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Learning heuristics for determining slurry wall panel lengths

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Abstract

Determining panel lengths for slurry walls is an engineering issue that involves complex geotechnical, design, and site considerations. In practice, the decision is made through a trial-and-error process. Relevant principles extracted from experts are not sufficiently detailed to generate a solution. This research proposes an inductive learning model for solving this problem. Given a new project whose panel lengths need to be determined, the model chooses similar cases from existing cases, based on case-based reasoning, performs an inductive learning, and uses correctness and coverage rates, and then static rules to verify the induced results.

Keywords: Construction scheduling; Critique; Schedule review; Rule-based; Case-based reasoning

1. Introduction

Knowledge acquisition is the transformation of problem solving expertise from knowledge sources such as human experts, texts, data and documents to another human or computer program [4]. People are interested in acquiring knowledge because (1) it may help solve major problems of today and the future with technological solutions; and (2) it may satisfy certain needs by filling the gap between what is at present, and what will be tomorrow [11].

Knowledge acquisition has also been identified as a key bottleneck in the development of any knowledge-based system (KBS) [3]. Knowledge acquisition is an expensive process, and good knowledge engineers are hard to find. In addition, engineering knowledge sometimes has the habit of being dynamic, unstable, subjective, incomplete, and conflicting in nature.

Slurry wall technology has been used as an independent construction approach, or in conjunction with ground control techniques for the temporary support of deep excavations and/or as part of the permanent foundation. Slurry walls are characterized as having a water resistant and high strength design, and their construction as being a low-noise and low-vibration construction method. The increased building density in urban areas has led to a proliferation of slurry wall systems being used as temporary support of deep excavations, or as part of a permanent foundation structure. The advantages of slurry walls include the feasibility of deeper construction, a reduced and more controllable risk of disturbance and damage to adjacent buildings, absence of noise and vibrations, reduced disruption of surface activities, minimum surface restoration, and in the end often resulting in the fastest construction time [18].

The pre-construction planning of a slurry wall system includes the determination of trenching equipment required, panel length, etc. Optimal engineering decisions involve complex geotechnical (e.g., groundwater and soil chemistry), design (e.g., wall bracing, settlement, anisotropy), site (e.g., space availability, existing utilities, transportation) considerations, as well as complex calculations (e.g., finite element). In practice, the decision is made through a repeated process of trial-and-error.

This research proposes an inductive learning model for acquiring knowledge about the decision making of an organization for determining panel lengths of slurry walls.

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The inductive learning approach is suitable for such engineering problem in which human experts rely on past experience, rule-of-thumbs, or subjective judgment. Given a new project whose panel length needs to be determined, the model chooses a set of similar cases from existing cases based on case-based reasoning, then performs inductive learning, and uses correctness and coverage rates to verify the induced rules. This model may be used to assist human experts with solving a new problem at hand. It can also be used to generalize the knowledge of existing cases so that this knowledge can be retained and shared by other engineers.

2. Slurry wall construction

2.1. Typical construction procedure

Slurry walls are prepared from the surface by excavating a vertical trench which is then supported by slurry, instead of bracing it to the required depth by a wall. The structure is constructed in the trench by the simultaneous extrusion of the supporting slurry. This slurry not only provides stability to the trench, but it may also become part of the final structure. A typical construction procedure of a slurry wall comprises four execution stages: excavation, insertion of steel tubes, placement of reinforcement cage, and concrete placement.

The first stage is to excavate a linear trench using one or more excavating equipment passes. A pass refers to one cycle of the excavation operation. Fig. 1 shows a typical three-pass excavated trench using clamshells. The numbers indicate the excavation sequence. The first pass begins away from the last concreted panel to allow extra time for the concrete to set. As the trench is excavated, the excavated soil is immediately replaced by a suitable bentonite slurry to provide trench stability. The length of trench prepared for one cycle of concrete pouring operation is called a **panel**. The average panel length is about 5 m for three passes, 7.5 m for five passes, and 10.5 m for seven passes [18].

On completion of the excavation, the next stage is to insert a round steel tube, called a stop-end tube, to form the panel joint with the adjacent panel. Panels that are installed first are referred to as **alternative panels** (or primary panels

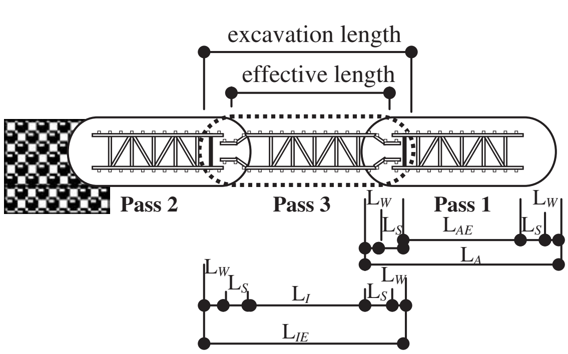

Fig. 1. Typical excavation sequence of a slurry wall construction.

or female panels), and panels that are joined later with the alternative panels are referred to as **intermediate panels** (or secondary panels or male panels). By connecting several panels, a continuous diaphragm wall can be made.

The third stage is to fabricate a reinforcement cage which is assembled on the ground according to the structural requirements, including stiffness necessary for its lifting. The cage is then lowered into the trench by suitable equipment and then fastened.

In the last stage, fresh concrete is continuously poured into the trench using tremie pipes, and the supporting slurry is simultaneously forced out of the trench due to the concrete's gravity. The slurry is pumped into a storage area for reconditioning and reuse, and the stop-end tube is gradually withdrawn after a suitable concrete setting time.

According to Si [16], the planning for the construction of a slurry wall includes a site study, facility design, basic plan, detailed plan, and management plan. The site study includes an investigation of the following:

- locations of site lines and foundations, and buried or over ground boulders or man-made obstructions that might affect or obstruct any excavation or lifting operation;
- site characteristics that might affect the selection of excavation equipment or help with the evaluation of the plans, such as surface and bearing capacity of the ground, soil permeability, underground water table and current velocity;
- adjacent site characteristics that might affect the quality of the slurry to be used, such as neighboring wells or rivers.

The facility design should be further reviewed against the resultant site investigation. The basic plan should determine the type and quantity of the excavation equipment to be used, the length and quantity of the slurry wall panels, the layout of major equipment and temporary facilities required, and an emergency plan. This plan also reviews the daily productivity and its relationship to the master schedule, stability of the trench and facilitative bracing methods, etc. The detailed plan describes the operation plan of excavation, slurry circulation and reconditioning, rebar assembly, concrete pumping, soil dumping, and the transportation of equipment, materials and surplus soil. This plan should also study the design and installation of any special panels such as corner panels or panels with a special shape or size. The management plan describes the management of the on-site construction, quality control, cost, as well as safety.

2.2. Determining the length of the panels

Determining the panel length is a critical decision for an optimal slurry wall system. Efficiency is maximized if the panel length is optimized in terms of equipment passes. In practice, a tentative panel length is first selected to accommodate trench stability and concreting requirements.

These requirements are then compared with the available excavating systems, and checked for other considerations that may impact upon the project. The panel length is not finalized until the construction phase, and not until a sequence has been established [18]. Generally speaking, it is advantageous to have a wall constructed in longer units, which reduces the number of operation cycles and the number of vertical construction joints, and results in lower operation cost and less water seepage. However, overlong panels can result in difficulty in controlling the quality of the concrete pour, and a possible collapse of the excavated trench. A collapse will endanger the operation safety of lifting the rebar cage, not to mention create extra work for clean-up and repairs. At the same time, each panel also has a minimum allowable length (usually equal to the thickness of the wall) because a rebar cage can be easily distorted when lowered into the trench. Any distortion may create further movement or distortion of the alternative panels due to lateral earth stress created by the excavation of the adjacent intermediate panels. Also, a panel cannot be shorter than one equipment excavation pass.

Based on Xanthakos [18] and our interviews of professionals experienced in the design and construction of a slurry wall, it was found that the following factors may affect the panel length.

2.2.1. Shape and size of the retaining wall

The panel length should be shorter for a wide or deep retaining wall so that the time required from excavation to concrete pouring is as short as possible, so as to prevent the trench from collapsing during excavation. The length of straight panels should also be adapted to allow for the corner panels.

2.2.2. Soil characteristics

Longer panels are suitable for more stable soil conditions, and unstable soil requires shorter panels. For example, clay is more stable than sand and gravel during excavation. Undesirable permeation may also occur if the soil contains gravel or if there is a high water table.

2.2.3. Length of the excavating pass

The panel length is related to the effective length (i.e., the actual usable length of each excavating pass, as depicted in Fig. 1) of each piece of excavating equipment. The number of excavating passes for each panel is usually an odd number, so as to prevent awkward maneuverability, curvature of the wall, or equipment breakdown caused by an unbalanced excavation. The excavating length for each equipment pass is usually not equal to the effective length. For example, the pass length of the MHL clamshell machine is 2.5 m while its effective length is only 2.2 m.

2.2.4. Joint type and required space

Each alternative panel is installed first and inserted with a stop-end tube, which forms the joint with the adjacent intermediate panel. As shown in Fig. 1, passes 1 and 2 install two alternative panels, and then pass 3 installs the intermediate panel in between. The space between two stop-end tubes is the actual space (i.e., effective length) where the concrete is poured. Taking the joint type as shown in Fig. 1 as an example, the excavation length is greater than the effective length for an alternative panel (i.e., Pass 1), and vice versa for an intermediate panel (i.e., Pass 3). The length difference is the sum of the length of the spliced reinforcement and the required working space to avoid collision during the adjacent excavation pass, as shown by Eqs. (1) and (2). The length of the spliced reinforcement ranges from 60 cm to 120 cm, and the working space from 20 cm to 25 cm, depending on the designer.

$$L_{\mathrm{A}} = L_{\mathrm{AE}} + L_{\mathrm{S}} + L_{\mathrm{W}}, \tag{1}$$

$$L_{\mathrm{I}} = L_{\mathrm{IE}} - L_{\mathrm{S}} - L_{\mathrm{W}}, \tag{2}$$

where L_{A} represents the excavation length for the alternative panel, L_{AE} denotes the effective excavation length for the alternative panel, L_{I} denotes the excavation length for the intermediate panel, L_{IE} denotes the effective excavation length for the intermediate panel, L_{S} denotes the length of the spliced reinforcement, and L_{W} denotes the length of the working space. Note that the excavation length for the intermediate panel (L_{I}), which is in a latter pass, does not need to include the L_{S} and L_{W}, which have been excavated in the preceding passes.

2.2.5. Economic quantity of concrete poured and tremie pipes used

After the reinforcing cage is lowered into the trench, the concrete is poured by means of tremie pipes. The tremie pipes are continuously fed to slowly force the slurry out of the trench. In practice, each concrete pour should not exceed 4 h to avoid setting of the fresh mix. The panel length should be coordinated with its width and depth to avoid a long pouring process.

It is common to use several tremie pipes during the concrete pouring to ensure continuous concrete feeding. Because the effective radius of a tremie pipe is 1.5 m, the space between tremie pipes should not exceed 3 m. For an alternative panel, the tremie pipes are laid out evenly to create an even rise of the poured concrete, so that the pressure on the stop-end tubes is reduced. For an intermediate panel, concrete is poured next to each stop-end tube. Thus, a tremie pipe is positioned near each stop-end tube to balance the existing pressure.

2.2.6. Storage capacity for excavated soil and bentonite slurry

Soil is excavated during each panel excavation pass. The excavated soil needs to be temporarily stored and transported to an appropriate dumpsite. During the excavation, the bentonite slurry is continuously fed into the trench, and is later reconditioned for reuse. Because of the continuous nature of panel excavation, the storage capacity for excavated soil and slurry affects the maximum allowable panel size. The storage capacity for excavated soil should be greater than the volume of a panel to allow for the expansion of the compressed soil, the clearance space required by the excavating equipment, and allow for any partial collapse of the trench. The storage volume of the slurry should also be greater than the volume of the excavated trench because of slurry losses during the slurry feeding and reconditioning phases.

2.2.7. Weight of reinforcement cage and capacity of lifting equipment

The reinforcement cage is lifted and lowered into the excavated trench when the trench is at its most unstable point (after excavation, but before being filled with concrete). The panel size determines the total weight of the reinforcement cage, which of course should not exceed the safe lifting and handling capacity of the available equipment.

2.2.8. Length of reinforcement cage

The length of the linear panels is usually affected by the design of the corner panels, which require a special assembly procedure. For example, an L-shape reinforcement cage is more stable when placed on the ground with the long end of the L on the ground. Also, the assembly work becomes much more convenient if one wing is substantially longer than the other. Also, the length of the shorter wing should be greater than the wall thickness, but should not exceed 2 m (a height where a worker can still reach the top from the ground).

2.2.9. Coordination with permanent structure or bracing system

When the slurry wall system is used as part of the permanent structure or is to be part of the bracing system, the panel configuration needs to be coordinated accordingly. For example, it is preferred that structural columns are resting on alternative panels so as to end up with a more precise placement of the reinforcement through the alignment of their stop-end tubes. Different configurations result in different panel lengths.

3. Knowledge acquisition

From the foregoing it can be concluded that determining the panel length is not a very exact process, but instead involves the consideration of a host of factors that are interrelated and may conflict with each other. Generally speaking, a tentative panel length is first selected to accommodate trench stability and concreting requirements. These requirements are then compared with the available excavating systems, and checked for other considerations that may impact upon the project. The panel design is not finalized until the construction phase, and not until the sequence has been established [18]. In practice, most experts determine the panel length based on heuristics without performing detailed calculations or optimization analysis. Under similar site conditions, different experts may propose different panel designs depending on their priority (e.g., cost, safety and quality), past experience, and equipment available. Such expert knowledge is implicit from the perspective of corporate knowledge management, and is easily lost because of change in personnel, retirement, etc.

Knowledge acquisition is a process of acquiring problem-solving knowledge from human experts, literature, computer files, and other knowledge sources. Knowledge acquisition has been recognized by researchers as the key bottleneck in the development of expert systems [12,15]. Knowledge acquisition is an expensive process, and good knowledge engineers are hard to find. In addition, engineering knowledge sometimes has the habit of being dynamic, unstable, subjective, incomplete, and conflicting in nature. Determining the panel lengths is such a problem. At first, developing a rule-based expert system to solve this problem did not appear feasible, because the explicit rules that we acquired are only for guidelines, and are not sufficient to reach a specific solution.

De La Garza and Ibbs [6] also explored the knowledge acquisition methods in depth. Their methods include analysis of public domain knowledge; unstructured or structured interviews; observation of familiar tasks, tasks with limited information, tasks with constrained processing, or tough tasks; and induction. In general, knowledge acquisition methods can also be divided into three categories: human communication, human–machine interaction, and machine learning methods [5]. The human–machine interaction method develops an interactive computer system such as SALT [8] that helps a knowledge engineer acquire knowledge from a domain expert. Machine learning includes rote learning, deductive learning, inductive learning, learning from observations, learning from analogy, case-based learning, and neural network-parametric learning [2,7].

Inductive learning produces generalized rules for solving a problem based on a set of cases with solutions. ID3 [13,14] and STAR [9] are two inductive learning algorithms that are commonly used in the field of artificial intelligence. The ID3 algorithm generalizes a set of examples, and represents the result as a decision tree, where each branch layer represents a problem attribute, each node an attribute value, and each leaf a solution node. Arciszewski et al. [1] demonstrated the feasibility of inducing rules that predict plausible construction accidents based on worker's characteristics and job site conditions using STAR methodology.

The STAR algorithm generalizes a set of positive examples (i.e., examples whose solutions match the goal of interest) and negative examples (i.e., examples whose solutions do not match the goal of interest). It tries to create STAR statements, which cover all positive examples, but do not cover any of the negative examples. These statements describe the conditions of examples that lead to the target solution.

4. IKAS

We recognized that only some principles about determining the slurry wall panel lengths can be acquired from experts and be represented in a specific, explicit form. Other principles are hard to acquire because there may not be a consensus among the experts on those principles, while other principles are of dynamic nature and depend on the characteristics of the project at hand. Our proposed expert system, named IKAS (Inductive Knowledge Acquisition System) for slurry wall construction, determines the panel lengths based on rules. Some of these rules are predefined static rules, and some are dynamic rules learned by the system based on case-based and inductive reasoning.

There are some limitations to this research. Because of the exploratory nature of this research, we investigated only the slurry walls of buildings, and only focused on the determination of the length of common panels. In practice, special panels are sometimes necessary to accommodate the design of building foundation, column positions, and corner situations. In addition, the determination of the panel lengths is only part of the solution to the design of a slurry wall. This research did not investigate the detailing of the panel, such as the design of the panel joints and stop-end tubes, which constitute an important part of the design.

4.1. Static and dynamic rules

In IKAS, both static and dynamic rules are represented in an *If–Then* form for easy readability and modification. The static rules are predefined and maintained by the end user or knowledge engineer. The dynamic rules are generated from scratch by IKAS, each time when it is initiated. Given a new project, IKAS searches for similar cases whose panel length information is available. It then induces new rules based on retrieved cases that are similar to the problem at hand. A screening mechanism is performed to remove noise information and rules that conflict with the activated static rules. Both static and qualifying dynamic rules are then used to determine the panel lengths for the project. During the course, the user may save selected dynamic rules as static rules.

4.2. Case

The objective of the case in IKAS is twofold. First, the case provides a representation form for storing the information about past projects. Second, the case is also the foundation for IKAS to perform a similarity calculation to find similar cases for inducing dynamic rules. A generalized case is predefined to describe available attributes, types of attribute values, whether the supply of each value is mandatory, and the weight or the screening statement associated with each attribute for similarity calculation. A new project or past projects can be described by instantiating the generalized case.

The attributes include those used for identifying a project (e.g., *project-name*), possibly affecting the determination of the panel length (e.g., *wall-depth*), and the solutions (i.e., *alternative-panel-length* and *intermediate-panel-length*). The following describes the attributes and their value types.

Project-ID-number (string)

The unique indexing number assigned to the project, e.g., “A0001”.

Project-name (string)

The name of the project, e.g., “ABC Office Building”.

Project-location (keyword)

The site location of the project, which can be chosen from a list of cities and counties in Taiwan; e.g., ‘Taipei City’.

Number-of-floors-of-superstructure (number)

Number of floors above the ground; e.g., 16.

Number-of-floors-of-substructure (number)

Number of floors below the ground; e.g., 4.

Basement-area (number)

The size of the area enclosed by the slurry walls, expressed in m^2; e.g., 200.

Space-availability-for-reinforcement-assembly (keyword)

Space availability for assembling the reinforcement cage, which can be ‘ample’, ‘mediocre’, and ‘constrained’. Within the capacity of lifting equipment, it is more efficient to assemble the whole cage on the ground and place it with a single lift and without splicing.

Capacity-of-slurry-mixers (number); *capacity-of-slurry-storage-tanks* (number); *capacity-of-mud-storage-area* (number)

The mud circulation and preparation plant consists of slurry mixers, storage tanks, mud separation units, and mud storage area. They separate the slurry from the soil particles mixed with it during the excavation operations. All the capacities are expressed in m^3. Estimating the average volume of slurry to be used for a given panel can be related to the type of soil, as a rule of thumb; in fine soils of low permeability the slurry volume is about 1.5 times the trench volume; for excavations in gravel and relatively pervious ground, an extra supply of slurry, often 100% of the panel volume, should be available [18].

Capacity-of-soil-storage-tanks (number)

The size of the storage capacity for excavated soil, expressed in m^3.

Soil-type (keyword)

The type of soil, which can be ‘clay’, ‘sand’, and ‘gravel’.

Soil-permeability (number)

Expressed in cm/s. Soil with low permeability reduces slurry loss to the ground. Highly permeable soil may require slurry controls or an additional slurry supply.

Bearing-capacity-factor (number)

The bearing capacity factor N of the soil.

Groundwater-table (number)

The level of the groundwater table, expressed in m.

Wall-depth (number)

The depth of slurry wall panel, expressed in m.

Wall-width (number)

The width of the slurry wall panel, expressed in cm.

Required-splice-length (number)

The required splice length between intermediate and alternative reinforcement cage, expressed in m.

Excavating-equipment-type (keyword)

Type of equipment used to excavate the trench for slurry walls; e.g., 'MHL 60100' or 'MHL 80120'. Commonly used excavating equipment for slurry wall may be categorized as bucket-and-grab, percussion, rotary-drilling, and reverse-circulation [18].

Number-of-passes-for-alternative-panel (number); *number-of-passes-for-intermediate-panel* (number)

The number of equipment passes for alternative and intermediate panels, respectively. The numbers are usually odd numbers (e.g., 3, 5).

Number-of-tremie-pipes-for-alternative-panel (number); *number-of-tremie-pipes-for-intermediate-panel* (number)

The number of tremie pipes planned to be used for concrete pouring in the excavated trench.

Alternative-panel-length (number)

The length of the alternative panel, expressed in m.

Intermediate-panel-length (number)

The length of the intermediate panel, expressed in m.

All of these attributes have a value for each existing case with panel length information. A new project has no value for the attributes *intermediate-panel-length* and *alternative-panel-length*, which may be determined by IKAS.

4.3. Inductive learning

Conventional inductive learning applied in common sense learning (e.g., identifying geometric shape) usually performs a generalization based on the entire amount of examples that are available. In this research, an 'example' is termed a 'case' and comprises several attributes. To reduce the search space and reasoning time, the IKAS allows its user to screen cases before they are generalized, by specifying a screening criteria. For example, one may ask IKAS to select cases whose *soil-type* is either 'clay' or 'sand', and cases where the *soil-bearing-capacity-factor* is smaller than 15. IKAS may also automatically select similar cases based on case-based reasoning.

The foundation of the IKAS' inductive learning is based on the STAR algorithm [9]. Another commonly used algorithm is ID3 [13,14]. We chose STAR over ID3 because STAR's induced result is represented as rules, whereas ID3's are represented as a decision tree, which is not as easy to comprehend and modify for human beings given the large number of attributes involved in a case. In addition, STAR's reasoning ability is better than ID3 when the cases may contain incomplete information, which is the situation we encountered when transforming the collected projects into cases. The attributes with continuous values (e.g., *wall-depth*, *capacity-of-slurry-mixers*) in a case also make the tree representation unnatural. The primary disadvantage of STAR is its comparatively slow reasoning speed.

The following uses simplified cases to describe the algorithm. Assume that each case comprises only five attributes: *project-ID-number*, *soil-type*, *wall-width*, *wall-depth*, and *alternative-panel-length*, where the last attribute represents the solution to the problem. Table 1 lists the attribute values of five exemplified cases.

The algorithm represents the knowledge of each case as a STAR statement. For example, case A001 can be represented as a STAR statement, which comprises an *If* statement (on the left) and a *Then* statement (on the right) as follows: (*soil-type* = 'clay') and (*wall-width* = 80) and (*wall-depth* = 30)⇒(*alternative-panel-length* = 4.0), which can be further simplified as follows:

$$(\text{'clay'}, 80, 30) \Rightarrow (4.0). \qquad \text{(STAR-1)}$$

STAR-1 states that for a project whose soil type is clay, with designed panel width for the slurry wall being 80 cm, and a panel depth of 30 m, the length for the alternative panel is 4.0 m.

Suppose we try to find all case conditions that will lead to a final decision of a 4.0 m long panel. Cases whose panel lengths are 4.0 m are called **positive cases** (i.e., cases A001 and A005), and others are called **negative cases** (i.e., cases A002, A003, and A004). The goal of the reasoning is to find a STAR statement that covers all positive cases (called **completeness condition**), but does not cover any of the negative cases (called **consistency condition**).

If an initial STAR statement cannot satisfy both completeness and consistency conditions, it has to be either generalized or specialized. For example, STAR-2 and STAR-3 are two statements generalized from STAR-1. STAR-2 states that for a site whose soil type is clay, and where the designed panel width for the slurry wall is 80 cm, the recommended panel length is 4.0 m. STAR-3 states that

Table 1
Attribute values of five simplified cases

Project-ID-number	Soil-type	Wall-width (cm)	Wall-depth (m)	Alternative-panel-length (m)
A001	'clay'	80	30	4.0
A002	'clay'	100	45	3.6
A003	'clay'	100	43.5	3.6
A004	'sand'	80	40	3.6
A005	'clay'	80	38	4.0

for a site whose soil type is either ‘clay’ or ‘sand’, the recommended panel length is 4.0 m.

$$(\text{‘clay’}, 80, \text{all}) \Rightarrow (4.0) \qquad \text{(STAR-2)}$$

$$(\{\text{‘clay’}, \text{‘sand’}\}, \text{all}, \text{all}) \Rightarrow (4.0) \qquad \text{(STAR-3)}$$

If a case satisfies a STAR statement, it must satisfy all of its generalized statements. However, a case that satisfies a generalized statement does not necessarily satisfy the original statement from which the statement is generalized. Thus, if a STAR statement cannot satisfy the completeness condition, it must be further generalized until it covers all positive cases.

Specialization is a reverse process of generalization. For example, STAR-2 is a specialized statement of STAR-3; and STAR-1 is a specialized statement of STAR-2. If a case satisfies a statement, the case does not necessarily satisfy its specialized statement. However, if a case satisfies a specialized statement, it must satisfy the original statement from which the statement is specialized.

Following the previous examples, the most generalized statement is (*all*, *all*, *all*), which cannot be further generalized. STAR-1 is an example of the most specific statement, which cannot be further specialized. The STAR algorithm attempts to find the most generalized statement that includes all positive cases but excludes all negative cases.

4.4. Search strategy

Inductive learning is a search problem. Based on Mitchell [10], search strategies can be classified into two categories: data driven and goal driven. The depth-first, breadth-first, and version space search strategies are examples of data driven search strategies. The general-to-specific and specific-to-general are examples of goal driven search strategies. Table 2 compares these five search strategies.

Based on Table 2, the version space strategy seems to be a good strategy for our research. However, the search path of this strategy is generally long, and the collections of specific and general cases tend to be large. As a result, the reasoning process will require more time and computing memory. In addition, the case in our research comprises attributes whose values are continuous, which make it difficult for the strategy to reach the convergence of the specific and general spaces.

The IKAS uses both general-to-specific and breadth-first search strategies. The system starts from the most general STAR statement, and continues to specialize the statement(s) until all negative cases are excluded. When all negative cases are excluded from the statements in memory, each statement is checked, and the statements that do not include all positive cases are removed.

Our strategy has the following characteristics:

(1) Compared to the version space strategy, the search path is shorter and the number of STAR statements kept in memory are fewer on average.
(2) Backtracking is not necessary, and each case needs to be checked only once.
(3) The strategy guarantees to find all STAR statements that satisfy the search goal.
(4) The strategy removes a statement only when at least one negative case proves it is wrong. Thus, the resulting statements may include incorrect statements but will not miss any correct statements. It has the advantage of possibly providing good information that human experts never thought of. Incorrect statements can be removed by the user through inspection.

4.5. Noise

Noise in this research refers to the cases whose solutions are not satisfactory. Because our cases are collected in real life, they may contain noises (i.e., the panel length used in the past is not recognized as a “good” decision by the expert), it is hard to obtain a useful result if the STAR algorithm must rigidly meet the completeness and consistency conditions. To remedy this problem, the completeness condition is considered to be met as long as some threshold conditions are met. However, the consistency condition still has to be rigidly met. We use the correctness rate and coverage rate as two thresholds. The rates are commonly used in the field of signal detection [17]. The following defines two terms.

Table 2
Comparisons of five search strategies

Item	Strategy					
	Depth-first	Breadth-first	Version space	General to specific	Specific to general	Our strategy
Need for backtracking	yes	no	no	yes	yes	no
Need for re-testing	yes	yes	no	yes	yes	no
Required memory for search	little	medium	much	little	little	medium
Search starting point	most specific	most specific	both	most general	most specific	most general
Search space	smaller	larger	larger	smaller	smaller	larger

For any STAR statement S:

$$\text{Correctness rate} = \frac{P^* + N^*}{P + N} \tag{3}$$

$$\text{Coverage rate} = \frac{P^*}{P} \tag{4}$$

P^*: the number of positive cases included in S, N^*: the number of negative cases excluded from S, P: the number of positive cases, N: the number of negative cases.

The IKAS allows the user to adjust the thresholds for the correctness and coverage rates. A STAR statement is considered to meet the completeness condition if both its correctness and coverage rates exceed the user's defined thresholds. In other words, a STAR statement is legitimate if its correctness and coverage rates exceed the thresholds, and the consistency condition is met. Appropriate threshold values depend on the quality and the number of the cases. In general, if the thresholds are too high, the induction may result in no rule. If the thresholds are too low, the induction may result in too many useless or nonsense rules. The user may start with 100% and gradually lower the thresholds until a satisfactory number of rules are generated. The default threshold values are $(P-1)/(P+N)$.

4.6. Induction goal

The IKAS allows induction learning with or without a specific goal. The purpose of learning with a specific goal is to solve a particular problem at hand. On the other hand, learning without a specific goal is to induce a set of general knowledge about each type of panels based on the cases available in the system.

The following describes IKAS' reasoning steps for learning with a goal (shown in Fig. 2).

(1) Determine the learning goal based on the new case.
(2) Determine the search space based on a user's specification or case-based reasoning.
(3) Generate the most generalized STAR statement, (*all*, *all*, ...), and keep it in the STAR pool.
(4) Randomly select a negative case, and check each statement in the STAR pool. If the statement covers the negative case, go to Step (5). If the statement does not cover the negative case, continue with the next statement. If no statement in the pool covers the negative case, go to Step (7).
(5) Specialize the selected statement. For each resulting specialized statement, continue to specialize the statement if it still covers the negative case. The statement is removed if it is covered by other statements currently kept in the pool. The resulting statements are those that do not cover the negative case and whose coverage does not overlap with those currently in the pool.

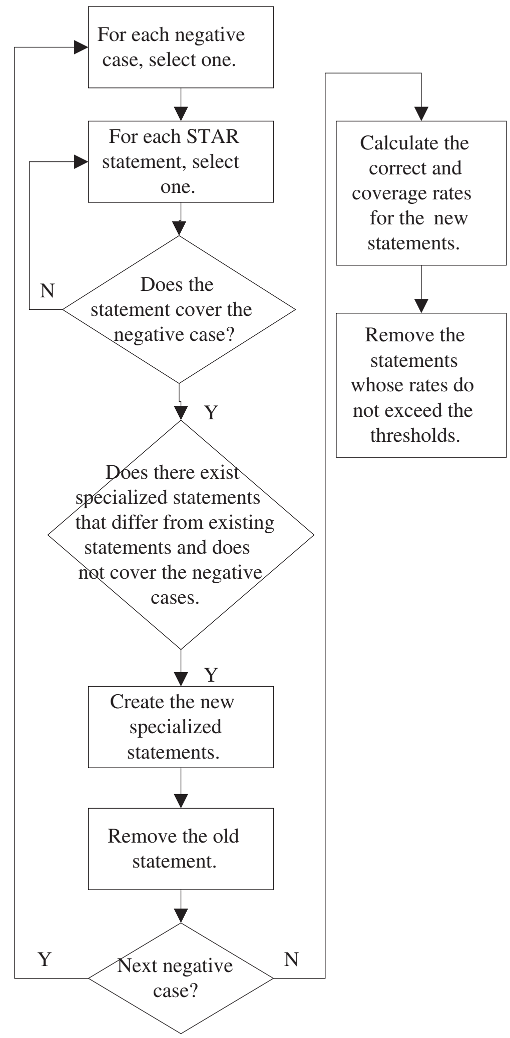

Fig. 2. The flow chart for IKAS' induction.

(6) Remove the statements that do not cover the learning goal. The resulting statements are those that do not cover the negative case but cover the learning goal.
(7) Go to Step (4) unless all negative cases have been checked.
(8) For each kept statement, compute its correctness rate and coverage rate. Keep only those statements for which both rates exceed the user's specified thresholds.

Use the five cases in Table 1 again as an example. Given a new case whose attribute values for *soil-type*, *wall-width*, and *wall-depth* are 'gravel', 80, and 40, respectively. Assume the learning goal is 3.6 m (*alternative-panel-length*). In Step (4), assume that Case A001, ('gravel', 80, 30), is the randomly selected negative case, which is covered by (*all*, *all*, *all*). Statement (*all*, *all*, *all*) is specialized and results in the following specialized statements that do not cover ('gravel', 80, 30).

$$(\{\text{'sand'}, \text{'gravel'}\}, \text{all}, \text{all}) \tag{STAR-4}$$

Table 3
Correctness and coverage rates for example statements

STAR statements	Positive cases			Correctness	Coverage
	A002	A003	A004		
({'sand', 'gravel'}, all, all)			✓	3/5	1/3
(all, all, (38 45])	✓	✓	✓	5/5	3/3

$$(\text{all}, (80\ 100], \text{all}) \qquad \text{(STAR-5)}$$

$$(\text{all}, \text{all}, [30\ 45]) \qquad \text{(STAR-6)}$$

Go to Step (4), and select another negative case A005 ('clay', 80, 38). STAR-4 and STAR-5 do not cover case A005, but STAR-6 does. STAR-6 is specialized, and the resulting statements that do not cover case A005 are as follows.

$$(\{\text{'sand'}, \text{'gravel'}\}, \text{all}, (30\ 45]) \qquad \text{(STAR-7)}$$

$$(\text{all}, (80\ 100], (30\ 45]) \qquad \text{(STAR-8)}$$

$$(\text{all}, \text{all}, (30\ 38)) \qquad \text{(STAR-9)}$$

$$(\text{all}, \text{all}, (38\ 45]) \qquad \text{(STAR-10)}$$

Among the statements, STAR-7 and STAR-8 are covered by STAR-4 and STAR-6, respectively, and have to be removed. In Step (6), the statements that do not cover the learning goal (i.e., 3.6 m) are removed. Therefore, only STAR-4 and STAR-10 are kept in the pool. In Step (7), all negative cases have been checked and the pool does not change. In Step (8), IKAS uses all positive cases to calculate the correctness and coverage rates for the statements in the pool (shown in Table 3).

Assuming the threshold for both correctness and coverage rates is 0.4, (*all*, *all*, (38 45]) is the only satisfactory STAR statement for 3.6 m long alternative panels. Next, IKAS performs another similar process for the other learning goal, 4 m, and finds no satisfactory statement. Therefore, the solution to our new problem is 3.6 m.

The reasoning steps for learning without goals are similar to those for learning with goals except that there is no Step (6), i.e., no need to remove the statements that do not cover the learning goal. Using the same example and thresholds, the result is (*all*, (80 100], *all*) and (*all*, *all*, (38 45]) for 3.6 m long alternative panels; and ({'sand', 'gravel'}, [80 100), *all*), ({'sand', 'gravel'}, *all*, (30 43.5)), and (*all*, *all*, [30 40)) for 4 m.

5. Experiment

The IKAS' database currently includes 25 real life cases about slurry wall construction, which are located in the northern part of Taiwan. We tested IKAS and found that the number of selected cases used for induction greatly affects the required time for induction and the number of induced rules. We tried different combinations of number of positive and negative cases used for induction in each experiment. For a given experiment setting (e.g., 4 positive cases and 2 negative cases), we first randomly selected an induction goal (e.g., alternative-panel-length = 3.6). Then we randomly selected required positive cases and negative cases according to the experiment setting, and performed the induction. We repeated the process 10 times (i.e., 5 times for the alternative panel and 5 times for the intermediate panel), and recorded the average induction time, and the number of induced rules as the experiment result. The experiments were conducted on a Microsoft Windows XP platform with Intel Pentium 2.4 GHz CPU and 1 GB RAM.

Table 4
IKAS' average induction time (seconds)

*N**	*P**			
	1	2	3	4
1	2.0	1.7	1.2	1.1
2	13.9	7.2	6.1	5.9
3	48.2	30.6	26.5	23.1
4	201.2	135.4	106.6	85.4

Tables 4 and 5 list the average induction time and number of induced rules in various experimental settings. The columns represent the number of selected positive cases, and the rows represent the number of selected negative cases. For example, when there are 4 positive cases and 2 negative cases that are considered relevant to the induction goal and are used for the induction, the average induction time is 5.9 s, and the average number of induction rules is 10.2. Figs. 3 and 4 illustrate the same data in a histogram.

Fig. 3 indicates that raising the number of negative cases greatly increases the induction time, but raising the number of positive cases can greatly reduce the induction time. Fig. 4 indicates a similar result where raising the number of negative cases results in a greater number of induced rules, but raising the number of positive cases results in a smaller number of induced rules. Comparing Figs. 3 and 4 shows a positive correlation between the number of induced rules and the induction time. Understanding this phenomenon helps an IKAS user to determine the appropriate search criteria for the case screening process.

Raising the number of negative cases exponentially increases the induction time, because IKAS may need to specialize all intermediate STAR statements to remove the negative case from the coverage of the original statement.

Table 5
IKAS' average number of induced rules

*N**	*P**			
	1	2	3	4
1	11.6	8.3	5.2	4.7
2	61.5	25	15.5	10.2
3	129.7	72.4	32.3	22.3
4	199.2	136.2	73.0	51.2

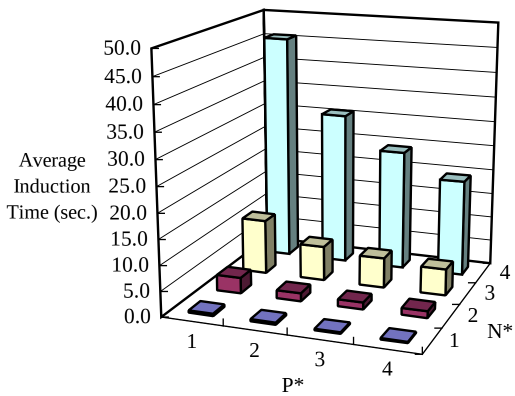

Fig. 3. IKAS' average induction time (seconds).

Specialization results in more STAR statements, which means a larger search space. For an attribute whose value is a keyword, specialization of a STAR statement generates only a new STAR statement. For example, to remove the coverage of a negative case whose *soil-type* is ('sand') from a STAR statement whose *soil-type* is ({'clay', 'sand', 'gravel'}), the *soil-type* of the specialized statement is ({'clay', 'gravel'}) while other attributes remain unchanged.

For an attribute whose value is a number, specialization of a STAR statement generates at most two statements for "search without goal", and one statement for "search with a goal". For example, to remove the coverage of a negative case whose *wall-depth* is 30 m from a STAR statement whose *wall-depth* is [10 50) (i.e., 10 m ≦ *wall-depth* < 50 m), the *wall-depth* of the specialized statements are [10 30) and (30 50] for "search without goals". For "search with a goal", only one statement can be true because the goal can only satisfy one of the mutually exclusive statements.

The IKAS' case has 25 attributes. Except for *project-ID-number* and *project-name* that are used only for identification and not for reasoning, there are four attributes whose values are keywords, and 19 attributes whose values are numbers. Thus, a STAR statement may generate at most (4 + 19 × 2) = 42 for "search without goals", and (4 + 19) = 23 for "search with a goal". The generated statements may also generate another set of statements for the next negative case. Therefore, without counting the covered statements, e.g., [10 30 m) is covered by [10 40), the maximum number of STAR statements generated for "search without goals" is:

$$\sum_{k=1}^{n} C_k^{43}, n \leq 42, \text{where } n \text{ is the number of negative cases.} \quad (3)$$

For "search with a goal", the maximum number is:

$$\sum_{k=1}^{n} C_k^{24}, n \leq 23, \text{where } n \text{ is the number of negative cases.} \quad (4)$$

This large search space is one of the reasons for IKAS' slow induction process. Another bottleneck for reducing the induction time is the coverage checking among the statements. For example, given 10 statements currently kept in the system memory, the newly generated 11th statement needs to be checked against the 10 statements for coverage, the 12th statement needs to be checked against the 11 statements, and so on. That means, when there are *n* statements kept in memory, IKAS has performed at least *n* times of coverage checking. The screening mechanism of IKAS provides a means to reduce the search space. The following experiment demonstrates the effect of the reduced search space through screening.

Suppose Case A0006 is the new case, and IKAS has 25 cases whose *alternative-panel-lengths* were 5.6 m or 6 m, and *intermediate-panel-lengths* are 4 m or 4.4 m. After CBR screening, only 4 cases were used for induction as opposed to 25 cases when screening was not used. Table 6 compares the results of two experimental settings. With screening, IKAS performs considerably faster, and also produces a lesser number of rules and target rules (the rules used to derive the solution). Fewer rules make it feasible for experts to modify or verify the induction results.

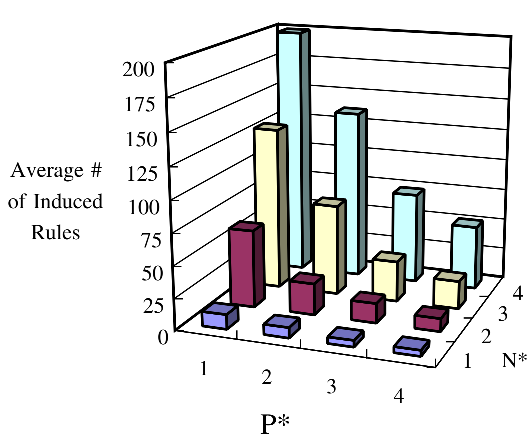

Fig. 4. IKAS' average number of induced rules.

Table 6
Comparison of results of induction with and without screening

	Screening	No screening
Time (search without goal)	19.2 s	4091 s
Time (search with goal)	1.5 s	111.3 s
Number of solutions (*alternative-panel-length*)	4	4
Number of rules (*alternative-panel-length*)	42	116
Number of target rules (*alternative-panel-length*)	4	26
Number of solutions (*intermediate-panel-length*)	6	6
Number of rules (*intermediate-panel-length*)	38	92
Number of target rules (*intermediate-panel-length*)	4	9

6. Conclusions

Determining panel lengths for slurry wall construction is a complex engineering problem. Some principles can be extracted from experts. However, they are not sufficiently detailed to generate a solution. They can only be used as guidelines to a solution. This research proposed an inductive learning model, IKAS, for determining the panel lengths. The solution is generated by induced rules and is verified by static rules. Static rules are based on our survey of the literature and on interviews. Induced rules are created during the run time, based on the STAR algorithm. IKAS also has a screening mechanism, specified by either the user or based on case-based reasoning, in order to reduce the search space of the induction process, and to increase the relevance of induced rules of the problem at hand. IKAS also uses correctness and coverage rates to deal with the noise of cases. Two induction modes are available in IKAS. Inducing rules with a specific goal helps experts determine the panel lengths for a new slurry wall project. Inducing rules without goals transforms a company's past experiences (i.e., cases) into a set of rules, which helps the company manage their knowledge and share it, and ensure minimum quality by providing a base for double-checking new solutions. The experiments also demonstrated an improved induction performance in both time and result by using the case-screening mechanism.

The proposed model is suitable for those engineering problems where human experts rely on past experience, rule-of-thumbs, or subjective judgment. However, it is difficult to prove the usefulness of the induction outcomes because of the heuristics nature of the problem. IKAS' cases are ones that were successful in the past, but that does not guarantee them to be economically optimal; therefore the same can be said for its induced solution. IKAS' induced results may be useful to an inexperienced engineer, but may not be so to an experienced one. Nevertheless, IKAS' induced results do represent a true snapshot of patterns of decision making in an organization.

Acknowledgement

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