An expert system for selection of retaining walls and groundwater controls in deep excavation

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Abstract

A rule-based expert system has been built for selection of both retaining wall types and groundwater control methods in deep excavations in Wuhan city. For this expert system, a new type of generation rule is developed in which one condition is able to be defined with a “third state” that not only contributes directly to reaching the conclusion in a rule, but also factors into calculating the reliability of the conclusion. The traditional backward chaining technique has been improved to accommodate the change of a rule type and a fuzzy backward chaining method IRO has been established to increase reasoning flexibility. Using IRO as a fundamental element, it is convenient to form a complicated reasoning network in the inference engine. Finally, two knowledge bases are built from more than 100 case histories and other resources, and the new expert system proves to be effective in case studies.

Keywords: Expert system; Deep excavation; Improved backward chaining technique; Equivalence degree; Retaining wall types and groundwater control methods

1. Introduction

Wuhan, the capital of Hubei province, lies at the confluence of the Yangtze and Han rivers, roughly midway between Beijing and Guangzhou. The city, one of the most populous zones in Central China, is comprised of three towns, that is, Wuchang, Hankou, and Hanyang, that face each other across the rivers and are linked by five bridges. The three towns are underlain by complex geological and hydrological conditions, such as high groundwater level and poor soil strength and so on, and construction projects involving deep excavation are especially challenging. Since high-rise buildings first began to appear in the mid-1980s, there have been almost 500 case histories involving deep excavation. Most of these cases were successful, but a few were failures. Much useful data have been collected about the design and construction of deep excavations in this area. These data have been used to develop a new and innovative expert system.

An expert system is a computer program that uses non-numerical domain-specific knowledge to solve problems with a competence similar to that of human experts. Expert systems are recognized as valuable tools for dealing with complicated problems and have been applied in geotechnical engineering for more than 10 years. Moula et al. [1] introduced expert systems developed up to 1993 and Toll [2] updated and reviewed a large number of artificial intelligence systems of geotechnical engineering established until 1996. Using PROLOG, Davey-Wilson et al. [3] developed an expert system for the selection of groundwater control methods and then created a spreadsheet-based decision system for assisting in the selection of groundwater controls for deep excavations [4]. Hutchinson et al. [5] described the implementation of an expert system called RETWALL for the selection and preliminary design of
Retaining structures. An expert system using a best-first search algorithm was developed by Chamean and Santamaria [6] to select soil improvement methods. A case-based retaining wall selection system using 254 previous retaining wall cases was established by Yau and Yang [7] and the system, based on the user’s requirements, was able to search for a set of feasible retaining wall types from the case base. A new expert system shell was developed and applied to solve site classification [8] and some useful conclusions were obtained. Using VP-expert shell, Amirkhania et al. [9] built an expert system with 930 rules, and this system was tested with the requirements from an actual project.

Most expert systems act as tools to acquire expert knowledge or suggestions, and each one has a unique development method and characteristics. Some excellent methods have been developed and applied using weighting and similarity score to derive a conclusion [4,7,10]. Expert knowledge with the largest similarity score is acquired during the reasoning process. This is the so-called “fore-evaluation” method which has been widely applied in developing many expert systems. In this paper, however, we introduce the ‘third state’ in the rule to enhance the flexibility of the reasoning. After a conclusion has been deduced/acquired, its reliability is estimated with the equivalence degree (ED) value. This is a form of post-evaluation that emphasizes the ‘close state’ in the calculation. Some fuzzy terms in a rule can more effectively and accurately be dealt with when using post-evaluation. For example, ‘very far’ in a sentence ‘the distance is very far’ is difficult to quantify for a user. But the post-evaluation method allows the user to match fuzzy terms to meet specific conditions in a site.

The quantification of expert opinion is a challenging part of formatting expert knowledge. In this paper, a new type of a rule is presented and applied in the development of the expert system.

In this paper, the development of an innovative rule-based expert system is introduced for selection of retaining walls and groundwater controls in deep excavations in Wuhan city. After the expert knowledge for deep excavations is acquired and characterized, a new type of generation rule that reflects the natural and specific relationship among conditions in a premise is developed. In order to accommodate the new generation rule, the conventional backward chaining technique is modified, and a fuzzy reasoning method is established in which ‘equivalence degree’ is used to compute the reliability of an acquired expert suggestion or recommendation.

Two knowledge bases with more than 40 rules are formed for the selection of both retaining wall types and groundwater control methods.

2. New expression of a rule

2.1. Expert knowledge and its analysis in deep excavation

The collected information forms the knowledge base of an expert system for selecting retaining wall types and groundwater control methods for deep excavations. Before being compiled as part of the knowledge base, however, the expert knowledge must be classified and expressed as rules with relative weighting of conditions and confidence factors [11]. Some distinctive characteristics of converting expert knowledge into a knowledge base are described in deep excavation below.

2.1.1. Uncertain and fuzzy terms

Some uncertain and fuzzy terms, such as ‘probably’, ‘most’, ‘small’, ‘very close’ are often cited in expert knowledge either to demonstrate the state of a conclusion or to explain the restraint conditions. On the other hand, terms such as ‘depth less than 6 m’, seldom appear in expert knowledge. Uncertain and fuzzy words are easier for experts to use to explain complex conditions or relationships. For example, “in accordance with the geological and environmental conditions at the site, a soil nail wall is ‘probably’ the best retaining wall to meet with construction time limitations and engineering safety concerns” and “the surrounding buildings are ‘too far’ away from excavation boundary to affect its construction”. The uncertain or fuzzy terms ‘probably’ and ‘too far’ have to be modified before they are entered into the knowledge base. For example, confidence factors can be used to replace the term ‘probably’ to demonstrate the expert’s confidence in his decision. Also, a formula can be developed to define the distance ‘too far’.

2.1.2. Complicated relationships in the premise

A conventional generation rule is defined by the following expression:

\[
\text{IF } F \text{ THEN } C
\]

where \( F \) indicates the premise and \( C \) represents the conclusion of the rule. A properly designed expert system allows complex relations within the premise \( F \). For example, the following statement regarding selection of an internally-propped retaining wall from the technical document [12], issued by the municipal experts association as a guide line in deep excavation in Wuhan and Hubei region:

\[
\text{IF there exists important buildings adjacent to the boundary of deep excavation (F1) and the excavation area is very small (F2) or the excavated shape is rectangular with two very short opposite sides (F3) and}
\]
displacement induced by excavation is required to be very small ($F_4$).

**THEN**  internally-propped structure can be adopted ($C$).

Even though this expert's suggestion seems to be very clear, there are confusing relationships between the premise and conclusion as revealed in the following:

1. Different conditions have different degrees of importance in deriving the conclusion. For instance, in Wuhan city it has been shown that internally-propped structures are the best method for restricting slope deformations caused by excavation. So the fourth condition is the most important, relevant to the use of internally propped structures. Therefore, a ‘weighting’ parameter is used to measure the relative importance among the conditions in the complex premise. The fourth condition is given maximal weighting value, and the other conditions are given a lesser value proportional to their importance in deriving the conclusion.

2. Not each condition is absolutely necessary to obtain the conclusion $C$. The expert system developed for this study attempts to distinguish conditions, which are strictly necessary for deriving the conclusion from those that are important for establishing the validity of the experts’ opinion. In the example above, the $F_2$ and $F_3$ conditions reflect the effect of project cost and construction operations on the selection of the retaining wall type. In a way, $F_2$ and $F_3$ conditions are important for deciding the retaining wall type, but both are not necessary conditions for selecting an internally-propped structure. On the other hand, limiting the amount of slope deformation is a necessary premise for selecting this kind of retaining structure. Premises like $F_2$ and $F_3$ are called ‘third state’ conditions. Though ‘the third state’ condition is unnecessary, it cannot be completely omitted in a rule. This kind of condition mirrors the integration of different factors in making a judgment. In a sense, the third state condition is ‘necessary’ to improve the reliability of expert knowledge, but it cannot accurately be described by weighting.

3. A condition in the premise is sometimes made up of several sub-conditions. For instance, ‘Engineering geological conditions are very good’. This sentence means that: (a) soil has high shear strength; (b) soil has the ability to resist seepage failure; (c) strata distribution benefits the stability of excavated slopes. Therefore this sentence could be considered to consist of three sub-conditions. Only after the sub-conditions are known can the condition be accurately defined. It has been shown that a neural network can be used to simulate the complex structure of conditions and sub-conditions [11].

The measures that this study adopted to deal with the above conditions are summarized as follows:

1. specific values or formulas are used to replace or quantify expert knowledge with fuzzy or uncertain terms;
2. weighting is used to represent the relative importance among conditions in the premise;
3. some special conditions are designated as ‘third state’ conditions to identify their special relationship within the premise, and improve the inference technique and fully demonstrate the integrality in the premise; and
4. a neural network is used to represent the complex structure of conditions and sub-conditions contained within the expert knowledge.

### 2.2. New format of a rule

For this study a new rule is developed to match the characteristics of the expert knowledge compiled for deep excavations in Wuhan city. This new rule has the following distinctive features:

1. a confidence factor indicating the reliability of the expert’s conclusion;
2. a weighting expressing relative importance of a condition in the premise; and
3. a third state describing special conditions.

This new rule is illustrated as follows:

$$ \{ \text{rule expression} \} :\!\!\!\!\!\!\!\!:\!: = ( \{ \text{its premise} \} \Rightarrow ( \{ \text{a deduced conclusion} \} | \{ \text{a deduced conclusion} \} | \{ \text{its premise} \}) :\!\!\!\!\!\!\!\!:\!: = ( ( \{ \text{premise body} \} | ( \{ \text{condition definition} \} ) ) \{ \text{premise body} \} ) :\!\!\!\!\!\!\!\!:\!: = ( ( \{ \text{logical definition} \} | ( \{ \text{condition expression} \} | ( \{ \text{condition expression} \} ) ) \{ \text{premise body} \} ) = ( ( \{ \text{condition expression} \} | ( \{ \text{condition expression} \} ) ) \{ \text{condition expression} \} ) ;\!\!\!\!\!\!\!\!:\!: = ( \{ \text{character string} \} ) \{ \text{condition definition} \} ) ) = ( ( \{ \text{the third state} \} | ( \{ \text{no definition} \} ) ) \{ \text{a deduced conclusion} \} ) = ( ( \{ \text{character string} \} ) \{ \text{confident factor} \} ) ;\!\!\!\!\!\!\!\!:\!: = ( ( \{ \text{value variable from 0.6 to 1.0} \} ) \{ \text{weighting value} \} ) ;\!\!\!\!\!\!\!\!:\!: = ( ( \{ \text{value variable from 0.0 to 1.0} \} ) \{ \text{weighting value} \} ) ;\!\!\!\!\!\!\!\!:\!: = ( ( \{ \text{weighting value} \} ) ) \{ \text{premise body} \} = \{ \text{equal}; | = \text{and}; \| = \text{or}. \}

In this new rule, the confidence in the conclusion or the relative importance of a condition increases as the confidence factor or weighting increases, respectively. One of the distinctive features in this new type of rule is
that a condition can be defined as a ‘third state’. If a condition is labeled ‘third state’, it is auxiliary and does not contribute directly to reaching the conclusion in a rule. However, it does factor into the calculation of the reliability of an expert suggestion. One of the advantages to the ‘third state’ in the premise of a rule is that inference is flexible. This technique reflects the subjective relationship of expert knowledge. It also helps to avoid mechanical matches such as ‘yes’ or ‘no’.

3. New backward chaining technique

3.1. Improved backward chaining method

In conventional backward chaining techniques, when an inference engine begins to be executed, a rule is placed in the knowledge base and a request for additional information is presented to the user. Only after the user has responded with either a ‘yes’ or ‘no’ can the inference process continue. If the appropriate knowledge has been stored in the knowledge base, and the user supports all conditions of a rule, the result or conclusion from this rule can be obtained. If the user rejects any one condition of the rule, a new rule replaces the old one, and the search and match process is repeated. The process does not end until a conclusion or suggestion is found in the knowledge base, or no new rule can be placed. If the user’s response is ‘yes’ to a condition, a conclusion may be obtained from the condition. If the user presents a negative reply to one condition, the conclusion will never be derived from the condition.

This conventional backward chaining method is not appropriate for the new type of generation rule developed for this study because it does not support the ‘third state’ condition, confidence factors or relative weighting. Therefore a new backward chaining method was developed.

For a condition designated as ‘the third state’, the user can reply using ‘permitted’ in addition to ‘yes’ and ‘no’ in this new method. If the user answers using ‘permitted’, then it is possible to obtain a conclusion from this condition. However, the ‘equivalence degree’ for a ‘yes’ or ‘permitted’ will be different (see the next section in the paper).

One of the main disadvantages in a conventional chaining method is that it is difficult to get knowledge from the expert base because of the mechanical match mechanism in the inference engine. But by adding the ‘permitted’ response to the traditional ‘yes’ and ‘no’, reasoning flexibility increases and a multi-solution method can be applied. This new reasoning technique avoids mechanical or stiff matching of the conventional backward chaining method.

3.2. Calculation of equivalence degree (ED)

After a conclusion has been deduced from the expert system, its reliability must be calculated. It should be pointed out that in the following discussion both reliability and confidence factor will be used. The former we designate as equivalence degree (ED), and the latter is defined as the confident factor (see Section 2.2) quantifying expert opinion in knowledge bases.

Many calculation methods have been presented for determining the reliability of a conclusion from an expert system or case-based system \[11,13,14\]. Eq. (1) below represents a distinctive new calculation method used for this research. The term ‘ED’ stands for equivalence degree, and represents the reliability of a conclusion. The higher the ED value, the more reliable the conclusion. The term ‘ED’ has a value from 0.7 to 1.0 by Eq. (1).

\[
ED = X \frac{\sum_{i=1}^{n} \mu_i W_i^{m-1}}{\sum_{i=1}^{n} W_i^m}
\]

where \( \mu = \mu_i \circ W_i \), and symbol \( \circ \) indicates the fuzzy algorithm between weighting and close state of the \( i \)-th condition, and \( \mu_i \) is the close state to the \( i \)-th condition (defined in Table 1); \( X \) is the confidence factor of conclusion \( C \) in a rule; index \( m = 5 \) (see the next part in this section).

A new parameter ‘close state’ is introduced here to illustrate the similarity in state of the condition to the actual state on site when the user answers using ‘yes’ to a prompt of the reference engine. The relation is described in Table 1.

If the fuzzy algorithm is taken as multiplication, \( ED \) will be normalized to a variable and its value changes from 0.7 to 1.0 by Eq. (1).

If \( \mu_1 = \mu_2 = \ldots = \mu_n = \mu \), \( ED = \mu X \) from Eq. (1) and \( ED \) value has nothing to do with the weighting value, \( W_1, W_2, \ldots, W_n \) when fuzzy algorithm is as multiplication. In fact, parameters \( \mu_i \) and \( W_i \) should have a different contribution to \( ED \). Weighting \( W_i \) represents the relative importance of the \( i \)-th condition and is proportional to the other conditions. It is an internal constant in the premise of a rule. However, close state \( \mu_i \) represents the closeness degree of the user’s requirement to the \( i \)-th condition in a rule and is an external variable, and it is the actual situation in practice. The close state

<table>
<thead>
<tr>
<th>User’s response</th>
<th>Accepted</th>
<th>Confident</th>
<th>Very confident</th>
<th>True</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu )</td>
<td>0.7</td>
<td>0.8</td>
<td>0.9</td>
<td>1.0</td>
</tr>
</tbody>
</table>
mirrors the user’s views and can be changed based on a particular engineering problem, while the weighting is the expert’s opinion and fixed as a constant in a rule. Higher \( \mu_i \) values mean that the objective status is closer to one condition of a rule, so it is natural that the conclusion or suggestion from the condition will have a higher \( ED \) value. As evident in Eq. (1), the parameter \( \mu_i \) is more important than \( W_i \) of the \( i \)-th condition to evaluate the reliability of an acquired conclusion. In order to detailledly demonstrate this, a sample is taken in the following.

Suppose that in four calculation schemes for the same conclusion, the values of weighting \( W_i \) and closeness state \( \mu_i \) are different in each scheme (weighting is assumed changed in a rule). Using Eq. (1), and assuming \( X=1 \) and \( n=3 \), let us see the affect on \( ED \) value with different \( W_i \) and closeness state \( \mu_i \). Tables 2 and 3 are used to illustrate the effect of varying \( W \) and \( \mu \) on \( ED \). The weighting value \( W \) remains unchanged while \( \mu \) changes. In Table 2 when \( \mu_2 \) decreases from 0.9 to 0.8, notated \( \downarrow \), the difference in \( ED \) is 0.092. In Table 3, the \( \mu_2 \) value varies from 0.9 to 0.8 and the \( ED \) difference is 0.0678.

Keep \( \mu_i \) fixed and change \( W_i \): comparing the rows \( \mu \) (1) in Tables 2 and 3, the difference in the \( ED \) value is 0.0302 (=0.898−0.8678) when \( W_1 \) value increases from 0.2 to 0.3 and \( W_2 \) decreases from 0.5 to 0.4. In the same way, when we compare rows \( \mu \) (2) in the two tables, we get an \( ED \) difference of 0.06 (=0.806−0.8).

Therefore, when the parameter \( \mu \) changes, the difference in the \( ED \) value is larger (0.0658 and 0.047 compared to 0.0312 and 0.013, respectively) though difference in \( W_i \) and \( \mu_i \) is equal to 0.1. This indicates that closeness state \( \mu \) has a greater influence on the \( ED \) value than the weighting \( W \) value. Other calculation schemes have been tried and similar results have been obtained.

The weighting \( W_i \) and close degree \( \mu_i \) have different roles to get the equivalence degree of any expert knowledge from the expert system and close degree is more important than weighting and this idea is reflected in Eq. (1). It is the first time that reliability of an acquired expert knowledge is accounted for with this method, which is often neglected in expert system setup.

Now comparison is given between Eq. (1) and other calculation methods. As stated at the beginning of this section, many methods have been developed to judge expert knowledge, but the most widely-adopted calculation method is likely the mean value method, similar to the one introduced by Yau [7], here modified to the formula like Eq. (1):

\[
ED = \frac{\sum_{i=1}^{n} \mu_i W_i}{\sum_{i=1}^{n} W_i}
\]  

Using data of weighting and close degree in four cases in Tables 1 and 2, \( ED \) values can be evaluated with Eqs. (1) and (2), respectively, and results are shown in Table 4.

According to the Table 4, \( ED \) value computed by Eq. (2) is smaller in most cases and especially, as close degree role is not mirrored more obviously in it, because the difference in \( ED \) is smaller.

If \( m=2 \), the \( ED \) values are very close from Eqs. (1) and (2) if fuzzy algorithm is taken as multiplication in Eq. (1). If \( m>5 \), the \( ED \) value varies a little and so \( m=5 \) is considered proper in Eq. (1).

As illustrated at the end of Section 2, the ‘third state’ condition has a different contribution to \( ED \). The above calculation in this section is appropriate for the answer ‘yes’. If a third state condition emerges and is ambiguous or difficult to estimate or the user does not too much care about it, he neglects it and gives a ‘permitted’ answer to proceed to the next step in the inference engine. Under such a status, the corresponding close score condition will decreases because of the user’s uncertain reply and so the equivalence degree of a conclusion will be certain to decrease. If ‘permitted’ is applied to the condition, it is given \( \mu_i = 0.6 \). So the \( ED \) value of the associated expert knowledge will vary from 0.6 to 1.0 if a ‘third state’ condition is accepted as ‘permitted’.

Using the above backward chaining technique, a complex reasoning network can be formed [13]. Taking

<table>
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<tr>
<th>Table 2</th>
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<tbody>
<tr>
<td><strong>F1</strong></td>
</tr>
<tr>
<td>( W )</td>
</tr>
<tr>
<td>( \mu_1 )</td>
</tr>
<tr>
<td>( \mu_2 )</td>
</tr>
<tr>
<td>( \Delta ED )</td>
</tr>
</tbody>
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<table>
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<tr>
<th>Table 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>F1</strong></td>
</tr>
<tr>
<td>( W )</td>
</tr>
<tr>
<td>( \mu_1 )</td>
</tr>
<tr>
<td>( \mu_2 )</td>
</tr>
<tr>
<td>( \Delta ED )</td>
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<table>
<thead>
<tr>
<th>Table 4</th>
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<tbody>
<tr>
<td><strong>ED value from different methods</strong></td>
</tr>
<tr>
<td><strong>Cases</strong></td>
</tr>
<tr>
<td>Case1</td>
</tr>
<tr>
<td>Case2</td>
</tr>
<tr>
<td>Case3</td>
</tr>
<tr>
<td>Case4</td>
</tr>
</tbody>
</table>
this inference technique as a basic element, notation $I \rightarrow R \rightarrow O$, a complex network can be established. For example, putting two elements in serial, a multi-reasoning model can be obtained, $I_1 \rightarrow R_1 \rightarrow O_1 \Rightarrow I_2 \rightarrow R_2 \rightarrow O_2$; arranging two elements in parallel connection, parallel inference engine can be formed, $I_1 \rightarrow R_1 \rightarrow O_1 \Rightarrow I_2 \rightarrow R_2 \rightarrow O_2 \Rightarrow I_3 \rightarrow R_3 \rightarrow O_3$; combining several elements with serial and parallel connections, it is easy to form a complex reasoning network to find a solution. When a back propagation neural network is coupled into such a complex network as the other kind of element, a more powerful reasoning network will be developed.

4. Building the knowledge base for deep excavations

4.1. Sources for expert knowledge

The first step in developing an expert system for deep excavations is to collect relevant information. The sources of this information include: (1) case histories; (2) published papers; (3) books about deep excavations; (4) actual project specifications, and (5) minutes about questionnaires and interviews. For the purposes of this research, information from these sources was categorized into two classes: (1) retaining walls and (2) groundwater control methods. In each class, information is rearranged and classified into sub-classes. For example, soil nail wall is one sub-class in the class of retaining wall. In the final step, the expert knowledge is refined and abstracted.

4.1.1. Reliable case histories

Yangtze River separates Wuhan city into three towns. The geology and hydrology vary widely throughout the city. Conditions vary between shallow groundwater and poor soil strength in some parts of the city, to deep or no groundwater and high soil strength in other parts. Therefore, many different types of retaining walls have been designed for different deep excavations. Since the mid-1980s, 20–30 deep excavations for high-rise buildings have been completed each year. More than 100 case histories, representing many types of retaining walls and groundwater control have been collected for the purposes of compiling a knowledge base for a deep excavation expert system.

4.1.2. Publications

To deal with some special engineering problems, such as the prevention of seepage failure, a meeting organized by the Wuhan expert committee for deep excavations is often held to find solutions. This committee also assembles relevant experts to inspect design plans and give some suggestions, and these are compiled for each case study. Conferences are also held to discuss problems associated with deep excavations. Some specifications are published to guide design and construction. Altogether, 10 books of published information and two local specifications were collected for this study.

4.1.3. Expert’s recommendations

Construction involving deep excavations has proceeded for more than 15 years and some engineers have accumulated a wealth of experience. Experts’ suggestions, explanations and definitions often play an important role in the formation of expert knowledge. For this study, approximately 20 experts have been interviewed about many aspects of deep excavations, and their comments were documented for incorporation into the knowledge base.

4.2. Knowledge base for retaining walls

Seven kinds of retaining walls are widely used in deep excavations in Wuhan city: soil nail walls (w1), gravity retaining walls (w2), anchored-pile walls (w3), open excavations (w4), diaphragm walls (w5), internally-propped pile walls (w6) and cantilever pile walls (w7). Relative cost is a very important factor in selecting a retaining wall. So these seven types are first ranked from least expensive to most expensive (w4, w1, w2, w3, w6, w7 and w5) and entered in the knowledge base so they are considered in this order.

In practice, these seven kinds of retaining structures are seldom applied as independent methods, and auxiliary measures are often taken to improve the stability of excavated slopes. For example, soil nail walls are sometimes reinforced with long anchors to keep a troublesome slope stable. Therefore, several sub-categories for each of the seven main retaining wall types have been defined to build the knowledge base for selection of retaining walls (see Table 5).

4.3. Knowledge base for groundwater control methods

There are four common kinds of groundwater treatment practices used in Wuhan city: (1) drainage in the bottom surface of the pit; (2) use of a deep well to lower groundwater level; (3) prevention against seepage failure; (4) combining the second and the third method. The deep well (method 2) is the most popular in Wuhan city, however, as in the selection of retaining walls, one or more practices are often combined. Altogether, eight types of groundwater controls have been defined to form the knowledge base (see Table 6).

5. Program design

There are various commercially available expert system (ES) shells for development of expert systems. The
choice of the ES shell is based on both the nature of the research and specific features of ES shells. No existing ES shells could accommodate the new features developed as part of this study, most importantly the new format of a rule for this study, the ‘third state’ condition, and calculation of an $ED$ value. Therefore, a new expert system “ESDE” (Expert System for Deep Excavation) was developed using Visual C++, an object-oriented programming language.

### Table 5
Retaining walls in knowledge one

<table>
<thead>
<tr>
<th>Main type</th>
<th>Type of retaining wall in knowledge base one</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open excavation</td>
<td>Open excavation with grouting jet cover&lt;br&gt;Open excavation with thin concrete cover&lt;br&gt;Open excavation + soil nailing reinforcement</td>
</tr>
<tr>
<td>Gravity retaining wall</td>
<td>Grouting jet gravity retaining wall&lt;br&gt;Deep mixing gravity retaining wall&lt;br&gt;Compacting grouting gravity retaining wall&lt;br&gt;Gravity retaining wall + soil nailing&lt;br&gt;Gravity retaining wall + horizontally-propped mass in wall’s bottom</td>
</tr>
<tr>
<td>Soil nail wall</td>
<td>Soil nail wall&lt;br&gt;Soil nail wall + short resistant slippage pile&lt;br&gt;Soil nail wall + long grouting anchors&lt;br&gt;Soil nail wall + reinforcement block</td>
</tr>
<tr>
<td>Cantilever pile wall</td>
<td>Cantilever, boring hole pile wall&lt;br&gt;Cantilever, man-made hole pile wall&lt;br&gt;Cantilever, driven pile wall&lt;br&gt;Cantilever pile wall + horizontally-propped support in wall’s bottom</td>
</tr>
<tr>
<td>Anchor-pile wall</td>
<td>Boring hole, anchored- pile wall&lt;br&gt;Man-made hole, anchored- pile wall&lt;br&gt;Driven, anchored- pile wall&lt;br&gt;Anchored- pile wall + horizontally-propped block in wall’s bottom&lt;br&gt;Multi-layer anchor pile wall</td>
</tr>
<tr>
<td>Internally-propped pile wall</td>
<td>Boring hole, internally-propped pile wall&lt;br&gt;Man-made hole, internally-propped pile wall&lt;br&gt;Driven, internally-propped pile wall&lt;br&gt;Internally -propped pile wall with steel support&lt;br&gt;Internally -propped pile wall with reinforced concrete support&lt;br&gt;Multi-layer prop pile wall</td>
</tr>
<tr>
<td>Diaphragm wall</td>
<td>Diaphragm wall&lt;br&gt;SMW diaphragm wall&lt;br&gt;Diaphragm wall with internally-propped support&lt;br&gt;Diaphragm wall with anchors</td>
</tr>
</tbody>
</table>

### Table 6
Groundwater control in knowledge two

<table>
<thead>
<tr>
<th>Main method</th>
<th>Method of water treatment in knowledge base two</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drainage</td>
<td>Drainage</td>
</tr>
<tr>
<td>Deep well</td>
<td>Deep well</td>
</tr>
<tr>
<td>Seepage prevention</td>
<td>Curtain grouting around pit&lt;br&gt;Curtain grouting around pit + impervious blanket&lt;br&gt;Impervious blanket in the bottom of pit&lt;br&gt;Deep well + curtain grouting around pit&lt;br&gt;Deep well + impervious blanket in the bottom of pit&lt;br&gt;Deep well + curtain around pit + blanket in the bottom of pit</td>
</tr>
</tbody>
</table>

### 5.1. The input and output interfaces

The ESDE is designed to run under Microsoft Windows. Using different dialogue boxes, expert knowledge can easily be entered and stored in two knowledge bases. The information is clearly presented and easily accessible. The ESDE has a user-friendly interface. In the inference process, the user follows the prompting of the inference engine and only presses
the appropriate buttons with a mouse, and it is easier to operate than a DOS-based program [5]. The final solution or "expert knowledge" is displayed on the screen in natural language. If the user wants to use the ESDE to get expert suggestions, there is little or no learning requirement. He only needs to follow the instructions from the software and press a button to answer the questions.

5.2. Knowledge base

The knowledge base (KB) in the ESDE consists of two bases and it is independent of the inference engine. The computer language, Visual C++, is used as the development tool to facilitate programming the KB and its own data structure gives perfect performance of KB: data inserting, increasing, decreasing automatically, which is the so-called dynamic save in data. In the ESDE, the basic functions in the KB include filing, displaying, saving and updating. Expert knowledge is filed into the KB as a new rule and stored in ASCII format. In each base, its flow chart is shown in Fig. 1.

5.3. Inference engine

Two kinds of methods are coupled into the inference engine in the ESDE: improved backward chaining technique (as stated previously) and back propagation neural network. The former dominates the overall inference process, while the latter is taken as an inference element to judge the geology status of the main soil layer(s) in a site [11]. In the reasoning process, a third state condition can be recognized and the user can answer 'permitted', 'yes' and 'no' by selecting corresponding buttons. According to the user's responses, the ED value can be calculated to evaluate the reliability of an acquired conclusion or expert suggestion after he has finished the reasoning process. All the user needs to do is to press corresponding buttons to get the experts' recommendations or suggestions if there exists enough expert knowledge in the knowledge base. It is not necessary for the user to understand the reasoning process. The basic flow chart in Fig. 2 demonstrates the reasoning process. In Fig. 2, kb = knowledge base; ED = equivalence degree; Yescon, Nocon and Percon are data structures from CObList in Visual C++ and used to store conditions accepted, rejected and permitted by a user when he replies using 'yes', 'no' and 'permitted', respectively. According to the prompt in the inference process, the user decides whether BP neural network is used. After the user finishes the inquiry, they press the 'solution list' menu on inference menu, and all recommendations and suggestions from this knowledge system are displayed on the screen in natural language easy to understand.

![Fig. 1. Knowledge base maintenance flowchart.](image-url)
6. Application

6.1. Restraint environments

Conditions in and around a deep excavation can vary significantly. The relative proximity of other buildings or underground facilities, such as water or gas pipes, changes around the perimeter. Depth may vary throughout the excavation because of different foundation structures. The length of the excavated boundary varies with project size. Excavations in Wuhan city can be 100, 200, 500 m and even more than 1000m long and so hydrogeology and geology can vary within a particular site. All these factors form what are called ‘restraint environments’ in deep excavations. Before using ESDE, it is recommended that the boundary of the site be divided up into different sections with the same or similar restraint environments. The ESDE is then applied to each defined section along the boundary. Two cases with their reasoning process are briefly illustrated below.

6.2. Case one

Site one is located in the Wuchang district of Wuhan city. Within the excavated area the depth varies from 5.0 to 6.0m. Along the northern boundary, the excavated depth is 6.0 m and its boundary is only 1.5 m away
from an existing 8-storey building, which has shallow foundations. Along the other three boundaries, the depth of the excavation is about 5.0 m deep, and there is more than 8.0 m between existing buildings and underground facilities. Site investigation indicates that big stones or blocks do not exist in the ground and so there is no obstruction for drilling a hole in the ground if an anchor-pile wall is selected as the retaining type. The following two strata define the excavated materials:

1. Top layer is a fill with average thickness 0.4 m. Its parameters: soil density $\gamma = 19.0$ kN/m$^3$; internal friction angle $\phi' = 15^\circ$ and cohesive force is ignored;
2. Underlying the fill is a clay layer with an average thickness is 30.0 m. Its parameters: soil density $\gamma = 19.7$ kN/m$^3$; internal friction angle $\phi' = 17^\circ$ and cohesive force $C' = 40$ kPa.

Water is present at the site both as limited amounts of surface water from rainfall and human habitation that permeates into the top fill, and groundwater from the Yangtze River with a surface approximately 7.0 m below ground level.

Because an 8-storey building is very close to the excavated boundary along the northern side, the excavation boundary is divided into two sections: northern and the rest. Along the northern section, the ESDE system suggests using an anchored-pile wall with $ED$ value 0.987 and surface drainage can be adopted with $ED$ 0.96. Along the remaining boundary of the excavation a soil nail wall is selected as the most suitable retaining wall with $ED$ 0.943. The drainage method selected is the same as in the northern section.

The above results from the expert system ESDE are in full agreement with the design adopted in practice [15].

6.3. Case two

This deep excavation is 6.0 m deep in the Hankou district of Wuhan city. The total area of the excavation is 600 m$^2$ and is rectangular in shape. Some buildings and underground facilities are as close as 3 m from the excavation boundary. Site investigation reveals that four strata underlie the site. From the top down they are:

1. Top layer is fill with average thickness 2.1 m. It consists of clay and much cobbles. Its main parameters: soil density $\gamma = 19.0$ kN/m$^3$; internal friction angle $\phi' = 15^\circ$ and cohesive force was neglected.
2. Saturated clay layer. It has an average thickness of 1.5 m and typical soft soil in this district. Its main parameters: soil density $\gamma = 18.3$ kN/m$^3$; internal friction angle $\phi' = 7.5^\circ$ and cohesive force $C' = 18$ kPa.
3. The third layer is about 14.0 m thick and is silty clay with poor soil strength. It is typical of soft soils in this area and water content is more than the liquid limit $I_L$. Its main parameters: soil density $\gamma = 17.3$ kN/m$^3$; internal friction angle $\phi' = 6.0^\circ$ and cohesive force $C' = 14$ kPa.
4. Beneath the silty clay is a fine sand layer which has average thickness 4.5 m. It is highly permeable. Its main parameters: soil density $\gamma = 19.3$ kN/m$^3$; internal friction angle $\phi' = 23.0^\circ$ and cohesive force $C' = 2$ kPa.

All strength parameters above are effective stress strength parameters and not residual.

Two kinds of water are present at the site. One is rainfall in the top fill and clay layer; and the other is from the Yangtze River and lies in two layers of silty clay and fine sand (layers 3 and 4). The permeability coefficient $Ks$ of the silty clay is very small.

Based on the recommendation from the ESDE, a boring hole, internally-propped pile wall is selected with 0.965 $ED$ and curtain grouting method acts as groundwater control method with 0.968 $ED$ value.

The above results deduced from the ESDE are fully in agreement with the design plan in practice [16]. If the excavated area in this case is neither ‘small’ nor ‘narrow’, but the user neglects them and ‘permitted’ button is selected to these ‘a third state’ conditions in the process of retaining wall selection, internally-propped pile wall will be still adopted, but its $ED$ value will drop to 0.788.

6.4. Remarks

The three steps of applying the ESDE to a particular site for selection of the retaining wall type and groundwater control methods are summarized in the following:

1. the perimeter of the excavated area is divided up into multiple sections with the same or similar conditions;
2. by responding to the questions submitted from the ESDE, the user can get conclusion(s) for the type of the retaining wall and estimates its reliability;
3. in the same way, the user obtains the groundwater control method(s) deduced from the ESDE and estimates of reliability.

In Case 1 above, the acquired conclusions/suggestions have $ED$ values varying from 0.943 to 0.987, indicating
that the types of retaining walls and groundwater controls deduced from the ESDE are safe and rational and also cost-effective. They also agree with the actual designs. In Case 2, when a condition with the ‘permitted’ attribute is accepted during the reasoning process, the internally-propped structure is also recommended, but its $ED$ value is lower. This lower $ED$ value means that the internally-propped pile wall is suitable at this particular site, but the cost will be higher and construction may not be as ‘convenient’ for workers.

It can be noted that the value of $ED$ varies from 0.6 to 1.0 when considering these ‘permitted’ conditions. The more reasonable the inferred suggestion from expert system is, the larger the value of its $ED$. Table 7 is used to further identify the degrees of reasonable choices for the ESDE expert system.

It can be found, reflecting the procedures of using the ESDE, that not much background knowledge in geotechnical engineering is needed and its operation is also simple for solutions. The user with limited experience or much expertise in this domain, is able to operate this expert system and gets conclusions he tries to seek.

The ESDE has been applied to 10 additional cases to compare the recommended types of retaining walls and groundwater control methods with those actually used [17]. The deduced conclusions in 8 of the cases are in agreement with the actual designs. Two of the cases recommend different retaining walls than those actually used. The disagreements in these two cases result from limitation in the knowledge base in this version of the ESDE. The actual retaining walls used consisted of combined retaining wall profiles—open excavation in upper part and a soil nail wall in the lower part in one case, and open excavation in the upper part and a cantilever pile wall in the lower section in the other case. The use of combined retaining wall types is not embedded in the knowledge base of the current version of the ESDE, so conflicting conclusions arose.

It is important to point out that this version of the ESDE can only be applied to the Wuhan area, since its knowledge base consists of site specific geological and hydrological conditions as well as successful cases and expertise from the area. Some modifications are therefore required before this expert system can be extended to use in the other regions.

### Table 7

<table>
<thead>
<tr>
<th>Degree</th>
<th>Poor</th>
<th>Fair</th>
<th>Good</th>
<th>Very good</th>
</tr>
</thead>
<tbody>
<tr>
<td>$ED$</td>
<td>0.6–0.7</td>
<td>0.7–0.8</td>
<td>0.8–0.9</td>
<td>0.9–1.0</td>
</tr>
</tbody>
</table>

### 7. Discussions

Expert systems are an extremely effective tool to manage and apply the collected expertise from many experts to complicated problems. However, expert systems should not replace human expertise or other valid approaches [2]. It can supply engineers with a powerful support tool to investigate alternative methods for different development purposes or site conditions. Expert systems provide non-accurate conclusions when compared to numerical analysis methods. However, the non-uniform and uncertain characteristics of soil, rock and water in geotechnical engineering makes it difficult to quantify the physical properties to apply in mathematical models. For this reason the non-accurate method such as expert systems should not be overlooked. Numerical analysis methods are necessary to quantify parameters during the design process. For instance, determining the factor of safety of a cut slope is a necessary prerequisite for design of a stable slope. If both accurate and non-accurate methods can be integrated into the same design process, engineers may gain a better understanding of the critical design issues. Furthermore, the design process can be extended to other areas, such as detailed engineering design and construction [11].

Fig. 3 shows an example of the application of both accurate and non-accurate methods in the engineering design process. For example, the expert system, such as that introduced in this paper is might first used to define retaining wall options based on equivalence degree, cost, convenience, as well as other factors contained within the knowledge base. Then the “accurate methods” are applied to design the physical structure. Mathematical models and physical properties are input to calculate quantitative results, like the factor of safety for a retaining wall. This process leads to a more sophisticated and “informed” design that considers many points of view. In this manner a fairly detailed analysis and design can be accomplished even for the most demanding conditions.

![Fig. 3. Architecture of expert system integrated with accurate knowledge.](image)
8. Conclusions

Deep excavation is an important branch of geotechnical engineering. Many factors must be considered in the selection of retaining structures and groundwater control methods, including excavated depth, groundwater level, soil shear strength, restraint environments along the excavated boundary, construction time and so on. No matter how much expertise an engineer has, it is very difficult to put forward a rational and safe design without the input from other engineers, but expert system is a good way to supply engineers with more information and help them make decisions.

In this paper, a new expression for a rule is put forward and a new backward chaining technique is developed to fit the new rule format. In this reasoning method, the ED concept is presented to describe the reliability of the acquired expert knowledge or suggestion. Though a conventional rule-based expert system is relative simple, it is still exploited to solve complicated problem after having been adjusted and modified.

Based on the study in this paper, the following conclusions are obtained:

1. just like the other expert systems, a specific method is used to develop the expert system ESDE in the paper;
2. the expert system ESDE is developed for deep excavations. The new generation rule mirrors the complicated relationships among conditions in the premise and it leads to a new more flexible reasoning method. The improved backward chaining method described in this paper breaks down the idea of mechanical judgment, ether right or wrong, and makes reasoning flexible;
3. in this paper, a new idea on the ED value, is presented to evaluate the reliability of an acquired conclusion;
4. the conventional backward chaining technique has been improved by inclusion of the third state, allowing the user to designate a third state condition as ‘permitted’. A complex reasoning network can easily be formed when the inference method is taken as a basic element;
5. two kinds of knowledge base have been established, and the information is successfully applied for selection of retaining walls and groundwater control methods in deep excavations. Case studies have shown that rational results can be obtained from the ESDE;
6. this expert system (ESDE) is suitable for engineers who have limited expertise for the selection of retaining walls and groundwater controls in Wuhan city.

The quality and correctness of the knowledge base is very important for obtaining rational results from the expert system. The expert knowledge should be complete, authoritative and definitive. Formation of the expert knowledge is probably more important than the inference method. In developing an expert system, one should be prepared to spend a lot of time on determination of quantitative parameters for weighting and equivalence of a condition, confidence of a conclusion, and definition of the relations among conditions in a rule.

Though rational solutions and results can be obtained from the ESDE, its knowledge base still needs to be enlarged. Different combinations of methods are sometimes used along a single profile, for example, a cut slope above a soil nail wall. Future applications of the ESDE will be used to build and revise the knowledge base to improve the correctness of the acquired conclusions.

References


