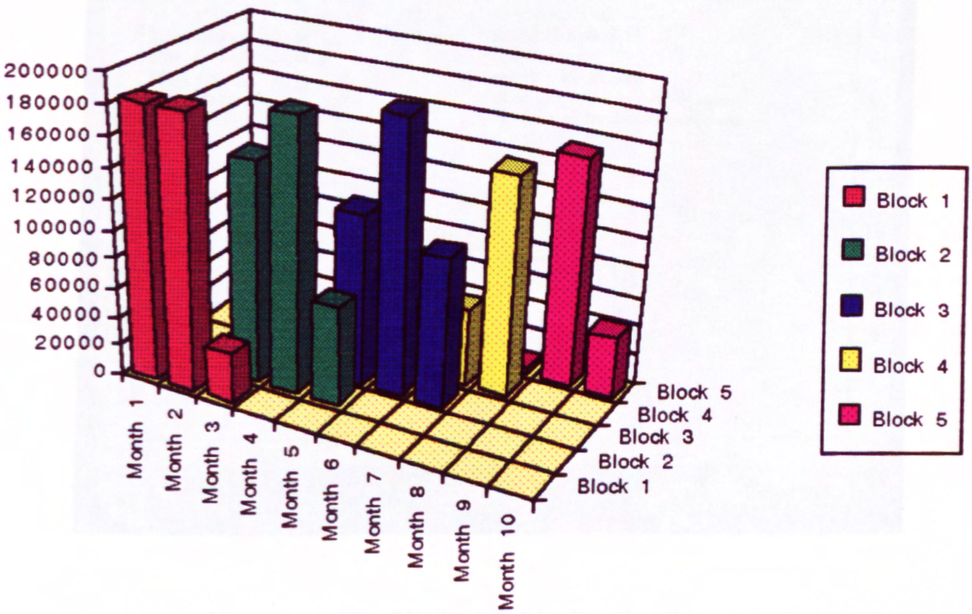


Figure 4.27 An Example of a Scheduling Graph

4.11 Induction Systems Development

Knowledge acquisition has been performed using induction techniques as a parallel operation to the development of the MINDER system. The equipment selection rules have been induced using Xi Rule, an aid to building knowledge bases for use with Xi Plus. It allows the user to define a set of examples of correct decision making, and then converts these into rules. These rules can then be exported directly into Xi Plus and used as the basis for an Xi Plus knowledge base. Xi Rule uses the ID3 induction algorithm, the workings of which have already been discussed in Chapter 3. The Xi Rule software can be split into four main sections :

- **Tasks :** The loading and saving of Xi Rule applications.
- **Attributes :** Defining the variables, used in the application.
- **Examples :** The training set of data from which the system leans.
- **Rules :** Controls the generation of a decision tree.

To generate rules for an equipment selection decision a new task was created and given a title and description, the system attributes and examples were defined and then a decision tree was created.

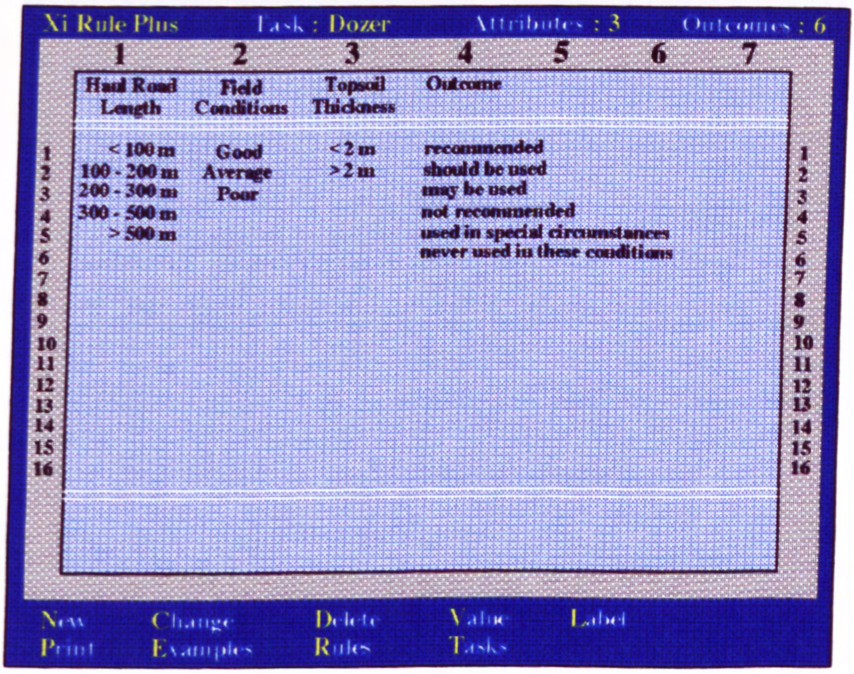


Figure 4.28 Xi Rule Attributes Screen

Within Xi Rule a series of columns are created, each defining an attribute to be used in the induction. These attribute are then assigned their possible values, a simple example of a set of attributes needed for a topsoil equipment decision is shown in figure 4.28. The outcome defines whether or not a dozer should be used to remove the topsoil. A preference structure has been set up defining the possible values of the outcome.

Once the attributes have been defined a training set of data is created using the examples screen. These examples can be either typed into the system or imported from a text file. To replicate the MINDER decisions large text files of equipment selection criteria with target goals were created and imported into the system.

A complete examples screen for the simple dozer example is shown in figure 29. It should be noted that the complete training set of data scrolls of the bottom of the screen. As the examples are entered the system checks each value and informs the user of any unidentified values.

When a set of training data is present the rules can be induced using the rules facility. As the induction procedure is started any rules currently in the memory are lost.

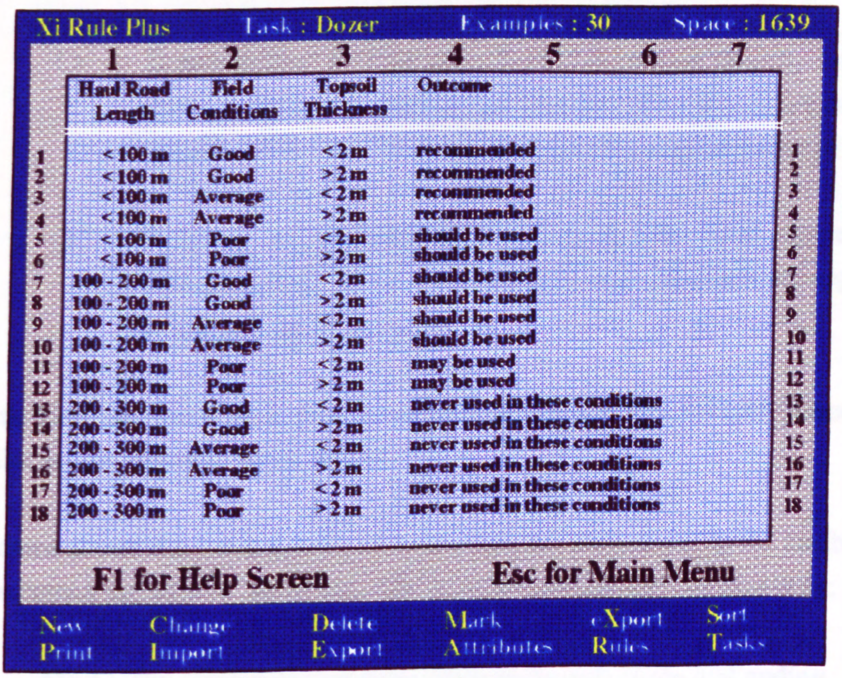


Figure 4.29 Xi Rule Examples Screen

A range of different induction methods can be selected.

- **Automatic :** Automatic induction is the simplest form. Induction starts immediately and displays a counter as it proceeds.

- **Manual :** Xi Rule informs the user of the most discriminatory variable, and displays its 'entropy' value. The user may use this value or select a preferred attribute for this branch. This process is repeated at each branch until the induction is completed, or the user selects Automatic. This enables the user to have manual control over the order in which the attributes are branched on, which may be desirable for certain tasks.

- **Semi-Auto :** Semi-automatic induction allows the user to specify three main aspects of the way you want the induction to proceed, and includes an element of manual induction. Xi Plus specifies the following three attributes:

    - **Starting Attributes** : Used to override the Xi Rule choice of best attributes.

    - **Consecutive Attributes** : If one of these attributes is used then a consecutive attribute must be used first. For example the system will ask for sex before asking if the user is pregnant.

    - **Priority of Attributes** : If two entities have identical 'entropy' values, Xi Rule will take the order the attributes appear on the Attributes screen.

An automatic induction carried out upon the examples shown in figure 4.29 produces a screen similar to that shown in figure 4.30.

The rules screen shows the induced rules in a 'decision tree' format, using the attribute headings, outcomes and values. Associated with each leaf ending are two numbers :

- **First :** The number of examples filtering through to the leaf ending.
- **Second :** The probability of an outcome being correct.

There are also two additional outcome values the Xi Rule can display :

- **Clash :** Indicates that the current examples produce a clash when the decision tree is followed to this point.
- **Empty :** Indicates that the outcome value is not defined by the examples.

The decision tree shown in the rules screen can be exported to an Ascii (text) file in the form of rules. These rules can be read into an Xi Plus knowledge base using the load facility from the toolkit. Only one parameter needs to be entered, this is the name of the export file to contain the exported rules. Xi Rule checks if the file specification is valid before proceeding.

Once in Xi Plus a control structure, such as queries, definitions and forms may need to be added before the raw knowledge may be consulted to yield practical results.

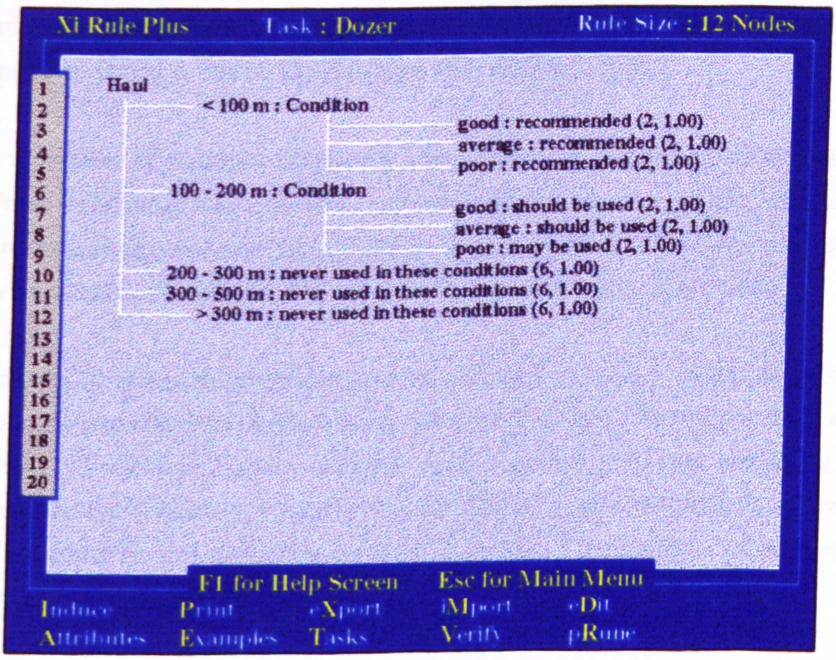


Figure 4.30 Xi Rule Rules Screen

4.12 Neural Network Development

A neural network differs from an expert system in that is not programmed in the conventional sense but is taught to give acceptable answers to sets of input parameters. Known information is entered, weighted values are assigned to the connections, within the architecture, in order to give the required output. The network is then repeatedly run until the output is satisfactorily accurate. The weighted matrix of interconnections allows the networks to learn and remember. As a result, when new information that is not stored in the network is entered they can still provide adequate responses. Among the variety of available learning algorithms discussed in Chapter 3, among the most popular are the back and counter-propagation algorithms. These are examples of supervised learning methods, where the network is exposed to the data with corresponding outputs and attempts to self-organise.

IBM PC/PS 2's, compatibles and personal workstations play very important parts in the neural network world. Simulations can be run on them, and new software allows neural networks to be developed on them (Australian Personal Computer 1989). Neural networks are being used and produced in the form of either 'neurocomputers' (hardware that models the parallelism of neurons), or 'netware' (software that emulates neurons and their interconnections on conventional serial computers). An important aspect of netware is that it can be simulated on conventional computers.

There are a number of vendors offering a wide variety of neural network products, ranging from relatively inexpensive software tools for developing one's own applications to turnkey systems for specialist applications. Accordingly prices vary from a few hundred to a few thousand pounds (Chemical Engineering 1990).

The Advanced Computer Research Group has invested in Neural Works Explorer, a piece of training and development software which enables the development of small applications. This software comes complete with InstaNet a facility for generating standard network types from an extensive library. Future neural network development will take place using Neural Works Professional II, a full-fledged network development tool (NeuralWare Inc. 1990).

InstaNet allows the user to load a standard network type and specify it's attributes to suit a given purpose. The number of layers are specified along with the number of processing elements in each layer. A set of experimental neural networks have been created using the Neural Works Explorer software to replicate certain equipment decisions made by the MINDER system. Back-propagation and counter-propagation networks have been created, but the counter-propagation networks were found to have the best pattern classifying characteristics for simulating expert system decision making.

4.12.1 Creating a Counter-Propagation Network

InstaNet is selected from the main menu which produces a dialog box, similar to that shown in figure 4.31. A standard network architecture is then selected, for example in the case of a top level topsoil equipment decision a counter-propagation network was defined, based on three input parameters, and making a choice between nine types of equipment. The middle hidden layer was defined with sixteen processing elements.

Neural Works Explorer then created the counter-propagation network shown in figure 4.32, this network contains randomly initialised internal weightings, which means it is untrained. It should be noted that the software adds a normalising layer to the network.

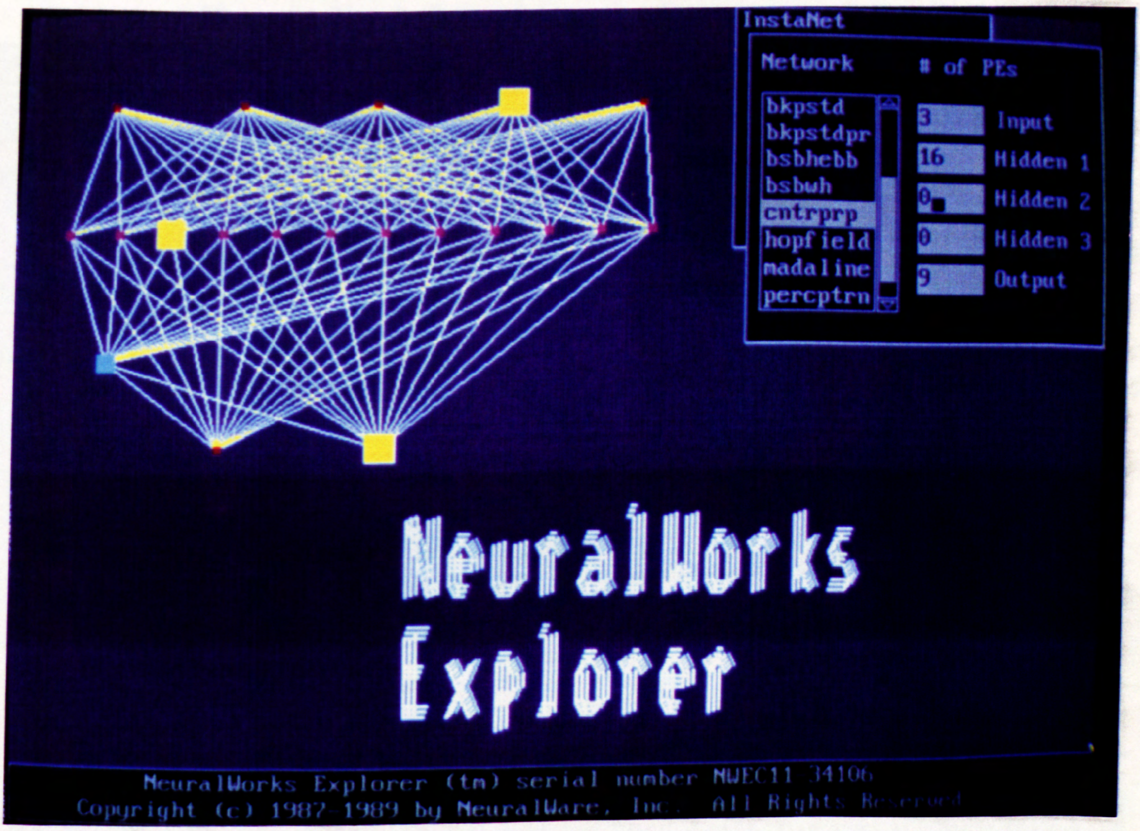


Figure 4.31 InstaNet Dialog Box

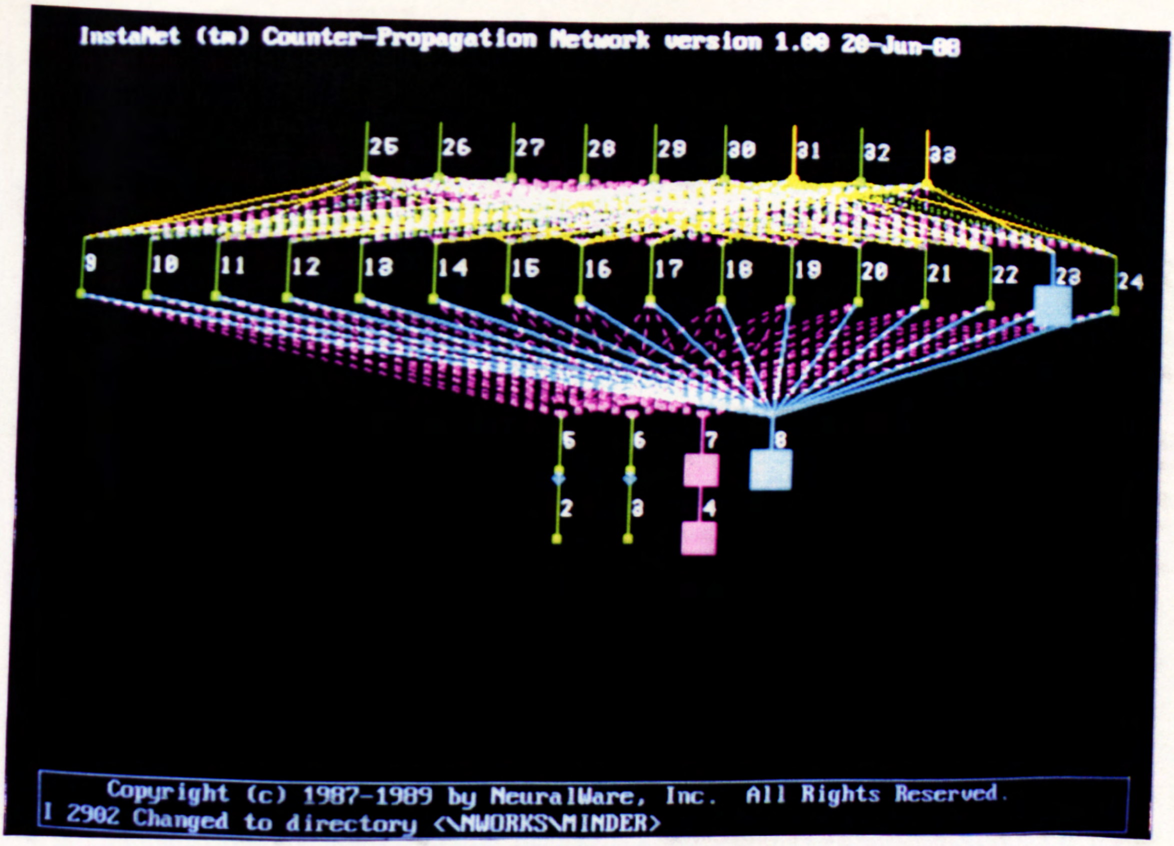


Figure 4.32 A Sample Counter-Propagation Network

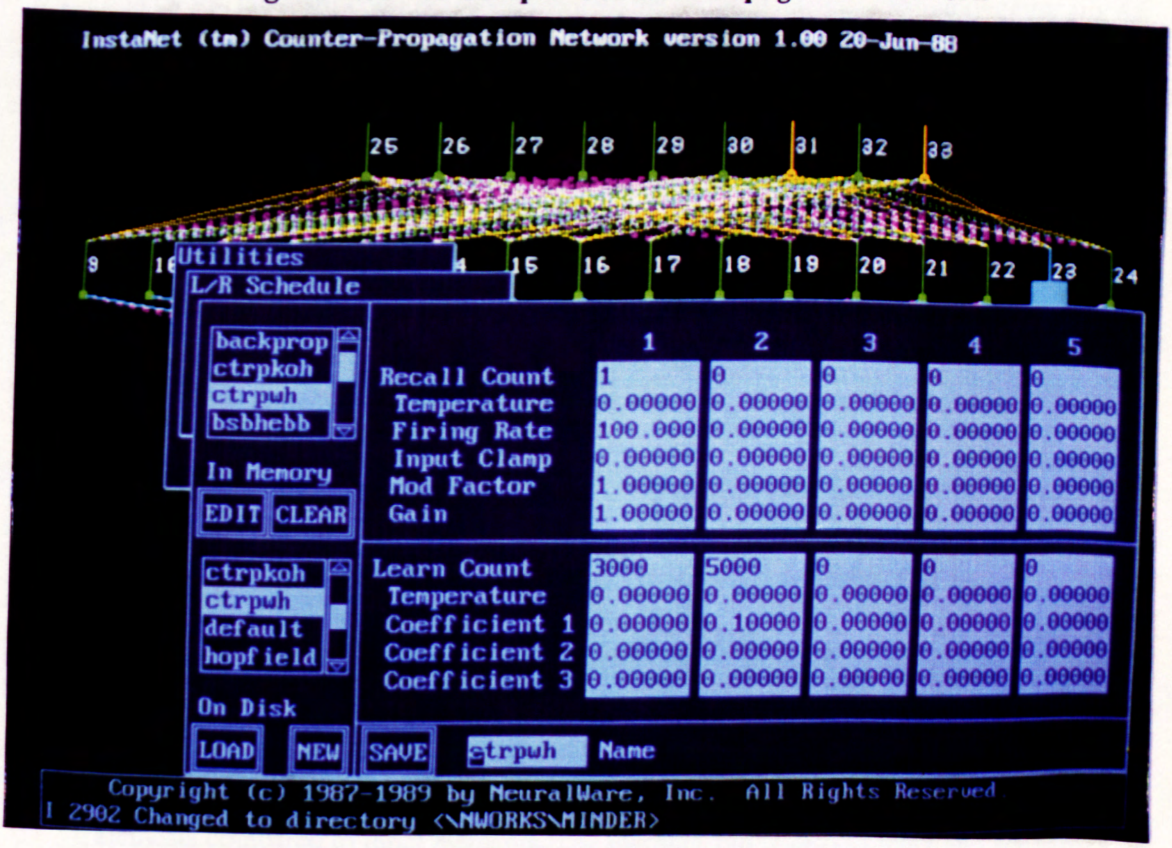


Figure 4.33 Counter-Propagation Learning and Recall Schedule

This is required for a counter-propagation network and has one element more than the input layer, in this case four nodes. The four layers of the network are an input layer, an input buffer (or normalising layer), a Kohonen (or hidden) layer and a Widrow Hoff output layer. The counter-propagation network selects from a set of exemplars by allowing them to compete against each other. Normalised inputs and competition between exemplars selects the nearest neighbour (Hecht-Nielsen 1987).

A neural network can learn using a variety of different learning and recall parameters. The Neural Works software has a learning and recall schedule submenu. The schedule for a counter-propagation network model is shown in figure 4.33.

The learning and recall schedule contains all of the additional parameters required by a processing element and not contained in the layer parameters. Only one column from the recall subsection and one column from the learn subsection are used at one time. All others are ignored. The recall counter is reset and incremented through it's entire set of values during each recall. During learning, the counter is incremented once for each training cycle and holds it's value. Each time a new training example is presented to the network, the learn counter is incremented, the learning rate can change dynamically as the learning process proceeds.

The recall column factors are used to introduce and control noise in the data, introduce randomness, designate weights and define the processing element transfer function. The learning temperature is again used to introduce noise into the data and the learn coefficients control the learning rate. It is worth noting that the learning and recall schedule selected in figure 4.33 is ctrpwh (counter-propagation Widrow Hoff).

Neural Works also allows the user to edit network global parameters such as :

- Network title
- Network type
- Control strategy
- Display Style
- System information
- Display mode
- Learn and recall schedules

The global network editing screen for the network shown in figure 4.32 is illustrated in figure 4.34. For a counter-propagation network, the network is defined as hetro-associative, that is the network has a different number and type of output processing elements compared to input elements. The learning and recall counters and schedules have already been set.

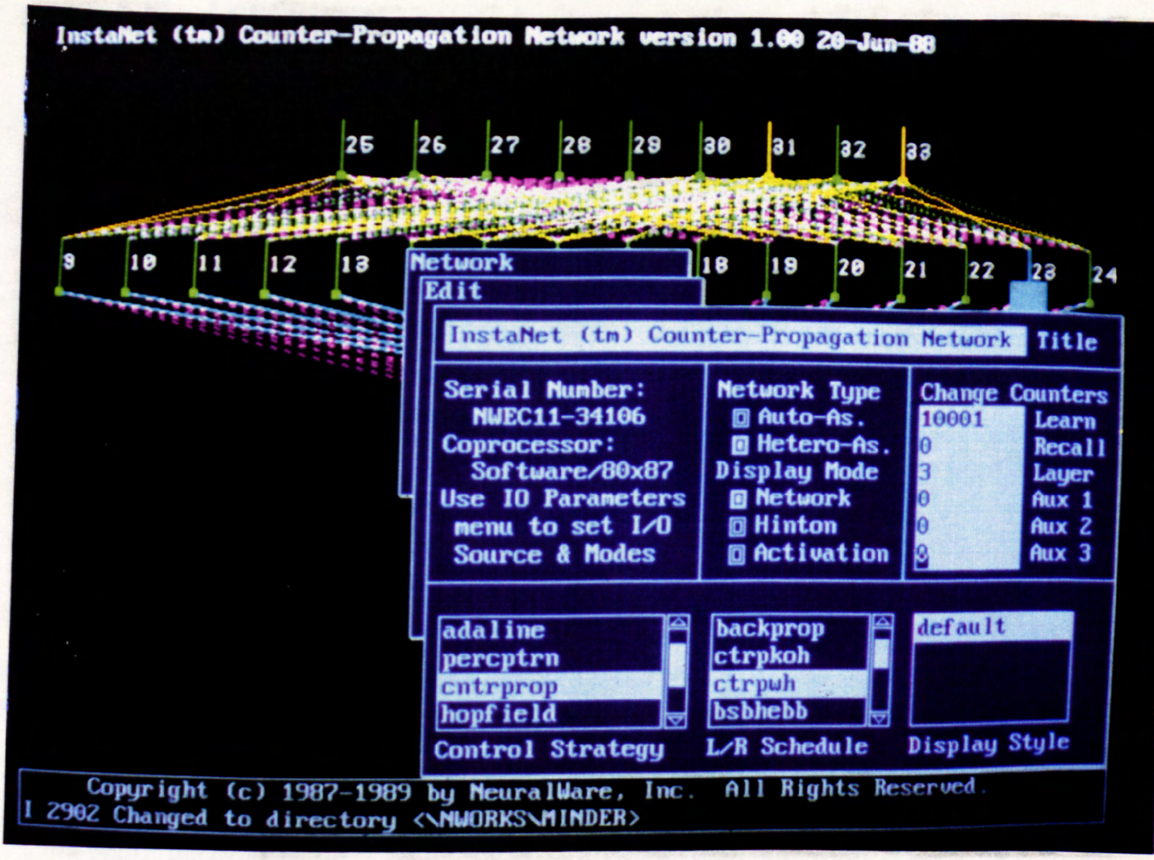


Figure 4.34 Global Network Parameters

Once the network is defined it needs to be trained. A large set of numerical training data was placed in text files, covering a large range of topsoil equipment removal equipment case studies. The data consisted of numerical values for the three inputs together with a selected output. The network is trained using the Neural Works execute menu, the learn source and recall sources must be defined, and data ranges specified. The training of a neural network can take from a few minutes to a few days depending on the complexity of the network and the size of the training data set.

Neural networks require substantial amounts of repeatable training data. They do not tolerate large systematic errors, although 'noise' or random errors are less of a problem. Neural networks have an intrinsic 'robustness'. Even if a data set is incomplete and contains gaps, errors and duplications, there are ways to accomplish data-quality assessment, data sorting for errors and duplications, and 'filling in the gaps' through supervised learning approaches.

4.13 Conclusions

The ideal of integrating software systems used is now widely recognised, but in practice has presented many problems. Computer companies have seen no benefits in making their software compatible with other suppliers systems, and most information transfer has been achieved through human means.

Some software has begun to incorporate linkages to other packages, for example modern word processing systems allow graphic images and spreadsheet information to be included within documents. These connections allow software to gain the extra benefits available from these external sources.

An expert system shell is a very strictly bounded environment not allowing large scale data storage or complex algorithmic calculations. Thus, if any application problem requires significant amounts of computation and data handling phrases, it becomes imperative for the developer to perform these functions using other software packages which can then be coupled to the shell.

Research is moving away from large, stand alone, expert systems and development is being undertaken towards integration of knowledge based techniques with more conventional programs. The expert systems act as front and back ends of complicated suites of software and by their very nature may be highly interactive.

In keeping with this desegregate philosophy the MINDER system utilises external software for the storage of large amounts of data, complex algorithmic processing, data file handling and process simulation. The use of a knowledge based system to control this software provides a step towards the rapprochement of the world of expert systems with the diverse attributes of the real world.

The expert system 'bottle-neck' of knowledge acquisition is being eased by the application of knowledge induction systems to generate or test expert system rules. Accurate task representation is the key to successful knowledge capture, and to the production of valid rules. Within Xi Rule task representation is reflected in the choice of Attributes and Outcomes. It is important :

- To select all possible Outcomes for a particular task.

- Determine all Attributes affecting a specific Outcome, if unsure the Attribute should be included as Xi Rule only uses relevant Attributes.

- If there is a large number of Attributes and Outcomes then the task should be split into smaller separate tasks.

The earlier rule induction systems did not perform well when presented with contradictory or probablistic data, and the outputs had to be interpreted with care. The development of decision tree pruning techniques, such as the C4 algorithm, have led to greater confidence in rules generated from inducted systems. These induction procedures may also be used in parallel with conventionally generated expert system rules to identify questions and provoke discussion with the expert about gaps, contradictions and data redundancy.

The potential benefits of neural networks extend beyond the high computational rates provided by massive parallelism. Neural networks typically provide a greater degree of robustness than standard von Neuman sequential computers because there are so many more processing nodes, each with primarily local connections. This provides a high fault tolerance, the ability to make an 'educated' guess and the ability to recover gracefully from process element failure.

The process of developing a neural network remains something of an 'alchemic' business. Nevertheless, some principles are emerging. The first question, as in any software development programme, is to decide precisely what you want the system to do. With neurocomputing, this means 'asking the right questions' and teaching the network a meaningful classification system. The use of InstaNet within the Neural Works software environment has led to the successful generation of a set of counter-propagation decision support networks.

Chapter 5

Application Modules

5.1 Introduction

The MINDER expert system is used primarily for surface mining excavation and haulage equipment selection. The methods of storing knowledge, interrogating and controlling external programs and reaching conclusions using multiple knowledge bases have been discussed in Chapter 4. This chapter will detail the application modules, each consisting of a series of large interconnected knowledge bases, used by the MINDER system.

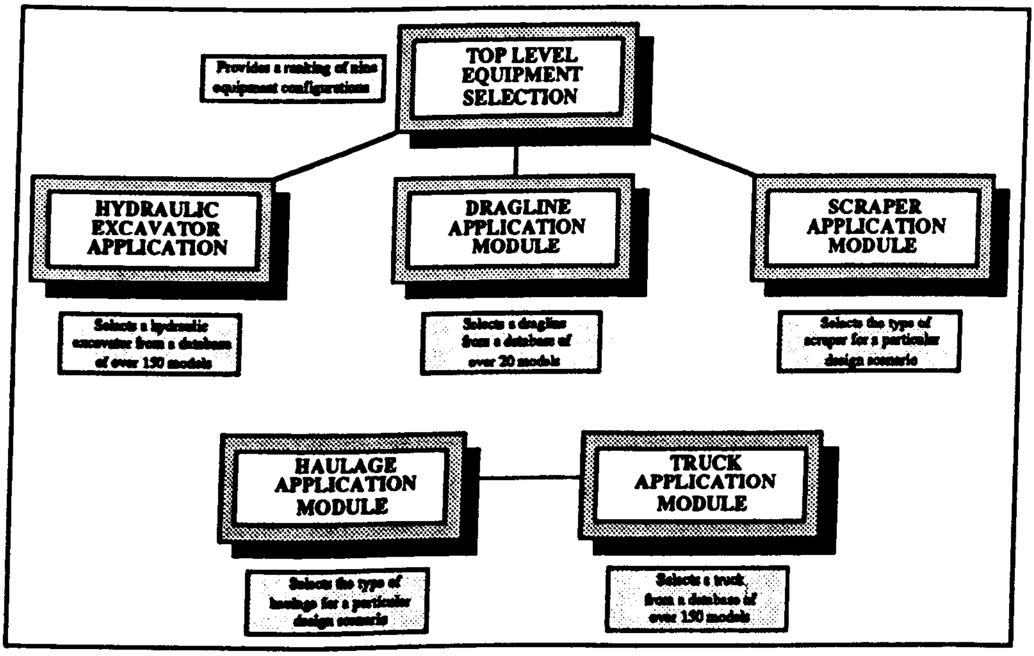


Figure 5.1 MINDER Application Modules

The MINDER application modules are shown in figure 5.1, a brief description of each of the module's respective selections is also shown. Each module runs independently from the others, but may call upon information from a previous consultation through cerebral text files. Hydraulic excavators, draglines and truck models are ranked from databases of equipment specifications, while a more general suggestion of scraper type is provided by the scraper module.

A haulage system can be selected from six alternatives, if a truck haulage system is chosen then the haulage module will suggest the general type of truck to be used. Finally it is possible to select a truck model from a database of over 200 trucks in the truck application module.

Application Module	Size in Bytes
Equipment Type	522,073
Hydraulic Excavator	648,450
Dragline	995,572
Scraper	365,812
Haulage	470,418
Truck	582,950
Spreadsheet Module	79,313

Table 5.1 The Size of the Application Modules

Each MINDER application module is stored on the 30 MB 'D:' partition of a 120 MB hard disk on an IBM PS 2, Model 70. The directory structure of each application module is similar to that described in Chapter 4, with a directory for the knowledge bases, one for Pascal software, one for the application's databases and three data directories : one for fuzzy logic matrices, one for Surpac data and one for the cerebral system data. Table 5.1 shows the memory sizes of the various MINDER application modules. The large amount of disk space used is mainly due to the large knowledge bases used in each application. The total size of the MINDER system excluding back-up files is approximately 3.5 MB.

The MINDER system is dependant upon a range of commercial software, this integration allows flexibility for system development and use. The Xi Plus expert system shell is needed to access the knowledge bases and to control the associated software, shown in table 5.2. The associated software occupies approximately 8.5 MB of disk space.

Application Software	Size in Bytes
Xi Plus	936,272
Turbo Pascal	1,116,412
DbaseIV	2,848,066
GPSS-PC	730,335
Excel	2,708,249
Mine Planning Software	**Size in Bytes**
Datamine	4,789,432
Surpac	14,050,180

Table 5.2 The Size of the Associated Software.

If the results from a commercial mine design package are to be used then much more disk space will be needed to install this software. The size of the Datamine and Surpac Mining systems are also shown in table 5.2. Using Surpac means that a total of approximately 25 MB needs to be available to run the complete MINDER system. It should be noted that this associated software is not dedicated and a proportion of it will already be used by modern mine planners.

This chapter also contains details of equipment selection decisions made using knowledge induction and neural network software. The techniques used to generate the inducted rules and to create the counter-propagation networks have been discussed in previous chapters.

5.2 Equipment Type Application Module

This application module is split into a number of sections. Firstly during the course of a consultation the system gives the user general advice on the mining method. Secondly the equipment selection and ranking sub-system is consulted. This is partitioned into three parts depending upon the material to be excavated, topsoil, coal or waste.

The basic structure of the equipment selection application module is shown in figure 5.2. Information called from the resource level knowledge bases is listed at the bottom of figure 5.2, these knowledge bases involve multiple connections and recursive inferencing procedures too complex to be represented on the diagram.

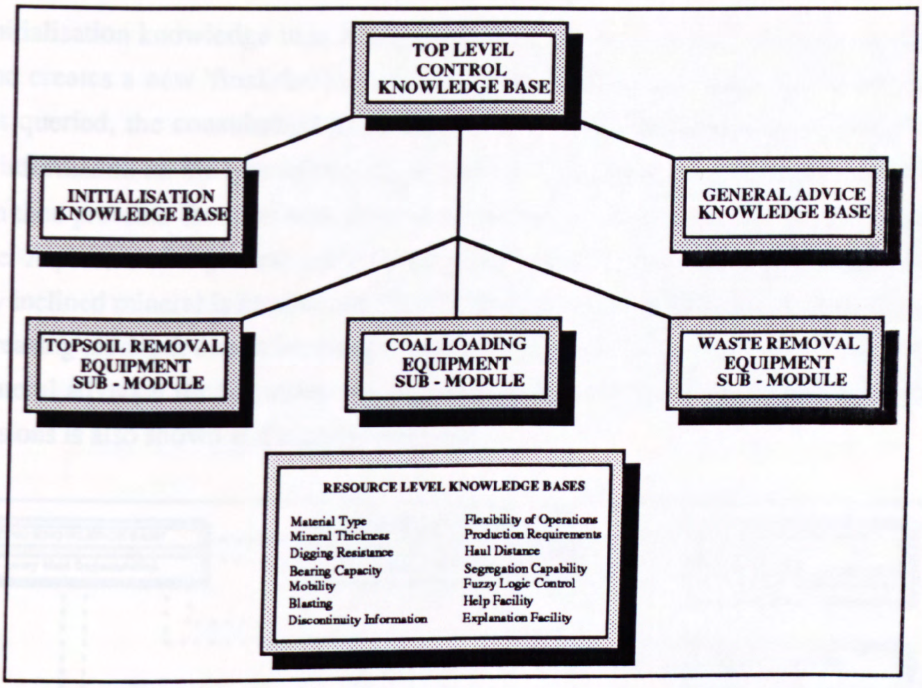


Figure 5.2 The Equipment Type Module.

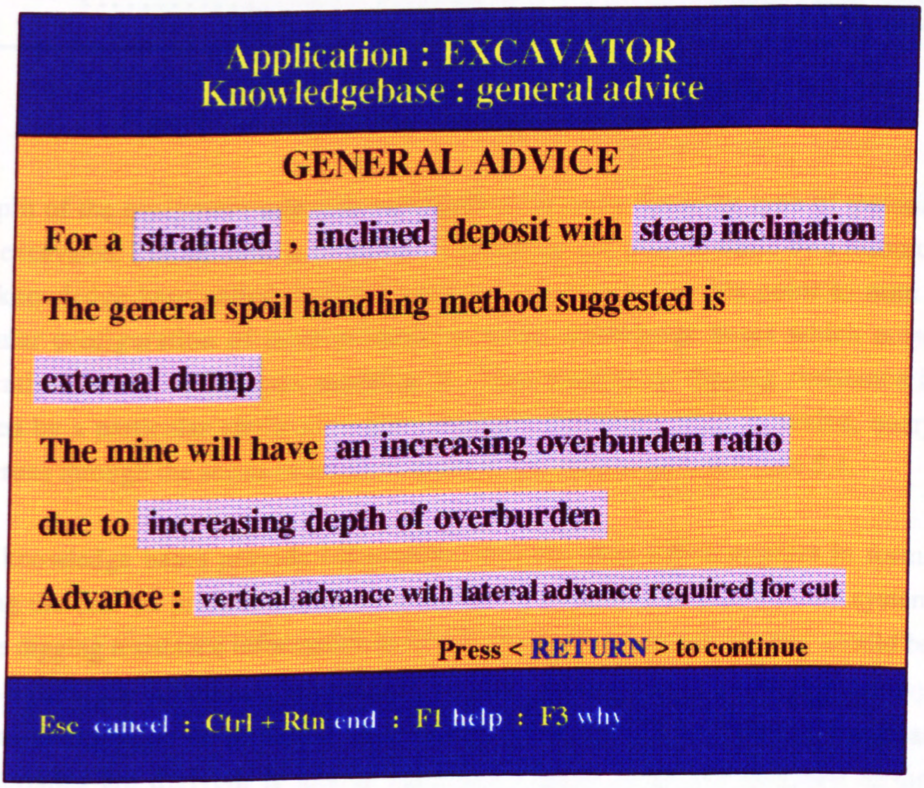


Figure 5.3 The General Advice Form.

The initialisation knowledge base is accessed first, this resets the application cerebral file and creates a new 'final.dat' report file. Secondly the general advice knowledge base is queried, the consultation progresses through this knowledge base collecting initial information on the type of deposit, deposit inclination and overburden depth. The system then presents the user with general advice on the basic techniques of working the site. A picture of a general advice report is given in figure 5.3, where a stratified steeply inclined mineral is considered. The MINDER system suggests an external dump, an increasing pit depth due to increasing overburden ratio and advices vertical advance with lateral advance for the safety cut-off. Notice that the initial data leading to the conclusions is also shown at the top of the form.

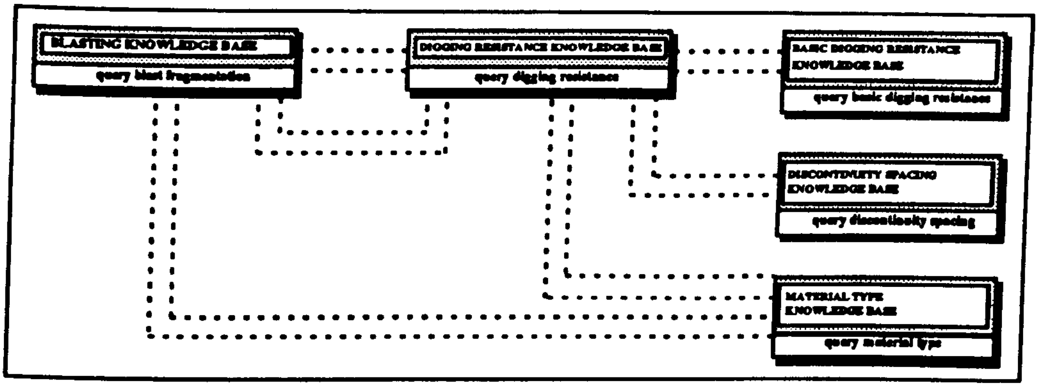


Figure 5.4 Resource Level Knowledge Bases

The split of the equipment selection sub modules is based upon the type of material being excavated. The material is classified as either topsoil, coal or waste by a resource level knowledge base called material type. It is convenient at this point to note a particular configuration of interconnected resource knowledge bases which occur frequently in many application modules. If either blasting or digging resistance is required by a particular application this initiates a sub-level, often recursive, query which runs through the series of resource knowledge bases shown in figure 5.4.

These knowledge bases provide information to each other which appears in forms advising the user on preferred answers to certain questions. For example the system will use digging resistance information to advise the user on whether blasting should be used in a particular situation (see section 4.3, on recursion between knowledge bases). Material information is retrieved from databases and basic excavation material characteristics are derived. If any of these knowledge bases are accessed at the equipment selection application level the specific equipment modules will use information taken from the cerebral files.

The topsoil removal equipment selection sub-module considers seven equipment alternatives, shown in table 5.3. This selection is based upon three factors drawn from the resource level knowledge bases, these factors are also shown in table 5.3. The knowledge base provides a matrix of fuzzy set membership values as output, for example if the topsoil thickness is thin then the dozers and scraper will have a higher membership value than the dragline and bucket-wheel-excavator alternatives. This is equivalent to the creation of a fuzzy evaluation matrix from a knowledge matrix. Three fuzzy similarity rankings are performed, one with equal weightings, one biased towards overburden thickness and one biased towards the length of the haul route.

Equipment Alternatives	Decision Factors
Bulldozer	Topsoil Thickness
Front-End Loaders	Haul Distance
Scraper	Operational Flexibility
Dragline	
Hydraulic Shovel	
Bucket Wheel Excavator	
Front-End Loader and Truck	

Table 5.3 Topsoil Removal Equipment Alternatives and Decision Factors

The coal loading equipment knowledge base considers the six alternatives shown in table 5.4. The ranking is based upon the six factors shown to the right of table 5.4. The factors, again estimated from resource level knowledge bases, are mainly expressed as linguistic variables.

Equipment Alternatives	Decision Factors
Electric Shovel	Coal Seam Thickness
Front-End Loaders	Fragmentation
Front-End Hydraulic Excavators	Floor Conditions
Backhoe Hydraulic Excavators	Mobility
Scrapers	Operational Flexibility
Bucket Wheel Excavator	Production Requirements

Table 5.4 Coal Loading Equipment Alternatives and Decision Factors

For example, the production requirement is either high, medium or low. These variables are assigned a fuzzy membership value based on a knowledge base defined preference structure. Three fuzzy similarity rankings are again performed, one with equal weightings, one biased towards material size and coal thickness and one biased towards the mine production requirements.

The overburden removal equipment selection knowledge base is slightly more complex than the topsoil and coal ranking procedures. It ranks eight equipment types shown in table 5.5 against the ten factors listed. Two sets of rules, generating two knowledge matrices, have been inserted into the application. One of these is based on the opinion of an English expert and the other is based on an American mining opinion. The same linguistic preference structure is applied for each knowledge matrix, this leads to the creation of two evaluation matrices. These matrices are not aggregated, but are treated separately. Two sets of fuzzy rankings are performed, the differences in the results only serves to demonstrate the subjectivity involved in the field of mine design. For each evaluation matrix the rankings are performed three times, one with an equal weighting, one biased towards material size and overburden thickness and one biased towards production and haul distances. Figure 5.5 (a & b) shows two typical results screens from this application module and allows a contrast to be drawn between the English and American opinions.

Figure 5.5 (a & b) English and American Results Screens

Equipment Alternatives	Decision Factors
Dragline	Overburden Thickness
Hydraulic Shovel	Overburden Characteristics
Hydraulic Shovel and Truck	Length of Haul Route
Front-End Loader	Coal Seam Support
Bulldozer	Segregation Characteristics
Front-End Loader and Truck	Production Requirements
Bucket Wheel Excavator	Operating Flexibility
Scrapers	Mobility
	Overburden Dip
	Pit Slopes

Table 5.5 Overburden Removal Alternatives and Decision Factors

5.3 Hydraulic Excavator Application Module

A series of interconnected knowledge modules make up the hydraulic excavator selection module, and leads to a ranking based on digging resistance, bearing capacity, bench dimensions and production requirements. Figure 5.6 shows the basic structure of the hydraulic excavator knowledge bases.

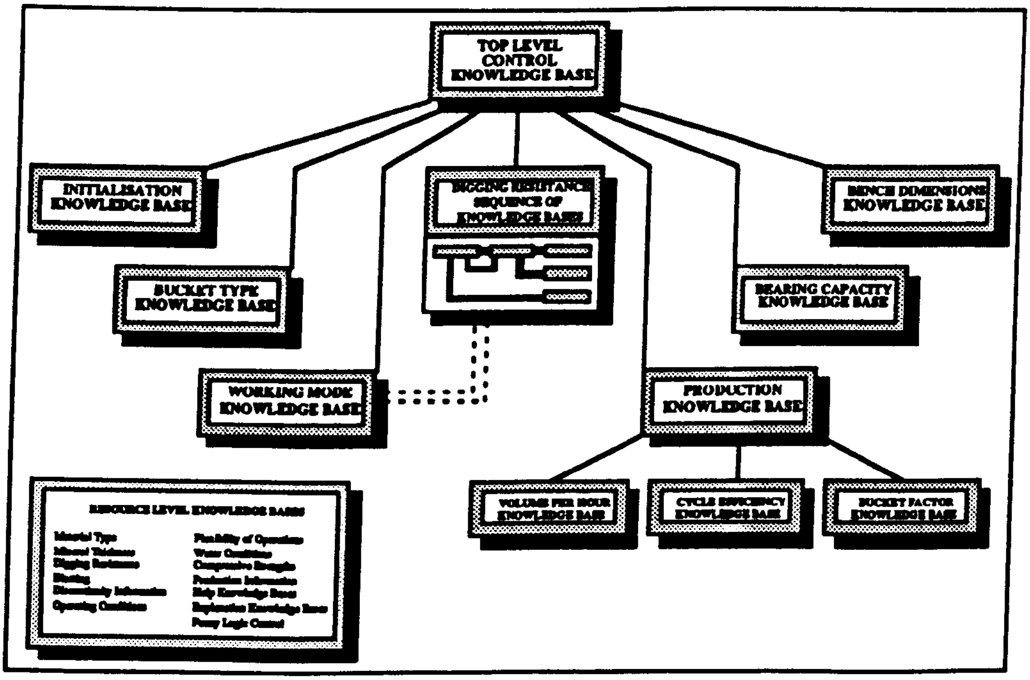


Figure 5.6 Hydraulic Excavator Application Module

The initialisation knowledge base is the first to be called, this resets the excavator cerebral data file and the results file and also checks the top level application module to collect information from any previous consultations. The hydraulic excavator ranking utilises the three tiered hierarchical hydraulic excavator database, the system requires a description of the working mode of the excavator, and needs to know the type of bucket to be used to ensure that the correct database is interrogated. The working mode knowledge base calls the digging resistance sequence of knowledge bases to gain information needed to make this decision.

The hydraulic excavator ranking is dependant on four factors, digging resistance, production requirements, bearing capacity and bench dimensions. The top level knowledge base calls each of these sub-knowledge bases in turn to procure values for these factors. Each knowledge base makes use of the large number of resource level knowledge bases for information and database interrogations.

Once the four factors have been determined a series of complex relational operations, as shown in figures 5.7 (a-d), are performed within the DbaseIV hydraulic excavator database.

A temporary database of relevant fields is created based on working mode and bucket type variables. This database includes new fields such as maximum digging force calculated using existing fields and knowledge base information

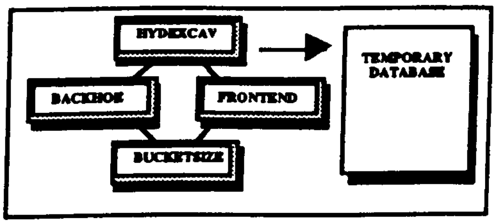


Figure 5.7 (a)

A relational operation, controlled from the expert system is then performed to negatively bias all hydraulic excavators in the database whose calculated digging resistance is below the minimum required for the particular scenario.

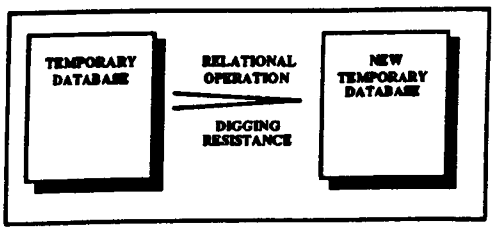


Figure 5.7 (b)

The expert system then controls a similar operation to negatively weight all excavators whose bucket size falls below the capacity required for the minimum required production.

information handling system to give advice on any equipment selected. An undergraduate dissertation in the Department of Mining Engineering, Nottingham University was based upon the addition of extra knowledge into the dragline advice module (Bower 1991).

The hierarchical structure of the dragline module of the MINDER system is shown in figure 5.8. The controlling knowledge base allows any combination of selection or advisory consultation to be performed. The normal inferencing route is from the top level MINDER selection of 'dragline' as the excavating method, to the selection of a specific dragline using the dragline module. The advice system is then used to offer geometric and operational advice on this particular item of equipment. SMMS is then run to design the cut schedule using values from the expert system.

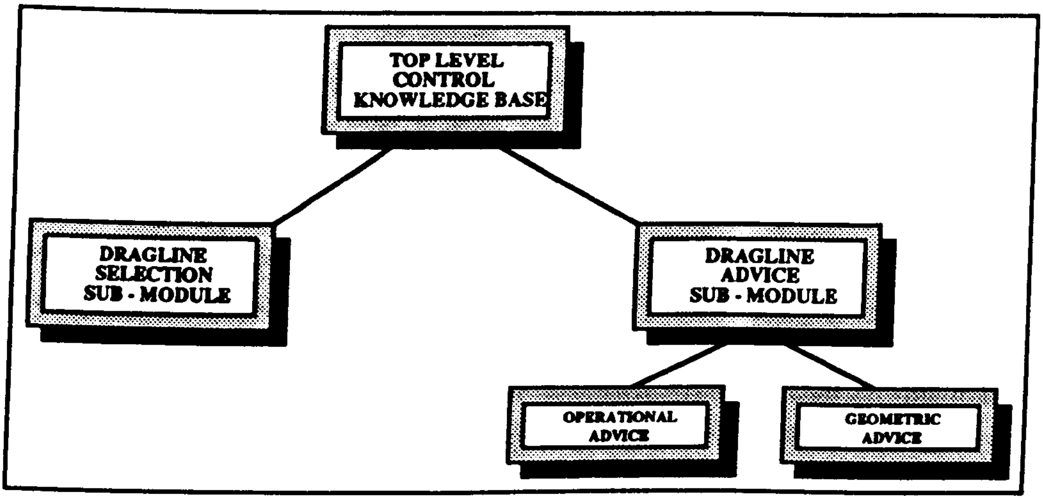


Figure 5.8 Dragline Module Knowledge Bases

Information is obtained from the top level cerebral file and from external databases. A materials database is used to obtain densities, swell factors and compressive strengths of particular materials. A dragline database has also been created containing a variety of information, such as bucket capacities, operating radii, dumping depths, fairlead heights and clearance radii.

When the dragline selection part of the module is consulted the system operates upon the database of draglines and ranks them in order of suitability for a particular scenario. When the dragline advice part of the module is consulted the system interrogates the database to retrieve operating information about the dragline selected.

5.4.1 Dragline Selection

The dragline related knowledge has principally been acquired by the interrogation of experts and examination of relevant technical literature including published papers, operators manuals and codes of practice. The dragline selection is principally based on four criteria (Martin Consultants Inc. 1982). Figure 5.9 shows the main knowledge bases which make up the selection part of the dragline module. The four main factors required are as follows :

- **Bucket size :** The ideal dragline bucket size is based upon the required production, modified by a bucket factor. The bucket factor is dependant upon the digging and blasting characteristics of the material being excavated.

- **Operating radius :** The ideal operating radius is dependant upon initial estimates for the pit dimensions, such as overburden depth, spoil angle and a subjective judgement of the maximum pit width.

- **Digging depth :** The digging depth is based upon the height of the advance bench and the depth of the overburden.

- **MUF :** The maximum usefulness factor can be calculated by multiplying the bucket size by the operating radius.

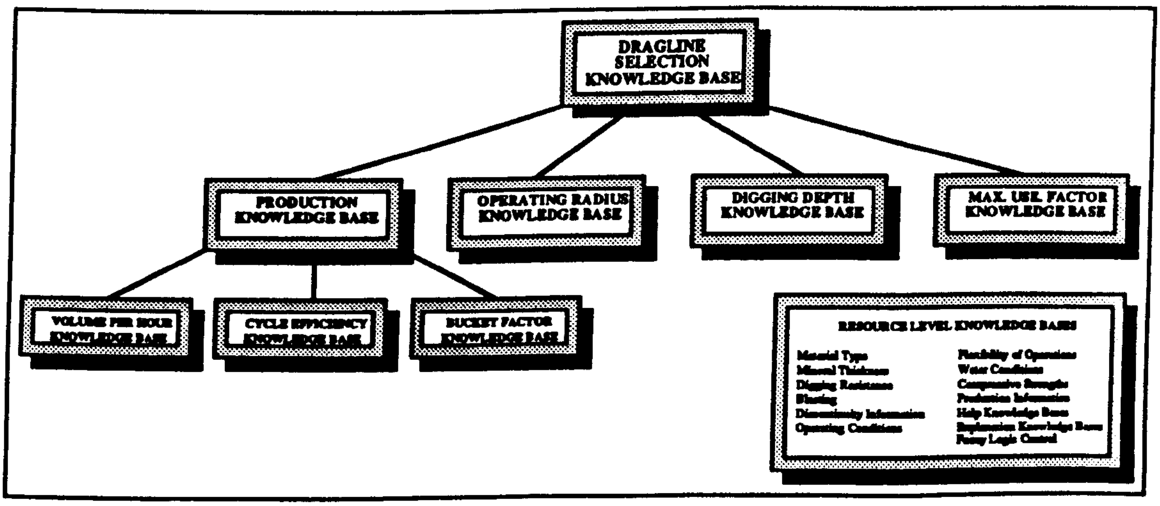


Figure 5.9 Dragline Selection Knowledge Bases

During a consultation with the dragline selection knowledge bases, the four results listed above are estimated based on information from the resource level knowledge bases. The system then accesses the dragline database and calculates a MUF for each dragline. The user then has an option of applying a negative bias to any draglines whose values fall outside the limits specified by the expert system. The database is then written to a text file in the form of an matrix, this matrix is used as an actual evaluation matrix in the fuzzy similarity ranking performed upon the draglines. The draglines are compared to a text file containing the expert system ideal values.

Weightings are applied to the factors within the matrix to give a more realistic opinion. The MINDER system repeats the fuzzy similarity ranking algorithm three times, each recursion using a different weighting mechanism. The weighting mechanisms are as follows:

- An equal weighting.
- A weighting favouring the bucket size and operating radius.
- A MUF biased weighting.

The three rankings produced gives the user a range of results which allows a decision to be made with more confidence. The dragline selected from this part of the module is passed into the advice knowledge bases.

5.4.2 Dragline Advice

The dragline advice sub-module is split into operational and geometric sections. The operational section suggests mining methods (such as whether an advanced bench is to be used), the geometric focuses on numerical attributes (such as the height of a proposed advanced bench). Advice is given by the respective knowledge bases of each advice section on the factors shown in table 5.6.

The dragline advice part of the module is divided into smaller knowledge bases in much the same way as the dragline selection knowledge bases in figure 5.8. These are used to advise on particular factors for a particular mine scenario. During a consultation information is drawn from the following sources :

- Dragline selection consultation (cerebral files).
- More detailed knowledge bases (linked to the factor knowledge bases).
- Dragline database (dragline configuration information).

Operational Advice	Geometric advice
Use of Key Cut	Maximum and Minimum Pit Width
Method of Bucket Loading	Suggested Pit Width
Spoil Placement Method	Suggested Dig Out
Spoil Placement Technique	Advanced Bench Height
Advance Benching	Miscellaneous Advice

Table 5.6 Dragline Advice Main Knowledge Bases

The suggested pit width relies upon subjective judgements and as such is a contentious value (Mining Magazine 1979). Within the expert system it is estimated using certainty factors. Firstly the maximum pit width is determined using several mine parameters such as ; rehandle material, overburden depth, spoil and highwall angles and operating radius of the selected dragline. Then the minimum pit width is calculated based upon the minimum width needed for turning circles and drainage requirements. The following factors affect where the suggested pit width should lie between these two limits (Denby and Schofield 1991) :

- Highwall Instability
- Dragline Productivity
- Restoration
- Geological Disturbance
- Mining method
- Coal Recovery
- Number of in pit machines
- Operation Flexibility Requirement

As information on each of these values is obtained, a positive or negative certainty factor is applied to the average suggested pit width, denoting whether this value should be wider or narrower respectively. The combining function detailed in Chapter 3 blends the certainty factors to give a final measure of belief. The suggested dig out length is also determined using certainty factors.

5.5 Scraper Application Module

The scraper module does not deal with a database of individual scraper models, but ranks the five types of scraper equipment available, shown in table 5.7. The ranking is based upon seven factors drawn from resource level knowledge bases. Consultation of the scraper module allows the expert system to create an evaluation matrix. Three fuzzy logic rankings are again performed, one with equal weights, one biased towards the required production and one dependant upon the material size and haulage distance.

Equipment Alternatives	Decision Factors
Tractor-Drawn Scraper	Material Size
Under-Powered Rubber Tyred Scraper	Length of Haul
Full-Powered Single Engine Scraper	Ground Conditions
All-Wheel-Drive Scraper	Maximum Adverse Grade
Rubber-Tired Tractor with Trailer Scraper	Operating Flexibility
	Daily Production Rate
	Total Tonnage

Table 5.7 Scraper Type Equipment Alternatives and Decision Factors

5.6 Haulage Application Module

The haulage application module ranks a variety of haulage systems depending on a set of relevant factors, the haulage systems and applicable factors are shown in table 5.8. All the factors used are available from previous equipment consultations.

Equipment Alternatives	Decision Factors
Bulldozer	Material Size
Truck	Length of Haul
Train	Ground Conditions
Conveyor	Maximum Adverse Grade
Skip	Operating Flexibility
Pipeline	Daily Production Rate
	Total Tonnage

Table 5.8 Haulage Method Alternatives and Decision Factors

The haulage module checks whether a top level and/or specialist equipment module has been consulted and then retrieves as much information as possible from the cerebral data files, this operation is shown graphically in figure 5.10. If the top level consultation suggests that a dragline is used then the haulage module reminds the user that draglines usually direct cast across the pit and do not require a haulage system. Scrapers also have their own inherent haulage systems and do not require any additional equipment to be selected.

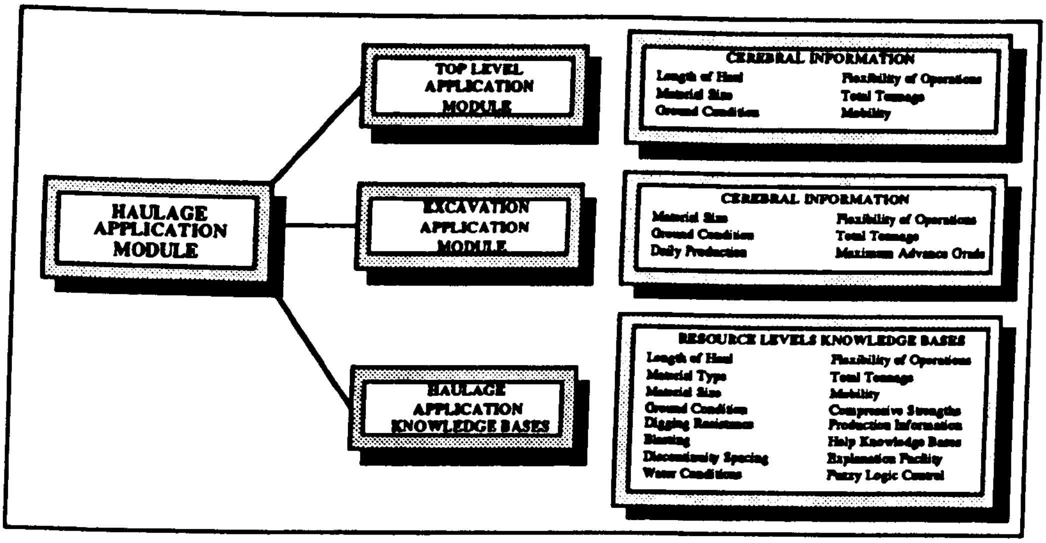


Figure 5.10 Haulage Module Information Retrieval

A large amount of control needs to be applied to the haulage module to ensure that values are not repeatedly checked and overwritten with blank values. A full compliment of resource level knowledge bases is also present and can be accessed if no previous consultation information is available. Three fuzzy logic rankings are performed on the haulage types, one with equal weights, one biased towards the required production and one dependant upon the material size and haulage distance.

5.7 Truck Application Module

The truck module has a different emphasis to the previously described application modules. It is designed to match the optimum truck model for a chosen hydraulic excavator model. The structure of the truck application module, as shown in figure 5.11, is similar to the others within the MINDER system to retain compatibility and ensure the free flow of information. A ranking of preferred truck models is produced based on production capabilities and suitability to the selected excavator characteristics.

The truck application module first accesses the initialisation knowledge base, which resets the truck cerebral data file and the final results file and then draws information from any top level or specialist excavation equipment consultations which have been performed. The system then checks the excavation model to which the truck is to be matched, information on this excavator model can then be drawn from the hydraulic excavator database. To access this hierarchical database, the excavator working mode and bucket type are needed, and should be retrieved from the excavator cerebral file. If not available, the truck application module is capable of ascertaining these values through a series of resource level knowledge bases. The excavator bucket size, and dumping height are read into the truck module from the database for the particular model under consideration.

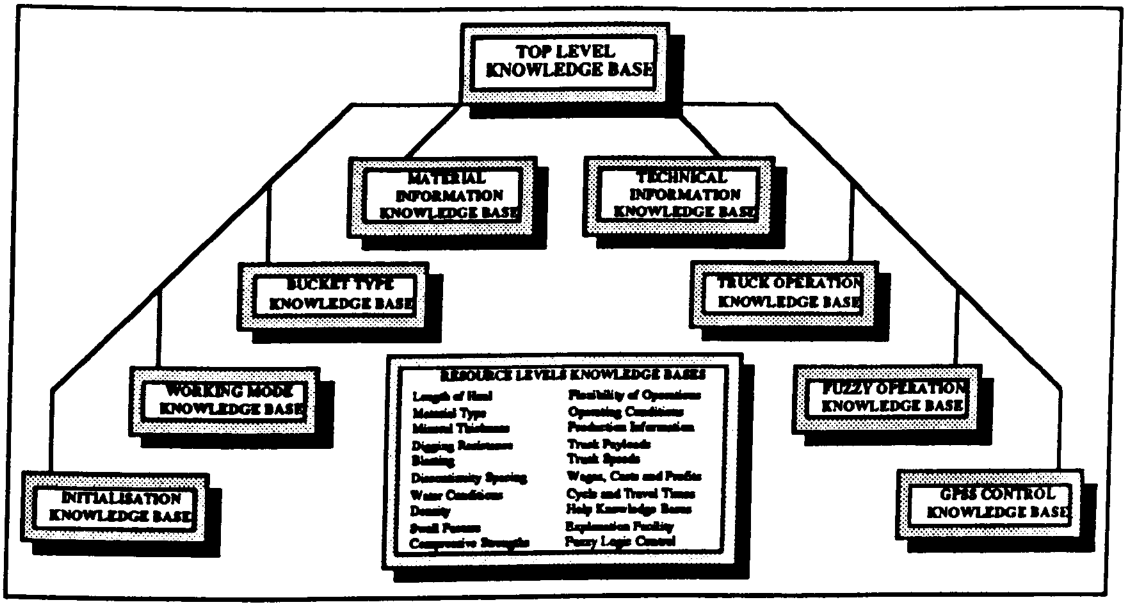


Figure 5.11 Truck Application Module Structure

The material information knowledge base then interrogates its respective database to provide excavation material data, such as density, swell factors and compressive strengths. In the technical information knowledge base the system determines the minimum and maximum truck capacity and the minimum dump height.A minimum truck capacity is provided by some manufacturers and is read from the excavator database, where it is not available a value is calculated. The truck capacity limits are estimated based on the truck loading requirements of between 3 and 7 excavator buckets. The minimum dump height is calculated using either the front end or backhoe dumping height.

The truck operation knowledge base then performs DbaseIV relational operations on a temporary truck database. All trucks whose payloads fall outside the minimum or maximum truck capacity limits are either deleted or negatively biased. This operation is repeated for all trucks larger than the minimum dump height of the excavator model selected.

The fuzzy operation knowledge base converts this modified temporary truck database into an evaluation matrix. Ideal values from the expert system are sent to an ideal matrix text file. Three truck rankings are performed, one with equal weightings, one biased on the production capabilities of the truck and one weighted on the ideal excavator dump height. The user is asked to select a truck model from these three rankings.

The GPSS control knowledge base performs a truck - shovel simulation to determine the optimum number of trucks to be used with the selected excavator. Programs are written by the MINDER system to text files using the techniques described in Chapter 4. The knowledge base first assimilates the information needed to write the GPSS programs, a list of this data is shown in table 5.9.

GPSS Information	Source of Information
Truck Payload	From Truck Database, based on truck model selected
Truck Speed Empty	From Truck Database, based on truck model selected
Truck Speed Full	From Truck Database, based on truck model selected
Drivers Hourly Wage	From User
Truck and Mine Daily Costs	From User
Required Production	From User
Bucket Size	Excavator Module, or Resource Level
Cycle Times	Excavator Module, or Resource Level
Number of Bucket Loads	Payload / Bucket Size
Loading and Dumping Cycle Times	Number of Bucket Loads x Cycle Time
Length of Haul Route	Top Level, or Resource Level
Travel Time to Dump	Length of Haul Route / Truck Speed Full
Travel Time from Dump	Length of Haul Route / Truck Speed Empty

Table 5.9 A List of GPSS Information

The GPSS programs simulate ten days operation with a variable number of trucks, from one to ten. The results reported correlate with the optimum number of trucks to meet the required production.

Figure 5.12 shows a GPSS program with the bold numbers representing variables passed from the expert system into the program. The profit results are reported to a GPSS formatted text file which can be interpreted and read back into the MINDER system.

```
;    GPSS/PC Program File Truck Simulation ; 3 Trucks
10           SIMULATE
20           INITIAL       X$PROD, 3410                          ; (production)
30           INITIAL       X$WAGES,50                            ; (Drivers Wage)
40           INITIAL       X$COST,3000                           ; (Truck Cost)
50   AMT1    FVARIABLE     (X$PROD#FC#SHOVL-N$TRUCK#X$WAGES#80)/100
60   AMNT    FVARIABLE     V$AMT1-N$TRUCK#X$COST#10/100-2500     ; (Mine Fixed Cost)
70           RMULT         123
80   TRUCK   GENERATE      ,,,3                                  ; (Number of Trucks)
90   TOP     QUEUE         WAIT
100          SEIZE         SHOVL
110          DEPART        WAIT
120          ADVANCE       55,15                                 ; (Loading Time)
130          RELEASE       SHOVL
140          ADVANCE       73,15                                 ; (Travel Time Full)
150          ADVANCE       55,15                                 ; (Dumping Time)
160          ADVANCE       58,15                                 ; (Travel Time Empty)
170          TRANSFER      , TOP
180          GENERATE      48000                                 ; (Simulation Time)
190          SAVEVALUE     NETPR,V$AMNT
200          TERMINATE     1
210          START         1
220          END
```

Figure 5.12 A GPSS Program Simulating The Use of Three Trucks

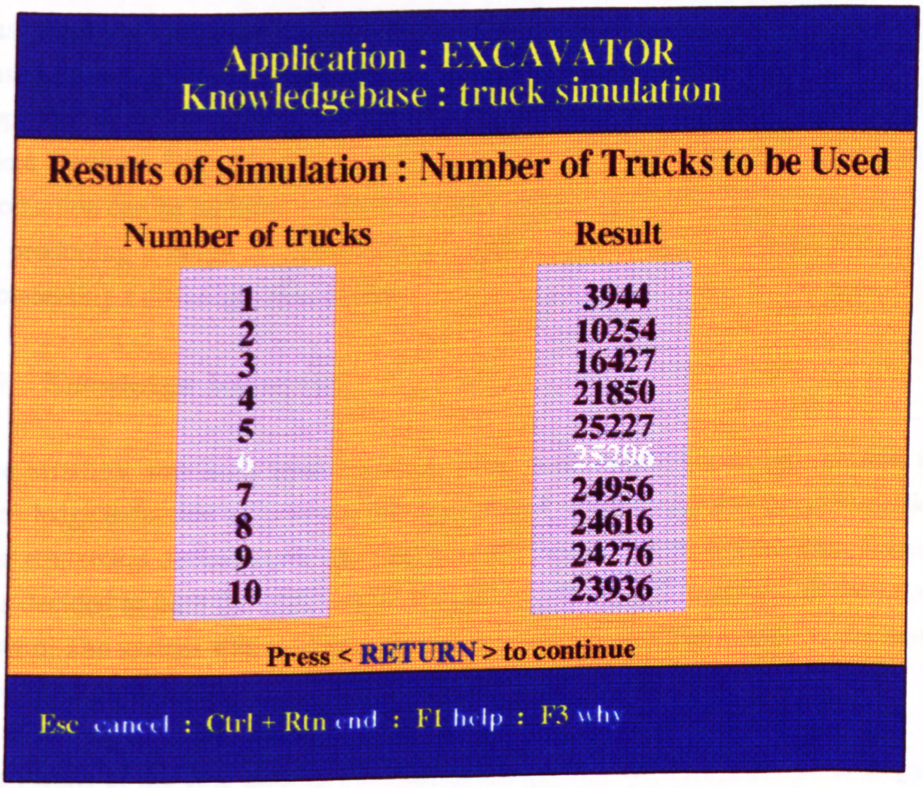


Figure 5.13 Output From a Full GPSS Simulation

Figure 5.13 shows the results of a complete GPSS truck simulation, controlled from the MINDER system. The values can be treated as relative figures and if the proportions are approximately correct a realistic number of trucks will be suggested. For example, in figure 5.13 either five or six trucks are needed to gain a maximum return on investment.

5.8 Spreadsheet Application Module

The spreadsheet application module is a small reporting module the operation of which is shown in figure 5.14. The knowledge based component of the module interrogates other application modules which have been consulted. Information is taken from the cerebral files of the applications since these are not reset until a new consultation is initiated. The top level module provides information on the type of equipment to be used, the spreadsheet module then queries the individual excavation equipment application to obtain production information, equipment specifications and operational factors. The running of the spreadsheet module involves a minimum amount of user interaction since all information is obtained from previous application modules.

Pascal software is called from the expert system to calculate the scheduling information based upon equipment production rates and block tonnages, this information is then appended to previous scheduled data in the spreadsheet file. It is important that there is some feedback from the Pascal software into the expert system so that any leftover production can be included in the scheduling of the next block. This module is capable of producing a range of spreadsheets during the planning of a surface mine, each representing a different mined horizon.

5.9 Knowledge Induction

The MINDER top level equipment decision was chosen to be reproduced using knowledge induction techniques. The first stage in this process was the assimilation of past equipment decision case studies. The attributes to be used were then defined, it was decided to base the decision on the same input variables as used in the MINDER system. The system was split into the same three sub-modules based on the material type being excavated.

The results of the case studies were not given as absolute decisions but as linguistic variables. Each item of equipment was classified for each situation according to a semantic preference structure, shown in table 5.10, to enable a proximate ranking to be carried out.

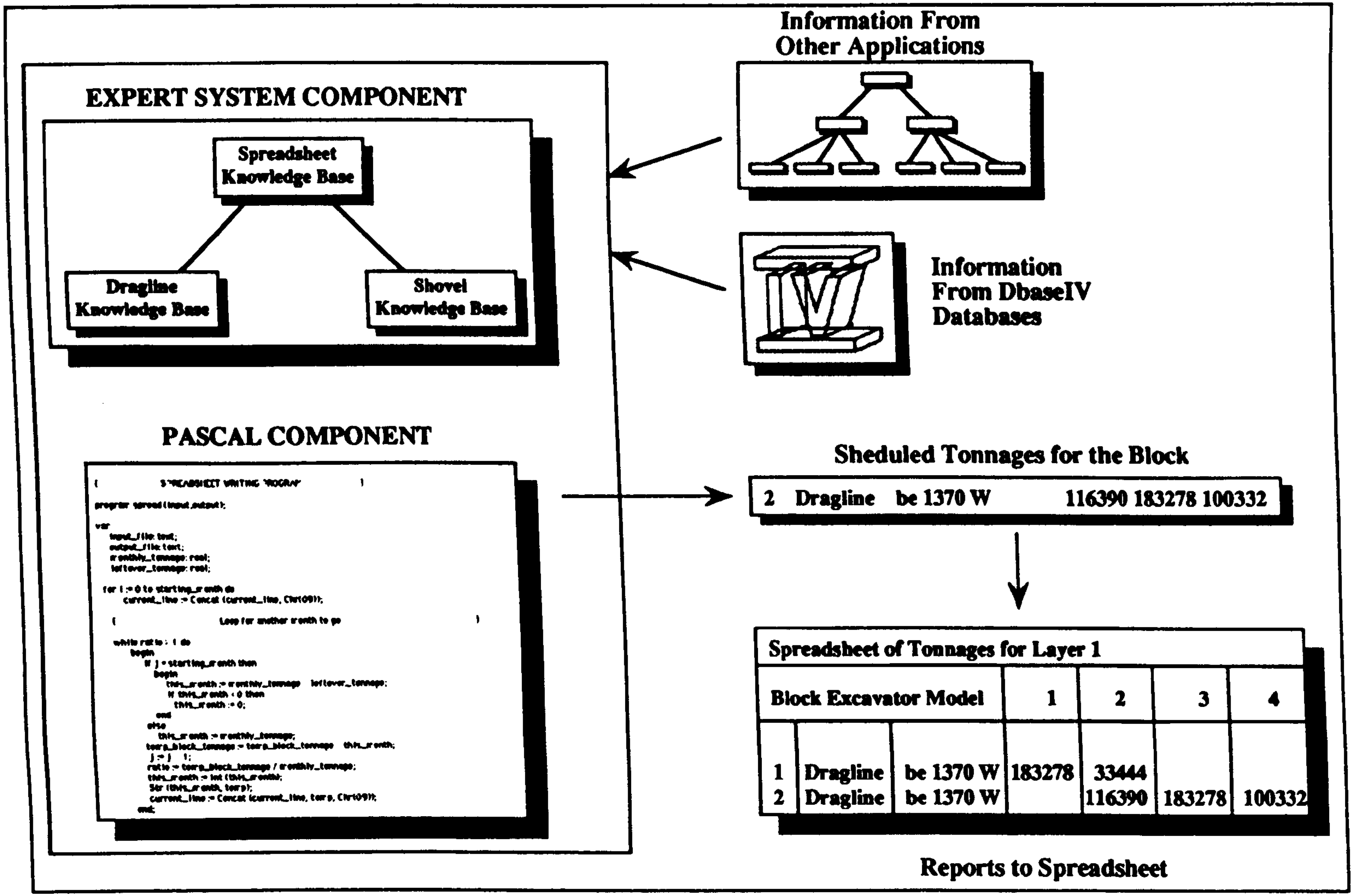


Figure 5.14 Operation of Spreadsheet Application Module

Ranking	Description
1	recommended
2	should be considered
3	may be considered
4	not recommended
5	not applicable to these conditions

Table 5.10 Semantic Ranking of Equipment Suitability

There were a large number of attributes and outcomes involved in the equipment decisions so, as discussed in Chapter 4, the task has been split into smaller separate tasks. Since this ranking was applied to each equipment type a knowledge base was created for each each item of equipment. This result in a system architecture similar to that shown in figure 5.15.

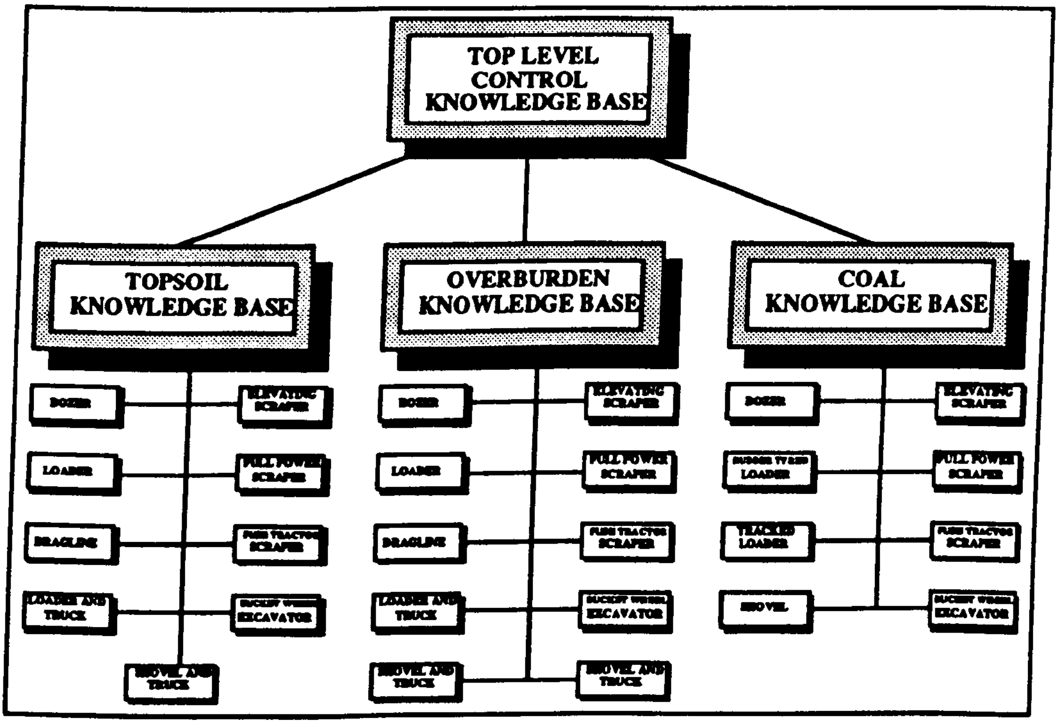


Figure 5.15 Knowledge Induction Module Architecture

The rules were induced using the Xi Rule software, and the decision trees created were pruned using the C4 algorithm to eliminate any errors due to contradicting case studies or missing information for decision nodes. The decision trees were then imported into

Xi Plus as complete knowledge bases made up of a number of interconnected rules. A network of inference queries and top level control was added manually within the framework of the Xi Plus expert system shell.

The knowledge induction module occupies over 1MB of disk space, twice the size of the equivalent MINDER application module. This increase in size is due to the system gathering all the information needed to perform the consultation and the performing the equivalent of a fuzzy logic ranking using rules. No external software is accessed. The inducted rules were tested against a test set of case studies and performed well. These case studies are reported in Chapter 6.

5.10 Neural Networks Equipment Selection

The application of neural networks to the field of equipment selection has been demonstrated by the creation of a variety of neural network decision models. It was initially envisaged that back-propagation network models would be used, but a thorough testing revealed spurious answers, and an unsuitability to the training data.

Eventually a series of counter-propagation networks were created, one of which is shown in figure 5.16. This network is a four layer network used to select equipment types for topsoil removal. The network has been trained using a file of past equipment case studies.

The network is based on three input criteria : topsoil thickness, haul distance and flexibility under varied conditions. These factors are entered as numerical inputs to the network in the range of 0 to 1. The first hidden layer adjusts the inputs into normalised vectors consistent with the Kohonen learning rule used in the second hidden layer. The Kohonen layer uses this learning technique to adapt the processing elements to recognise particular codes. The Widrow-Hoff learning technique used in the output layer is a method of computing the error signal in the output and adjusting the weights in the input connections to eliminate this error.

In figure 5.16 the input values, represented by the size of the boxes on the processing elements, are 0.3, 0.6 and 0.4 respectively. This illustrates a low topsoil thickness, an average flexibility requirement and a haul distance of 300-600 m.

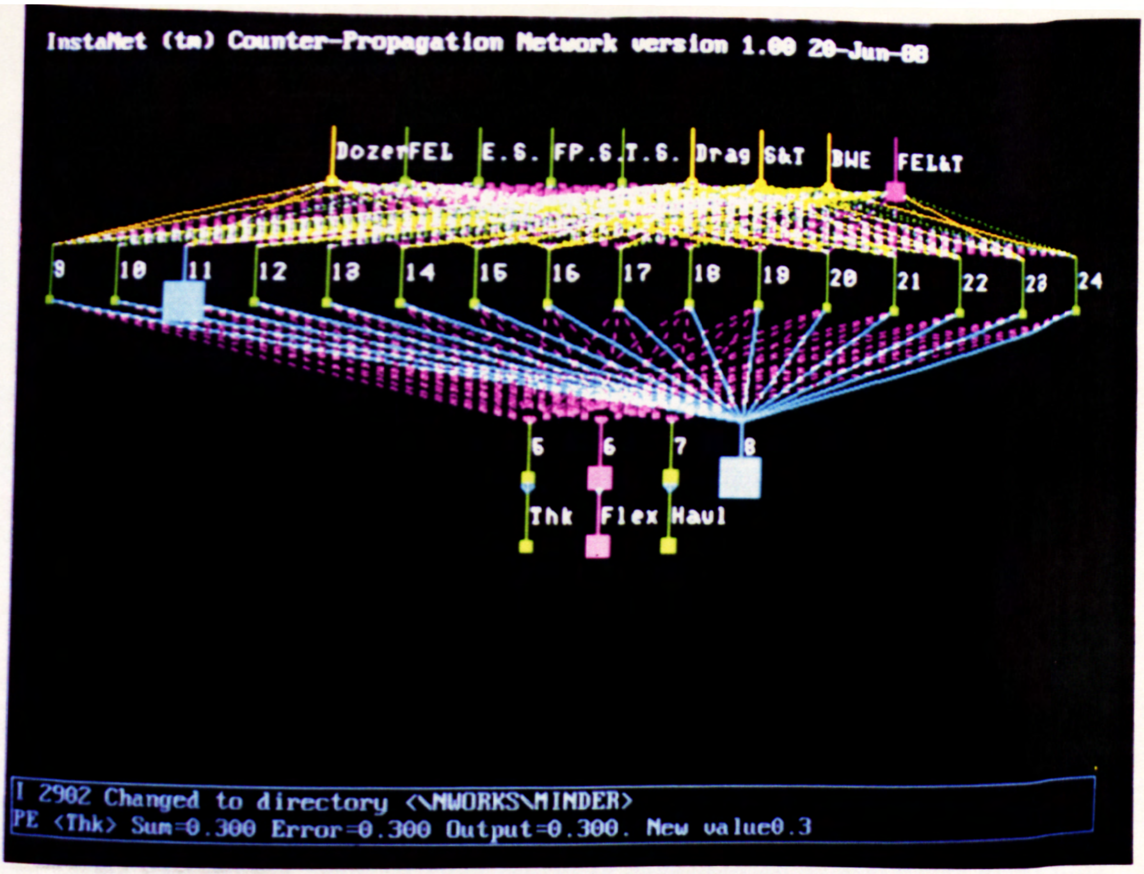


Figure 5.16 Neural Network to Select Topsoil Removal Equipment

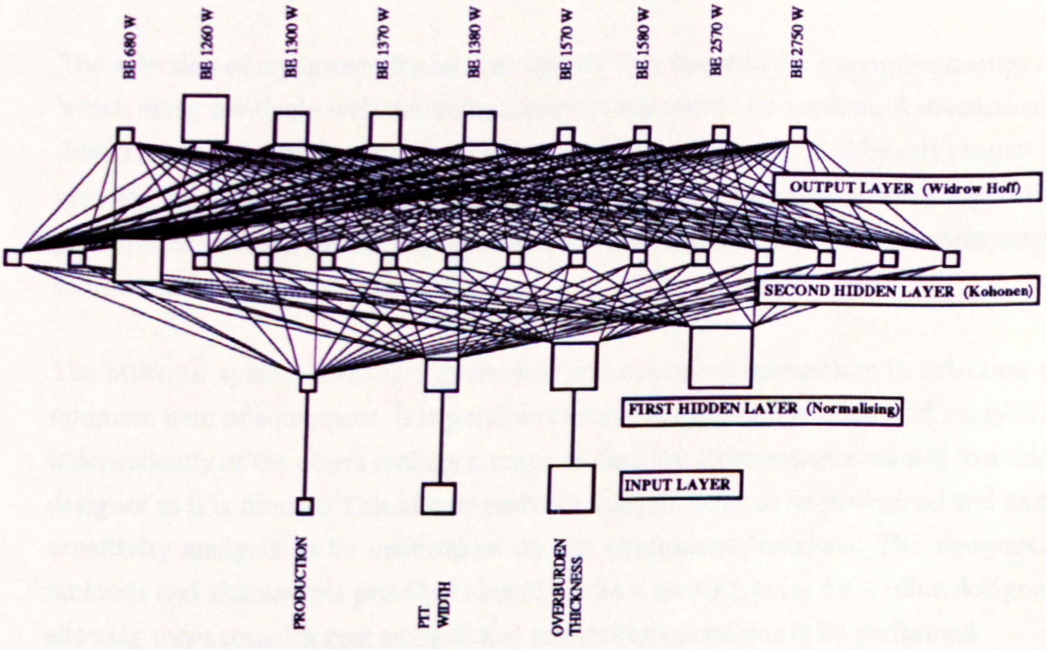


Figure 5.17 Neural Network to Select a Dragline Model

The neural network provides the following ranked results.

O	Front End Loader and Truck	0.50
O	Scraper and Tractor	0.20
O	Full Power Scraper	0.15
O	Elevating Scraper	0.15

A more detailed counter-propagation network allowing dragline models to be selected was created using the Neural Works software. A representation of this network is shown in figure 5.17. This network was iteratively trained using small sets of training data allowing an estimation of the required data for complete training to be made.

5.11 Conclusions

Competition between the manufacturers of hydraulic excavators and draglines is intensive. The costs of overburden and mineral removal have been reported in many technical journals and at conferences (Atkinson 1971, Straam Engineers 1978). Over the past decade opencast mine operators have trended to use larger excavating machinery (Mine and Quarry, 1991). The single greatest area of advance in opencast mining equipment in the last decade has been in the area of diesel hydraulic shovels which now challenge the long accepted dragline and electric rope shovel (Adams 1990).

The selection of equipment for an opencast mining operation is a complex decision in which many relatively well defined parameters are taken into account. A discussion of these factors and which equipment they influence has been provided by this chapter. In practice, mine operators when purchasing an item of equipment display a personal predisposed opinion, based on past service records, parts maintenance, manufacturer's location and a host of other such factors.

The MINDER system considers geometric and operating parameters in selecting an optimum item of equipment. It is possible to run any application module of the system independently of the others making a range of decision information available to a mine designer as it is needed. This allows multiple consultations to be performed and basic sensitivity analysis to be undertaken on the equipment decisions. The equipment rankings and simulations provided should act as a starting point for a mine designer, allowing more complex cost analysis and scheduling operations to be performed.

To retain flexibility in the design stages some computing or mining knowledge is usually needed to decide on the order the application modules should run. In this context, it should be remembered that one of the most important aspects of an expert systems is the help and explanation facilities. Often the decision reached is not as important as the reasons for the decision.

Chapter 6

Case Studies

6.1 Introduction

This chapter presents a selection of MINDER case studies. Information from geological models and pit reports is used to select working methods in addition to equipment types and advise an engineer on their use. The objective is to evaluate the MINDER system performance, providing a validation of the thesis and suggesting potential applications.

Equipment selection is often based upon subjective judgement and the aim of the MINDER system is to provide optimum equipment configurations based upon site constraints. This chapter will consider three case studies. The first is a simple test to demonstrate the capabilities of the system. The second is an example of a large Australian opencast mine and uses a mixture of real and created data. The third case study was performed using real data from a large opencast site in Scotland, which allowed the MINDER results to be compared with actual equipment used.

The case studies will be reported in a condensed format, the sites will be described and the equipment results given. Small parts of the design will be considered in detail to illustrate the workings of the MINDER system. Tables of data and results are reported in appendices to keep the main body of the text readable.

6.2 Case Study 1

The first case study to be considered has a simple three layered geology, with a horizontal topsoil layer of earth overlying a variable thickness of shale. This small area could be part of a larger mine planning exercise. Below the shale lies a coal seam of uniform thickness but variable depth. A schematic of this case study with an extended vertical scale is shown in figure 6.1. This was generated using AutoCad based upon a Surpac model of the deposit.

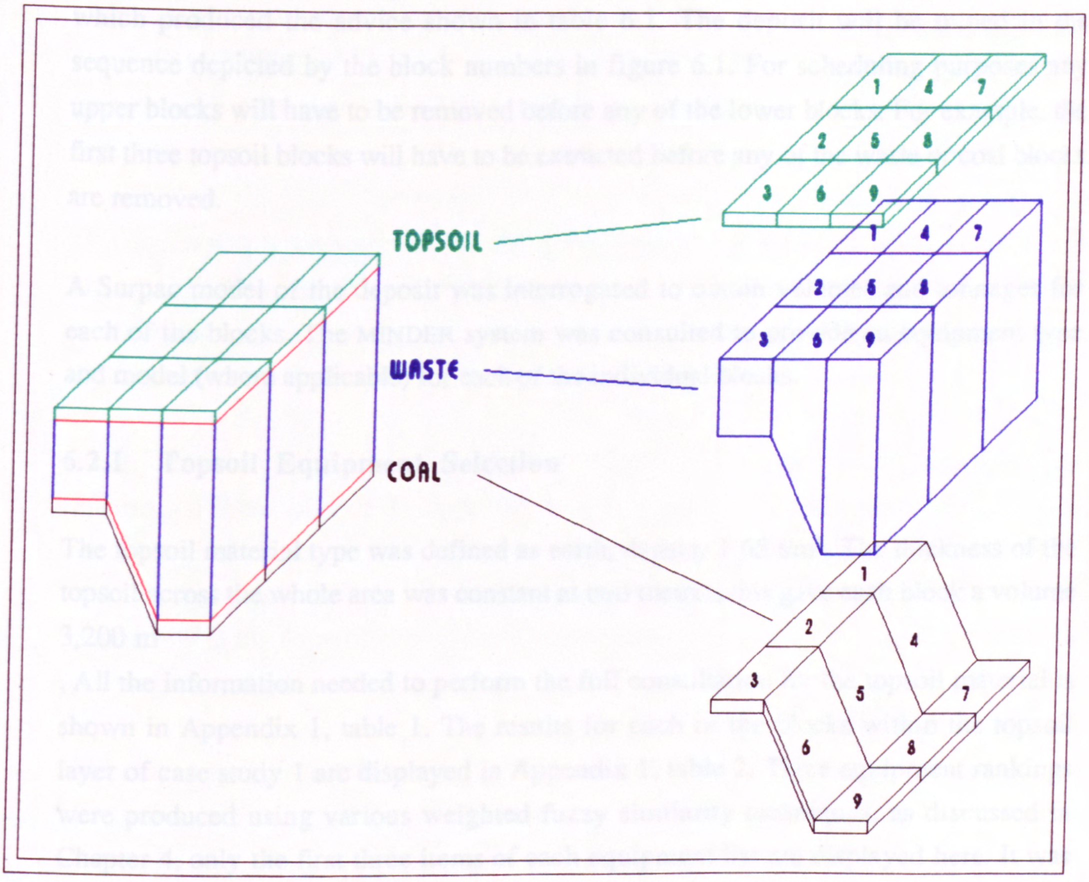


Figure 6.1 Block Representation of Case Study 1

Each layer of the deposit has been split into a series of nine blocks for evaluation purposes. Each block has lateral dimensions of approximately 40 m x 40 m, the vertical dimension depends upon the thickness of the layer. For the topsoil and coal levels each block in the layers may be considered similar, since it is assumed that the material is homogeneous. In the waste (shale) layer the material can be split into three sets of three equal blocks, each of different sizes.

Data		Advice
Stratified Deposit Inclined Seams Gentle Inclination	------------>	Use an External Dump The Overburden Ratio will Increase Lateral Advance with Vertical Advance to cut off

Table 6.1 General Advice for Case Study 1

Initially the general advice module of the top level MINDER knowledge base was run which produced the advice shown in table 6.1. The deposit will be mined in the sequence depicted by the block numbers in figure 6.1. For scheduling purposes any upper blocks will have to be removed before any of the lower blocks. For example, the first three topsoil blocks will have to be extracted before any of the waste or coal blocks are removed.

A Surpac model of the deposit was interrogated to obtain volumes and tonnages for each of the blocks. The MINDER system was consulted to provide an equipment type and model (where applicable) for each of the individual blocks.

6.2.1 Topsoil Equipment Selection

The topsoil material type was defined as earth, density 1.65 t/m^3. The thickness of the topsoil across the whole area was constant at two metres, this gave each block a volume 3,200 m

. All the information needed to perform the full consultation for the topsoil material is shown in Appendix 1, table 1. The results for each of the blocks within the topsoil layer of case study 1 are displayed in Appendix 1, table 2. Three equipment rankings were produced using various weighted fuzzy similarity techniques, as discussed in Chapter 4, only the first three items of each equipment list are displayed here. It was decided to use a scraper to remove the topsoil overlying the deposit.

The scraper module was consulted to select a suitable type of scraper for the conditions encountered, the information was taken from Surpac results files and from interrogation of the user. The Surpac results file was made up of the volume calculated between two digital terrain models, these were the topography and the base of the topsoil. The Surpac file also includes geological descriptors, such as material type, density and swell factor. Table 2 in Appendix 1 shows the results of the scraper consultation, it can be seen that the preferred item of equipment is an under-powered rubber tyred scraper.

6.2.2 Waste Equipment Selection

The waste material was defined as shale, density 2.35 t/m^3. Although the thickness of the shale across the deposit area varied between 13 and 33 metres, the blocks can be considered as three sets of three blocks, one set of 13 m thickness, one of 23 m and the last set 33 m thick.

Table 3 in Appendix 1 details the information used for the analysis of the waste material. The volume of each of the first three blocks was calculated by the Surpac software as 20,800 m^3, the next three blocks had a volume of 36,800 m^3, and the last three waste blocks contained 52,800 m^3 of material. The base of topsoil and top of coal digital terrain models were used by the Surpac software to calculate these volumes.

The equipment types suggested by both the American and British opinionated fuzzy logic mechanisms are shown in tables 4, Appendix 1. Only the first three items of each of the rankings is shown in each of the tables. It was decided on the basis of these results to pursue a design using a truck and shovel combination.

The hydraulic excavator module was consulted using the numerical and linguistic information listed in table 3, Appendix 1. It should be remembered that the MINDER system had full access to the data used in all previous consultations while selecting a hydraulic excavator model. In addition, some of the information given to the expert system was in the form of conclusions, previously arrived at by the system which the user was then asked to verify.

Table 5 in Appendix 1 provides the three fuzzy logic equipment rankings for the waste blocks. It can be seen that the MINDER system advised the use of a variety of excavators across the site. As the thickness of the shale increased so did the production requirements. For the smaller block volumes the MINDER system preferred the Liebherr 'r 991' hydraulic excavator, and for the larger volumes a Demag 'h 285' was the selected item of equipment. For the purposes of this case study it was decided to use the Demag 'h 285' hydraulic excavator to remove the shale to ensure that the excavator was capable of meeting the site production requirements.

6.2.3 Coal Equipment Selection

The coal was defined as bituminous coal, density 1.25 t/m^3. The thickness of the coal seam across the whole area was constant at two metres, giving each block a volume of 3,200 m^3. The Surpac software calculated these volumes using digital terrain models of the top and bottom of the coal seam. Table 6 in Appendix 1 gives a list of the information needed to perform the consultation to determine an optimum item of excavation equipment for the coal seam.

Using the three equipment rankings provided by the MINDER system, shown in table 7, Appendix 1, it was decided to use a hydraulic excavator to remove the coal. The hydraulic excavator module was consulted to select an excavator to match the coal seam conditions. A Komatsu 'pc 400-1' hydraulic excavator was selected to remove the coal.

6.2.4 Machine Learning Modules

The information for case study 1 was read through the knowledge induction expert system modules and the topsoil equipment selection neural network. The reason for this consultation duplication was to test the accuracy of the learning systems compared to the knowledge based system. The results from these tests are shown in table 8, Appendix 1.

The inducted rules suggested an elevating scraper for the topsoil and a shovel truck combination for the waste and coal seams, a good correlation with the MINDER results. The neural network divided it's output between scrapers and a front end loader and truck combination, agreeing with previously obtained equipment selections.

6.2.5 Scheduling Modules

The results of the equipment selection modules were automatically read into the scheduling module and Excel spreadsheets were created using the techniques described in previous chapters. The case study information was gathered and organised into three spreadsheets, as shown in schedule 1, Appendix 1. In the table layer 1 refers to the topsoil, layer 2 is the waste and layer 3 is the coal seam.

It can be seen that the schedule developed fulfils the requirement that the topsoil is removed from a block before the waste and the shale is excavated before the coal. The last of the waste and coal are removed in the tenth month, giving this area a life of ten months.

These three spreadsheets can be converted into a graphical format as shown in charts 1, 2 and 3 in Appendix 1, which illustrate the removal of the blocks on a monthly basis.

6.2.6 Case Study 1 Summary

The MINDER system has analysed a simple three layer geology, with seams of varying thickness. The deposit was split into nine separate blocks, each of which was considered individually.

The system selected an under-powered rubber-tyred scraper to remove the two metre thick layer of topsoil overlaying the deposit. A Demag 'h285' hydraulic excavator was suggested as the optimum item of equipment capable of meeting the production requirements of the site. The system selected a Komatsu 'pc 400-1' hydraulic excavator to extract the coal. An initial working schedule for these items of equipment was suggested using a spreadsheet and associated graphs.

6.3 Case Study 2

The second case study is a multi-seam deposit adapted from an Australian mine in the Hunter Valley. The Permian coal measures have a major basal seam overlain by three thinner coal seams. The deposit has been mined to a depth of 40 m, the purpose of this case study was to select equipment for future mining which will progress to greater depths. Equipment selection alternatives are available for this design allowing a comparison to be made between the MINDER selected equipment and the equipment selected by a team of mine planners (The Warren Centre, 1985).

6.3.1 Geology

The surface is relatively flat and the seams dip gently between 0 and 10 degrees. The deposit displays lateral consistency in both lithology and seam thickness. A typical geological section is shown in figure 6.2 and figure 6.3 is a simplified stratographic column. The basal coal seam is eight metres thick and the three overlying seams are each two metres thickness. The interburden thickness between the coal seams varies between 25 and 35 m. The area is overlain by a layer of topsoil, drift material and weathered sandstone.

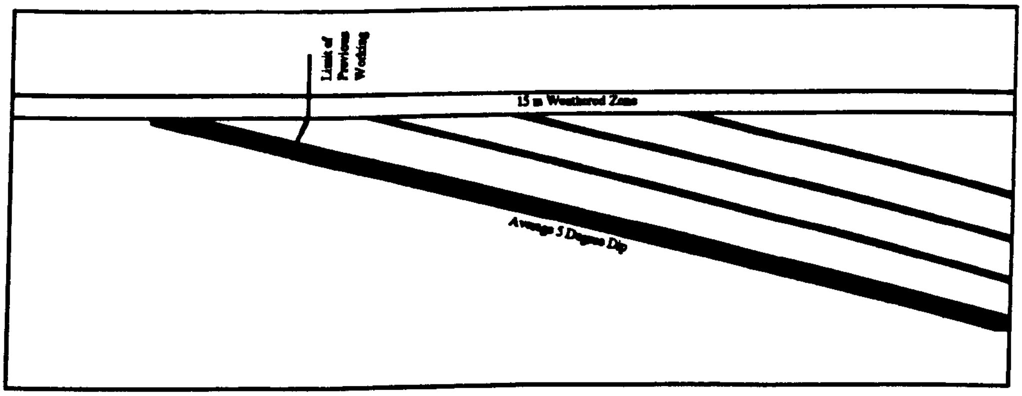


Figure 6.2 Typical Geological Section

For this study there was assumed to be no limit to the deposit down dip. Lateral extension is limited to four kilometres in the strike direction. The deposit is to be mined over a twenty five year period.

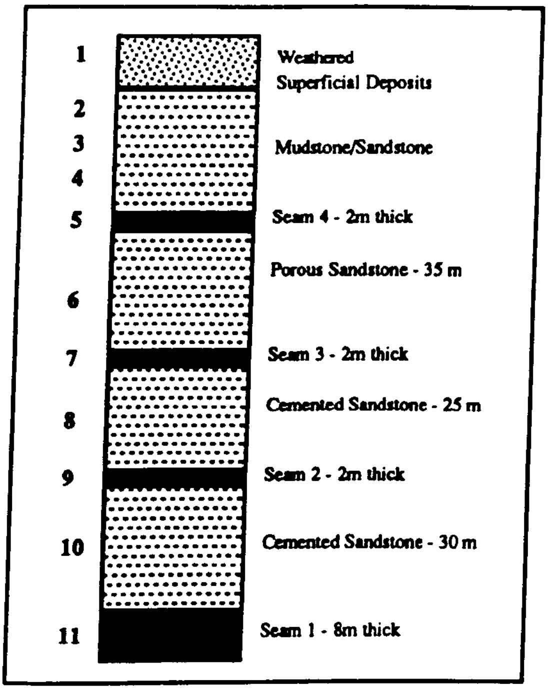


Figure 6.3 Stratographic Sequence

The stratographic sequence shown in figure 6.3 contains a series of reference numbers, these are used to denote the individuate layers considered during the assessment by the MINDER system. The material properties given for the deposit included a coal in-situ density of 1.3 t/m^3 and a waste in-situ density of 2.2 t/m^3. Table 6.2 gives the volumes and tonnages of the respective layers until the cut off depth is reached.

Layer Number	Material Type	Thickness (m)	Volume (Mm^3)	Tonnage (Mt)
1	Topsoil	15	38.30	84.26
2	Waste	20	8.02	17.64
3	Waste	15	10.17	22.37
4	Waste	35	42.28	93.02
5	Coal	2	5.60	7.28
6	Waste	35	67.21	147.86
7	Coal	2	8.55	11.12
8	Waste	25	63.14	138.91
9	Coal	2	10.56	13.73
10	Waste	30	78.64	173.01
11	Coal	8	47.27	61.45

Table 6.2 Reserve Estimation

The uniformity of the deposit meant that each layer was considered as a single block. The top level MINDER module suggested that an internal dump was used and that the deposit was mined by a lateral advance down dip with a vertical advance to the stripping ratio cut off point.

6.3.2 Equipment Selection

A consultation was performed for each strata layer within the area under consideration, and MINDER selected a particular item of equipment for each of the layers. The information used and the ranked equipment results are listed in tabular form in Appendix 2. Table 6.3 below gives a summarised list of the equipment selected for each layer.

Layer	Equipment	Model	Manufacturer
1	Shovel	rh 120	O & K
2	Shovel	h 241	Demag
3	Shovel	h 185	Demag
4	Dragline	be 1300 w	Bucyrus Eire
5	Shovel	rh 40	O & K
6	Dragline	be 1300 w	Bucyrus Eire
7	Shovel	rh 40	O & K
8	Shovel	h 285	Demag
9	Shovel	rh 40	O & K
10	Dragline	be 1380 w	Bucyrus Eire
11	Shovel	h 85	Demag

Table 6.3 Summarised Results

The preferred items of equipment were large hydraulic excavators and draglines. The hydraulic shovels being used to mine the weathered zone, the coal and the thinner waste layers, the draglines to extract the thicker sandstone strata. The MINDER dragline module offered advice on the dragline working configuration to be used, an example of a result from this case study is shown in figure 6.4.

The haulage application module suggested that rear dump trucks are used for the transportation of the spoil. The preferred truck models varied depending on the production requirements of the particular excavator. Tables 10 and 11 in Appendix 2 show the aggregated results of the haulage consultation.

```
                Dragline  Advice  System

**      Operational  Advice      **

The use of a key cut is not recommended.
Selective placement is not necessary.
Due to there being no abnormal conditions, layer
loading is advised as the method of bucket loading.
Spoil placement using the curvilinear technique
is advised.
Lack of special conditions suggest a dig and cast
technique of spoil placement.
An advance bench is to be used.

**      Geometric  Advice      **

The maximum pit width is estimated as 75 m
The minimum pit width is estimated as 32 m
Number of in-pit machines suggests congestion.
The pit width certainty factor is 0.37.
Suggested pit width is 48.0 m
Maximum dig out is estimated as 43.7 m
Minimum dig out is estimated as 13.2 m
Suggested dig out is 27.5 m
A steady reduction in pit width as mining progresses
is advised.
```

Figure 6.4 General Dragline Advice

Simulation programs written by the expert system were run within GPSS, they advised that a fleet of three trucks should be used for each of the hydraulic excavators on layers 1 and 3, four trucks for the h 241 excavator on layer 2 and five trucks for the large h 285 shovel on layer 8.

The inducted expert system and topsoil neural network were consulted using part of the data from case study 2. The aggregated results of these tests are shown in table 12 of Appendix 2. The induced rules ranked the equipment types in a similar order to the MINDER results while the neural network differed slightly, showing an increased preference for a scraper to remove the weathered material.

A schedule for the 25 year life of the mine has been prepared by the spreadsheet module of the expert system, this is shown in schedule 1 of Appendix 2. Due to the large scale of the deposit, the long time periods involved and the coarseness of the consultation this schedule provides a course estimate of the yearly volumes which could be removed using the selected equipment. It can be seen that the equipment suggested by the MINDER system is capable of removing the waste within the 25 year life of the mine.

The mining engineers who studied this site (The Warren Centre 1985) did not suggest individual items of equipment but proposed a variety of viable mining options. These options included :

- Dragline and truck / shovel operations.
- Dragline and shovels with mobile crushers.
- Draglines with mobile crushers.

The production sizes of the equipment needed which were estimated by the planning team fell within 5 - 10 % of the bucket sizes of the equipment suggested by MINDER. However, a discrepancy occurred between the MINDER system and the Warren Centre planning team with the choice of haulage systems. When selecting a truck haulage system, large 150-170 tonne trucks were selected and some of the mining configurations considered favoured in pit conveyors and mobile crushers.

The reason for this difference of opinion is based on the knowledge sources of the two planning alternatives. The Warren Centre team was at the time considering the use of advanced surface mining technology, and as such advocated the use of relatively new techniques in surface mine planning, such as the trend towards larger trucks and the use of mobile crushers with conveyor units. MINDER on the other hand uses new computer techniques to store the traditional knowledge of the surface mine planner.

6.3.3 Case Study 2 Summary

The MINDER system has analysed a large Australian coal deposit with simple geological conditions. The site was split into strata layers, each of which was considered individually. The material was considered to be homogeneous.

An O & K rh 120 hydraulic excavator with three Wabco 120 cm trucks was selected to remove the weathered surface deposits. Three O & K rh 40's were to remove the thinner upper coal seams and a larger Demag h 85 was chosen to extract the thicker basal seam. The waste is to be removed using a combination of draglines and hydraulic shovels. The draglines selected included two be 1300 w's and a larger be 1380 w for the lowest overburden layer. The hydraulic excavators selected for waste extraction were a h 241 front shovel for layer 2 which worked with four Rimpull rd 120 trucks, a Demag h 185 was selected for layer 3 with three Wabco 120 cm trucks and a h 285 excavator for layer 8 which worked with a fleet of five Wabco 150 ct trucks.

When compared to the mining configurations produced by the Warren Centre, MINDER's results correlate well. The differences in the haulage equipment selected could be overcome by incorporating new surface mining approaches and equipment trends into the expert system.

6.4 Case Study 3

The third case study is based upon a large opencast coal site in the Motherwell district of the Strathclyde region, Scotland. The site is presently being worked allowing a comparison of MINDER equipment estimates with the actual equipment used.

The topography falls from a high point of just over 240 metres above ordinance datum in the south-east corner of the site to a low point of just under 190 m in the north-west corner of the site (British Coal 1989).

In general the ground slopes towards the north-west. The gradients over most of the site are shallow ranging from 1 in 23 to 1 in 30, reaching a maximum of 1 in 3. There is a well defined valley feature developing westwards to the site boundary. The topography is clearly illustrated by the surface contours shown in figures 6.5. A shaded representation of the topography is shown in figure 6.6 which clearly shows the valley feature to the west of the site. The vertical scale in figure 6.6 has been exaggerated by a factor of ten. The site is in a state of dereliction containing colliery tips, abandoned buildings and a disused railway line.

6.4.1 Geology

The strata under consideration for this case study constitutes the section of the Coal Measures from the Lower Drumgray seam to the Armadale Main, which is taken as the basal seam over most of the site. A stratographic sequence with approximate thicknesses is shown in figure 6.7.

Superficial deposits cover the entire site and consist of boulder clay, peat, sand and gravel, with a thin covering of soil. The thickness of the drift material varies across the site from 0.20 m to a maximum of 12.85 m, averaging 2.98 m. The majority of the site has a cover of glacial till. Small deposits of peat have been located to the south-east and south-west of the site up to a maximum thickness of 6m. There are also deposits of colliery waste at various localities within the excavation area.

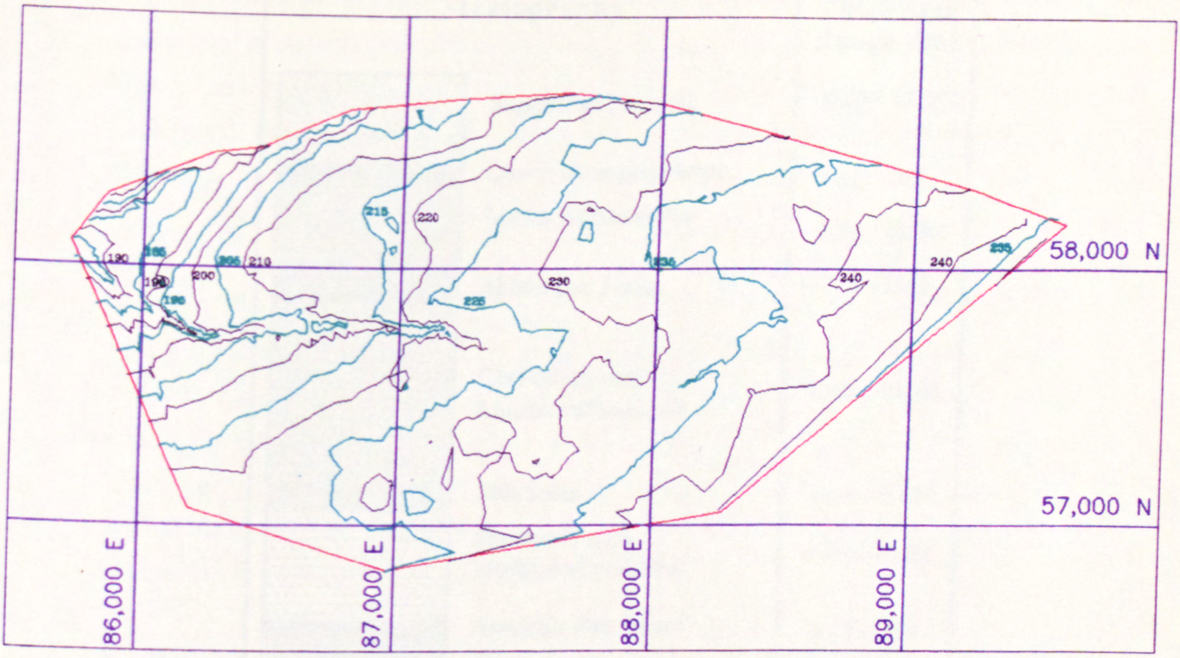


Figure 6.5 A Contoured Plan of Surface Topography

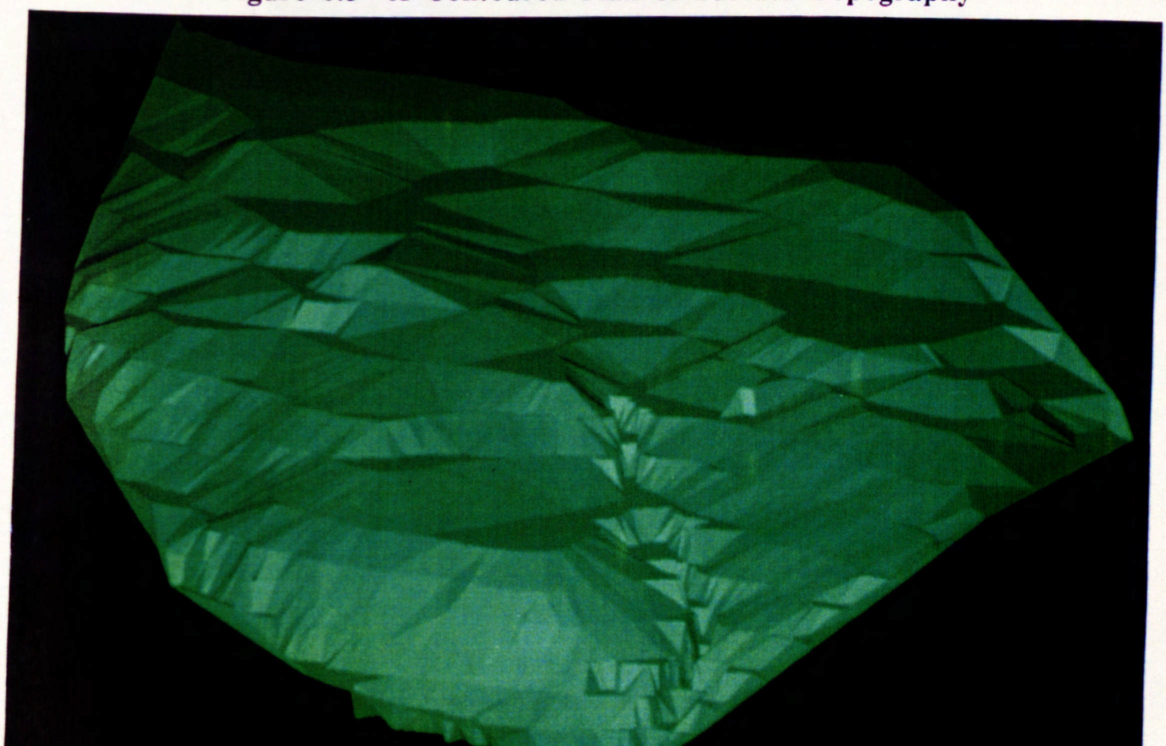
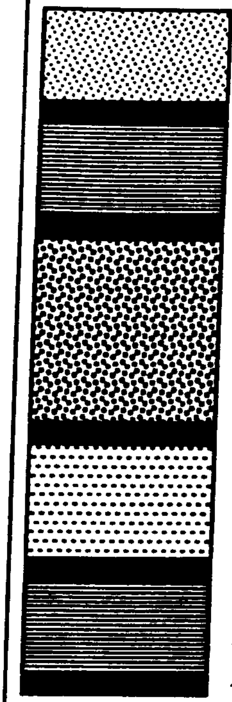


Figure 6.6 A Shaded Model of Surface Topography



Stratography	Thickness Range (m)
Superficial Deposits	0.20 - 12.85
Lower Drumgray Seam	0.56 - 0.73
Mudstone/Sandstone	8.50 - 12.00
Shotts Gas Seam	0.32 - 0.61
Clay overlaying Mudstone/Sandstone	20.45 - 24.50
Mill Seam	0.41 - 1.41
Sandstone with Mudstone/Sandstone	7.00 - 16.80
Armadale Ball Seam	0.19 - 0.65
Mudstone overlying Siltstone/Sandstone	2.24 - 8.10
Armadale Main Seam	0.37 - 0.86

Figure 6.7 Statography and Thickness Ranges (British Coal 1989)

Most of the coal seams are simple seams with mudstone roofs. The floor is normally mudstone or seatearth. Outcrop areas of the upper seams have been affected by drift disturbance and the coal area has been accordingly delineated. The exception to this coal description is the Mill seam which is a complex seam comprising two leaves and is the thickest on the site. The mudstone parting varies in thickness between 0.09 and 0.64 metres. The coal occasionally becomes shaly across the site, this shaly coal is not considered.

The Armadale Main seam is affected by thinning and washout over the site. A major north-south trending washout channel up to 190 metres in width separates the Armadale Main seam to the west of the site. The areas of working were also limited against a large washout feature in the centre of the site.

The overall dip of the strata is northwards with variations to north-west or north-east with dips generally no steeper than 1 in 20. Flat lying strata is present to the north and south of the site in very shallow synclinal structures.

The coal areas are generally unaffected by major faulting. However, there is one large fault in the south-west corner of the site, running east-west. This downthrows approximately forty metres to the north. Lesser, east-west trending faults have been detected in the west of the site, these have average throws of between six and eight metres.

6.4.2 Areas of Working

The site is to be worked in four areas these were defined by the site boundary, the major fault and the seam outcrop positions. These four are shown in figure 6.8 which was produced using Surpac software to create digital terrain models of the base of the lower seams within each of these areas. Areas A and C are to be worked to the base of the Armadale Main seam, area B is to be worked to the base of the Shotts Gas seam, and area D to the base of the Mill seam.

A section drawn across the site shows the relative elevations of the various seams. Figure 6.9 shows a section across line X-Y with the vertical axis exaggerated by a factor of ten. The pit will have two deep areas where the strata is extracted to the Armadale Main seam, with an raised area (area D) between them. The Armadale Main and Armadale Ball seams are not mined within area D due to washouts and seam thinning.

The size of the various areas has been estimated using Surpac software, and volumes have been produced, these are shown in table 6.4. The coal seams have been analysed to determine the amount of coal which can be exploited in each of the areas. The results of this analysis can be seen in table 6.5.

Working Area	Estimated Area (m^2)	Estimated Volume (m^3)
A	471,000	19,782,000
B	365,000	5,110,000
C	1,182,000	26,005,000
D	373,000	5,222,000

Table 6.4 Estimated Sizes of the Working Areas

It can be seen from these tables that the total coal in situ is some 2,358,000 m^3 in a total pit volume of 76,105,000 m^3 which gives an overall mine stripping ratio of approximately 22.5. The density of the coal has been taken as 1.33 t/m^3 across the site.

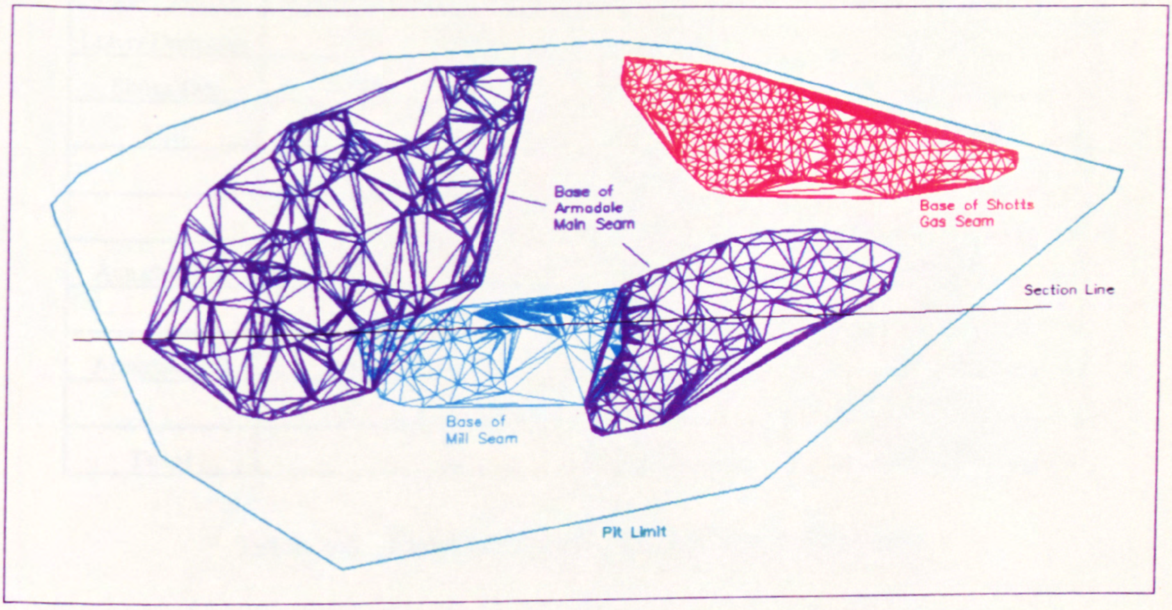


Figure 6.8 A Digital Terrain Model of the Base of the Coal Seams

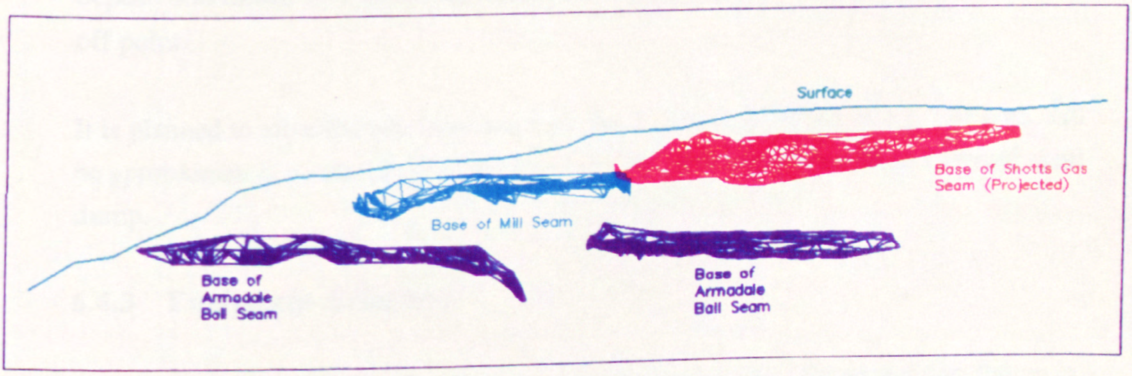


Figure 6.9 A Cross Section Through the Digital Terrain Model

The seam washouts and geological disturbances were taken into account during the volumetric calculations. Where it was not possible to calculate the volume of the disturbance then a percentage figure was used.

The site offices are placed between the four working areas and an external soil dump is to be placed in the southern area of the site. Figure 6.10 shows the site and the surrounding features, including geological disturbances and housing areas.

Coal Seams	Working Area	Estimated Volume (m^3)	Estimated Tonnage
Lower Drumgray	B	512,000	680,000
Shotts Gas	B	141,000	188,000
Mill	A	215,000	285,900
	C	197,000	262,000
	D	168,000	223,000
Armadale Ball	A	143,000	190,000
	C	256,000	341,000
Armadale Ball	A	233,000	412,000
	C	493,000	657,000
Total		2,358,000	3,238,000

Table 6.5 Estimated Coal Volumes and Tonnages

Initially the top level module of the MINDER system was run to give general advice on the working of the site. This suggested that an external dump was used and that the deposit was mined by a lateral advance with vertical advance to the stripping ratio cut off point.

It is planned to mine the site from west to east in less than fifteen years. The cuts will be approximately parallel to the strike and the waste is transported to an external spoil dump.

6.4.3 Equipment Selection

These four areas are further divided into sixteen smaller areas for analysis as shown in figure 6.11. A consultation was performed for each layer of strata in each of these small areas. The information used and the equipment rankings performed are listed in tabular form in Appendix 3. Table 6.6 below gives a list of the tables in Appendix 3.

The topsoil (drift) material was treated as boulder clay across most of the site, the exceptions being area C4 where a sand and gravel material was considered and area A3 where the material was a peat/earth mixture. Each working area was consulted to give three weighted rankings. The tabulated results in Appendix 3 show the overall aggregated rankings of the equipment for each block.

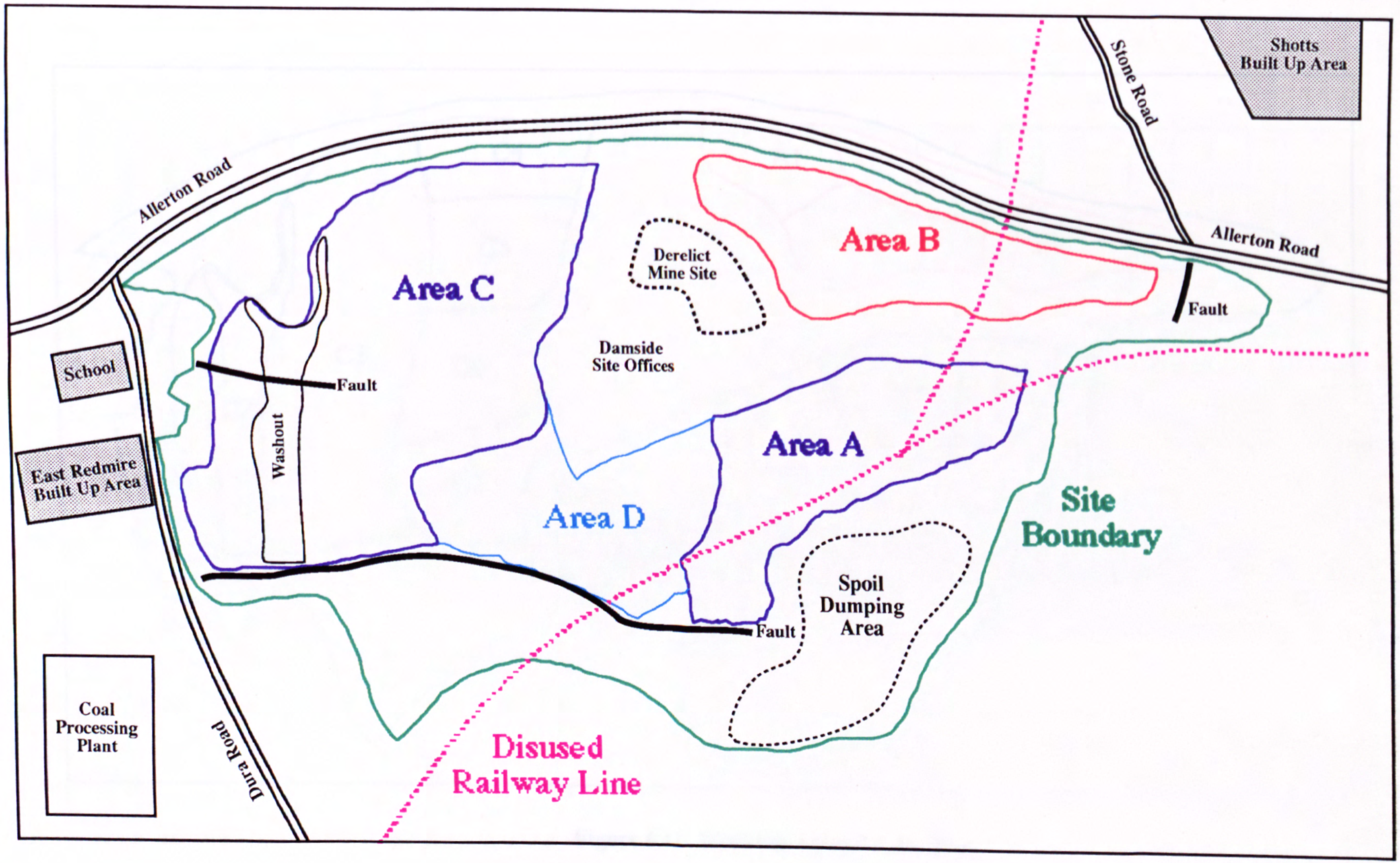


Figure 6.10 Site Location and Surroundings

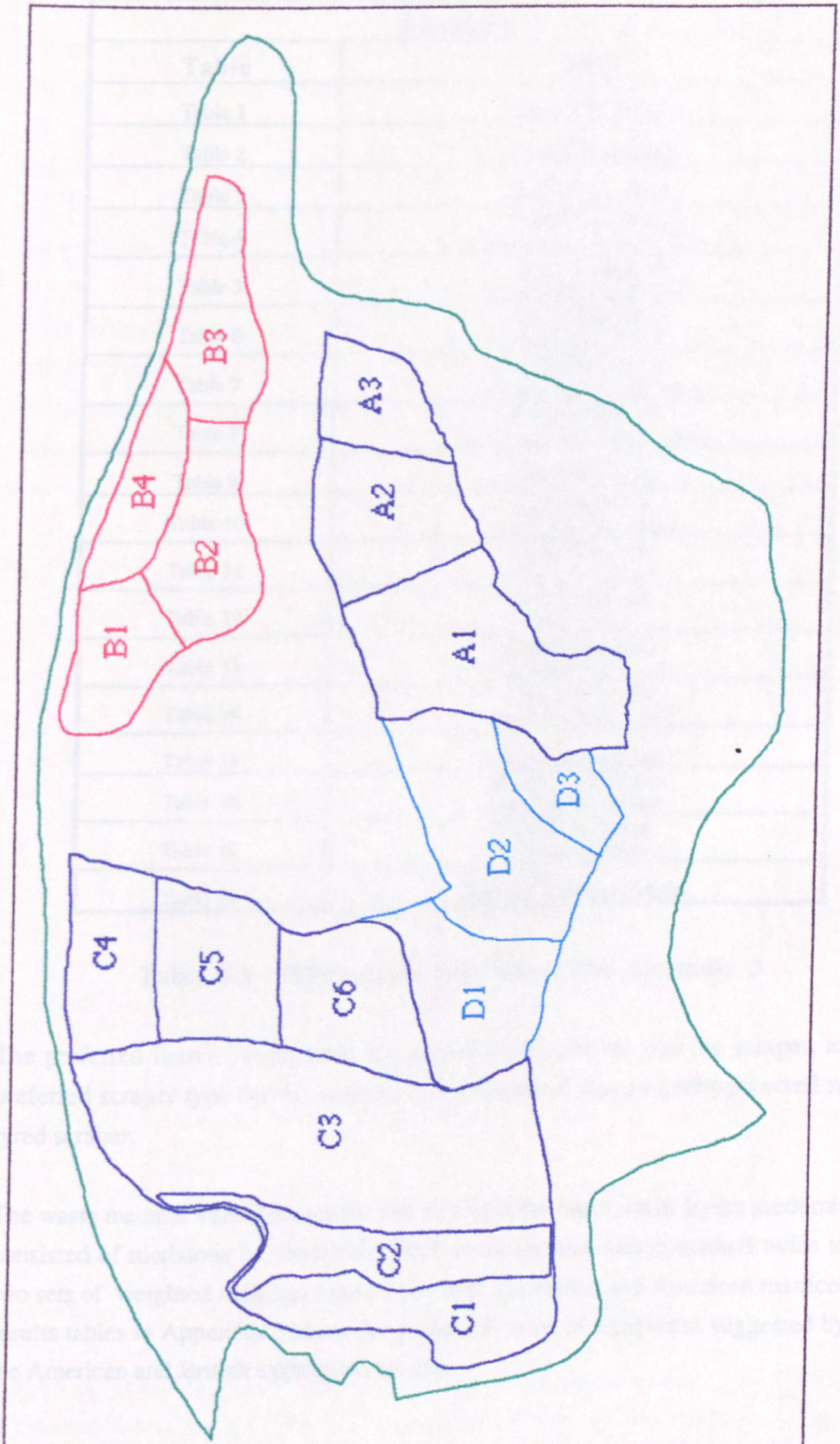


Figure 6.11 Working Areas for Analysis

Appendix 3	
Table	**Title**
Table 1	Topsoil Information
Table 2	Topsoil Equipment
Table 3	Waste Information
Table 4	Waste Equipment (above Lower Drumgray Seam)
Table 5	Waste Equipment (above Shotts Gas Seam)
Table 6	Waste Equipment (above Mill Seam)
Table 7	Waste Equipment (above Armadale Ball Seam)
Table 8	Waste Equipment (above Armadale Main Seam)
Table 9	Coal Information
Table 10	Coal Equipment (Lower Drumgrey Seam)
Table 11	Coal Equipment (Shotts Gas Seam)
Table 12	Coal Equipment (Mill Seam)
Table 13	Coal Equipment (Armadale Ball Seam)
Table 14	Coal Equipment (Armadale Main Seam)
Table 15	Haulage Information
Table 16	Haulage Equipment (Aggregated Results)
Table 17	Truck Equipment (Aggregated Results)
Table 18	Machine Learning Results

Table 6.6 Information and Results in Appendix 3

The preferred item of equipment for topsoil/drift removal was the scraper, and the preferred scraper type for the conditions encountered was an under-powered rubber-tyred scraper.

The waste material varied across the site although the interburden layers predominantly consisted of mudstone or sandstone. Each working area was consulted twice to give two sets of weighted rankings based upon both the British and American matrices. The results tables in Appendix 3 show the preferred items of equipment suggested by both the American and British aggregated results.

When the equipment type suggested by the top level consultation was a hydraulic shovel then two equipment item consultations were performed based on whether the equipment is to be used principally for this layer or for other layers within the site.

The optimum item of equipment suggested by the MINDER system varied across the site. The system indicated a general preference for hydraulic excavators with draglines being preferred in some of the thicker seam areas.

When a hydraulic excavator was considered principally for one layer of the site the system tended to select shovels such as the O & K rh 75 or the Demag h 85. If more layers were considered then larger models such as the O & K rh 120 or rh 185 were selected. A Bucyrus Eire 1260 w was the preferred dragline equipment item across the site.

```
              Dragline  Advice  System

**     Operational  Advice     **

The use of a key cut is recommended
to ensure good highwall profile and condition.
Selective placement is not necessary.
Due to their being no abnormal conditions, layer
loading is advised as the method of bucket loading.
Spoil placement using the curvilinear technique
is advised.
Lack of special conditions suggest a dig and cast
technique of spoil placement.
An advance bench is not to be used.

**     Geometric Advice     **

The maximum pit width is estimated as 52 m
The minimum pit width is estimated as 25 m
Coal recovery may be increased with wider pit width.
Number of in-pit machines suggests congestion.
Dozing requirements may be reduced by a
narrower pit width.
The pit width certainty factor is 0.43.
Suggested pit width is 36.6 m
Maximum dig out is estimated as 32.6 m
Minimum dig out is estimated as 10.9 m
Suggested dig out is 21.8 m
A steady reduction in pit width as mining progresses
is advised.
```

Figure 6.12 General Dragline Advice

Since a dragline had been suggested as a possible equipment alternative the dragline advice module of the MINDER system was run during the consultation. An example giving the general advice for a single block is shown in figure 6.12.

The coal material was constant across the site only varying in thickness from seam to seam and from area to area. Each working area in which a seam occurred was consulted to give three weighted rankings. The aggregated results of these consultations are shown in Appendix 3.

The preferred item of equipment for coal extraction was a hydraulic shovel, with a scraper being selected in a few areas where the coal lies at shallow depths. The system selected a range of different excavators as the seam thickness varied ranging from the Kubota kh 20 to the Demag h71.

The dominant suggestion of the haulage application module was for the used of rear dump trucks to transport the waste to the spoil dump. The overall selected truck model is a Euclid r-100, tables 16 and 17 in Appendix 3 show the aggregated results of the haulage consultation. The GPSS simulation software was run using programs written by the MINDER system, the results of the truck shovel simulation suggested that a fleet of eight trucks should be used, four working with each hydraulic excavator.

Selected information for case study 3 was used to consult the inducted expert system modules and to run the topsoil equipment selection neural network. The results of these tests are shown in table 18 in Appendix 3. A selection of blocks were used for these consultations and the results were aggregated into final equipment rankings. The inducted knowledge bases and neural networks agree with the MINDER system consultations to advise an elevating scraper as the topsoil/drift removal equipment and a hydraulic shovel to remove the coal. A slight difference between the systems is noticed in the waste consultation. Although the system suggests a shovel and truck as the optimum type of equipment, a front end loader and truck option is preferred above a dragline.

6.4.4 Equipment Scheduling

The MINDER equipment selection results for the site can be interpreted in a variety of ways, whether a suite of hydraulic excavators is to be used or a dragline/shovel combination as suggested for some of the deeper areas. For the purposes of simulating the production over the life of the mine it was decided to use two O & K rh 120 excavators to mine the waste layers, and an O & K rh 6 to remove the coal. A fleet of eight Euclid r-100 dump trucks will be used to transport the waste to the external dump.

Damside Plant (Dec. 1991)	
Waste Excavator	Demag 185 (1)
Waste Excavator	Cat 225 (1)
Coal Excavator	O & K rh 9 (1)
Dragline	BE 1260 w (1)
Dump Trucks	Cat 777B (4)
Dozer	Cat 814 (1)
Dozer	Cat D6 (1)
Dozers	Cat D9N (2)

Table 6.7 Actual Equipment used on the Opencast Site

The actual equipment used on the opencast site is shown in table 6.7. A Bucyrus Eire 1260 w dragline and Demag 185 hydraulic excavator make up the principle waste removal equipment. A Caterpillar 225 excavator is used for topsoil/drift removal and the coal is excavated using an O & K rh 9. A fleet of dozers are used for ancillary tasks such as the flattening of the spoil peaks.

The results of the equipment selection modules were read into the MINDER scheduling module creating Excel Spreadsheets of the production over the life of the mine. Two simulations were performed one based on the equipment configuration suggested by the MINDER system and one based on the actual equipment used.

The MINDER and actual schedules are shown in Appendix 3, schedules 1 and 2 respectively. It can be clearly seen that the equipment selected by the MINDER system has a lower production rate then the actual equipment used. The suggested equipment fulfils the requirements of the site within the specified time limits. The actual equipment appears to have a production over capacity.

6.4.5 Case Study 3 Summary

The MINDER system has analysed the complex multi-layer geology of a large opencast coal site. The site was split into sixteen working areas, each of which was considered individually. The large size of these areas introduces errors due to the assumptions which have to be made on the homogeneity of the material within these areas.

The system selected under-powered rubber-tyred elevating scrapers to remove the layers of topsoil and drift material overlying the coal deposits. Although a range of equipment was suggested for the removal of the waste material a preference was shown for hydraulic excavators. It was decided to excavate the waste using two O & K rh 120 hydraulic shovels, although applying some of the other suggested excavating equipment to the site may be a useful exercise during the planning of the full mine site. MINDER suggested a range of hydraulic shovels for coal removal, it was decided to schedule the coal excavation using an O & K rh 6 hydraulic excavator.

The shovel and truck simulation suggested that a fleet of eight trucks are used to transport the waste from the two rh 120 shovels, this is similar to the actual site which uses four trucks to transport the waste from one hydraulic excavator.

In comparing the results of the consultation with the actual equipment used, the major difference is the increased capacity of the actual excavating equipment. It is believed that this is due to the difference between the theoretical rates of working produced using manufacturers data and the actual production rates experienced by the contractors. Upon questioning, the contractors quoted the production rates of various machines 5-15 % lower than the production rates used by the MINDER system (Bell 1990).

It should be noted at this point that the MINDER system aims to select optimum equipment for the conditions encountered without considering cost constraints, which may alter the equipment decisions.

Overall the case study achieved it's objective, selecting an item of equipment which meets the constraints imposed by the conditions encountered. The comparison with the actual equipment used is inaccurate unless the financial aspects are considered and the equipment available to the contractor is taken into account.

Chapter 7

Conclusions

7.1 General Conclusions

The planning of an opencast mine is a complex process due to the inter-dependence of the decisions required. A wide range of externally imposed factors may prohibit a particular type of mining, these include mining and environmental law, deposit conditions, community attitudes and industrial policies. Except where conditions exist which prohibit a particular type of mining, the combined influences of the various factors is related to their impact on the costs of operation. The method that proves to be the most cost effective on an overall basis will be the one used to mine the deposit.

Changes in the economic climate and fiscal pressures have led to a situation where it is essential to obtain the mine design which best matches the conditions encountered. This methodology applies through all the stages of the design process. The decisions are based on collated information on the deposit, engineering knowledge and subjective judgement. This places increasing pressure on the mine planner to be an expert in a wide range of fields.

The selection of excavation machinery has a significant effect on the profitability of a opencast mining project, the importance of this decision is often overlooked by mine operators and contractors who display predisposed opinions based on past contracts, location and personal contacts.

Equipment selection is not an exact science and although the optimum selection for an opencast mine is a complex decision, it can be broken down into a series of relatively well defined parameters. The planning engineer often has inappropriate tools to cope with the decisions that need to be made.

In recent years the impact of computer technology on mine design has been profound, numerous pieces of software are available to assist the mine planner. The planning software available, however, is often unable to meet the complex demands arising from the individual nature of each deposit.

The software is not always applicable to the particular planning problem or incapable of dealing with large real data sets. This problem has not prevented some stages of the mine design process relying on computer techniques. Equipment selection remains a human task with the use of computer systems, such as databases and spreadsheets, limited to the periphery of the decision.

The computer tools available have advanced considerably in recent years. Reductions in the cost of hardware and the increasing availability of software has meant that computers are now being used more extensively than before.

The rapid expansion of the computer industry has led to new methods of storing and generating knowledge using computer systems, increasing the number of potential mining applications. This new technology does not fully simulate the breadth of human reasoning, but manipulates symbols following an inferred reasoning pattern.

Knowledge based techniques appear to be the most promising solution to mine planning problems involving subjective and imprecise information. A variety of rule based techniques have been applied to the field of mine design, storing and manipulating operating and design knowledge and providing advice to the mine planner. Initial applications of expert systems in the minerals industry have proved the economic benefits of these systems by resolving problems which conventional programs are incapable of solving due to the complex symbolic manipulation involved. The application of these systems is still slower than in other comparable industries.

Expert systems reduce time and effort, improve decision making and minimise the likelihood of errors. Although the final responsibility is often still dependant on a human choice, these systems will ultimately lead to improved decisions.

Expert systems use a variety of methods for handling uncertain information. Fuzzy logic is useful in dealing with ill defined information presented in the form of linguistic concepts, and is capable of dealing with both qualitative and quantitative information. The two fuzzy ranking techniques discussed in the thesis allow the subjectivity of differing expert opinions to be incorporated into the analysis.

An advantage of the expert system approach is the ability to explain any conclusions reached and justify the inferencing process. When a fuzzy logic technique has been used to rank alternatives it is often difficult to explain the conclusion reached, the user must have a knowledge of the technique as the conclusions are presented in the form of a numerical matrix.

An expert system is usually a strictly bounded environment which disallows large scale data storage or complex algorithmic calculations. Thus in mine planning applications it becomes imperative for these functions to be performed using other software packages which can be coupled to the shell.

Development is moving away from large independent expert systems and the emphasis is now on the modular integration of knowledge based techniques with conventional programs. This solution provides applications using knowledge driven algorithms, facilitating rapid analysis and generation of information. Often it is the intelligent use of these applications which ensures a correct decision.

The expert system is also capable of acting as a front or back end to a range of conventional software providing a new degree of 'user friendliness'. Two and three dimensional graphicalm interfaces are now being incorporated as standard into modern software, and the use of mouse and menu facilities can enhance the user interface.

The computer based research in the Department of Mining Engineering at Nottingham University has progressed from the design of conventional mining software into the development of intelligent systems which are applied to specialised areas of the design process. Individual modular expert systems are developed which link into and utilise software which is already available to the mine planner.

The MINDER system has been developed as a decision support tool for equipment selection, and provides initial estimates of equipment requirements to guide the user towards areas needing further detailed analysis. The system considers the geometric and operating factors affecting the selection of a particular item of equipment.

A minimal amount of initial knowledge of equipment selection techniques is required by the user as full on line help and explanation facilities are available. The help facility covers the equipment selection process and describes the mining terms involved, the explanation facility details the inferencing process under way and describes why a particular value is needed. No computer experience is necessary to use the system as the expert system relies on a question and answer interface with pull down menus used whenever necessary.

MINDER is capable of handling uncertain or missing information using a combination of linguistic variables, certainty factors and external fuzzy logic software. The provision of three fuzzy logic rankings for each MINDER equipment decision gives an insight into the fuzzy logic matrices used. This provides a form of explanation showing which factors were of greater importance for each equipment alternative.

The expert system is capable of not only linking with a range of commercially available mine design software, but of writing macros and controlling the automatic operation of this software. At present during the course of one consultation the expert system may :

- Interrogate geological model result files.
- Run external compiled Pascal software.
- Perform relational operations on material and equipment databases.
- Run truck/shovel simulations using GPSS.
- Report the results to a spreadsheet.

The use of a knowledge based system to control this complicated suite of software allows a mine planner with no computer experience to perform complex tasks on a range of commercially available software.

The MINDER system has itself been designed as a modular system, containing a hierarchy of individual applications and knowledge modules. Any module may be run independently of the others making a range of decision information available to the mine planner as it is needed. This allows multiple consultations to be performed and basic sensitivity analysis to be undertaken on the equipment decisions.

The modular structure of the MINDER system facilitates the inclusion of further rules and knowledge modules. This allows the system to keep in line with current trends in the mining industry and provides a more powerful directive tool.

The MINDER software has been repeatedly run in a number of case studies. These demonstrated the ability of the software to perform detailed examinations of the complex relationships between equipment geometry, operating methods and geological conditions over a range of mining sequences. The MINDER system selected a set of optimum equipment for the sites to meet the respective production requirements and predicted where production problems may occur and larger items of equipment may be needed.

An additional objective of this project was to evaluate the use of machine learning technologies, such as knowledge induction and neural networks, as decision support aids for the mine planner. The field of mine design is a pertinent application of machine learning systems due to the inherent complexity of the decisions and the large amounts of uncertain information involved. It would be possible to control these machine learning techniques using existing expert system technology.

Knowledge induction provides a solution to the expert system 'bottle-neck' of knowledge acquisition by automatically generating a series of rules from a set of data. To produce valid rules the example data must be split into a series of representative attributes and outcomes. The use of decision tree pruning techniques, such as the C4 algorithm have led to greater confidence in rules generated from inducted systems.

Neural networks have potential to increase both the speed and robustness of conventional computer systems. Within the next few years neural based circuitry will appear in silicon, allowing the intelligent control of both hardware and software systems. A neural network involves a large number of processing elements each with primary local connections. These connections may be weighted during a training cycle allowing a trained network to make educated guesses when presented with new information. As with knowledge induction, neural networks require the data to be described using a meaningful classification system. A major problem with neurocomputing is the lack of explanation, in a manner similar to fuzzy logic the user must understand the internal processes to glean any knowledge other than a simple output value.

The MINDER top level equipment module was recreated using the Xi Rule knowledge induction software. The decision tree created using the C4 algorithm was pruned to eliminate any errors due to contradicting data and missing information. The large module produced accessed no external software and attempted to select any item of excavating equipment exclusively using rules. These rules were tested in parallel with the MINDER system during the case studies and, although inefficient, they performed well.

Two neural network models were trained to make equipment decisions, one to select topsoil removal equipment and one to select a dragline model. These neural networks were created using the InstaNet option of the Neural Works Explorer Package. A series of counter-propagation networks were created after initial trials with back-propagation networks provided spurious answers. Output from these networks was compared with test results from the MINDER case studies, and similar rankings were obtained. These networks show the application of the technology and illustrate their potential for further use.

The current interest in machine learning is based on a number of scientific and economic expectations, some of which may be unreasonable. Although intelligent systems can analyse and discriminate complex patterns, they can not perform many simple human actions. In many fields such as learning the basic skills of a human operator it has been found to be easier to train a neural network than to design and build an expert system (Feldman 1990). The future of these machine learning systems depends on the advent of technologies that support their speed and storage requirements.

The mining industry still has to appreciate the full benefits of knowledge based and machine learning technology. This will no doubt occur in a similar manner to the way conventional computer systems have permeated into many aspects of mine design, and will soon be considered essential.

The MINDER expert system has concentrated on one aspect of the mine design process, attempting to eliminate the substantial economic losses arising from the selection of the wrong piece of opencast mining machinery. There is a need for logical approaches to eliminate weakness in the decision making process, this involves long term research into further applications of intelligent computer systems.

There is a continuing rise in the levels of expertise in the mining industry leading to a dissemination of expert knowledge. The loss of key personnel resulting in skill shortages and a fall in professional expertise has been well documented. The use of intelligent computer systems will not lead to the redundancy of experts, but will act as decision aids, enhancing their performance, acting as a second opinion and design guide. Whether these systems will mimic or eliminate the subjective opinions of the expert remains to be seen. Future computer systems may argue alternative viewpoints with the same convictions as humans.

7.2 Recommendations for Future Work

The large number of inter-related factors and variables requiring consideration justify the development of a detailed and comprehensive computer system to analyse the equipment selection process and improve efficiency. Often knowledge based and machine learning research can be too 'pure', losing applicability. Any mine design system must be able to give 'real' advice.

The MINDER system has been developed using a range of computer techniques, the software has been tested on three case studies with distinct success. The development work and case studies have identified areas where further work could be of value.

The refining of the knowledge within an expert system should be an on-going process, with knowledge on current developments within the industry being added regularly. In the case of the MINDER system, information should be provided on the trends within the industry towards larger equipment and increasing priority being given to in-pit crusher/conveyor haulage systems.

Extra knowledge to give advice on combinations of mining equipment would be an advantage, this would involve the system taking into account the equipment selected in other areas of the mine. It would also extend into preferred haulage items for different combinations of excavating equipment.

MINDER would also be improved by the inclusion of knowledge which enabled the expert system to spot erroneous equipment selections as they occurred. For example, if across a site a small hydraulic excavator was the preferred item of equipment and for a particular area, a dragline was selected the system should notice this and advise on why this particular item was selected at this time.

The case studies highlighted the difference between the theoretical rates of working calculated by standard methods using manufacturers data and the actual production rates experienced by the contractors. An investigation into this difference would allow a more realistic equipment decision to be made by the MINDER system.

The modular architecture of the MINDER system facilitates the addition of further rules and allows extensive inferencing facilities for external software. At present the expert system interrogates geological modelling result files after reserve estimations have been performed. Work is already under way to develop intelligent systems to control the geological modelling process (see section 3.11.2.1). The automatic control of a reserve calculation within a piece of commercial modelling software would be a difficult task to achieve and may require modifications to the modelling software.

The increased use of graphical interfaces in modern software has led to an increased 'user-friendliness' in mine planning software. Within the Department of Mining Engineering at Nottingham University expert systems have recently been linked to Geographic Information Systems (G.I.S.) for slope design analysis (Kizil 1992). The interface of graphical planning tools with the MINDER system would be a step towards a fully integrated mine planning tool.

In a similar manner, increased development of the links to software used to continue the planning process after the equipment selection decision would be of benefit. The intelligent control of mine design software such as S.M.M.S. (see section 5.4) would be an improvement, with variables being automatically passed from the expert system. The scheduling option of the MINDER system could be expanded to deal with scheduling information of increased complexity, on smaller time scales for short term planning.

After selecting an optimum item of equipment a full cost analysis should be undertaken. Research work being under taken in the Advanced Computer Applications Group at Nottingham University to develop software to perform costings of excavation machinery over time (Cebesoy 1991). There are also a wide range of commercially available algorithmic software packages which are capable of performing depreciation calculations on a selection of mining machinery.

The use of innovative machine learning techniques will change the appearance of computer hardware and software over the next few years. Within the Department of Mining Engineering at Nottingham University a number of projects are being initialised involving neural networks for reserve estimation (Burnett 1992) and process control (Denby, Schofie;ld and Bradford 1991). The use of these system in conjunction with established expert system technology provide excellent prospects for the future.

Appendix 1

Case Study 1

TABLE 1 : TOPSOIL INFORMATION		
Identifier		**Value**
Material	—	Earth
Material Thickness	—	2 metres
Block Volume	—	3,200 m^3
Length of Haul Route	—	100 - 200 metres
Flexibility of Operating Conditions	—	Fair
Material Below Earth	—	Shale
Yearly Production	—	126,720 tonnes
Yearly Holidays	—	3 weeks
Days Worked per Week	—	5 days
Maximum Adverse Grade	—	< 3°
Total Mine Production	—	Low

	TABLE 2 : TOPSOIL EQUIPMENT				
Rank	**Equal Weighting**		**Material Type and Thickness**		**Length of Haul**
1	Scraper		Scraper		Scraper
2	Dozer		Dozer		Dozer
3	Front End Loader		Hydraulic Shovel		Front End Loader
	SCRAPER SELECTION RESULTS				
	Equal Weighting		**Required Tonnage**		**Material Type Length of Haul**
1	Under-Powered Rubber Tyred		Under-Powered Rubber Tyred		Under-Powered Rubber Tyred
2	Full-Powered Single Engine		Full-Powered Single Engine		Tractor Drawn
3	Tractor Drawn		Tractor Drawn		Full-Powered Single Engine

TABLE 3 : WASTE INFORMATION		
Identifier		**Value**
Material	—	Shale
Material Thickness	—	*'varies'*
Volume of Block	—	*'varies'*
Length of Haul Route	—	150 - 300 metres
Flexibility of Operating Conditions	—	Fair
Discontinuity Type	—	Bedding
Bedding Descriptor	—	Thick
Blasting ?	—	No
Material Beneath Shale	—	Bituminous Coal
Condition of Shale	—	Moist
Mobility Requirement	—	Poor
Pit Slope Required	—	70 degrees
Segregation Capability	—	Low
Excavator Working Mode	—	Front End
Mine Type	—	Strip Mine
Suggested Bench Height	—	10 - 15 metres
Suggested Bench Width	—	15 - 20 metres
Yearly Production	—	*'varies'*
Yearly Holidays	—	3 weeks
Days Worked per Week	—	5 days
Hours Worked per Day	—	8 hours
Estimated Angle of Swing	—	75° - 120°
Management Condition	—	Fair
Job Condition	—	Poor

TABLE 4 : WASTE EQUIPMENT

Rank	Equal Weighting		Material Type and Thickness		Production Tonnage
	(AMERICAN RESULTS)				
1	Shovel and Truck		Shovel and Truck		Shovel and Truck
2	Shovel		Shovel		Shovel
3	Dragline		Dragline		BWE
	(BRITISH RESULTS)				
1	Dragline		Dragline		Shovel and Truck
2	Shovel and Truck		Shovel		Frontend and Truck
3	Frontend and Truck		Shovel and Truck		Dragline

TABLE 5 : SHOVEL SELECTION RESULTS

Rank	Equal Weighting		Digging Force and Production		Bench Dimensions
	(Blocks 1-3)				
1	r 991		r 991		r 991
2	rh 40		h 85		ms 1600
3	ms 1600		rh 40		h 185
	(Blocks 4-6)				
1	h 285		h 241		r 991
2	r 991		h 285		h 285
3	h 185		h 185		h 185
	(Blocks 7-9)				
1	h 285		h 285		r 991
2	r 991		h 241		h 285
3	h 185		h 185		h 185

TABLE 6 : COAL INFORMATION		
Identifier		**Value**
Material	—	Bituminous Coal
Material Thickness	—	2 metres
Volume of Block	—	3,200 m^3
Flexibility of Operating Conditions	—	Fair
Length of Haul Route	—	100 - 200 metres
Discontinuity Type	—	None
Material Beneath Coal	—	Hard Limestone
Condition of Coal	—	Moist
Mobility Requirement	—	Poor
Blasting ?	—	No
Segregation Capability	—	Low
Excavator Working Mode	—	Backhoe
Mine Type	—	Strip Mine
Suggested Bench Height	—	0 - 5 metres
Suggested Bench Width	—	10 - 15 metres
Yearly Production	—	40,000 m^3
Yearly Holidays	—	3 weeks
Days Worked per Week	—	5 days
Hours Worked per Day	—	8 hours
Estimated Angle of Swing	—	75° - 120°
Management Condition	—	Fair
Job Condition	—	Poor

TABLE 7 : COAL EQUIPMENT

Rank	Equal Weighting	Material Type and Thickness	Production and Length of Haul
1	Shovel	Shovel	Scraper
2	Scraper	Scraper	Shovel
3	Front End Loader	Front End Loader	Front End Loader

SHOVEL SELECTION RESULTS

Rank	Equal Weighting	Required Tonnage	Material Type Length of Haul
1	pc 400-1	r 991	pc 400-1
2	r 991	pc 400-1	200 ck
3	r 965 b	r 965 b	r 991

TABLE 8 : MACHINE LEARNING RESULTS
(Knowledge Induction)

Rank	Topsoil	Waste	Coal
1	Elevating Scraper	Shovel and Truck	Shovel and Truck
2	Full Power Scraper	Dozer	Loader and Truck
3	Tractor Scraper	Loader and Truck	Elevating Scraper

(Neural Network)

Rank	Equipment	Network Output
1	Elevating Scraper	0.325
2	Front End Shovel and Truck	0.295
3	Full Powered Scraper	0.234

Spreadsheet for Layer 1

Block	Excavator	Model		Month1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Month 9	Month 10	Month 11
1	Scraper	Under powered		5280										
2	Scraper	Under powered		1790	3490									
3	Scraper	Under powered			3580	1700								
4	Scraper	Under powered				5280								
5	Scraper	Under powered				90	5190							
6	Scraper	Under powered					1880	3400						
7	Scraper	Under powered						3670	1610					
8	Scraper	Under powered							5280					
9	Scraper	Under powered							180	5100				

Spreadsheet for Layer 2

Block	Excavator	Model		Month1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Month 9	Month 10	Month 11
1	Shovel	h 285			48880									
2	Shovel	h 285			33710	15170								
3	Shovel	h 285				48880								
4	Shovel	h 285				18460	68020							
5	Shovel	h 285					14490	71990						
6	Shovel	h 285						10520	75960					
7	Shovel	h 285							6550	82510	35020			
8	Shovel	h 285									47490	76590		
9	Shovel	h 285										5920	82510	35650

Spreadsheet for Layer 3

Block	Excavator	Model		Month1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Month 9	Month 10	Month 11
1	Shovel	pc 400-1				3200								
2	Shovel	pc 400-1				130	3070							
3	Shovel	pc 400-1					260	2940						
4	Shovel	pc 400-1						390	2810					
5	Shovel	pc 400-1							520	2680				
6	Shovel	pc 400-1								650	2550			
7	Shovel	pc 400-1									780	2420		
8	Shovel	pc 400-1										910	2290	
9	Shovel	pc 400-1											1040	2160

Case Study 1 :- Schedule 1

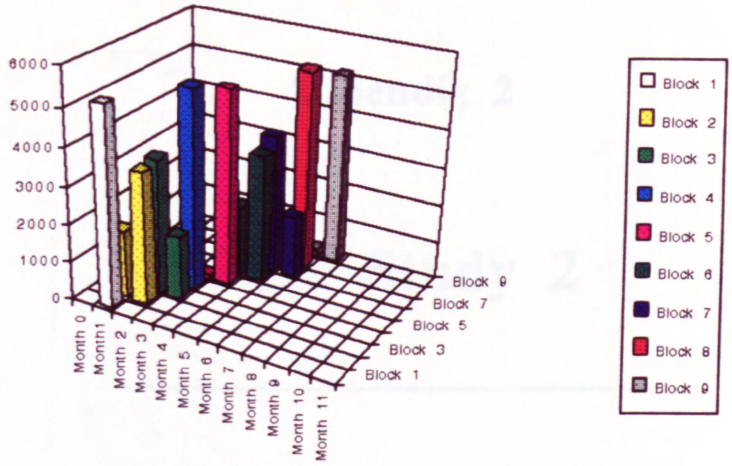


Chart 1 Scheduled Tonnages for Topsoil Removal

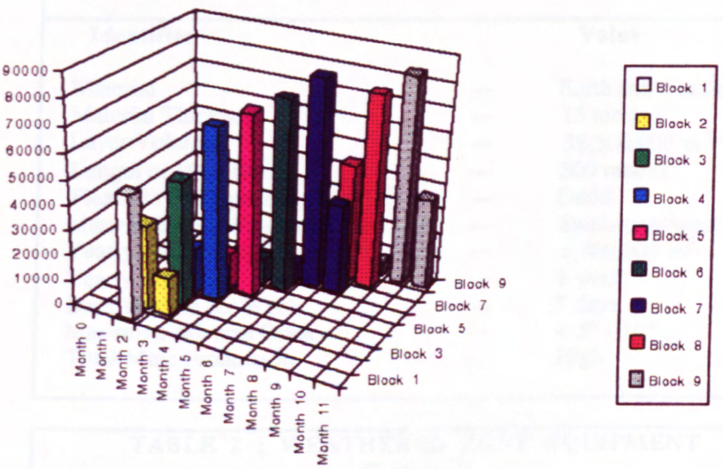


Chart 2 Scheduled Tonnages for Waste Removal

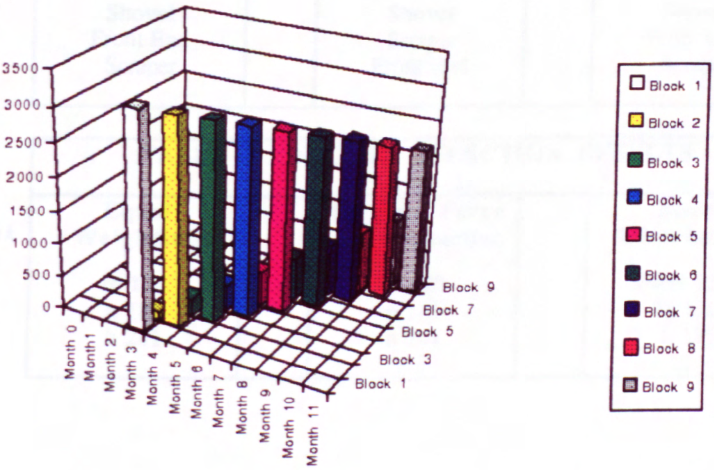


Chart 3 Scheduled Tonnages for Coal Removal

Appendix 2

Case Study 2

TABLE 1 : WEATHERED ZONE INFORMATION		
Identifier		**Value**
Material	—	Earth and weathered sst.
Material Thickness	—	15 metres
Layer Volume	—	38,300,000 m^3
Length of Haul Route	—	500 metres
Flexibility of Operating Conditions	—	Good
Material Below Weathered Zone	—	Sandstone/Siltstone
Yearly Production	—	1,500,000 m^3
Yearly Holidays	—	1 week
Days Worked per Week	—	7 days
Maximum Adverse Grade	—	< 5° - 10°
Total Mine Production	—	High

TABLE 2 : WEATHERED ZONE EQUIPMENT (Layer 1)

Rank	Equal Weighting		Material Type and Thickness		Length of Haul
1	Shovel		Shovel		Shovel
2	Front End		Scraper		Front End
3	Scraper		Front End		Scraper

TABLE 3 : SHOVEL SELECTION RESULTS (Layer 1)

Rank	Equal Weighting		Digging Force and Production		Bench Dimensions
1	rh 120		rh 120		P&H 1200
2	h 185		h 185		rh 120
3	h 241		h 241		h 185

TABLE 4 : WASTE INFORMATION		
Identifier		**Value**
Material	—	Sandstone
Material Thickness	—	*'varies'*
Volume of Layer	—	*'varies'*
Length of Haul Route	—	500 metres
Flexibility of Operating Conditions	—	Good
Discontinuity Type	—	Bedding
Bedding Descriptor	—	Thick
Blasting ?	—	Yes
Blast Fragmentation	—	Good
Material Beneath Sandstone	—	Bituminous Coal
Condition of Sandstone	—	Wet
Mobility Requirement	—	Fair
Pit Slope Required	—	62 degrees
Segregation Capability	—	Low
Excavator Working Mode	—	*'varies'*
Mine Type	—	Strip Mine
Suggested Bench Height	—	10 - 15 metres
Suggested Bench Width	—	15 - 20 metres
Yearly Production	—	*'varies'*
Yearly Holidays	—	1 weeks
Days Worked per Week	—	7 days
Hours Worked per Day	—	12 hours
Estimated Angle of Swing	—	75° - 120°
Management Condition	—	Fair
Job Condition	—	Good

	TABLE 5 : WASTE EQUIPMENT				
	British Results		**American Results**		**Equipment Selected**
Rank	(Layer 2)				
1	Shovel and Truck		Shovel and Truck		h 241
2	Front End / Truck		Dragline		h 285
3	Dragline		Front End / Truck		h 185
	(Layer 3)				
1	Shovel and Truck		Shovel and Truck		h 185
2	Dragline		Dragline		rh 120
3	Front End / Truck		Front End / Truck		h 241
	(Layer 4)				
1	Dragline		Shovel and Truck		be 1300 w
2	Shovel and Truck		Dragline		be 1260 w
3	Front End / Truck		Front End / Truck		be 1370 w
	(Layer 6)				
1	Dragline		Dragline		be 1300 w
2	Shovel and Truck		Shovel and Truck		be 1370 w
3	Front End / Truck		Front End / Truck		be 1260 w
	(Layer 8)				
1	Shovel and Truck		Shovel and Truck		h 285
2	Dragline		Dragline		h 241
3	Front End / Truck		Front End / Truck		h 185
	(Layer 10)				
1	Dragline		Dragline		be 1380 w
2	Shovel and Truck		Shovel and Truck		be 1570 w
3	Front End / Truck		Front End / Truck		be 1370 w

TABLE 6 : COAL INFORMATION		
Identifier		**Value**
Material	—	Bituminous Coal
Material Thickness	—	*'varies'*
Volume of Layer	—	*'varies'*
Flexibility of Operating Conditions	—	Good
Length of Haul Route	—	500 metres
Discontinuity Type	—	Bedding
Bedding Descriptor	—	Thick
Material Beneath Coal	—	Sandstone
Condition of Coal	—	Wet
Mobility Requirement	—	Fair
Blasting ?	—	Yes
Blast Fragmentation	—	Good
Segregation Capability	—	Low
Excavator Working Mode	—	Front End
Mine Type	—	Strip Mine
Suggested Bench Height	—	5 - 10 metres
Suggested Bench Width	—	10 - 15 metres
Yearly Production	—	*'varies'*
Yearly Holidays	—	1 weeks
Days Worked per Week	—	7 days
Hours Worked per Day	—	12 hours
Estimated Angle of Swing	—	75° - 120°
Management Condition	—	Fair
Job Condition	—	Good

TABLE 7 : COAL EQUIPMENT					
	Equal Weighting		**Material Type and Thickness**		**Production and Length of Haul**
Rank			(Layer 5)		
1	Shovel		Shovel		Shovel
2	Scraper		Scraper		Scraper
3	Front End		Front End		Front End
			(Layer 7)		
1	Shovel		Shovel		Shovel
2	Scraper		Scraper		Scraper
3	Front End		Front End		Front End
			(Layer 9)		
1	Shovel		Shovel		Shovel
2	Front End		Scraper		Front End
3	Scraper		Front End		Scraper
			(Layer 11)		
1	Shovel		Shovel		Shovel
2	Front End		Front End		Front End
3	Scraper		Scraper		Scraper

Rank	TABLE 8 : SHOVEL SELECTION RESULTS				
	Equal Weighting		**Required Tonnage**		**Material Type Length of Haul**
			(Layer 5)		
1	rh 40		rh 40		uh 80
2	uh 80		uh 80		Cat 245
3	Cat 245		Cat 245		rh 40
			(Layer 7)		
1	rh 40		rh 40		uh 80
2	uh 80		uh 80		Cat 245
3	Cat 245		P&H 650		rh 40
			(Layer 9)		
1	rh 40		Cat 245		rh 40
2	Cat 245		rh 40		uh 80
3	rh 75		rh 75		Cat 245
			(Layer 11)		
1	h 85		rh 75		h 85
2	rh 75		h 85		rh 75
3	pc 1500		pc 1500		rh 40

TABLE 9 : HAULAGE INFORMATION

Identifier		**Value**
Material	—	Sandstone
Material Thickness	—	*'varies'*
Volume of Layer	—	*'varies'*
Length of Haul Route	—	500 m
Maximum Adverse Grade	—	5° - 10°
Flexibility of Operating Conditions	—	Good
Discontinuity Type	—	Bedding
Bedding Descriptor	—	Thick
Blasting ?	—	Yes
Material Beneath Waste	—	*'varies'* (Coal/Sstone)
Type of Excavation Machinery	—	*'varies'* (Shovel/Dragline)
Excavator Working Mode	—	Front End
Hydraulic Excavator Type	—	*'varies'*
Yearly Production	—	*'varies'*
Yearly Holidays	—	1 weeks
Days Worked per Week	—	7 days
Hours Worked per Day	—	12 hours

Rank	TABLE 10 : HAULAGE EQUIPMENT (Aggregated Results)				
	Equal Weighting		**Length of Haul**		**Production Weighted**
1	Rear Dump Truck		Rear Dump Truck		Rear Dump Truck
2	Semitrailer Truck		Semitrailer Truck		Bottom Dump Truck
3	Bottom Dump Truck		Bottom Dump Truck		Semitrailer Truck

Rank	Equal Weighting		Height Weighted		Payload Weighted
	TABLE 11 : TRUCK SELECTION RESULTS				
	(Layer 1)				
1	Wabco 120 cm		Wabco 120 cm		Rimpull rd 120
2	Dart 4120		Cat 772		Dart 4120
3	Rimpull rd 120		Dart 4120		Wabco 120 cm
	(Layer 2)				
1	Rimpull rd 120		Dart 4120		Rimpull rd 120
2	Dart 4120		Rimpull rd 120		Dart 4120
3	Unit Rig mark 30		Unit Rig mark 30		Wabco 120 cm
	(Layer 3)				
1	Wabco 120 cm		Wabco 120 cm		Rimpull rd 120
2	Rimpull rd 120		Cat 772		Dart 4120
3	Dart 4120		Unit Rig mark 30		Wabco 120 cm
	(Layer 8)				
1	Wabco 150 ct		Terex 34-11c		Wabco 150 ct
2	Komatsu hd 1200		Wabco 150 ct		Rimpull cw 150
3	Terex 34 -11c		Komatsu hd 1200		Komatsu hd 1200

Rank	Topsoil		Waste		Coal
	TABLE 12 : MACHINE LEARNING RESULTS (Knowledge Induction)				
1	Shovel		Shovel and Truck		Shovel and Truck
2	Elevating Scraper		Dragline		Loader and Truck
3	Front End		Loader and Truck		Elevating Scraper

Rank	Equipment		Network Output
	(Neural Network)		
1	Shovel		0.426
2	Elevating Scraper		0.402
3	Front End		0.172

Schedule for Case Study 2																
Layer	Material	Excavator	Model	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12
1	Weathered	Shovel	rh 120	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47
2	Waste	Shovel	h 241													
3	Waste	Shovel	h 185													
4	Waste	Dragline	be 1300 w										0.6	1.75	3.2	3.83
5	Coal	Shovel	rh 40												0.09	0.53
6	Waste	Dragline	be 1300 w				0.68	2.88	3.32	4.6	5.91	7.06	8.05	8.08	8.08	8.08
7	Coal	Shovel	rh 40						0.16	0.6	0.6	0.6	0.6	0.6	0.6	0.6
8	Waste	Shovel	h 285		1.55	2.56	7.86	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77
9	Coal	Shovel	rh 40				0.53	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
10	Waste	Dragline	be 1380 w		6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92
11	Coal	Shovel	h 85		2.85	3	2.8	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4

Schedule for Case Study 2																
Layer	Material	Excavator	Model	Year 13	Year 14	Year 15	Year 16	Year 17	Year 18	Year 19	Year 20	Year 21	Year 22	Year 23	Year 24	Year 25
1	Weathered	Shovel	rh 120	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47
2	Waste	Shovel	h 241				2.19	2.19	2.19	2.19	3.26	3.26	0.66			
3	Waste	Shovel	h 185	0.55	1.19	2	3.3	3.46	3.46	3.46	2.48	1.27	1.2			
4	Waste	Dragline	be 1300 w	4.99	6.33	7.52	8.08	8.08	8.08	8.08	8.08	8.08	8.08	8.08	0.16	
5	Coal	Shovel	rh 40	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.04	
6	Waste	Dragline	be 1300 w	8.08	8.08	8.08	8.08	8.08	8.08	8.08	8.08	8.08	8.08	8.08	2.24	
7	Coal	Shovel	rh 40	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.16	
8	Waste	Shovel	h 285	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77
9	Coal	Shovel	rh 40	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
10	Waste	Dragline	be 1380 w	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92
11	Coal	Shovel	h 85	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4

NOTE : All figures are in million bank metres cubed

Case Study 2 :- Schedule 1

Appendix 3

Case Study 3

TABLE 1 : TOPSOIL INFORMATION		
Identifier		**Value**
Material	—	Clay/Peat/Sand/Gravel
Material Thickness	—	*'varies'* (0.2-12.8 m)
Block Volume	—	*'varies'*
Length of Haul Route	—	*'varies'* (0.3 - 2 km)
Water Condition	—	Moist
Mobility Requirement	—	Fair
Flexibility of Operating Conditions	—	Fair
Material Below Topsoil	—	Mudstone/Sandstone
Yearly Production	—	approx 745,000 m^3
Yearly Holidays	—	2 weeks
Days Worked per Week	—	6 days
Maximum Adverse Grade	—	Between 3° and 5°
Total Mine Production	—	High

TABLE 2 : TOPSOIL EQUIPMENT				
Block	**1**	**2**	**3**	**Scraper Type**
C1	Scraper	Dozer	Front End	U.P. Rubber Tyred
C2	Scraper	Dozer	Front End	U.P. Rubber Tyred
C3	Scraper	Front End	Dozer	U.P. Rubber Tyred
C4	Scraper	Dozer	Front End	U.P. Rubber Tyred
C5	Scraper	Dozer	Front End	U.P. Rubber Tyred
C6	Scraper	Front End	Dozer	U.P. Rubber Tyred
D1	Dozer	Scraper	Front End	—
D2	Dozer	Scraper	Front End	—
D3	Dozer	Scraper	Front End	—
A1	Dozer	Front End	Scraper	—
A2	Scraper	Front End	Dozer	U.P. Rubber Tyred
A3	Scraper	Front End	Dozer	F.P. Rubber Tyred
B1	Scraper	Dozer	Front End	U.P. Rubber Tyred
B2	Scraper	Dozer	Front End	U.P. Rubber Tyred
B3	Scraper	Dozer	Front End	U.P. Rubber Tyred
B4	Scraper	Dozer	Front End	U.P. Rubber Tyred

TABLE 3 : WASTE INFORMATION		
Identifier		**Value**
Material	—	Mudstone/Sandstone
Material Thickness	—	*'varies'*
Volume of Block	—	*'varies'*
Length of Haul Route	—	*'varies'* (0.3-2 km)
Flexibility of Operating Conditions	—	Fair
Discontinuity Type	—	Bedding
Bedding Descriptor	—	Thin
Blasting ?	—	No
Material Beneath Waste	—	*'varies'* (Coal/Sstone)
Water Condition	—	Moist
Mobility Requirement	—	Poor
Pit Slope Required	—	65 degrees
Segregation Capability	—	Low
Excavator Working Mode	—	Backhoe
Mine Type	—	Strip Mine
Suggested Bench Height	—	10 - 15 metres
Suggested Bench Width	—	15 - 20 metres
Yearly Production	—	*'varies'*
Yearly Holidays	—	2 weeks
Days Worked per Week	—	6 days
Hours Worked per Day	—	12 hours
Estimated Angle of Swing	—	75° - 120°
Management Condition	—	Good
Job Condition	—	Fair

TABLE 4 : WASTE EQUIPMENT (Interburden above Lower Drumgray Seam)

Block	British	American	Layer	Total
B4	Shovel	Shovel	exc. rh 75	exc. rh 75

TABLE 5 : WASTE EQUIPMENT (Interburden above Shotts Gas Seam)

Block	British	American	Layer	Total
B1	Shovel	Shovel	exc. rh 75	exc. rh 120
B2	Shovel	Shovel	exc. h 85	exc. rh 120
B3	Shovel	Shovel	exc. h 85	exc. P&H 1200
B4	Shovel	Shovel	exc. h 85	exc. rh 120

TABLE 6 : WASTE EQUIPMENT (Interburden above Mill Seam)

Block	British	American	Layer	Total
C3	Shovel	Shovel	exc. rh 120	exc. rh 185
C4	Dragline	Shovel	drag. 1260/1300	—
C5	Shovel	Shovel	exc. rh 120	exc. rh 185
C6	Shovel	Shovel	exc. rh 75	exc. rh 120
D1	Shovel	Shovel	exc. h 121	exc. P&H 1200
D2	Shovel	Shovel	drag. 1260	—
D3	Dragline	Shovel	drag. 1260	—
A1	Dragline	Shovel	drag. 1260	—
A2	Shovel	Shovel	rh 120	exc. rh 185
A3	Dragline	Shovel	drag. 1260/1300	—

TABLE 7 : WASTE EQUIPMENT
(Interburden above Armadale Ball Seam)

Block	British	American	Layer	Total
C1	Shovel	Shovel	exc. rh 75	exc. rh 120
C2	Shovel	Shovel	exc. rh 120	exc. rh 185
C3	Shovel	Shovel	exc. rh 75	exc. rh 120
C4	Dragline	Shovel	drag. 1260	—
C5	Shovel	Shovel	exc. h 85	exc. P&H 1200
C6	Shovel	Shovel	exc. h 85	exc. P&H 1200
A1	Dragline	Shovel	drag. 1260/1300	—
A2	Dragline	Shovel	drag. 1300	—
A3	Dragline	Shovel	drag. 1370	—

TABLE 8 : WASTE EQUIPMENT
(Interburden above Armadale Main Seam)

Block	British	American	Layer	Total
C1	Shovel	Shovel	exc. h 85	exc. rh 120
C3	Shovel	Shovel	exc. rh 75	exc. rh 185
C4	Shovel	Shovel	exc. rh 75	exc. rh 120
C5	Shovel	Shovel	exc. rh 75	exc. rh 120
C6	Shovel	Shovel	exc. h 121	exc. P&H 1200
A1	Shovel	Shovel	exc. h 85	exc. rh 120
A2	Shovel	Shovel	exc. rh 75	exc. rh 120
A3	Shovel	Shovel	exc. rh 75	exc. rh 120

TABLE 9 : COAL INFORMATION

Identifier		Value
Material	—	Bituminous Coal
Material Thickness	—	*'varies'* (0.2-1.41 m)
Volume of Block	—	*'varies'*
Flexibility of Operating Conditions	—	Fair
Discontinuity Type	—	None
Material Beneath Coal	—	Sandstone/Mudstone
Condition of Coal	—	Moist
Mobility Requirement	—	Poor
Blasting ?	—	No
Segregation Capability	—	Low
Excavator Working Mode	—	Backhoe
Mine Type	—	Strip Mine
Suggested Bench Height	—	0 - 5 metres
Suggested Bench Width	—	10 - 15 metres
Yearly Production	—	*'varies'* (0.3-0.5 mt)
Yearly Holidays	—	2 weeks
Days Worked per Week	—	6 days
Hours Worked per Day	—	12 hours
Estimated Angle of Swing	—	75° - 120°
Management Condition	—	Good
Job Condition	—	Fair

TABLE 10 : COAL EQUIPMENT (Lower Drugray Seam)

Block	1	2	3	Shovel Type
B4	Scraper	Front End	Shovel	exc. rh 6

TABLE 11 : COAL EQUIPMENT (Shotts Gas Seam)

Block	1	2	3	Shovel Type
B1	Shovel	Scraper	Front End	exc. uh 082
B2	Shovel	Scraper	Front End	exc. rh 6
B3	Shovel	Scraper	Front End	exc. rh 6
B4	Shovel	Scraper	Front End	exc. uh 30

TABLE 12 : COAL EQUIPMENT (Mill Seam)

Block	1	2	3	Scraper Type
C3	Scraper	Front End	Shovel	exc. kh 20
C4	Scraper	Shovel	Front End	exc. kh 20
C5	Shovel	Scraper	Front End	exc. rh 6
C6	Shovel	Scraper	Front End	exc. h 71
D1	Shovel	Scraper	Front End	exc. uh 30
D2	Shovel	Scraper	Front End	exc. uh 082
D3	Shovel	Front End	Scraper	exc. h 71
A1	Shovel	Scraper	Front End	exc. uh 082
A2	Shovel	Front End	Scraper	exc. uh 30
A3	Shovel	Front End	Scraper	exc. h 71

TABLE 13 : COAL EQUIPMENT (Armadale Ball Seam)

Block	1	2	3	Scraper Type
C1	Scraper	Front End	Shovel	exc. kh 20
C2	Scraper	Shovel	Front End	exc. kh 20
C3	Shovel	Scraper	Front End	exc. uh 082
C4	Shovel	Scraper	Front End	exc. rh 9
C5	Shovel	Scraper	Front End	exc. uh 30
C6	Shovel	Front End	Scraper	exc. uh 30
A1	Shovel	Front End	Scraper	exc. h 71
A2	Shovel	Front End	Scraper	exc. uh 30
A3	Shovel	Front End	Scraper	exc. h 71

TABLE 14 : COAL EQUIPMENT (Armadale Main Seam)

Block	1	2	3	Scraper Type
C1	Scraper	Front End	Shovel	exc. kh 20
C3	Shovel	Scraper	Front End	exc. uh 082
C4	Shovel	Front End	Scraper	exc. uh 082
C5	Shovel	Front End	Scraper	exc. rh 9
C6	Shovel	Front End	Scraper	exc. uh 30
A1	Shovel	Front End	Scraper	exc. h 71
A2	Shovel	Front End	Scraper	exc. h 71
A3	Shovel	Front End	Scraper	exc. h 71

TABLE 15 : HAULAGE INFORMATION		
Identifier		**Value**
Material	—	Mudstone/Sandstone
Material Thickness	—	*'varies'*
Volume of Block	—	*'varies'*
Length of Haul Route	—	*'varies'* (0.3-2 km)
Maximum Adverse Grade	—	5 - 10 %
Flexibility of Operating Conditions	—	Fair
Discontinuity Type	—	Bedding
Bedding Descriptor	—	Thin
Blasting ?	—	No
Material Beneath Waste	—	*'varies'* (Coal/Sstone)
Type of Excavation Machinery	—	Hydraulic Excavator
Excavator Working Mode	—	Backhoe
Hydraulic Excavator Type	—	O & K rh 120
Yearly Production	—	*'varies'*
Yearly Holidays	—	2 weeks
Days Worked per Week	—	6 days
Hours Worked per Day	—	12 hours

	TABLE 16 : HAULAGE EQUIPMENT (Aggregated Results)				
Rank	**Equal Weighting**		**Length of Haul**		**Production Weighted**
1	Rear Dump Truck		Rear Dump Truck		Rear Dump Truck
2	Semitrailer Truck		Semitrailer Truck		Semitrailer Truck
3	Bottom Dump Truck		Bottom Dump Truck		Bottom Dump Truck

	TABLE 17 : TRUCK EQUIPMENT (Aggregated Results)				
Rank	**Equal Weighting**		**Height Weighted**		**Payload Weighted**
1	Euclid r-100		Euclid r-100		Euclid r-100
2	Rimpull rd-100		Rimpull rd-100		Unit Rig m-100
3	Caterpillar 772		Unit Rig m-100		Caterpillar 772

	TABLE 18 : MACHINE LEARNING RESULTS (Aggregated Knowledge Induction Results)				
Rank	**Topsoil**		**Waste**		**Coal**
1	Elevating Scraper		Shovel and Truck		Shovel and Truck
2	Full Power Scraper		Loader and Truck		Loader and Truck
3	Tractor Scraper		Dragline		Elevating Scraper

	(Aggregated Neural Network Results)		
Rank	**Equipment**		**Network Output**
1	Elevating Scraper		0.415
2	Front End Shovel and Truck		0.372
3	Full Powered Scraper		0.213

Spreadsheet for Topsoil/Drift Material

Block	Excavator			Year 0		Year 1		Year 2		Year 3		Year 4		Year 5		Year 6		Year 7		Year 8		Year 9		Year 10		Year 11		Year 12		Year 13		Year 14
C1	Scraper		105404																													
C2	Scraper		194000																													
C3	Scraper		19720	370000	370000	163042																										
C4	Scraper					194150	370000	28000																								
C5	Scraper							377092	99527																							
C6	Scraper								284700	40050																						
D1	Scraper									391571	33000																					
D2	Scraper										314031																					
D3	Scraper										39000	370000	12165																			
A1	Scraper												349835	142845																		
A2	Scraper													359155	370000	40064																
A3	Scraper															328726	154981															
B1	Scraper																185110															
B3	Scraper																37983	371094														
B4	Scraper																	6886	290522													
B5	Scraper																		51470	379777												

Spreadsheet for Interburden Above Mill Seam

Block	Excavator			Year 0		Year 1		Year 2		Year 3		Year 4		Year 5		Year 6		Year 7		Year 8		Year 9		Year 10		Year 11		Year 12		Year 13		Year 14
C2	sh 120 (2)								765382																							
C4	sh 120 (2)								298000	411712																						
C5	sh 120 (2)									591957	1000650	406031																				
C6	sh 120 (2)											517119	190212																			
D1	sh 120 (2)												805480	600000																		
D2	sh 120 (2)													372762	911690																	
D3	sh 120 (2)														725061																	
A1	sh 120 (2)														93011	1000650	692000															
A2	sh 120 (2)																400761	1000650														
A3	sh 120 (1)																477640	730596														
A3	sh 120 (2)																		1000650													
A3	sh 120 (1)																	273963	79289													

Spreadsheet for Interburden Above Armadale Ball Seam

Block	Excavator			Year 0		Year 1		Year 2		Year 3		Year 4		Year 5		Year 6		Year 7		Year 8		Year 9		Year 10		Year 11		Year 12		Year 13		Year 14
C1	sh 120 (1)			608590																												
C2	sh 120 (1)			135052	986101																											
C3	sh 120 (1)				97540	1000650	1000650	1000650	204896																							
C3	sh 120 (2)						1000650	1000650																								
C4	sh 120 (1)											673055	1000650	209550																		
C5	sh 120 (1)													714300	1000650	180491																
C6	sh 120 (1)															615139	528016															
A1	sh 120 (1)																		585404	1000650	1000650	124785										
A2	sh 120 (1)																					670005	1000650	722916								
A3	sh 120 (1)																							280748	998671							

Spreadsheet for Interburden Above Armadale Main Seam

Block	Excavator			Year 0		Year 1		Year 2		Year 3		Year 4		Year 5		Year 6		Year 7		Year 8		Year 9		Year 10		Year 11		Year 12		Year 13		Year 14
C1	rh 120 (1)								719834	119559																						
C2	rh 120 (1)									894891	1088988	339817																				
C4	rh 120 (2)																			612975												
C5	rh 120 (2)																			398075	339857											
C8	rh 120 (2)																				611377											
A1	rh 120 (2)																								489145	868592						
A2	rh 120 (2)																									317298	391020					
A3	rh 120 (2)																										270912					

Spreadsheet for Interburden Above Lower Drumgray and Shotts Gas Seams

Block	Excavator			Year 0		Year 1		Year 2		Year 3		Year 4		Year 5		Year 6		Year 7		Year 8		Year 9		Year 10		Year 11		Year 12		Year 13		Year 14
B4	rh 120 (1)	Lower Drumgray Seam																	429844													
B1	rh 120 (1)	Shotts Gas Seam																			58420	519480										
B2	rh 120 (1)	Shotts Gas Seam																				484152	481590									
B4	rh 120 (1)	Shotts Gas Seam																					522801	390609								
B9	rh 120 (1)	Shotts Gas Seam																						790981	514585							

Spreadsheet for Coal Seams

Block	Seam	Excavator		Year 1		Year 2		Year 3		Year 4		Year 5		Year 6		Year 7		Year 8		Year 9		Year 10		Year 11		Year 12		Year 13		Year 14		Year 15
C1	Arm. Ball	rh 6					49992																									
C2	Arm. Ball	rh 6					38804																									
C3	Arm. Ball	rh 6					14712	91000	24142																							
C4	Mill	rh 6							27656																							
C5	Mill	rh 6							39210	91000	20133																					
C6	Mill	rh 6									64875																					
C4	Arm. Ball	rh 6										48900																				
C5	Arm. Ball	rh 6										42820	22002																			
C6	Arm. Ball	rh 6											48496																			
C1	Arm. Main	rh 6											20310	49335																		
C2	Arm. Main	rh 6												41673	91000	91000	9250															
A1	Mill	rh 6															81750	28611														
A2	Mill	rh 6																62597	30352													
A3	Mill	rh 6																	54656													
B4	L. Drumgray	rh 6																		58201												
A1	Arm. Ball	rh 6																		48807	29692											
A2	Arm. Ball	rh 6																			59725											
A3	Arm. Ball	rh 6																			1591	27309										
C4	Arm. Main	rh 6																				63499	27059									
C5	Arm. Main	rh 6																					63949	36791								
C6	Arm. Main	rh 6																						54217	17175							
D1	Mill	rh 6																							57403							
D2	Mill	rh 6																							16588	74033						
D3	Mill	rh 6																								10975	91000	10177				
A1	Arm. Main	rh 6																										80831	13661			
A2	Arm. Main	rh 6																											77127	20973		
A3	Arm. Main	rh 6																												45419		
B1	Shotts Gas	rh 6																												34616	16521	
B2	Shotts Gas	rh 6																													57801	
B9	Shotts Gas	rh 6																													21626	21286
B4	Shotts Gas	rh 6																														53651

Spreadsheet for Topsoil/Drift Material

Block	Excavator			Year 0		Year 1		Year 2		Year 3		Year 4		Year 5		Year 6		Year 7		Year 8		Year 9		Year 10		Year 11		Year 12
C1	h 185		163464																									
C2	h 185		194810																									
C3	h 185		645376																									
C3	255		287520	26072																								
C4	255			200048	287520	44698																						
C5	255					242822	289507																					
C6	255						84013	251379																				
D1	255							36141	287520	41576																		
D2	255									245944	60887																	
D3	255										21633	200835																
A1	255											86085	287520	133675														
A2	255													153045	287520	222254												
A3	255															65366	287520	130451										
B1	255																	157069	28047									
B2	255																		259473	150204								
B4	255																			137316	165512							
B3	255																				122008	239247						

Spreadsheet for Interburden Above Mill Seam

Block	Excavator			Year 0		Year 1		Year 2		Year 3		Year 4		Year 5		Year 6		Year 7		Year 8		Year 9		Year 10		Year 11		Year 12
C3	be 1280 w							765262																				
C4	be 1280 w							602750	47363																			
C5	be 1280 w								1320637	761481																		
C6	be 1280 w									606519	188812																	
D1	be 1280 w										1259188	177130																
D2	be 1280 w											1190862	617400															
D3	be 1280 w												750600	947950														
A1	be 1280 w													420050	1368000	4010												
A2	be 1280 w															1327590	1285049											
A3	be 1280 w																82951	1272964										

Spreadsheet for Interburden Above Armadale Ball Seam

Block	Excavator			Year 0		Year 1		Year 2		Year 3		Year 4		Year 5		Year 6		Year 7		Year 8		Year 9		Year 10		Year 11		Year 12
C1	h 185			888398																								
C2	h 185			335836	703317																							
C3	h 185				499117	1204434	1204434	1204434	1204434	83342																		
C4	h 185									183282																		
C5	h 185									937810	943976																	
C6	h 185										260450	1071362																
A1	h 185																376300	1204434	959718									
A1	be 1280 w																	95036										
A2	h 185																		244716	992709								
A2	be 1280 w																		1368000									
A3	h 185																			211725	999686							

Case Study 3 :- Schedule 2

Spreadsheet for Interburden Above Armadale Main Seam

Block	Excavator			Year 0		Year 1		Year 2		Year 3		Year 4		Year 5		Year 6		Year 7		Year 8		Year 9		Year 10		Year 11		Year 12
C1	h 185											133072	705741															
C3	h 185												498893	1204434	515231													
C4	h 185														689203	486334												
C5	h 185															718100	130178											
C6	h 185																270912											
A1	h 185																				204748	970789						
A2	h 185																					233645	614633					
A3	h 185																						270912					

Spreadsheet for Interburden Above Lower Drumgray and Shotts Gas Seams

Block	Excavator			Year 0		Year 1		Year 2		Year 3		Year 4		Year 5		Year 6		Year 7		Year 8		Year 9		Year 10		Year 11		Year 12
B4	h 185	Lower Drumgray Seam														421044												
B1	hs 1200 w	Shotts Gas Seam																		575918								
B2	hs 1200 w	Shotts Gas Seam																		792082	173459							
B4	hs 1200 w	Shotts Gas Seam																			728730							
B3	hs 1200 w	Shotts Gas Seam																			465611	845875						

Spreadsheet for Coal Seams

Block	Seam	Excavator		Year 1		Year 2		Year 3		Year 4		Year 5		Year 6		Year 7		Year 8		Year 9		Year 10		Year 11		Year 12		Year 13
C1	Arm. Ball	sh 6					45992																					
C2	Arm. Ball	sh 6					30504																					
C3	Arm. Ball	sh 6					68216	69646																				
C4	Mill	sh 6						27656																				
C5	Mill	sh 6						39210	117147																			
C6	Mill	sh 6							19565	45510																		
C4	Arm. Ball	sh 6								48980																		
C5	Arm. Ball	sh 6								42022	22008																	
C6	Arm. Ball	sh 6									48676																	
C1	Arm. Main	sh 6									65828	3817																
C3	Arm. Main	sh 6										132695	100252															
A1	Mill	sh 6											36260	74101														
A2	Mill	sh 6												62411	36338													
A3	Mill	sh 6													55446													
B4	L. Drumgray	sh 6													44728	5473												
C4	Arm. Main	sh 6														85535	5223											
C5	Arm. Main	sh 6															85785	14955										
C6	Arm. Main	sh 6																71392										
A1	Arm. Ball	sh 6																4661	65830									
A2	Arm. Ball	sh 6																	25170	34555								
A3	Arm. Ball	sh 6																		28900								
D1	Mill	sh 6																		27553	29900							
D2	Mill	sh 6																			61108	29305						
D3	Mill	sh 6																				61703	56457					
A1	Arm. Main	sh 6																					34551	60161				
A2	Arm. Main	sh 6																						30847	67253			
A3	Arm. Main	sh 6																							23755	21664		
B1	Shotts Gas	sh 6																								41137		
B2	Shotts Gas	sh 6																								28207	36654	
B4	Shotts Gas	sh 6																									42914	
B3	Shotts Gas	sh 6																									23440	30211

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