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A Prototype Expert System for Site Selection of a Sanitary Landfill

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Abstract
It is desirable to incorporate heuristic and empirical knowledge including hydrological and bio-geochemical considerations into the selection process of a potential landfill site. In this paper, a prototype expert system for the selection of a landfill site, with hybrid knowledge representation approach under object-oriented design environment in a blackboard architecture, is described. It incorporates an artificial neural network for training of partial hazardous scores and a fuzzy rule base for the representation of heuristic knowledge. The evaluation is based on the hazardous waste site ranking system recommended by the U.S. Environmental Protection Agency, adapted to Hong Kong conditions by incorporating the stipulation of some local regulations. It is shown to be a useful aid to assist novice engineers in the selection process of a potential landfill site during preliminary investigation.

Keywords: Artificial neural network; Blackboard architecture; Expert system; Fuzzy inference; Hazardous waste; Sanitary landfill; Site selection

Introduction

A sanitary landfill is one of the most popular refuse disposal means in an urban environment. In order to alleviate the nuisances to public health or safety, extensive studies have to be carried out to select the most feasible location. This site selection process involves the study of a proliferation of factors including hydrological as well as bio-geochemical considerations such as composition of contained wastes, possible migration paths of the wastes, soil properties, planned use of the landfill, population and land use, etc. The evaluation process involves many decisions to be made by the designer based on heuristics. It is difficult for various teams composed of engineers and scientists to possess the broad expertise and knowledge in performing such site selections in a consistent manner. Specifically, a novice engineer may face many difficulties in the design process. It is desirable to encapsulate this knowledge into the decision making process.

Previously, some algorithmic models were developed to deal with this problem, such as Leão et al. (2004), Gray et al. (2005), Shin et al. (2005), Tiruta-Barna et al. (2005), etc. In many instances, it is often difficult for anyone other than the model developer to use the model successfully. Moreover, heuristic knowledge is not necessarily expressed in an algorithmic manner. In fact, empirical rules, often being incomplete, cannot be easily placed in specific frameworks. With the advancement of artificial intelligence (AI), an expert system furnishes a solution to this decision making process through the incorporation of symbolic knowledge processing on the basis of pertinent heuristic rules.

During the past decade, the potential of AI techniques for providing assistance in the solution of engineering problems has been recognized. Expert systems are considered suitable for solving problems that demand considerable expertise, judgment or rules of thumb. Areas of early applications of expert system technology include medical diagnosis, mineral exploration and chemical spectroscopy. In recent years, expert systems have been applied to emulate domain problems in a variety of fields (Chau & Ng 1996, Ranga Rao & Sundaravadivelu 1999, Chau & Chen 2001, Lin & Albermani 2001, Chau & Anson 2002, Kao & Adeli 2002, Chau 2004, Chau & Albermani 2004, Yao et al. 2005). The blackboard architecture, appropriate in domains characterized by interaction between diverse knowledge sources, is one of the most popular systems in the implementation of expert systems in solving a wide range of tasks: control (Hayesroth 1985), speech recognition (Engelmore and Morgan 1988), dynamic rescheduling (Bharadwaj et al. 1994), industrial building design (Kumar 1995), interlaminar stress analysis of composite laminates (Adeli and Yu 1995), crankshaft design (Lander et al. 1996), damage assessment of steel bridge (Barai and Pandey 2000), control of a cryogenic cooling plant (Linkens et al. 2000), large space structures (Kao and Adeli 2002), etc. However, to the author's knowledge, an expert system addressing site selection of a sanitary landfill has never been reported in the literature.

The programming language designed for AI (LISP or PROLOG) entails tremendous programming effort. Nowadays, it is common in the literature that expert system shells, which can provide some knowledge representation methods and inference mechanisms, are used as tools to facilitate the development of expert systems. This paper delineates a prototype expert system for the selection of a landfill site, LANDFILL, which has been developed using an expert system shell VISUAL RULE STUDIO (Rule Machines Corporation 1998) under the Microsoft Visual Basic programming environment. The blackboard architecture with hybrid knowledge representation techniques including production rule system and object-oriented approach is adopted. An artificial neural network (ANN) for training of partial hazardous scores and a fuzzy rule base for the representation of heuristic knowledge are incorporated. The expert system developed is based on the uncontrolled hazardous waste site ranking system recommended by the US Environmental Protection Agency (1984), adapted to Hong Kong conditions by incorporating the stipulation of some local regulations, including Air Pollution Control Ordinance, Waste Disposal Ordinance, Waste Disposal (Chemical Waste) (General) Regulation, Water Pollution Control Ordinance, etc. Solution strategies and development techniques of the system are addressed and discussed. The innovation and original contribution of this manuscript is mainly on hybrid application of the latest AI technologies: expert system; ANN; and, fuzzy inference system, in this specific problem domain.

Domain knowledge

In general, landfills offer an economic and viable solution to the waste disposal problem. During the landfill operation process, engineering principles are applied to confine the refuse to the smallest practicable size, and to cover it with layers of soil cover at the end of daily operation or an interim cover at a higher frequency as appropriate. This operation requires systematically depositing, compacting, and covering the wastes in compliance with specifications such as placing 150 to 300 mm of soil over every 600 mm of compacted fill. In addition, the soil cover should have a minimum designated depth and the final cover should be grassed to prevent erosion. A common projected ultimate land use of a landfill is a park with recreational facilities that are not affected by long-term ground subsidence.

Thorough investigation has to be undertaken to select the most appropriate location for a landfill site. In the site selection process, though there may exist much more factors, four main factors are considered, namely, potential migration routes of the wastes, waste characteristics, planned features of the landfill, and potential targets at risks (Noble 1976).

For potential migration routes, the study of contaminant movement away from the disposal site through air, surface water and ground water is focused on. The movement of wastes depends not only on physical, geotechnical, geographic and environmental characteristics of the site, but also on the waste characteristics. This feature can be quantified by its toxicity, persistence, corrosiveness, reactivity, flammability, radioactivity, solubility and volatility. The planned features of the facility will affect the degree of contamination. Potential targets subsume population centers, critical habitats and sensitive ecological systems in its vicinity. The knowledge can be represented so as to minimize or prevent a contaminant from entering into a potential migration route and arriving at a potential target at risk.

The site selection process involves three types of factor, namely, (i) physical, geographic, climatic, soil, water quality and socioeconomic conditions; (ii) political considerations, guidelines, standards and regulations established by the pertinent authorities; and (iii) expert judgment and heuristics (US Environmental Protection Agency 1984). In this process, the expert plays a key role since an enormous expert effort is required in the synthesis and analysis of these components. The following tasks are also required, namely, designing the general scheme and a uniform ranking procedure, identifying constraining regulations, analyzing data, and selecting a specific landfill site together with size. The judgments and expertise employed by experts in solving the domain problem are then translated into a set of explicit rules.

LANDFILL

LANDFILL is a prototype expert system designed to provide surrogate consultation during preliminary hazardous waste site investigations. It provides a versatile framework for the interpretation, classification and diagnosis of environmental conditions at waste disposal sites. The objective of such a consultation is to obtain a site rating using the expert rules and the decision logic described in the system's knowledge base. The ranking criteria are based on: relative risk or danger, taking into account the population at risk; the hazardous potential of the substances at a facility; the potential for contamination of drinking water supplies, for direct human contact, and for destruction of sensitive ecosystems; and other appropriate factors. The system is compiled and encrypted to create a run-only system. This run-only system is installed on a microcomputer for office use. The user can always overrule any options and recommendations provided by the system. However, a mechanism is built-in to ensure that the user's overruled input is reasonable and consistent. In other words, it plays the role of a knowledgeable assistant only.

Besides the usual components in a typical expert system, namely, knowledge base, inference mechanism, session context, user interface, knowledge acquisition and explanation modules, it also incorporates an ANN tool, fuzzy rule system, and a database. The schematic diagram of this prototype system is shown in Figure 1.

Knowledge acquisition and representation

Knowledge plays an important role in an expert system. The knowledge used has been acquired from written documents such as codes of practice, textbooks and design manuals and complemented by interviews with ten experts, from whom fairly consistent views were acquired within a six month period. In order to acquire knowledge, it is better to work with the expert in the context of solving particular problems, instead of directly posing questions about rules. Hybrid knowledge representation schemes, including object-oriented programming, procedural methods, and production rules are employed to express engineering heuristics and standard design knowledge. This approach renders it possible to take advantage of the characteristics of each method and to tailor for each type of domain knowledge in the knowledge base.

Object-oriented programming

Figure 2 shows the details of the blackboard architecture, which are classified into knowledge modules and the blackboard. Knowledge modules corresponding to procedural expertise knowledge are divided into Decision Process and Process Control whilst objects in the blackboard are classified into Decision Stage and Decision Entities.

The blackboard is partitioned into a number of hierarchical levels, corresponding to different stages of the decision process. Decision Stage only comprises a single object whereas there are several objects in the Decision Entities level. Data inside the Decision Stage are employed by the Process Control knowledge modules to determine the next possible action, or to check the validity of the function triggered by the user. Forward chaining inference mechanism is employed here to derive the next process. After a specific decision stage has been satisfied, the pertinent Decision Stage indicator will be assigned one of the preset values, which are numerical values from 0 to 9.

Decision Process modules determine largely the scope of decision to be solved by the expert system. The attached procedural method is processed when the value of the attribute changes, either by assignment under another method or by the user. A mixed problem-solving strategy is used here. The user is required merely to supply the relevant data during each decision stage and the system will determine the order in which different decision knowledge modules are executed.

Process Control modules ensure the proper and effective application of knowledge in Decision Process modules and undertake conflict resolution. They evaluate the current attribute values in Decision Stage of the blackboard, which provides the indicator to assist this decision making. The Main Decision Process class monitors the decision stage of all key tasks during the decision process and decides either to continue to next step or to prompt a warning message. All primary tasks in Process Control module are expressed on command buttons together with procedural methods attached. Process Control knowledge modules work closely with the user-interface module to produce user-friendly main menu displays. Moreover, the relevant entries and decision parameters under Decision Entities, the corresponding attribute values of Decision Stage are synchronized through the Process Control knowledge modules.

Production rules

Some heuristic knowledge is represented in the IF/THEN/ELSE production rules with confidence factors that can be assigned either automatically, or in response to the user's request. These rules are a formal way of specifying how an expert reviews a condition, considers various possibilities, and recommends an action. The explicit expertise under the production rule format in the knowledge base are employed to rank the potential landfill locations to identify the more feasible sites for further detailed studies. The following is a typical example of the production rules.

Rule to find HazardGroundwaterDepth: 1 of 8
IF GroundwaterRoute.DepthOfGroundwater >= 6 AND
    GroundwaterRoute.DepthOfGroundwater < 25

THEN HazardScore.HazardGroundwaterDepth:= risky CF 70

In the production rules, the confidence factor (CF) is employed as the determining factor to control the inference process for the evaluation of each parameter. The range is from 0 to 100, representing the degree of confidence with which the statement is known. A higher value represents higher degree of confidence and hence is better. The confidence factors are set by weighted opinions of various experts based on their heuristic and experience. Depending on the responses of the user, appropriate rules will be executed.

The system accounts for the facts that describe the domain knowledge on preliminary landfill site selection. The production rule also incorporates the fuzzy description. For some continuously varying conditions, such as the total population or net seasonal precipitation, the user can specify them with fuzzy descriptions or with definite numerical values. The system can automatically transfer the numerical values into fuzzy descriptions with the fuzzy membership curve to calculate its relevant confidence of membership before searching the rule base. Figure 3 shows the fuzzy description of total population within 300 m of the site with different curves representing the definitions of “very low”, “low”, “medium”, “high” and “very high”, respectively. The membership functions are also set by weighted opinions of various experts.

All landfill site selection parameters are categorized into four independent types of factors, namely, groundwater route characteristics, targets at risk, facility characteristics and waste characteristics. The groundwater route characteristics hazard score (S_{gr}) considers a number of parameters including the depth of the groundwater at the aquifer, net seasonal precipitation, soil permeability, physical state of the waste at the time of disposal, aquifer soil type, the depth to bedrock, geology, seismicity, faults, stratification, heterogeneity and isotropy. The target score (S_t), representing the level of risk to potential targets, is related to the potential use of the aquifer of concern, the vicinity of nearest production wells, and nearby population served by the groundwater. The executed assigned value about the planned containment characteristics of the proposed landfill facility is defined as the facility characteristics score (S_{fc}).The waste characteristics hazard score (S_{wc}) considers the toxicity, persistence, corrosiveness, reactivity, ignitability, radioactivity, solubility and volatility of each potential waste substance, along with its projected disposed quantity. The substance with the highest sum of the assigned values among all projected waste substances is selected as the representative waste material.

The user has to choose appropriate answers to all these questions in order to assign a hazard rating score to each parameter. The expert system then matches the selected answers with each rule, executes the appropriate ones, and computes the four partial scores from an ANN. The weighted sum of executed assigned hazard values represents independent variables. It ultimately derives the overall hazard rating score of the site (S), as follows:

$$S = w_1 S_{gr} + w_2 S_t + w_3 S_{fc} + w_4 S_{wc} \tag{1}$$

where w_1, w_2, w_3, and w_4 are the weights of the partial score respectively, with values assigned by expert opinion after iterated cycles of training and validation of the ANN. The overall site hazard rating score is normalized between 0 and 100, which is utilized as a measure for the relative ranking of the specific site. A lower value represents a safer potential site location. The scores can be employed as a yardstick for the relative safety of different sites. In a preliminary study, locations with high scores might be eliminated as potential landfills, whereas sites with low scores can remain for further comprehensive investigation.

Artificial neural network (ANN)

An ANN is used as the learning mechanism to transfer engineering experience into knowledge in determining the hazard scores. The back-propagation learning algorithm is employed to train the network for extracting knowledge from training examples (Rumelhart et al. 1994). An ANN architecture with 36 inputs (one attribute and one confidence factor for each feature), 4 outputs (one for each partial score), and one hidden layer of 18 nodes is created for the problem. The learning control parameters, including learning rate = 1.0 and momentum factor = 0.5, are chosen to control learning process. The initial network weights are assumed with uniformly distributed random values from the interval -0.5 to 0.5. The S-shaped sigmoid curve, as shown in eq. (2), is used as a transfer function on each neuron to represent the input-output relation in the hidden layer and output layer whilst a linear function is employed for the input layer.

$$S(x) = \frac{1}{1+e^{-x}} \qquad (2)$$

The major advantage of employing eq. (2) is that it can normalize all the input data into the range between 0 and 1, which is more manageable in terms of data interpretation. The normalized root-mean-square error (NRMSE) between target and output results is computed to evaluate the training performance. Let N be the number of testing example, T_{ij}, O_{ij} be the target values and the computed value of the i^{th} test example and j^{th} output node respectively, and $\overline{T_j}$ be the average target value of j^{th} output node, then the definition of the above-mentioned statistical quantity is as follows:

$$NRMSE = \frac{\sum_{i=1}^{N}\sum_{j=1}^{4}(T_{ij}-O_{ij})^2}{\sum_{i=1}^{N}\sum_{j=1}^{4}(T_{ij}-\overline{T_j})^2} \qquad (3)$$

Figure 4 shows the relationship between NRMSE and number of training cycles. It is found that the error rate is converged in about 30 cycles. Self-learning mechanism is accomplished by the use of ANN. System validation is performed through the validation process of the ANN and by comparison of the results with those by the experts. The knowledge base is dynamic and if more input-output data pairs are provided by other experts in different locations of the world, the generalization capability of the ANN will yield different output results.

Inference engine

The inference engine controls the strategies that determine how, from where, and in what order, a knowledge base draws its conclusions. It controls the selection of procedure methods and production rules from the knowledge base to derive a conclusion or decision context. All the decision steps can be seen explicitly on the main screen display. The validity of the user’s choice on the preferred sequence of decision processes is checked by Process Control knowledge modules, which act opportunistically upon being triggered. An event-driven inference processing mechanism is adopted so that the ensuing action of the system will depend on the input made by the user. For example, the factors affecting the site characteristics are considered depending on the nature of ground in the vicinity. If rock has been selected, the user is prompted to enter whether or not there are any faults. If soil has been selected, the above question will not be asked.

After the network is trained, this system is capable to diagnose new cases of site selection, even for the cases that some input values are unknown owing to unavailable or missing records. A hybrid reasoning strategy that combines forward and backward reasoning schemes is used in order to arrive at a reasonable conclusion with minimum information. Forward chaining inference is employed to infer the output values given the current input values, part of which may be unknown initially. The prototype arrives at a conclusion when no unknown input can alter the current decision significantly. However, if the system has not yet arrived at a certain conclusion with a defined threshold value of confidence factor, backward chaining reasoning is employed. The system automatically highlights the unknown input units that have a significant effect on the current most plausible conclusion, and prompt the user to enter their values.

User interface

The system offers a friendly user interface. Whilst input data entries are kept at minimum, they are provided by the user mostly through selection of appropriate values of parameters from the menus and answers to the queries made by the system. If the input data provided by the user is not within the specified range, it will be rejected and a warning message will be prompted. The system provides a contemporary multi-window graphics text display, which is valuable to novice engineers.

Case example

A case example is employed to demonstrate the application of the system. The overall landfill hazard rating of a potential rural site located at Tseng Kwan O is evaluated. User-friendly displays are used to interact with end users by prompting for values and showing the output data. The sample run commences with inputs on various groundwater route characteristics in the main menu. The depth of groundwater to aquifer is less than 6 m and the net seasonal precipitation is 2400 mm/year. The aquifer soil type is sandy soil with soil permeability 5 x 10^{-6} m/s. The depth to bedrock is more than 50 m. The soil properties are homogeneous in all directions without any stratification and there are no faults nearby. The waste is in a solid state and is unconsolidated. It will release unpleasant smell with pH value of 8. The waste is not inflammable and its temperature is below 25°C. Its toxicity and radioactivity are low. Its total quantity is about 500 tons/m^3. The landfill will have a non-permeable liner and a leachate collection system. The land use at the vicinity of the site is mainly public area and there are no potential hazardous installations within 1 km of the site. The total population within 300 m of the site is about 50 people. The distance to the nearest drinking water well is about 200 m. The system transforms these production rules into user-friendly interactive menus. Based on the responses of the user, the system searches the knowledge base and generates the overall landfill site rating score, which is shown in Figure 5. In general, a range of scores between 0 and 50 would indicate a site to be feasible for sanitary landfill. In this case, the score of 41 is of medium value and it is feasible as a site for sanitary landfill. The recommendation is that detailed investigations can be further undertaken, which was verified by independent but consistent assessments of experts.

Conclusions

The integration of the heuristic and empirical knowledge into a decision support system is useful in the selection process of a potential landfill site, since a simple score can represent a diversity of complicated factors. A prototype expert system, which assists in making decisions on selection of an appropriate landfill site, was developed and implemented. It incorporates an ANN for training of partial hazardous scores and a fuzzy rule base for representation of the heuristic knowledge. It is shown that the hybrid application of these latest AI technologies is appropriate to act as storage for empirical knowledge so that advice on landfill site selection can be furnished in the preliminary design stage. The evaluation of the prototype system is based on the hazardous waste site ranking system recommended by the U.S. Environmental Protection Agency, adapted to Hong Kong conditions by incorporating the stipulation of some local regulations. The knowledge base is transparent and can easily be updated, which renders the expert system an ideal tool for incremental programming. Increase in efficiency, improvement, consistency of results and automated record keeping are among the advantages of such a system. Furthermore, the educational spin-off of an expert system in training novice engineers or in transferring knowledge is significant.

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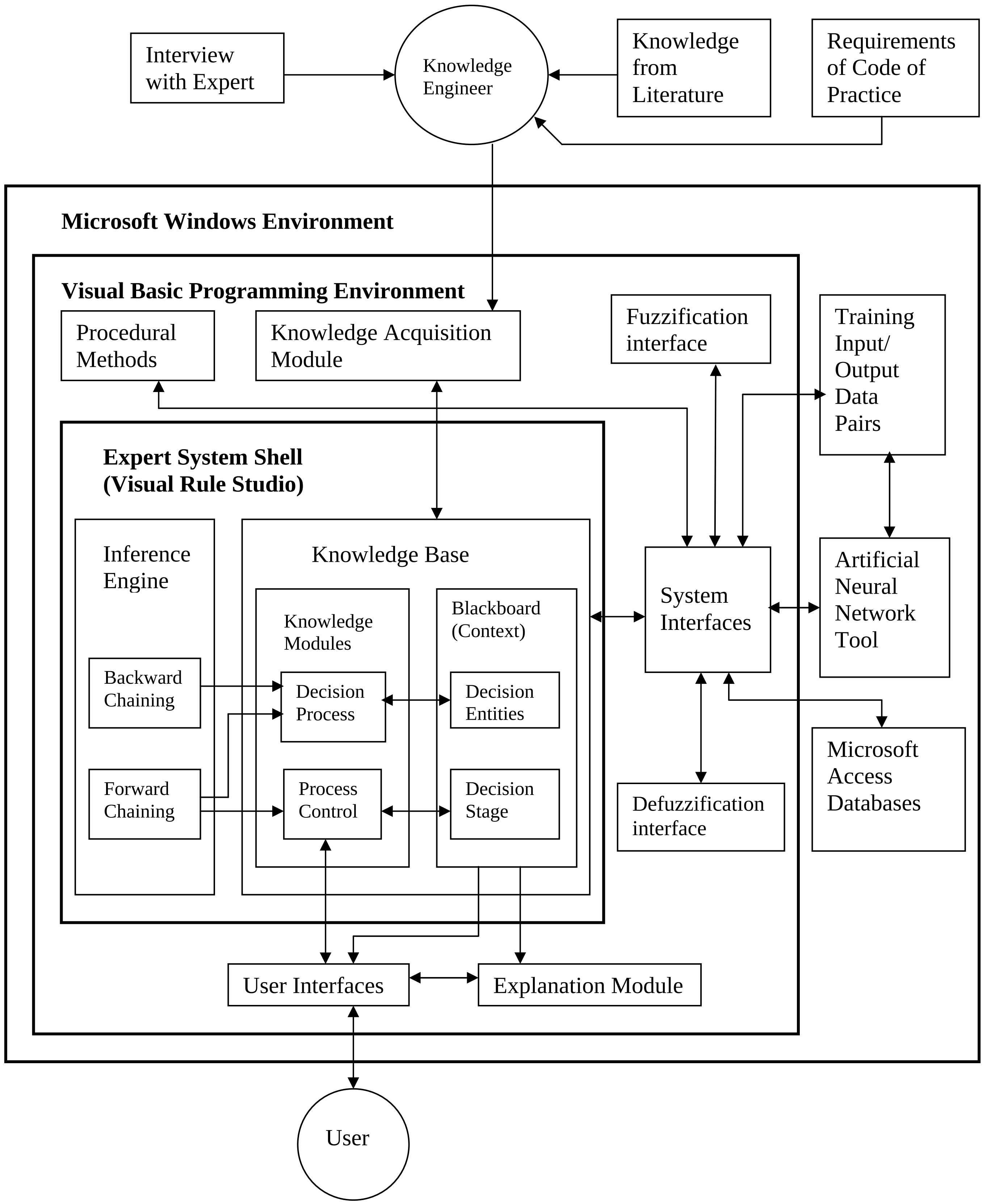

Figure 1. Schematic diagram of the prototype expert system

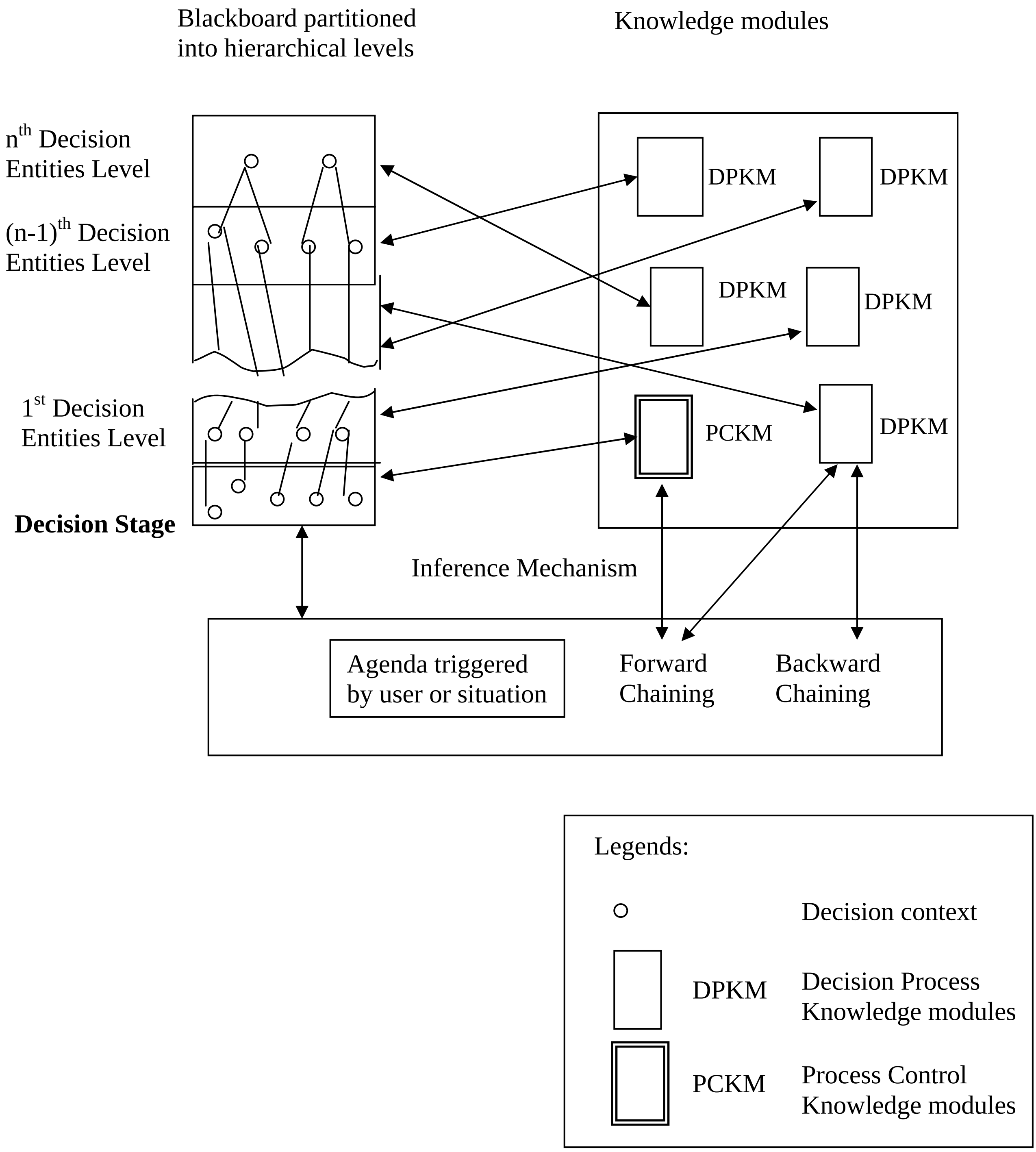

Figure 2. Details of the blackboard architecture

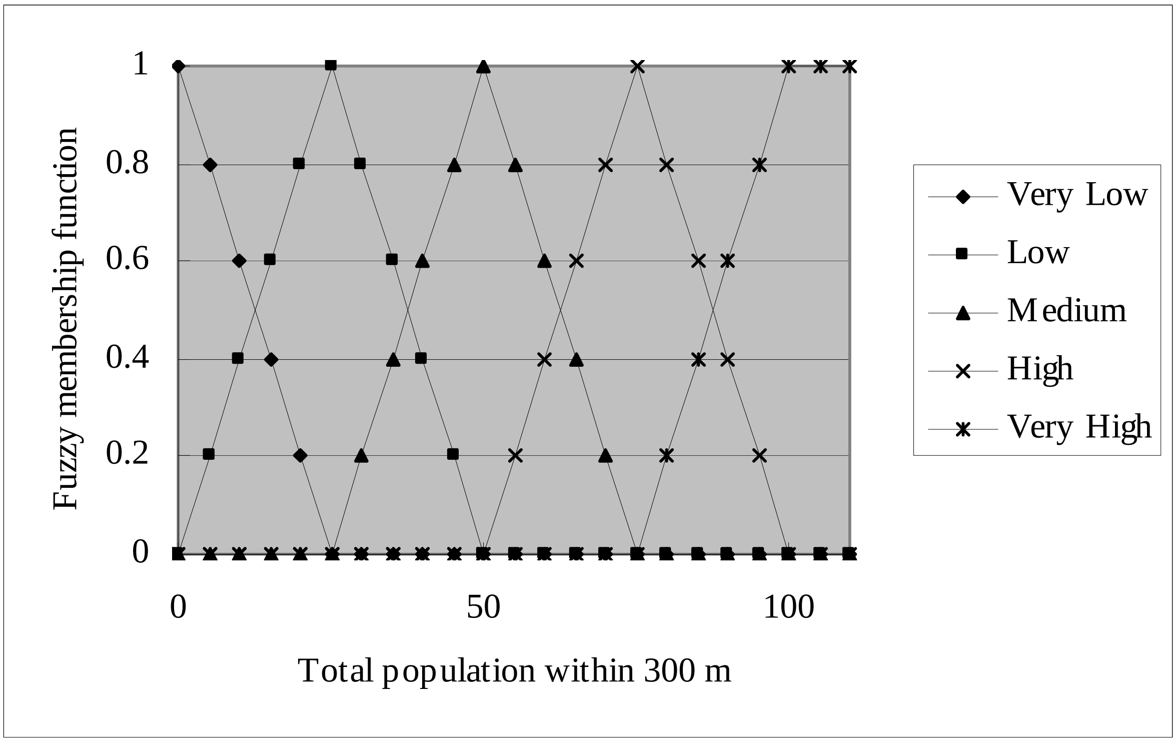

Figure 3. Fuzzy description of total population within 300 m of the site with different curves

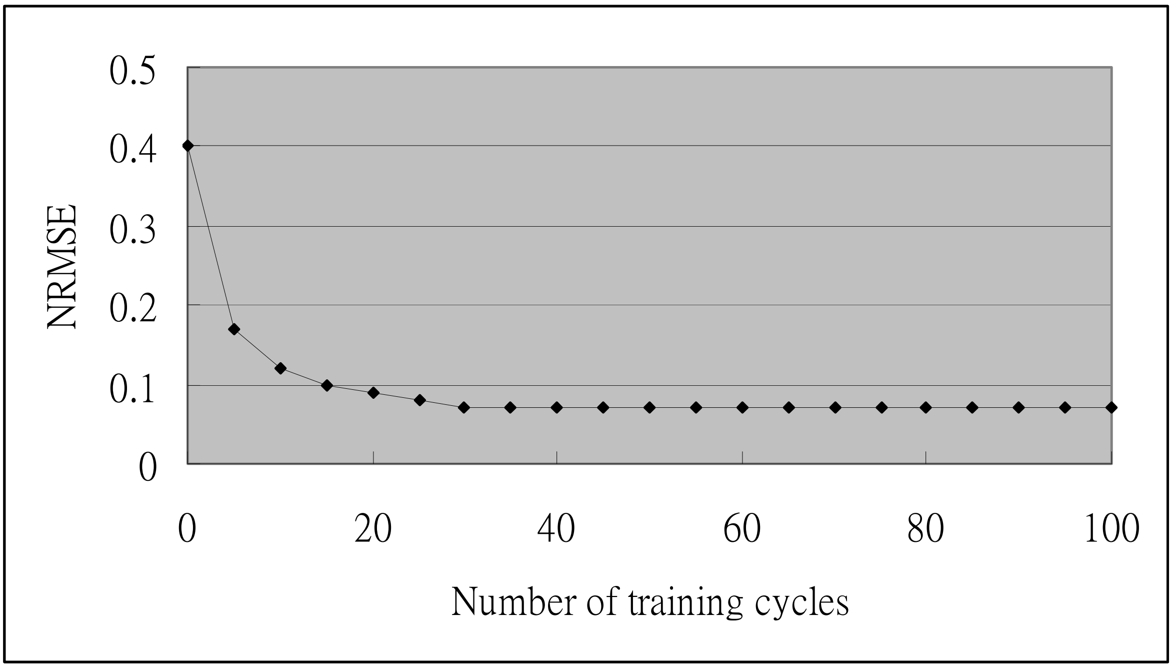

Figure 4. Relationship between NRMSE and number of training cycles

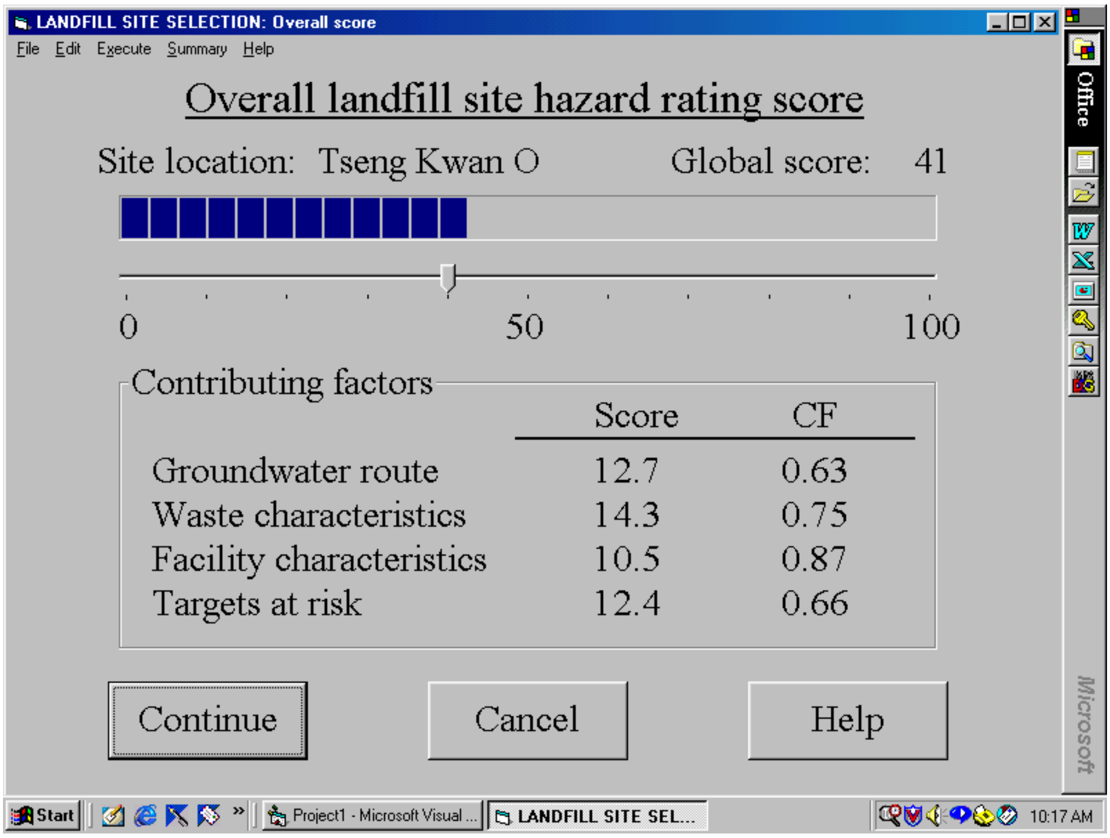

Figure 5. Screen displaying overall landfill site hazard rating score