NEURAL NETWORK METHOD OF ESTIMATING CONSTRUCTION TECHNOLOGY ACCEPTABILITY

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ABSTRACT: A neural network (NN) based approach is proposed for predicting the adoption potential or acceptability of a new construction technology. The acceptability of a technology for a target operation is defined as the proportion of users that choose to use the technology in comparison to a conventional (base) technology. All existing alternative technologies for the considered operation are collected as samples for study. The performance characteristics of each sample technology are stored in a vector comprising eigenvalues determined by using the analytical hierarchy process (AHP) method, and its acceptability is determined using a poll. The obtained performance-acceptability pairs are used to train a neural network using the back-propagation algorithm. The trained network can then be used to predict the acceptability of a new technology in question, given its performance attributes. Possible information sources for training set construction and possible applications of the approach are discussed. An example estimate of the adoption prospect of a new concrete distribution system for concrete placement on a mid-rise building project is provided. Tests of the presented NN approach with simulated data show a promising result, especially when the poll size used is sufficiently large.

INTRODUCTION

Recent construction technology developments have resulted in a number of highly specialized technologies and products applied to various types of construction operations. Examples include slip-form paving machines in highway and airport construction, tower cranes in plant and high-rise building construction, specialized excavators in underground diaphragm wall and deep foundation construction, shotcrete machines, and geotextile materials in geotechnical engineering. Depending on its ability to meet the requirements of a target operation, a technology or a product achieves a certain level of success in terms of acceptability by the industry.

On the other hand, for virtually every construction operation, there are alternative methods that can accomplish the required tasks and functions. Further, within the same method, there often exist alternative models and makes of equipment or material that can substitute for each other. Examples include alternative formwork and support systems for bridge deck and pier erection, different trenching methods and models of equipment for pipeline excavation, and so on. Since each alternative method, equipment, or material always has some advantages as well as disadvantages for a considered operation, a selection is based on not only the objective attributes of a technology but also the subjective preferences and priorities of a contractor in a given project scenario. Since each individual organization or decision maker has his own criteria weights for evaluation, different contractors may make different selections under the same conditions.

Therefore, in most cases, a new technological product will have to compete with existing methods and models for adoption in a target operation and it is important for a technology developer to estimate its adoption prospect or acceptability when it is still in the inception stage. In fact, the estimated acceptability of a new construction technology makes sense only if it is compared to an existing technology used for the same purpose. Since different architecture/engineering/construction (A/E/C) firms in the same situation might arrive at different evaluation results and hence different choices, what matters to the success of a construction technology is its overall acceptability among all industry users, not an individual contractor. Thus, the acceptability of a new technology can be defined as the proportion of AEC firms at large that choose to use it for a defined task or operation instead of a status-quo technology (thereafter referred to as base technology) when the two technologies are presented.

Predicting a priori the acceptability of a new technology is a complex issue and has to be based on experience and judgment. The prediction ability may come from the knowledge of existing comparable technologies, their strengths and weaknesses in meeting operational re-

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quirements, and the general priorities and preferences of industry users. Existing prediction methods range from an ad-hoc approach that makes an educated, case-by-case guess, to a fuzzy expert system approach that relies on a set of fuzzy rules describing relevant cause-and-effect relationships. Given certain inputs, such expert systems reach a conclusion as a result of fuzzy set operations on the implemented fuzzy rules (Lin et al. 1991). One major drawback of the fuzzy expert-system approach is that it is difficult to determine the term membership functions for input and output variables.

It is possible to use linear regression to establish from acquired data an empirical function that relates a forecast to relevant parameters. An example of judgmental forecasting using regression can be seen in Al-Tabtabai and Diekmann (1992). However, the problem with using regression methods for new technology acceptability estimation is, as shown later, that the relationships between independent and dependent variables are nonlinear with unknown degrees. To provide the needed mapping function, a neural network with a multilayer structure and a nonlinear activation function can be used as a computing model. By self-adjusting the connection weights within the structure, a network can adapt to the complex input-output relationships in the presented patterns during training and develop the required mapping function. Neural networks have been explored for a variety of civil engineering problems in pattern recognition, classification, and estimation [see Moselhi et al. (1991) and Yeh et al. (1993)].

To deal with the unavoidable subjective judgment involved in feature assessments of alternative technologies, the analytical hierarchy process (AHP) method can be used, which provides a set of well-defined procedures to calculate the relative strengths of compared alternatives in a simple, intuitive, yet consistent way (Saaty 1980; Skibniewski and Chao 1992; AbouRizk et al. 1994). This paper presents a neural-network-based approach that incorporates the AHP method and makes use of eigenvalues of technology performance comparison matrices as the input parameters of a neural network model. Unlike an expert system, the network is trained with collected comparable examples to generalize the performance-acceptability relationships behind the example patterns without the need to acquire explicit rules. An example is given to illustrate the viability of the approach in performing acceptability estimation for a new construction technology.

ASSUMPTIONS FOR APPROACH

Three assumptions are made for the presented approach:

1. The identified technology performance factors (to be discussed later) that serve as the criteria of evaluating a technology can be set clearly and are sufficient for characterizing all alternative technologies, existing and new, in a considered construction operation scenario.
2. The comparison of alternative technologies with respect to each performance factor can be made objectively and a comparison result is consistent with the ranks of the compared technologies in attributes and capabilities. In reality, this depends on the availability of information and knowledge of the technologies.
3. Since the acceptability of a new technology is defined as the proportion of users that choose to use the technology for a defined operation instead of the base technology, it is assumed that a user makes a rational choice between the two technologies according to their relative performance strengths weighed by his or her personal judgment. For the same operation, the judgmental weightage provided to each performance factor by a user does not change with a different technology being evaluated.

DESCRIPTION OF APPROACH

The presented approach is explained in the following, in the sequence of producing an acceptability estimate for a given new construction technology for a considered operation.

Identifying Technology Performance Factors

Identify a set of technology performance factors that are relevant to the success of the operation in question and hence have an impact on the acceptability of the new technology to be implemented in the operation. With respect to each of the identified performance factors, alternative technologies will be compared and the comparison results will serve as the inputs to a neural network that estimates technology acceptability. Common construction technology performance factors may include cost, risk, flexibility, maneuverability, and so on.

Selecting Base Technology

To estimate the acceptability of the new technology for the considered operation in comparison to an existing technology, a conventional technology, that is a status-quo candidate and common selection for the operation, is used to serve as the base technology on which an acceptability

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estimate is based. Other comparable technologies will also be compared to the base technology in producing their performance characteristics vectors and constructing training data for a neural network, as explained later.

Producing Performance Characteristics Vectors for Alternative Technologies

Collect as samples for study all comparable technologies in addition to the base technology that might be used as alternatives for the considered operation. Compare each sample technology with the base technology with respect to each of the listed performance factors, based on the capabilities of one technology against those of another. A matrix is constructed for each comparison, following the application of the AHP method and using a predefined relevance scale in Table 1, to produce a principal eigenvector that represents the relative strength of one technology versus another with respect to a performance factor. For details of the AHP method see Saaty (1980) or Skibniewski and Chao (1992). Note that the normalized eigenvalues of a two-element comparison matrix are complementary to each other and can be obtained using

$$E_1 = 1 - 1/(1 + R) \quad \text{and} \quad E_2 = 1/(1 + R) \tag{1, 2}$$

where R = AHP rating of one element against the other.

An example of comparing a sample technology with a base technology for an operation is shown in Tables 2–4, each with respect to one of three identified performance factors: cost, reliability, and quality. Note the relationships that the two technologies have with each other in a comparison matrix, i.e., the reciprocal ratings and the interpretation. Putting together the obtained three eigenvectors, we can produce the relative performance matrix for the two technologies as

$$\mathbf{M} = \begin{bmatrix} 0.750 & 0.167 & 0.500 \\ 0.250 & 0.833 & 0.500 \end{bmatrix} \tag{3}$$

Horizontally, the matrix consists of an upper vector $\mathbf{X}$ = [0.750, 0.167, 0.500] and a lower vector $\mathbf{Y}$ = [0.250, 0.833, 0.500] for the sample technology and the base technology, respectively. Elements in the lower vector are just complements to those in the upper vector. Hence, the upper vector $\mathbf{X}$ alone is sufficient to characterize the overall comparison result and is used thereafter as the performance characteristics vector for the sample technology in comparison to the base technology.

The performance characteristics vector comprising eigenvalues will be used as input to a neural network model. The reason is given by Saaty (1980). Saaty concludes through a mathematical proof and extensive experiments that the normalized eigenvalues of a comparison matrix can represent consistently the relative strengths of its elements in aggregating a final evaluation. Trial runs of training and testing in this research also show that using eigenvalues instead of original ratings as the input data scheme of a neural network results in a better generalization and prediction ability of the network.

Determining Acceptability of Alternative Technologies

The defined technology acceptability is the output parameter of the proposed neural network model. To construct a training set for the neural network, the acceptability of each studied

TABLE 1. Comparison Scale and Eigenvalues for Two-Element Comparison [Adapted from Saaty (1980)]

Rating (1)	Eigenvalue (2)	Definition (3)
9	0.9	absolute superiority
8	0.889	
7	0.875	verv strong superiority
6	0.857	
5	0.833	strong superiority
4	0.800	
3	0.750	weak superiority
2	0.667	
1	0.500	equal

TABLE 2. Comparison of Two Technologies: Sample Technology Has Weak Superiority over Base Technology in Cost

Cost (1)	Sample technology (2)	Base technology (3)
Sample technology	1	3
Base technology	1/3	1
Principal eigenvector	0.750	0.250

TABLE 3. Comparison of Two Technologies: Sample Technology Is Strongly Inferior to Base Technology in Reliability

Reliability (1)	Sample technology (2)	Base technology (3)
Sample technology	1	1/5
Base technology	5	1
Principal eigenvector	0.167	0.833

TABLE 4. Comparison of Two Technologies: Sample Technology Is Equal to Base Technology in Quality

Quality (1)	Sample technology (2)	Base technology (3)
Sample technology	1	1
Base technology	1	1
Principal eigenvector	0.500	0.500

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sample technology has to be determined and will be coupled with its performance vector to form a training pair.

One way to determine technology acceptability is to conduct a survey with a group of randomly selected users familiar with existing technologies for the considered operation to collect their choices. Each user in the poll will be asked to make a choice between a sample technology and the base technology for the operation. Since each user has his or her own criteria weights for making a judgment, one user may choose the sample technology and another user may choose the base technology. However, the proportion of users in the poll who choose the sample technology (denoted by P) can be used to estimate its acceptability, since in statistical terms this proportion is an unbiased estimator of the population proportion. When the poll size I is large, the probability distribution of P is approximately normal and its standard deviation s (the poll error) is small, as estimated by

$$s\{P\} = \sqrt{P(1 - P)/(I - 1)} \quad (4)$$

In the same way, the poll method can be applied to all studied sample technologies to estimate their acceptability. The general rankings in acceptability of all existing alternative technologies can also be determined. Other possible approaches to collecting information on technology acceptability are discussed later.

Network Training

A technology performance vector and the corresponding approval rating from the poll form the input and output parts of an example pattern that relates the acceptability of an existing technology to its performance attributes. In the previous example, suppose that the surveyed acceptability of the sample technology is 52%, i.e., 48% of the users' choices are for the base technology. With the obtained example performance vector, the input-output pair for the sample technology is

$$[0.750 \quad 0.167 \quad 0.500] \Rightarrow [0.520] \quad (5)$$

The input-output pairs for all sample technologies are then used as training data to train a feed-forward multilayer neural network in order to generalize the relationships between the performance attributes of a technology and its acceptability for the given operation scenario. To render the network an accurate prediction ability, the collected training pairs should cover as many representative cases in the input space as possible. However, to be practical, the number of training pairs should be kept as small as possible since data collection is always expensive. To produce a sufficiently accurate estimate with a reduced number of training pairs, it is important to use an effective and efficient distribution of training data, which depends on the characteristics of a particular problem. Some practical details of network training and testing can be found in Chao and Skibniewski (1994).

The back-propagation (BP) supervised learning algorithm is used in the approach as the network training method, whose derivation can be found in Pao (1989).

Estimating Acceptability of New Construction Technology

The new technology in question is also compared with the base technology with respect to each of the identified performance factors to produce its performance vector, following the same procedure as before. The obtained vector is then input into the trained network to produce the predicted acceptability of the new technology. For example, an output of 0.7 represents the proportion of users that likely will choose the new technology for the considered operation instead of the base technology, whereas its complement, i.e., 0.3, represents the proportion that likely will reject the new technology and choose the base technology. By comparing the acceptability among all alternative technologies, existing and new, ranking their adoption potential for the operation is possible.

RATIONALE FOR NEURAL NETWORK MODEL

The presented approach uses a feed-forward, multilayer neural network with a sigmoidal activation function as the model to estimate the defined acceptability of a new technology. The reason why we do not use a regression method to model the relationships between technology performance attributes and technology acceptability is the nonlinear nature of the stated problem as explained in the following.

From the three previously made assumptions, an individual user's making a choice between an alternative technology and the base technology can be described mathematically as

$$\mathbf{X} \times \mathbf{W} = [x_1, x_2, \ldots, x_N] \times [w_1, w_2, \ldots, w_N]' = \sum_{n=1}^{N} x_n w_n = a \quad (6)$$

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where $\mathbf{X}$ = performance vector for an alternative technology; $\mathbf{W}$ = user's subjective weight vector for a considered operation; N = number of technology performance factors; and a = score of the alternative technology in comparison to the base technology. Since $0 \le x_n, w_n \le 1$; $n = 1, 2, \ldots, N$; and $\Sigma_{n=1}^{n} w_n = 1$, it can be readily proven that $0 \le a \le 1$.

Suppose $\mathbf{Y}$ is the complementary vector of $\mathbf{X}$; $\mathbf{Y}$ can be interpreted as the performance vector for the base technology in comparison to the alternative technology. $\mathbf{Y}$ has the same properties as $\mathbf{X}$ and is related to $\mathbf{X}$ as described by

$$\mathbf{X} \times \mathbf{W} + \mathbf{Y} \times \mathbf{W} = (\mathbf{X} + \mathbf{Y}) \times \mathbf{W} = [1] \times \mathbf{W} = \sum_{n=1}^{N} w_n = 1 \qquad (7)$$

or

$$a + b = 1 \qquad (8)$$

where $b = \mathbf{YW}$; b = score of the base technology in comparison to the alternative technology; and b has the same property as $\mathbf{a}$. Therefore, a rational decision rule for the user can be stated in pseudocode as

```
IF a > 0.5 then
  choose the alternative technology
ELSE
  choose the base technology
END IF
```

The choice-making by a user can be represented by a two-layer neural network as shown in Fig. 1. A threshold function f is used to model the foregoing decision rule and the choice output O in binary terms is

$$O = f(a) = 1 \text{ for } a > 0.5; \quad O = f(a) = 0 \text{ for } a \le 0.5$$

Since the acceptability of a technology is estimated by the proportion of users in a poll that choose the technology instead of the base technology, the process of producing an acceptability estimate can be represented by a three-layer neural network that aggregates the choice outputs of all polled users as shown in Fig. 2. On the basis of one user–one choice, the linkage weights

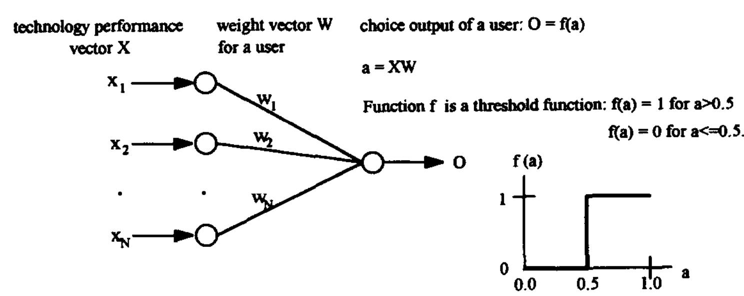

FIG. 1. NN Representation of Choice-Making by Technology User

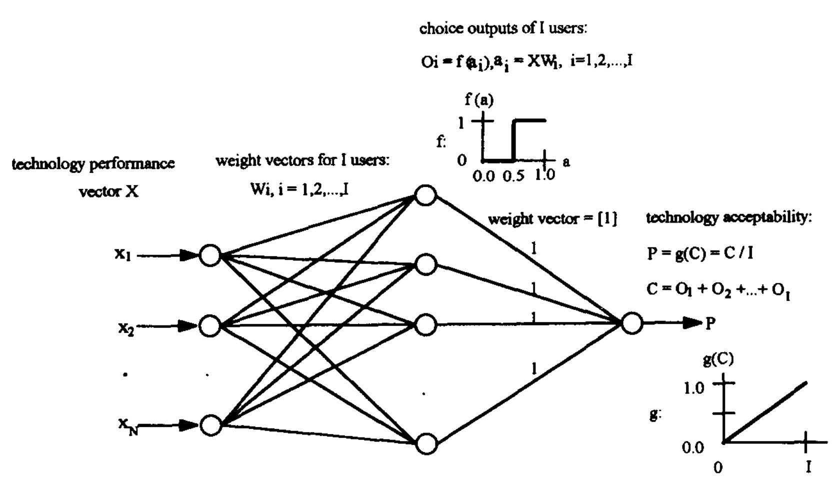

FIG. 2. Producing Technology-Acceptability Estimate by Combining Choices of I Users

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between the second and the third layers are all equal to 1. The total number of users that choose the alternative technology is

$$C = \sum_{i=1}^{I} O_i = \sum_{i=1}^{I} f(a_i) = \sum_{i=1}^{I} f(\mathbf{XW}_i) \tag{9}$$

where I = number of users in a poll.

Then, acceptability P is obtained from count C through a linear function g, as the proportion of C in I

$$P = g(C) = \frac{C}{I} \tag{10}$$

In contrast to (9), the sum of the scores of the alternative technology made by all I users is

$$S = \sum_{i=1}^{I} a_i = \sum_{i=1}^{I} \mathbf{XW}_i = X \sum_{i=1}^{I} \mathbf{W}_i = \mathbf{X\hat{W}} \tag{11}$$

where $\hat{\mathbf{W}}$ = a vector that is the sum of all I weight vectors.

The difference between C in (9) and S in (11) exists because of the existence of threshold function f in (9). If S were used instead of C to calculate the acceptability of a technology, it would simply be

$$\mathbf{P}' = \frac{\mathbf{S}}{I} = \frac{\mathbf{X\hat{W}}}{I} = \mathbf{X\bar{W}} \tag{12}$$

where $\bar{\mathbf{W}}$ = a vector that is the average of all I weight vectors.

Hence, if **S** rather than **C** were used in calculating technology acceptability, the evaluation would reduce to a linear problem, i.e. the acceptability assessment would be just the result of linear operation of vectors. If the stated estimate problem were of such a linear type, it would be effectively solved using a linear regression model.

However, because of the definition of technology acceptability, (11) and (12) do not represent the stated problem and cannot be used for acceptability evaluation. The stated problem, as represented by (9) and (10), cannot be reduced to a linear equation and is in fact nonlinear, due to the effect of threshold function f in (9). Hence, we cannot use linear regression for evaluating technology acceptability, which calls for a nonlinear model to deal with the contained nonlinearity. We propose to meet this requirement functionally by using a general feed-forward, multilayer neural network as the estimating model, and using the back-propagation (BP) algorithm to train the network to establish the input-output mapping ability.

SOURCES OF INFORMATION FOR PROPOSED APPROACH

As suggested previously, an opinion poll can be used to find out the relative acceptability of a construction technology, by questioning the users in the poll about their choices. For the poll result to be representative, the users should be randomly selected over their entire population. The larger the number of users polled, the closer an obtained proportion in a poll is to a real proportion in the population. As shown in an illustrative example later, the number of users polled also has an impact on the prediction accuracy of a neural network that is trained with the poll results.

The collected samples should include various alternative technologies, both well adopted and less employed for the considered operation. For the purpose of constructing training data, imaginary but possible variations of existing technologies can be provided in the survey for the users to make their choices. For example, assumed variations of an existing model of equipment can be made, with modifications of its original attributes that have an impact on the acceptability, to reproduce several varying but comparable examples in the training set.

In addition to the suggested poll method to collect data, possible sources of information for the presented approach may include: trade statistics of related technological products, past application records of competing technologies within a particular sector of industry, etc. For example, the proportion of the sales amount of a model of equipment in a certain period to that of another model during the same time can imply their relative acceptability. Subject to necessary adjustments according to a situation at hand, such information can be used in determination of acceptability of alternative technologies.

After the required information is obtained and the neural network is trained, a desired acceptability prediction can be made. After the present problem is solved, however, the established knowledge base does not lose its value because it can expand as technology development continues and information accumulates into the future. New information, whenever available, can add to the existing training set to retrain the network and update the knowledge base for a better prediction ability thereafter.

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POSSIBLE APPLICATIONS

The presented approach can be used by either a technology developer or technology user. First, when a new technological product for a target operation is being developed, there always exist alternative designs with trade-off attributes such as cost versus quality to be evaluated. An estimate of the acceptability of each alternative among industry users is useful in deciding an optimal design with features that maximize its acceptability. However, it is not feasible to poll a group of industry users to judge the acceptability of a design, since it is still on paper and cannot provide hands-on experience for a user to make a choice.

By constructing a knowledge base from comparable examples with the presented approach, the estimating ability can be acquired in the form of a trained neural network. Then, the relative acceptability of a design can be estimated, which can be compared to that of other alternative designs to determine their rankings. This can help finalize the design of a new technology before committing resources to its realization, such that the implementation and transfer of the technology in the construction industry can be accomplished more successfully.

Aside from a technology developer, the ability to predict the adoption prospect of a new construction technology can also benefit a technology user. When a contractor is presented with a new technological product that is an alternative to existing methods and models but has not yet been widely used, the approach can be used to estimate its acceptability and the estimate can be compared to those of existing technologies to see its adoption potential within the industry. This can help decision making for a timely implementation of the technology to provide a lead in performance and experience, since the timing of implementing a new technology can be important to the competitiveness and even survival of a construction company as in other industries.

ILLUSTRATIVE EXAMPLE: ACCEPTABILITY ESTIMATE OF CONCRETE DISTRIBUTION SYSTEM

Problem Background

Concrete placement for building construction projects deals with moving concrete from a truck mixer to its final position in places such as columns, girders, beams, slabs, and walls. Methods and equipment commonly used include cranes with buckets, hoists with wheelbarrows or buggies, concrete pumps with manually installed pipeline, truck-mounted concrete pumps equipped with articulated placement booms, and so on. To ensure the quality, the concrete has to be placed without segregation before it has achieved an initial set. If a concrete pump is used, it is important to use concrete suitable for pumping and maintain enough pipeline pressure to avoid blockage (Peurifoy and Ledbetter 1985). As existing methods require workers to handle and reposition the pipe outlet to discharge concrete, safety hazards such as swinging objects, sticking-out reinforcements, and other obstacles are present.

Assume that the idea of a semiautomated concrete distribution system has been conceived by a technology developer and is now in the stage of a feasibility study. The system design mainly involves a hydraulically operated, articulated placement boom with a climbing base built in a lift shaft along the floors of a building. Concrete is pumped by a conventional concrete pump at ground level from a truck mixer vertically to a floor to be poured and horizontally into position through the boom, which has a maximum reach of 40 m from the base. The movement of the boom and the discharge of concrete is remotely controlled by an operator who at a convenient location within the floor can move the discharge end to any desired corner. Obstacle avoidance can be achieved through the manipulation of the articulated boom. Properties of the concrete being pumped and the pipeline pressure will be continuously monitored by the system. It is aimed at improving productivity and quality and reducing work hazards by eliminating manual handling of pipe and the discharge end at floors above ground level as well as the need of a signal man between the pump and a pouring location.

The management of the engineering equipment company is faced with the decision whether or not to adopt the proposed design and make required investments in succeeding development efforts. However, before a decision can be made, the management wants to determine the acceptability of the system among users in the industry as it is related to its sales potential. Therefore, a survey is conducted to estimate its adoption prospect in comparison to the already available methods and equipment, the potential competitors.

Furthermore, many possible design options exist concerning the configuration, the extent of automation, the level of control, the selection of actuators and parts for the boom and base, which all have an impact on the cost and quality of a realized system, and hence its acceptability. The estimated acceptability of a current design can be compared to that of an alternative design and the result will be the basis of making necessary changes to achieve optimization.

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Technology Performance Factors

The concrete placement on floors above ground level for a hypothetical typical building construction project is selected as the target operation for which various possible methods and models are compared. The building is a 15 story (50 m) high, reinforced-concrete commercial building with a footprint area of 1,200 m^2 located in an urban area. A maximum pouring rate of 350 m^3 per day is required by the project schedule. Based on the requirements of the considered operation, technology performance factors are set up to serve as method and equipment selection criteria, which include the following five items: (1) "Production cost," including labor, equipment, and material required; (2) "reliability," concerning the probability of failures such as breakdown or pipe blockage; (3) "flexibility"—the ability to deal with all possible job conditions such as placing concrete to locations difficult to reach; (4) "labor-saving ability," to require fewer less-skilled laborers; and (5) "quality," concerning accuracy, vibration, and noise. These factors are most relevant to the success of the considered operation and sufficient to characterize any technology in its application scenario. They are fixed for all alternative methods and models of equipment and can be used as input parameters of a neural network model for estimating the acceptability of the new technology in question.

Suggested Approach

Available methods and configurations of equipment for concrete placement are collected as sample technologies, which could provide viable alternatives to the considered new technology in the target operation. They include different makes, sizes, and combinations of truck- or trailer-mounted concrete pumps, with or without a placement boom, as well as the older methods of various combinations of cranes, buckets, hoists, and buggies. Each method and configuration should be able to meet the technical and schedule requirements of the target operation, e.g., some may use two small pumps. Each alternative method and equipment will be compared to a selected base technology with respect to the listed performance factors. This will produce a technology performance vector, based on the features and capabilities of an alternative technology versus the base technology.

In this example, the selected base technology is a truck-mounted piston concrete pump of a capacity of 70 m^3/hr, equipped with a hydraulically powered articulated boom with a vertical range of 75 m, as it is a common choice for the considered operation. Even though it can move around the periphery of the building, some spots above the 10-story level are difficult to reach directly, where wheelbarrows are needed for delivering concrete to placement locations. This will add to production cost and affect its flexibility. Similar considerations are given to all other sample technologies in rating their performance.

The consistency of AHP rating assignments with respect to a quantifiable factor such as cost or reliability can be maintained by using a table that translates a quantitative attribute into an AHP rating and that applies to all alternatives. An example is shown in Table 5, which is used to obtain the rating of cost for each sample technology being compared to the base technology (when cost for the base technology is \$10/m^3). In contrast, the consistency of AHP ratings of a qualitative attribute such as flexibility is achieved by judgment of an evaluator in perceiving the differences between involved placement methods and equipment. The eigenvalues corresponding to the AHP ratings of a sample technology for all five factors form its performance characteristics vector as discussed previously.

A group of technology users are randomly selected and asked to make a choice between a sample technology and the base technology when the two are presented for the operation. The proportion of users that choose to use a sample technology instead of the base technology

TABLE 5. Translation of Cost into AHP Rating for Alternative Placement Technologies

Placement cost ($/$m^3$) (1)	AHP rating (2)
.	.
.	.
.	.
7–8	4
8–9	3
9–10	2
10	1
10–12	1/2
12–15	1/3
15–18	1/4
.	.
.	.
.	.

TABLE 6. Example Comparison of Tangible and Intangible Factors in Their Impact on Overall Assessment

Overall assessment (1)	Tangible factors (2)	Intangible factors (3)
Tangible factors	1	4
Intangible factors	1/4	1
Principal eigenvector	0.800	0.200

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represents its acceptability. The polling process continues to produce the acceptability of all sample technologies. Then, the obtained pairs of performance vectors and their corresponding acceptability are used as training data to train a neural network for establishing the relationships between the performance attributes and the acceptability of a technology for the considered concrete placement operation. The trained network can then be used to predict the acceptability of various designs of the new placing system, given their performance-characteristics vectors.

Training Set Construction

In the following, as a way to show the feasibility of the suggested approach, possible scenarios for the foregoing example are simulated with hypothetical data in construction of training and testing sets. Assume that a poll is conducted with a group of 60 hypothetical users. The AHP method is used again to develop a generic decision attribute hierarchy for the considered operation for all those in the group and generate a criteria weight vector for each individual. As shown in Fig. 3, at its third level the hierarchy incorporates all five performance factors as criteria items. Then, production cost and reliability are grouped as tangible factors while flexibility, labor-saving, and quality are grouped as intangible factors at the second level of the hierarchy. Both groups have an impact on the overall assessment at the top level.

Within this generic framework, differences in attitude and judgment among individual users can be reflected by assigning different ratings to the elements in the top three levels of the hierarchy. An example of assigning ratings for a user is shown in Tables 6–8, in which the same-level elements are compared with each other concerning their impact on an element at the next-high level and their relative strengths are shown in a principal eigenvector. By aggregating the resulting eigenvectors, the criteria weight vector for this user is obtained as

$$\mathbf{W} = \begin{bmatrix} 0.75 & 0.00 \\ 0.25 & 0.00 \\ 0.00 & 0.60 \\ 0.00 & 0.20 \\ 0.00 & 0.20 \end{bmatrix} \times \begin{bmatrix} 0.80 \\ 0.20 \end{bmatrix} = \begin{bmatrix} 0.60 \\ 0.20 \\ 0.12 \\ 0.04 \\ 0.04 \end{bmatrix} \tag{13}$$

where each element in the weight vector corresponds to a performance factor.

The weight vector for a user will apply to all alternative technologies for the considered operation, based on the third assumption of the approach presented earlier. By varying all involved ratings within a reasonable range, the possible variations in attitude and judgment of an individual user are modeled, and 60 weight vectors are produced representing 60 users. A partial list of the weight vectors is shown in Table 9.

Then, the generated weight vectors are used in the simulation of a poll. A set of five random numbers are generated within the 9–1/9 range representing the AHP ratings of a sample technology versus the base technology with respect to the five criteria items. A corresponding performance vector can be produced from the five ratings using (1). The choice between the sample technology and the base technology by a user is determined by evaluating (6) according to the user's weight vector. The acceptability of the sample technology is calculated by evaluating (9) and (10) with all 60 weight vectors, as the proportion in the 60 users that choose it.

Following the same process, a large number of sample performance characteristics vectors

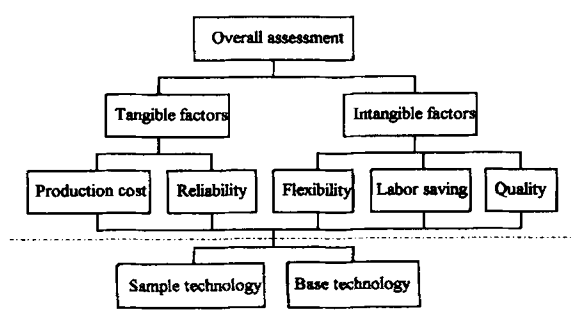

FIG. 3. Decision Attribute Hierarchy for Example

TABLE 7. Example Comparison of Production Cost and Reliability in Their Impact on Tangible Factors

Tangible factors (1)	Production cost (2)	Reliability (3)
Production cost	1	3
Reliability	1/3	1
Principal eigenvector	0.750	0.250

TABLE 8. Example Comparison of Flexibility, Labor-Saving, and Quality in Their Impact on Intangible Factors

Intangible factors (1)	Flexibility (2)	Labor-savings (3)	Reliability (4)
Flexibility	1	3	3
Labor-savings	1/3	1	1
Quality	1/3	1	1
Principal eigenvector	0.600	0.200	0.200

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TABLE 9. Partial List of 60 Weight Vectors

Production cost (1)	Reliability (2)	Flexibility (3)	Labor-savings (4)	Quality (5)
0.600	0.200	0.120	0.040	0.040
0.500	0.250	0.147	0.063	0.040
0.375	0.125	0.295	0.125	0.080
0.625	0.208	0.100	0.033	0.033
0.534	0.133	0.196	0.083	0.053
0.556	0.277	0.099	0.042	0.027
0.333	0.167	0.357	0.072	0.072
0.563	0.188	0.083	0.083	0.083
0.445	0.222	0.196	0.083	0.053

TABLE 10. Distribution of Random Samples

Count (C) (1)	Acceptability (C/60) (2)	Proportion in total (%) (3)
0	0.0	35
1–19	0.01–0.32	13
20–39	0.33–0.65	4
40–59	0.66–0.99	13
60	1.0	35

TABLE 11. Distribution of Training Pairs in 60-User Case (Total = 55)

Count (C) (1)	Acceptability (C/60) (2)	Pairs	
		Number (3)	% (4)
0	0.0	5	9.1
1–19	0.01–0.32	15	27.3
20–39	0.33–0.65	15	27.3
40–59	0.66–0.99	15	27.3
60	1.0	5	9.1

TABLE 12. Partial List of Training Pairs

Production cost (1)	Reliability (2)	Flexibility (3)	Labor-savings (4)	Quality ⇒ Acceptability (5)
0.500	0.833	0.167	0.333	0.200 ⇒ 0.40
0.750	0.667	0.143	0.125	0.250 ⇒ 0.80
0.143	0.875	0.875	0.800	0.667 ⇒ 0.27
0.750	0.111	0.250	0.100	0.111 ⇒ 0.33
0.333	0.667	0.800	0.667	0.857 ⇒ 0.63
0.500	0.900	0.250	0.200	0.250 ⇒ 0.58
0.167	0.833	0.333	0.167	0.500 ⇒ 0.00
0.500	0.200	0.800	0.857	0.100 ⇒ 0.35
0.667	0.333	0.333	0.667	0.200 ⇒ 0.77
0.889	0.875	0.100	0.889	0.833 ⇒ 1.00
0.250	0.889	0.167	0.875	0.800 ⇒ 0.07
0.333	0.875	0.833	0.889	0.250 ⇒ 0.87

TABLE 13. Distribution of Training Pairs in Five-User Case (Total = 55)

Count (C) (1)	Acceptability (C/5) (2)	Pairs	
		Number (3)	(%) (4)
0	0.0	12	21.8
1	0.2	8	14.5
2	0.4	9	16.4
3	0.6	13	23.6
4	0.8	5	9.1
5	1.0	8	14.5

TABLE 14. Results of Testing Neural Networks with Training Data

Error (converted) (1)	Case 1 (60 users) (%) (2)	Case 2 (five users) (%) (3)
Average error	1.28	1.26
RMS error	1.57	1.57
Maximum error	3.63	3.67

and their corresponding acceptability are generated and their distribution is shown in Table 10. Note that 70% of the samples produced by the random-sampling process fall into the extremes, i.e. having 0.0 or 1.0 acceptability, while fewer spread in between. However, due to the trade-off between cost and quality, most technologies in engineering practice usually have some advantages as well as disadvantages. Therefore, their acceptability among the total population of users tends to concentrate around the middle, resulting in an opposite distribution. To reflect the actual conditions in the training set, it is desirable to have more data points close to scenarios where a problem would likely occur than in either extreme where the answer is clear. Thus, training a neural network on a better data distribution would achieve a better prediction ability.

In our example, the number of training pairs in each acceptability bracket is arranged to have a much higher proportion of the training pairs in the middle three brackets than those from random sampling, in order to produce an acceptability distribution closer to real situations. The resulting distribution of the constructed training data is shown in Table 11. Nevertheless, training pairs in each bracket are random samples, i.e. the random-sampling process continues until an arranged number of training pairs within each acceptability bracket is generated, e.g., 15 random samples within the 0.33–0.65 acceptability bracket. A partial list of the constructed 55 training pairs that simulate 55 alternative technologies is shown in Table 12.

To compare the impacts of the number of users in a poll on the prediction accuracy that a neural network can achieve, a second experiment is conducted using only five weight vectors from the earlier 60 weight vectors representing five users that comprise a small poll. To facilitate comparison with the first case, the same 55 characteristics vectors for the simulated alternative technologies were used with the five weight vectors to produce their acceptability in constructing training pairs for the second network. The distribution of acceptability for the resulting 55 training pairs is shown in Table 13.

Network Training and Testing

In both the 60-user and the five-user cases, a feed-forward multilayer neural network was trained with the obtained training data to perform the characteristics-vector-to-acceptability mapping. First, in order to fit the sigmoidal activation function, the acceptability outputs P in the training pairs were linearly converted from the 0.0–1.0 range to the 0.05–0.95 range using

$$P' = 0.9P + 0.05 \tag{14}$$

By experiment, it was found that the network in both cases can achieve a better convergence with two hidden layers. Thus, both networks have five nodes in the input layer, 15 nodes in each hidden layer, and one node in the output layer. The other training parameters used were a momentum rate of 0.9 and a learning rate of 0.7. The cyclic training process continued until the system error defined by (15) decreased to 0.0001, in order to decrease the root mean square (RMS) error to within 2%.

$$\bar{E} = \frac{1}{2T}\sum_{t=1}^{T}(O_t - D_t)^2 \tag{15}$$

where T = number of input-output pairs; O_t = output produced by the network corresponding to pair t; and D_t = the desired (target) output in pair t. It took 1,148 cycles in case 1 and 6,048 cycles in case 2 to reach the specified termination condition. Then, a trained network was tested first with the training data to calculate the average error defined by (16), the RMS error defined by (17), and the maximum error.

$$E_{avg} = \frac{\sum_{t=1}^{T}|O_t - D_t|}{T}; \quad E_{RMS} = \sqrt{\frac{\sum_{t=1}^{T}(O_t - D_t)^2}{T}} = \sqrt{2\bar{E}} \tag{16, 17}$$

Note that the test results should be divided by 0.9 to convert back to the original scale, because of using (14) previously. The training errors produced in both cases are shown in Table 14. It shows that the trained networks perform the mapping over the training data satisfactorily.

However, to verify the prediction ability of a trained network, testing with data unseen by the network is necessary. For this purpose, a large number (2,400) of different performance characteristics vectors were generated using a random-sampling process. Then, as in constructing training data, the same weight vectors (60 in case 1 and 5 in case 2) were used to produce the acceptability for the 2,400 samples according to (9) and (10). Meanwhile, the characteristics vectors are propagated through a trained network to produce the acceptability estimates. The obtained estimates are compared with the target acceptability values in the constructed testing pairs and the previously defined errors are calculated to determine the prediction performance of the trained network. The results of testing are shown in Tables 15 and 16, for cases 1 and 2, respectively.

Note that a user's choice for a sample technology in case 1 corresponds to an increment of its acceptability of 1/60 = 1.67%. Hence, either the average error or the RMS error of the total 2,400 pairs in the overall range (0–60 count) is within two users' choices. Testing with only the 703 pairs in the more realistic middle brackets (1–59 count) results in a slightly higher average error and RMS error, as it is more difficult to estimate the acceptability for cases in this range than the two extremes for which the answers are obvious. Out of the total 18 pairs (0.75%) that have an error over 10%, 15 pairs occur in the middle brackets with a maximum error of 16.16%. However, they are only 2.13% of those in the middle brackets, reflecting the prediction accuracy of the network.

In case 2 a user's choice for a sample technology accounts for an acceptability increment of 1/5 = 20%, causing a much rougher estimate than in case 1. Yet, both the average error and the RMS error in either the overall 2,400 pairs (0–5 choices) or the middle 524 pairs (1–4

TABLE 15. Results of Testing in Case 1 (60 Users)

Test items (1)	Overall range: 0–60 count (2,400 pairs) (%) (2)	Middle brackets: 1–59 count (703 pairs) (%) (3)
Average error	1.74	2.72
RMS error	2.53	3.66
Maximum error	16.16	16.16
% with error < 10%	99.25	97.87

TABLE 16. Results of Testing in Case 2 (Five Users)

Test items (1)	Overall range: 0–5 count (2,400 pairs) (%) (2)	Middle brackets: 1–4 count (524 pairs) (%) (3)
Average error	5.78	15.00
RMS error	10.51	18.72
Maximum error	67.15	67.15
% with error < 20%	91.46	72.52
% in the same side of 0.5	96.38	83.40

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TABLE 17. Results of Testing Case 2 Network with Case 1 Data

Test items (1)	Overall range: 0–60 count (2,400 pairs) (%) (2)	Middle brackets: 1–59 count (703 pairs) (%) (3)
Average error	6.07	14.50
RMS error	11.30	19.29
Maximum error	59.02	59.02
% with error < 20%	90.33	71.83
% in the same side of 0.5	95.17	83.50

TABLE 18. Results of Testing Linear Regression Model with Case 1 Data

Test items (1)	Overall range: 0–60 count (2,400 pairs) (%) (2)	Middle brackets: 1–59 count (703 pairs) (%) (3)
Average error	11.92	11.06
RMS error	15.17	14.49
Maximum error	47.11	44.89
% with error < 10%	52.38	56.47

choices) are within one choice. Overall, 91.46% of the testing pairs have an error less than one choice. However, only 72.52% of those in the middle range have an error below one choice. On the other hand, 96.38% overall or 83.4% in the middle range have an estimate in the same side as the target value (both above 0.5 or both below 0.5).

Observations and Comment

Three observations can be made regarding the performance of the neural networks in this example. First, so far the obtained average and RMS testing errors reflect the ability of a network in predicting for various input conditions the poll outcome from the same group of users as in training set construction. Since the case 1 network was trained with the results of a fairly large poll which are statistically close to the population proportions and the network also has clearly small testing errors, it can rather confidently produce a satisfactory acceptability estimate. This is not true for the case 2 network since only a small poll was used in training set construction and further the network has much larger testing errors. To verify this, the case 1 poll results were assumed to be true population proportions and used to test the case 2 network. As shown in Table 17, the obtained test errors are quite large, similar to those in Table 16. Only 90.33% overall or 71.83% of those in the middle range have an error below 20%.

Next, for comparison of estimating accuracy, a linear regression equation was built using the same 55 pairs of data that were used to train the case 1 network. The obtained equation is

$$p = 1.44x_1 + 0.25x_2 + 0.33x_3 + 0.13x_4 + 0.15x_5 - 0.67 \tag{18}$$

where p = estimated acceptability; and $x_1, x_2, \ldots, x_5$ = performance vector.

Eq. (18) was then tested using the same data that were used to test the case 1 network. The results of testing are shown in Table 18. Compared to the errors produced by the case 1 network in Table 15, the errors produced by this linear model are quite large, as the relationships between the dependent variable and the independent variables are nonlinear in nature.

Finally, because there are five performance factors each with 17 (1/9 ~ 9) possible assignments, the number of different combinations (vectors) and hence input-output relations is $(17)^5$ = 1,419,857. Since only a tiny portion (55) of such a vast number of possible situations were used as training pairs, we can conclude that the prediction performance of the network in either case, especially case 1, is satisfactory. This shows the neural networks' generalization ability and efficiency, which is useful because collection of training data using a poll is expensive and training with a large number of data pairs is time-consuming.

CONCLUSIONS

Based on three basic assumptions, a neural network approach to estimating the acceptability of a new construction technology was presented along with its theoretical concept. Even though we demonstrate the feasibility of the approach via a hypothetical example with simulated data, several relevant implications can be drawn from these experimental results. First, it is shown that although using only a very limited number of training examples, the approach is capable of achieving satisfactory estimating accuracy in comparison with the results of a linear regression model. The effectiveness and efficiency of the approach for the defined problem is due to the ability of neural networks in nonlinear mapping and generalization that matches the nonlinear nature of the problem.

Next, the importance of representation and distribution of training data should not be overlooked in training set construction. The use of the eigenvalue data scheme and the arrangement of training data in different levels of acceptability are shown to be beneficial. Equally important is the impact of the number of users polled. It is shown that a network trained with the results of a large poll that are statistically close to the population proportions can also achieve good

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testing accuracy. Thus, a reliable acceptability estimate can be ensured by using a sufficiently large poll size in training data construction.

Due to high competition in the construction industry, only those technologies that best fit industry needs should be selected for development and implementation to avoid wasting resources and to increase competitiveness. The key to achieving this selectivity is to develop the ability to reliably estimate the adoption potential of proposed new technologies. Our approach provides a systematic way to perform this estimate with a justifiable data collection effort, as an expandable knowledge base is established in the same time that is useful into the future. It is hoped that with an efficient technology evaluation method to select a technology that best meets the users needs, the spread of new technology applications in construction can be facilitated, which is the underlying purpose of this research.

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