Estimating the Acceptability of New Formwork Systems Using Neural Networks

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Abstract: Continual development in construction techniques results in emergence of specialized formwork systems. A new system will have to compete with in-use systems for adoption in a target operation. Thus, it is essential that decision makers anticipate the acceptability of new systems before making decisions to acquire them. Estimating acceptability basically assesses how features of a new system are comparable to that of in-use systems. Therefore, analogy is a focal factor for the acceptability estimating process. Neural networks (NNs) are more suitable to model construction problems requiring analogy-based solutions. A NN-based approach was employed to anticipate the acceptability of new formwork systems. The study collected data from a group of 40 users in Egypt. A set of six performance characteristics that mostly pertain to acceptability estimating were identified. The study used the analytical hierarchy process to produce pairs of a performance characteristics' vector and the corresponding acceptability value, and utilized the developed pairs to train NNs. Finally, tests on trained NNs using unseen data indicated satisfactory performance.

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Introduction

Recent developments in formwork technologies resulted in a number of highly specialized formwork systems that are already in use. Depending on its ability to meet the requirements of a target operation, any formwork system achieves a certain level of success in terms of acceptability by the industry. Chao and Skibniewski (1995) defined the acceptability of a formwork system for a target operation as the proportion of users that choose to use that system compared to the base formwork system. Chao and Skibniewski (1995) defined the base formwork system as the most common for achieving a specific operation.

Estimating acceptability of new systems necessitates knowledge of strengths and weaknesses of in-use substitute systems regarding meeting operational requirements. Thus, the acceptability estimating process has to be based on experience and judgment and involves consideration of many factors that characterize performance of formwork systems. This study offers an approach that enables decision makers to estimate acceptability of new formwork systems based on analogy with past experience with in-use systems that perform the same operation.

The problem of selecting optimal formwork systems had been extensively studied (Hanna and Sanvido 1990, 1991; Hanna et al. 1992; Kamarthi et al. 1992; and Abd Elrazek 1999). These researchers developed many approaches to select an optimal formwork system for a particular job. However, acceptability estimating can be substantiated from the selection of optimal systems in many aspects. Acceptability is a system's attribute that must be drawn from a large population of users, whereas selection decision is a process that can be done by an individual. In addition, acceptability assessment is more meaningful for a new system that is not known for users, possibly not produced yet, and therefore involves the element of prediction. This study focuses on compiling data to determine the achieved success of candidate in-use systems for a target operation and uses the collected data to predict acceptability of new systems.

This study employs a neural network (NN)-based approach to predict the adoption potential or acceptability of a new formwork system. Chao and Skibniewski (1995) outlined a NN approach to estimate acceptability of a new construction technology using hypothetical data. The objective of the current study was to present this systematic methodology and demonstrate its applicability to estimate acceptability of new horizontal formwork systems in Egypt. Thus, decision makers are now equipped with a tool that can be used with their own compiled data that represents the peculiars of their situations.

The target operation represents the construction of flat-slab floors in high-rise buildings. Candidates for this operation represent flat-slab formwork systems that are in use in Egypt. Data are compiled from users concerning the performance characteristic values of every candidate system. Performance characteristics are a set of criteria that decision makers consider to evaluate success of in-use systems, and estimate acceptability of new systems. The

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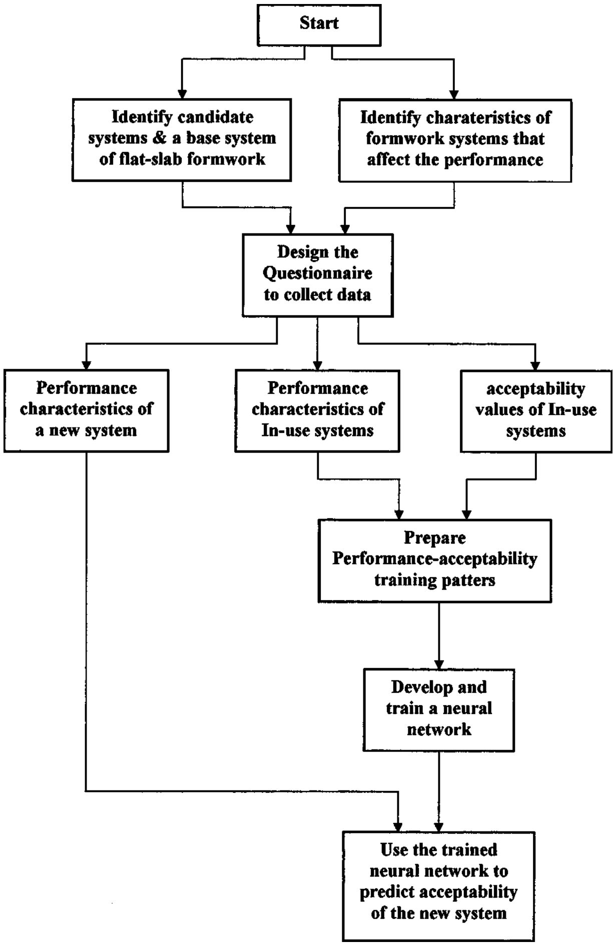

Fig. 1. Outline of study methodology

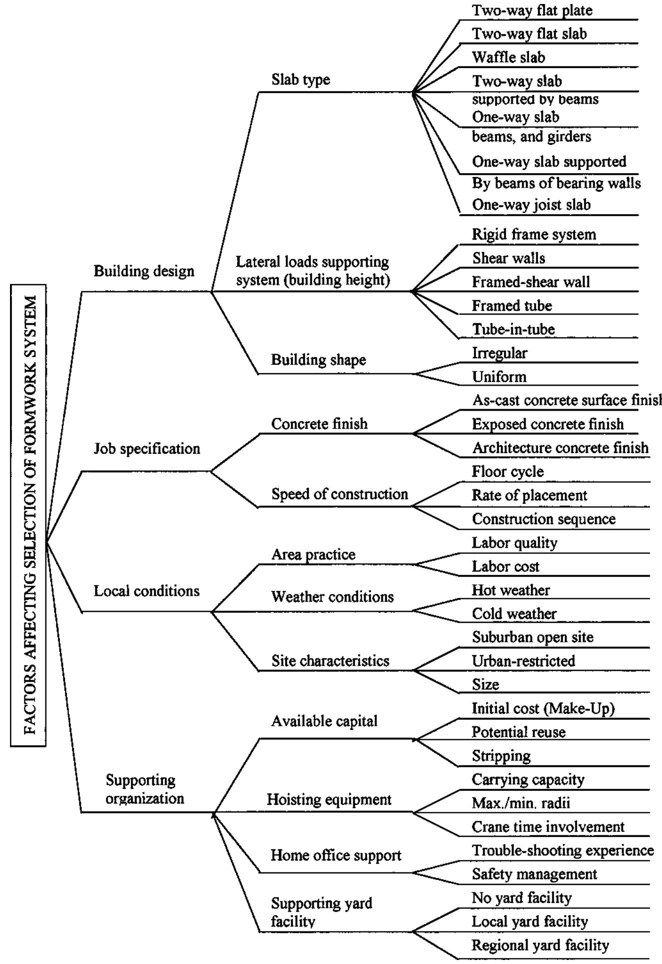

Fig. 2. Factors affecting selection of optimum formwork system (Hanna 1999)

performance characteristics values of each candidate system is stored in a performance vector and its acceptability is calculated using the analytical hierarchy process (AHP) (Saaty 1980). The obtained performance–acceptability pairs are used to train NNs. Trained NN can then be used to predict acceptability of a new system in question, given its performance vector. The methodology of the study is outlined in the next section.

Methodology

This section outlines procedures of performing the study, as shown in Fig. 1, which involves identifying in-use flat-slab formwork systems as well as the base flat-slab formwork system in Egypt; identifying a set of performance factors; collecting data using a questionnaire to gather the experience of a sample of formwork users; preparing training patterns that comprise performance vectors and the corresponding acceptability values; and developing a neural network model.

Identifying In-Use Flat-Slab Formwork Systems

Initially, a literature review identified many flat-slab systems which included: conventional wood formwork, a telescopic beam and props system, a telescopic beam and shore brace system, a shore brace system, an s-beam and props system, an s-beam and shore brace system, an early striking system (drop-head system), a table form system, and a tunnel form system. Conventional wood formwork is considered as the base formwork system in this operation. Subsequently, formwork departments of big contractors and formwork manufacturers were visited to identify the systems that are in use in Egypt and determine the projects that used these systems. It was found that the most commonly used systems in Egypt, beside the conventional wood formwork, include the: telescopic beam system and props system, shore brace system, table form system, and early-striking system (drop head system). These four systems represent candidates for which users' experience is gathered and formulated as performance–acceptability pairs. The other systems were actually used in Egypt but in very limited scale which would make data collection about these systems a very difficult task, and therefore were omitted.

Table 1. Comparisons of Candidate System (Telescopic Beam System and Props) Against Base System with Respect to Cost

Cost	Candidate system	Base system
Candidate system	1	1/3
Base system	3	1
Principal eigenvector	0.250	0.750

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Table 2. Comparisons of Candidate System (Telescopic Beam System and Props) Against Base System with Respect to Construction Time

Construction time	Candidate system	Base system
Candidate system	1	2
Base system	1/2	1
Principal eigenvector	0.667	0.333

Table 4. Comparisons of Candidate System (Telescopic Beam System and Props) Against Base System with Respect to Flexibility

Flexibility	Candidate system	Base system
Candidate system	1	4
Base system	1/4	1
Principal eigenvector	0.800	0.200

Identifying Performance Factors

Hanna (1999) identified factors to consider in selecting optimal formwork systems. These factors are shown in Fig. 2 and comprise: factors related to building architectural and structural design, factors related to project (job) specification and schedule, factors related to local conditions, and factors related to supporting organizations. In this study, some of these factors were deemed representative to characterize performance of formwork systems. The argument behind the identification of performance factors in this study is given in the next paragraphs.

Factors related to building architectural and structural design, shown in Fig. 2, are represented in this study by "flexibility" of the formwork system. Factors related to job specifications and schedule are represented by both "quality" and "construction time." Factors related to local conditions which include area practice, weather conditions, and site characteristics are represented by "expected familiarity" to express the area practice factor. Effects of factors including weather conditions and site characteristics are ruled out because the target operation is constructed under prevailing weather conditions of Egypt and unrestricted site conditions that feature the target operation. Finally, factors related to supporting organizations are represented by factors of "cost" and "safety."

The six identified performance factors can be classified as quantitative factors including cost and construction time, and qualitative factors including expected familiarity, flexibility, quality, and safety. Cost of formwork is influenced by factors including fabrication cost, potential reuse, and stripping cost. Construction time (speed of construction) is influenced mainly by floor cycle time which involves the time components of erecting, setting time, stripping, and moving to the next floor. Expected familiarity assesses how local labor will become familiar with the new system. For systems in use, familiarity describes the degree the local labor is comfortable with the system. Flexibility characterizes features that make the system suitable for different sized rooms. Quality expresses the quality of system components and quality of the resulting concrete surface. Safety is the factor that measures how the design and operation of the system conforms to safety requirements and regulations.

As discussed above, the six identified performance factors are representative of the factors given by Hanna (1999). In addition, performing pairwise comparisons in questionnaires by users, as will be explained later, using more than six factors would be very lengthy, intricate, and troublesome, which could negatively affect the accuracy of data. Thus, these six factors were considered the most relevant to the success of formwork systems and deemed valid and sufficient to characterize systems performance.

Data Collection

A questionnaire was prepared to gather users' experience regarding the four candidate systems. A group of 40 users who worked for ten contractors completed questionnaires. An extensive search for the users of these systems in Egypt resulted in this group. Site visits were made to hand out blank questionnaires to users and give instructions to help correctly complete questionnaires. Subsequent visits were made to follow up and eventually collect the completed questionnaires.

The questionnaire was divided into three parts. The first part categorizes the six performance factors into a quantitative and qualitative group of factors and prompts users to specify a superior group and rank the relative superiority based on their perceived impact on the overall assessment. The relative superiority is evaluated according to a scale of five levels that is given to users in the body of the questionnaire. The second part holds pairwise comparisons between factors within each group. Users are inquired to compare each factor with the rest of the factors in the same group, specify a superior factor in each comparison, and give the perceived relative superiority. Superiority evaluation is performed according to the same scale used in the first part. The third part involves users' evaluation of the four candidate systems. The evaluation process is performed identically for the four systems. Users are asked to compare each system against the base system with respect to the performance factors using the same scale mentioned above. For each performance factor, a superior system is selected and the level of superiority in indicated. Comparisons indicate the capabilities of a candidate system against those of the base system when the two systems are presented for the target operation.

Appendix I presents the first two parts of the questionnaire as well as one system of the third part. The data collected are presented in Appendix II. The collected data are then processed to obtain performance vectors and acceptability values that represent training patterns.

Table 3. Comparisons of Candidate System (Telescopic Beam System and Props) Against Base System with Respect to Expected Familiarity

Expected familiarity	Candidate system	Base system
Candidate system	1	1
Base system	1	1
Principal eigenvector	0.500	0.500

Table 5. Comparisons of Candidate System (Telescopic Beam System and Props) Against Base System with Respect to Quality

Quality	Candidate system	Base system
Candidate system	1	5
Base system	1/5	1
Principal eigenvector	0.833	0.167

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Table 6. Comparisons of Candidate System (Telescopic Beam System and Props) Against Base System with Respect to Safety

Safety	Candidate system	Base system
Candidate system	1	1/5
Base system	5	1
Principal eigenvector	0.167	0.833

Preparing Training Patterns for Neural Network Model

This section outlines the procedure for preparing training patterns that will be used to train the neural network. This involves producing performance vectors of candidate systems, and using AHP to determine acceptability values.

Producing Performance Vectors

A matrix is constructed for each comparison in the third part of the questionnaire using a quantitative scale. The qualitative scale with five degrees of superiority was transformed to a quantitative scale of 1–5. According to Saaty (1980), the human brain can simultaneously process a range of 5–9 levels of superiority, therefore, this quantitative scale was used. A rating of 1 corresponds to equal superiority of two systems with respect to a given factor. A larger value indicates greater superiority for one system over the other. For instance, if one system is strongly favored over another, a rating of 3 is assigned to the favored system. The reciprocal of that number, i.e., 1/3, is assigned to the other system. This scale was used throughout pairwise comparisons in order to maintain consistency. Then, a normalized principal eigenvector was produced to represent the relative strength of one system versus another with respect to a performance factor. The normalized eigenvalues of a two-system comparison matrix are complementary to each other and can be obtained using the equations

$$E_1 = 1 - 1/(1+R) \tag{1}$$

$$E_2 = 1/(1+R) \tag{2}$$

where E_1=normalized eigenvalue of the first system; E_2=normalized eigenvalue of the second system; and R=rating of one system against the other.

An example of comparing a candidate system against the base system with respect to performance factors is presented in Tables 1–6. Similar comparisons are performed for the other four candidate systems by each member of the group of 40 users. The output eigenvectors of comparisons in Tables 1–6 with respect to cost, construction time, expected familiarity, flexibility, quality, and safety, respectively, are tabulated in the following matrix:

$$M = \begin{bmatrix} 0.250 & 0.667 & 0.500 & 0.800 & 0.833 & 0.167 \\ 0.750 & 0.333 & 0.500 & 0.200 & 0.167 & 0.833 \end{bmatrix}$$

Horizontally, the matrix M consists of an upper vector $\mathbf{X}$ and a lower vector $\mathbf{Y}$, where

$$\mathbf{X} = [\mathbf{0.250} \quad \mathbf{0.667} \quad \mathbf{0.500} \quad \mathbf{0.800} \quad \mathbf{0.833} \quad \mathbf{0.167}]$$

and

$$\mathbf{Y} = [\mathbf{0.750} \quad \mathbf{0.333} \quad \mathbf{0.500} \quad \mathbf{0.200} \quad \mathbf{0.167} \quad \mathbf{0.833}]$$

for the candidate and base systems, respectively. Elements in the lower vector are just complements to those in the upper vector. Thus, the upper vector $\mathbf{X}$ alone is sufficient to characterize the overall comparison result and is used thereafter as the performance vector for the candidate system.

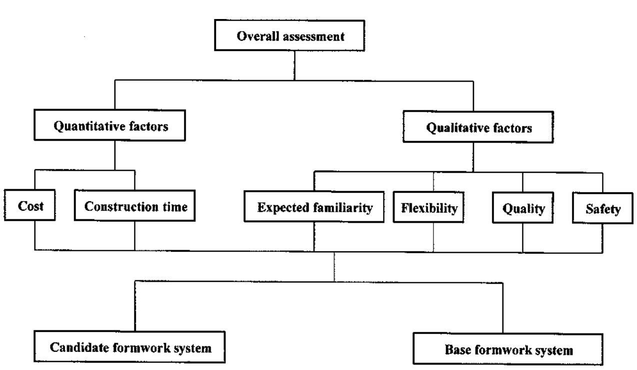

Fig. 3. Hierarchy of overall assessment

Table 7. Comparison of Quantitative Against Qualitative Factors Regrading Impact on Overall Assessment

Overall assessment	Quantitative factors	Qualitative factors
Quantitative factors	1	4
Qualitative factors	1/4	1
Principal eigenvector	0.800	0.200

Determining Acceptability Values

Subsequent to producing a performance vector of a candidate system, the acceptability of the same system is determined and coupled with the performance vector to form a training pattern. The acceptability of a candidate system is calculated by the equation below

$$a = \mathbf{X} \cdot \mathbf{W} = [X_1, X_2, \ldots, X_N] \cdot [W_1, W_2, \ldots, W_N]^t \tag{3}$$

where a=acceptability of a candidate system as perceived by a user; $\mathbf{X}$=performance vector of the candidate system; $\mathbf{W}$=user's criteria weight vector; and N=number of performance factors.

The AHP is used to develop a generic decision attribute hierarchy and generate criteria weight vectors as shown in Fig. 3. The hierarchy shown in Fig. 3 incorporates at its third level all six performance factors as criteria items. Then, cost and construction time are grouped as quantitative factors at the second level of the hierarchy while expected familiarity, flexibility, quality, and safety are grouped as qualitative factors. 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 elements in the three levels of the hierarchy.

For instance, a particular user assigned ratings, as shown in Tables 7–9, for comparing quantitative against qualitative groups, quantitative factors against each other, and qualitative factors

Table 8. Comparing Quantitative Factors Against Each Other

Quantitative factors	Cost	Construction time
Cost	1	3
Construction time	1/3	1
Principal eigenvector	0.750	0.250

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Table 9. Comparing Qualitative Factors Against Each Others (Largest Eigenvalue=4.02062)

Qualitative factors	Expected familiarity	Flexibility	Quality	Safety
Expected familiarity	1	1	1/2	1/3
Flexibility	1	1	1/2	1/2
Quality	2	2	1	1
Safety	3	2	1	1
Principal eigenvector	0.15	0.16	0.33	0.36

against each other, respectively. Elements at the same level are compared with each other concerning their impact on an element in the next higher level in the hierarchy and their relative strengths are represented as principal eigenvectors. By aggregating the resulting normalized eigenvectors, the criteria weight vector **W** for this particular user is obtained as

$$\mathbf{W}=\begin{bmatrix}0.75 & 0.00\\ 0.25 & 0.00\\ 0.00 & 0.15\\ 0.00 & 0.16\\ 0.00 & 0.33\\ 0.00 & 0.36\end{bmatrix}\times\begin{bmatrix}0.80\\ 0.20\end{bmatrix}=\begin{bmatrix}0.600\\ 0.200\\ 0.030\\ 0.032\\ 0.066\\ 0.072\end{bmatrix}$$

It should be noted that eigenvalues and the corresponding eigenvectors for the (4×4) matrix in Table 9 are calculated by using *Mathematica 3.0* software. This software calculates the eigenvalues and the corresponding eigenvectors. The principle eigenvector corresponds to the largest eigenvalue. Then, the principal eigenvector is normalized by dividing each component in the principal eigenvector by the sum of all components. The sum of all normalized components must equal one. The normalized principal eigenvector is used in the aggregation process to determine the weight vector **W** for this particular user.

According to Saaty, a check for the consistancy of making comparisons needs to be performed. Consistency in a comparison matrix is measured by the consistency ratio (CR) given by the equation below:

$$\mathrm{CR}=\frac{\mathrm{CI}}{\mathrm{RI}} \tag{4}$$

where

$$\text{Consistency index (CI)}=\frac{\text{Largest eigenvalue}-n}{n-1} \tag{5}$$

Random index (RI) is given in Saaty (1980) for matrices according to their order n. Saaty suggested that a CR value in the neighborhood of 0.1 is acceptable. In this study a CR value less than or equal to 0.15 is considered acceptable. For instance, the consistency ratio for the matrix in Table 9 with the largest eigenvalue of 4.02062 and a RI value of 0.52 was calculated as 0.00687, which is acceptable. The consistancy test resulted in excluding 14 questionnaires out of the obtained 40 questionnaries. However, the remaining 26 questionnaires are used to demonstrate the methodology rather than drawing conclusions or keeping as standard inventory data.

Finally, the acceptability of this particular user for this candidate system is calculated as follows:

$$a=[0.250\quad 0.667\quad 0.500\quad 0.800\quad 0.833\quad 0.167]\times\begin{bmatrix}0.600\\ 0.200\\ 0.030\\ 0.032\\ 0.066\\ 0.072\end{bmatrix}$$

$$=0.39$$

The weight vector **W** for this user applies to calculate acceptability values of the other three candidate systems. Thus, the training pattern composed of the performance vector and the corresponding acceptability value is presented as follows:

$$[0.250\quad 0.667\quad 0.500\quad 0.800\quad 0.833\quad 0.167]\rightarrow[0.39]$$

Similarly, acceptability values of 26 questionnaires were calculated. These questionnaires encompass a total of 104 training patterns. These patterns were divided into 84 patterns for training the NN, and 20 patterns for testing.

Neural Network Model Development

This section involves development of NN models to predict acceptability of new formwork systems. The developed patterns of candidate systems are used to train a feed-forward multilayer NN in order to generalize a relationship between performance attributes and acceptability values. The model development involves three main aspects: acquiring knowledge which was covered in the previous section, selecting a NN configuration, and training and testing the trained NN.

Selecting Neural Network Configuration

A back-propagation supervised learning algorithm was used in the present study. The model was implemented using a coded algorithm (Pao 1989). Setting the configuration of a neural network that gives the best performance is a highly problem dependent task. Performance of a NN is measured by how well the NN can learn the training examples and produce a satisfactory response when presented with patterns outside the training patterns. Many variables need to be specified in the back-propagation algorithm to define a network configuration. The present NN model was configured as having a (generalized delta rule) back-propagation learning algorithm, and sigmoid transfer function to account for the continuous inputs. As shown in Fig. 4, the number of elements in input buffer are 6, and the number of processing elements (PEs) in the output layer is one. The number of hidden layers and number of PEs in each hidden layer were determined by experimentation as outlined in the following paragraphs.

The number of hidden layers and number of PEs in each were varied, and the corresponding network training error defined by the following equation was observed for short training sessions (an iteration represents a complete sweep of the 84 patterns). Experimentation showed that one hidden layer of 12 PEs was the optimum configuration since it produced the minimum error as calculated by the following equation. Therefore, this configuration was selected. This result was produced at a learning rate coefficient of 0.9 and a momentum coefficient of 0.7:

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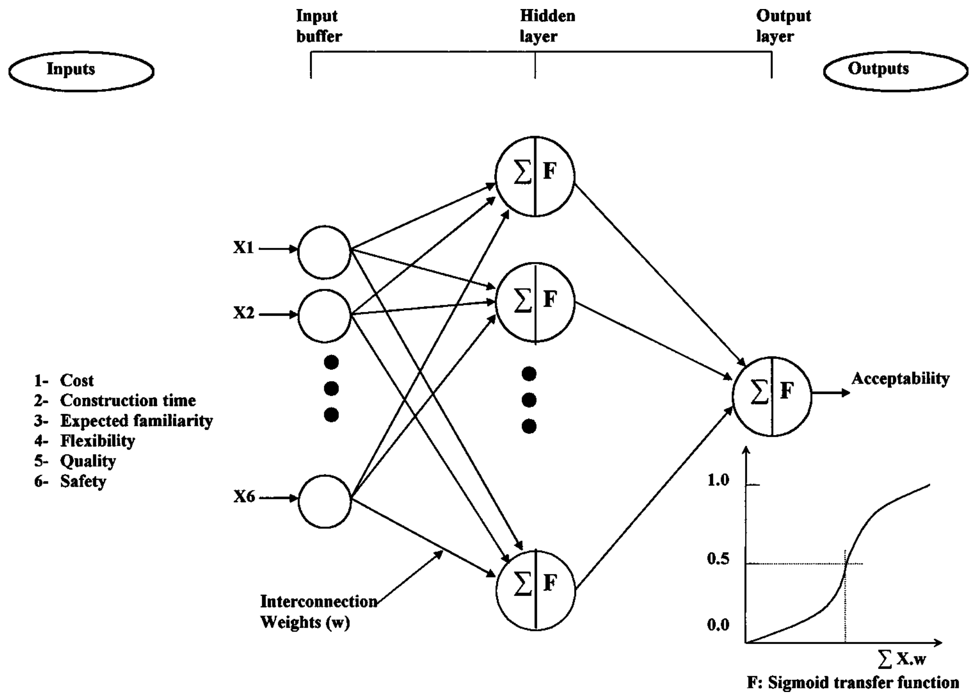

Fig. 4. Neural network model

$$E=\frac{1}{2T}\sum_{t=1}^{T}(O_t-D_t)^2 \tag{6}$$

where T=number of input–output pairs; O_t=output produced by the network corresponding to pair t, and D_t=desired (target) output of pair t.

Neurol Network Training and Testing

Once the network configuration was selected, the NN was subjected to a long training session. The neural network was trained on its 84 patterns for 57,465 iterations. This number of iterations was enough to produce the minmum error of 0.0000428 as calculated by Eq. (6) and reduce the value of the root mean square

Table 10. Errors of Testing Patterns of Trained Neural Network

Sample	Output (O)	Desired output (D)	Errors (O-D)	Squared errors $(O\text{-}D)^2$
1	0.737352	0.77	−0.032648	0.001066
2	0.603342	0.51	0.093342	0.008713
3	0.777020	0.77	0.007020	0.000049
4	0.766073	0.78	−0.013927	0.000194
5	0.717912	0.70	0.017912	0.000321
6	0.777020	0.77	0.007020	0.000049
7	0.780810	0.78	0.000810	0.000001
8	0.685669	0.69	−0.004331	0.000019
9	0.782245	0.80	−0.017755	0.000315
10	0.720267	0.77	−0.049733	0.002473
11	0.753835	0.76	−0.006165	0.000038
12	0.767539	0.77	−0.002461	0.000006
13	0.773931	0.78	−0.006069	0.000037
14	0.761704	0.76	0.001704	0.000003
15	0.738941	0.77	−0.031059	0.000965
16	0.749589	0.74	0.009589	0.000092
17	0.811313	0.71	0.101313	0.010264
18	0.688077	0.78	−0.091923	0.008450
19	0.748341	0.79	−0.041659	0.001735
20	0.724377	0.74	−0.015623	0.000244

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(RMS) error defined by the following equation to 0.00926. The training process took about 10 min on a Pentium II, 266 MHz processor PC

$$E_{\mathrm{RMS}} = \sqrt{\frac{\sum_{t=1}^{T} (O_t - D_t)^2}{T}} \tag{7}$$

The next step on completion of training constituted the testing. To verify the generalization ability of the trained network, testing with the remaining 20 patterns that were still unseen by the NN was performed. The results of testing are tabulated in Table 10. Results indicated an average error of −0.00373 defined by the following equation and a RMs value of 0.04185:

$$E_{\mathrm{avg}} = \frac{\sum_{t=1}^{T} (O_t - D_t)}{T} \tag{8}$$

Results indicate that the NN model could learn the training examples with practically insignificant errors.

Estimating Acceptability of New System

A new system in question is compared with the base system with respect to each of the performance factors to produce its performance vector. Preliminary investigation and conceptual design of the new system can help decision makers predict values of the performance vector. The obtained performance vector is then input to the trained NN to produce an estimated value for acceptability. For instance, an acceptability value of 0.7 approximates the proportion of users that will likely choose the new system. By comparing the obtained acceptability value of a new system with those of other candidate systems, it will be possible to assess the adoption potential of the new system.

Conclusion

This study is concerned with the problem of estimating the acceptability of new horizontal formwork systems. The main objective of the current study was to present a systematic methodology and demonstrate its applicability to estimate acceptability of new horizontal formwork systems in Egypt. A NN-based approach was used to predict acceptability before acquisition. Formwork systems that are most commonly used for flat-slab high-rise buildings in Egypt were considered as candidates for the data collection in this study. Performance characteristics of candidate systems are gathered from a group of 40 users. Evaluation weights and acceptability values are caculated using the AHP. The obtained performance–acceptability patterns are used to train a NN using the back-propagation algorithm. Results indicated that the developed NN model can be used satisfactorily to predict the acceptability of a new horizontal formwork system.

Appendix I. Study Questionnaire

First Part: Relative Superiority of Groups

Q: In your opinion, which group is more superior? What is the degree of superiority?

Group A quantitative factors	Group B qualitative factors
Cost	Expected familiarity
Construction time	Flexibility
	Quality
	Safety
More superior group:	Degree of superiority
Level of superiority:	Absolute superiority
	Very strong superiority
	Strong superiority
	Slight superiority
	Equal superiority

Second Part: Relative Importance of Factors within Each Group

Q: What is the more superior factor and the degree of superiority (use the table above)

	Comparison	More superior factor	Degree of superiority
Group A	Cost versus construction time		
Group B	Expected familiarity versus flexibility		
	Expected familiarity versus quality		
	Expected familiarity versus safety		
	Flexibility versus quality		
	Flexibility versus safety		
	Quality versus safety		

Third Part: Comparison of Systems with Base System

Q: What is the more superior system with respect to each factor? (use the above table)

(Props and Telescopic Beam System versus Base System)

	Factor	Superior system	Degree of superiority
Group A	Cost		
	Construction time		
Group B	Expected familiarity		
	Flexibility		
	Quality		
	Safety		

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Appendix II. Collected Data of Study Questionnaire

		Superiority of Performance factors							Telescopic beam and props system						Shore brace system						Table Form system						Early-striking system					
Repondent	Superior group	Cost versus construction time	Expected familiarity versus flexibility	Expected familiarity versus quality	Expected familiarity versus safety	Flexibility versus quality	Flexibility versus safety	Quality versus safety	Cost	Construction time	Expected familiarity	Flexibility	Quality	Safety	Cost	Construction time	Expected familiarity	Flexibility	Quality	Safety	Cost	Construction time	Expected familiarity	Flexibility	Quality	Safety	Cost	Construction time	Expected familiarity	Flexibility	Quality	Safety
1	I3	1	E3	E3	E3	F3	F3	S3	A2	A4	A3	A4	A4	A2	G3	G3	G3	G3	G4	G2	D2	D3	D3	D3	D3	D2	H2	H3	H3	H3	H3	H2
2	I2	C2	E3	E3	E2	Q2	S2	Q2	B3	A5	A4	B2	A4	A3	B2	G3	G2	G2	G3	G2	B4	D3	D3	B4	D4	D3	B2	H3	H2	H3	H3	H2
3	I4	T3	F3	1	S3	1	S3	S3	A5	A5	A5	A5	A5	A5	G5	G5	G5	G5	G5	G5	D2	D5	D5	D5	D5	D5	H5	H5	H5	H5	H5	H5
4	I4	1	E3	Q3	S3	Q3	S3	S3	A2	A3	B3	A3	1	1	G2	G3	B3	G3	1	1	D3	D3	D3	D3	1	1	H3	H3	H3	H3	1	1
5	I2	1	1	Q2	S3	Q2	S2	1	B3	A3	B3	A3	A3	A3	B2	G2	1	G3	G3	G3	B3	D3	B3	B2	D3	D3	B3	H5	B2	H3	H3	H3
6	I3	C2	E2	Q3	E2	Q3	S3	1	A3	A3	B2	B3	A4	A4	G3	G3	B2	B2	G4	G3	D3	D3	D3	B3	D4	D3	H3	H3	B3	H2	H3	H3
7	I3	1	F3	Q3	S3	F3	F3	Q3	A3	A3	A3	A3	A3	A3	G3	G3	G3	G3	G3	G3	D2	D2	D2	D2	D2	D2	H4	H4	H4	H4	H4	H4
8	I2	T3	E4	Q3	1	Q3	S5	1	A3	A4	A5	B3	A5	A5	G3	G3	G5	B3	G5	G5	B3	D2	D3	1	D3	D3	H5	H5	H3	H3	H5	H5
9	I4	C4	E4	Q3	S3	Q3	S3	1	A5	A5	A5	A4	A5	A5	G5	G5	G5	G5	G5	G5	D5	D5	D5	D5	D5	D5	H5	H5	H5	H5	H5	H5
10	I	C4	F3	Q3	S4	1	1	1	A5	A5	1	A4	A4	A4	G5	G5	G5	G5	G5	G5	D2	D5	D2	D3	D3	D3	H4	H5	H3	H3	H5	H5
11	I4	1	F3	Q3	S4	1	S3	1	A3	A3	A3	B3	1	1	G3	G3	G3	B2	1	1	D3	D3	D3	D2	1	1	H4	H4	H3	1	1	1
12	II3	C5	E4	E3	1	Q2	1	1	A3	A3	A3	A3	A3	A3	G2	G3	G3	G3	G3	G3	D5	D5	D4	D3	D3	D3	H5	H5	H3	H3	H3	H3
13	I5	T2	E3	Q3	S5	Q2	S3	Q3	A3	A4	A2	B2	A5	A4	G5	G3	G3	B2	G3	G3	D2	D3	D5	B3	D3	D5	H2	H3	H2	B3	H5	H5
14	I	1	E2	Q2	E3	1	F2	Q2	A3	A3	A3	A3	A3	A3	G3	G3	G3	G3	G3	G3	D2	D3	D3	D3	D3	D3	H3	H3	H2	H3	H3	H3
15	I2	T3	F4	Q4	S5	1	S3	S4	A5	A5	B5	B2	A5	A5	G3	G5	B3	1	G4	G4	D4	D5	B3	B3	D4	D4	H5	H5	B4	H3	H4	H4
16	I3	C2	E3	E3	E3	Q2	S2	Q2	A3	A3	B3	A3	A3	A3	G4	G5	G3	G3	G3	G3	D3	D3	B3	D3	D3	D3	H3	H3	B3	H3	H3	H3
17	I4	C3	E3	E5	E4	F5	F5	Q3	A5	A3	A3	A3	A3	A5	G5	G3	G2	G5	1	G3	D5	D5	D5	D5	D5	D5	H5	H5	H5	H5	H5	H5
18	I5	C3	F4	Q3	E3	Q2	S2	Q2	B3	A4	B3	B2	A4	A3	B3	1	G2	B2	G3	G2	B2	D4	B2	D3	D4	D3	B2	H3	B2	H2	H3	H3
19	I3	1	E3	E3	S3	1	S3	S3	A4	A4	A3	B2	A4	A4	B3	G4	G2	G3	G4	G3	D3	D4	D3	D4	D4	B4	B2	H4	H3	B2	H4	H3
20	I3	C2	F2	Q2	S2	Q2	S3	Q2	A4	A5	A4	A3	A5	A4	G5	G5	G4	G4	G5	G4	D5	D5	D5	B3	D4	D4	H5	H5	H4	H4	H5	H5
21	I4	C3	F3	1	S2	1	F2	Q2	A3	A4	A3	A3	A3	A4	G2	G3	G4	G3	G2	G3	D3	D5	D4	1	D4	D5	H2	H3	H3	H4	H3	H3
22	I	1	E3	1	S5	Q3	S5	S5	A4	A4	B3	B3	A3	A4	G3	G4	B4	G3	G4	G5	D4	D4	B3	B3	D4	D5	H4	H5	B4	H3	H3	H5
23	I3	C4	F2	Q4	E4	Q3	F3	Q3	A3	A3	B3	B3	A3	A3	G3	G3	B3	G3	G3	G3	D2	D3	B3	B2	D3	D3	H3	H3	B2	H2	H2	H3
24	I3	C2	F3	Q3	S4	Q3	S4	1	A3	A3	B2	A3	A2	A3	G3	G3	B2	G3	G2	G3	D4	D4	D3	D3	D4	D4	H3	H3	B3	H3	H3	H3
25	II3	1	F3	Q4	S5	1	S5	S5	A2	A4	B3	A5	A4	A4	G2	G4	B3	1	G5	G5	B3	D3	B4	B4	D4	D4	H4	H4	B3	H4	H4	H4
26	I	1	F5	Q5	S2	1	F3	Q3	A5	A3	B3	A3	A3	A4	G5	G5	G3	G3	G3	G3	D5	D4	D3	D3	D3	D3	H4	H3	H3	H3	H3	H3
27	I	C3	F3	Q5	S5	Q5	S5	S2	A5	A5	B3	A5	A5	A5	G5	G5	B3	G5	G5	G5	D5	D5	B3	D5	D5	D5	H5	H5	B3	H5	H5	H5
28	I4	C5	E3	E3	S2	F3	S3	S2	A5	A5	A5	A5	A5	A5	G5	G5	G5	G5	G5	G5	D5	D5	D5	D5	D5	D5	H5	H5	H5	H5	H5	H5
29	I3	C2	E3	Q2	S2	Q4	S4	1	A2	A3	A3	A2	A4	A4	G2	G3	G3	B2	G4	G4	B2	D4	D3	B3	D4	D4	H2	H4	H3	H2	H4	H4
30	I2	T2	E5	1	S3	Q3	S2	S2	A2	A4	A2	A2	A3	A3	G4	G5	G3	G3	G5	G5	D3	D5	D3	B3	D3	D3	B3	H2	B3	B3	H2	H2
31	I3	T4	F4	Q3	E3	1	F3	Q3	A4	A4	B3	A4	A4	A4	G4	G4	B3	G4	G3	G3	D2	D4	D3	B4	D3	1	H3	H5	B2	H4	H4	H3
32	I	1	E3	Q3	S4	Q3	S4	1	A5	A4	A3	A4	A5	A4	G4	G5	G3	G4	G5	G4	D3	D4	D3	D5	D5	D4	H3	H5	H3	H4	H4	H4
33	II3	T4	E2	1	S3	Q3	1	1	A3	A5	A3	A2	A4	A4	G5	G3	G3	G2	G4	G4	D4	D4	D3	D2	D4	D4	H4	H4	H3	H3	H4	H3
34	I3	C3	E3	Q3	S2	Q3	S2	1	A2	A4	A2	A2	A3	A2	B3	G4	B2	G3	G3	G2	B4	D4	D3	B3	D3	B3	B4	H5	H3	H3	H3	H2
35	I3	T3	E4	Q3	S2	Q3	S3	Q2	A3	A4	B3	A4	A4	A4	G4	G3	B4	G4	G4	G4	D5	D5	D2	D5	D3	B2	H3	H3	H4	B2	H3	H3
36	I2	T4	F3	Q3	S4	Q3	S3	S2	A2	A4	A3	A4	A4	A3	G3	G4	G3	G3	G4	G3	D3	D4	D3	D3	D4	D4	H3	H4	H2	H4	H3	H2
37	I3	C4	E3	Q2	E2	1	F2	Q2	B2	A4	A4	A3	A3	A3	G2	G3	G3	G3	G3	G3	D2	D2	D4	D2	D3	D4	H3	H4	H3	H3	H3	H3
38	I4	C3	F3	Q3	1	F3	F3	Q3	A3	A4	A3	A4	A3	A4	G3	G4	G3	G4	G3	G4	D4	D4	D3	D3	D3	D4	H3	H4	H3	H3	H3	H4
39	I3	C4	F3	E2	S3	F3	S4	S3	A3	A3	A2	B2	A3	1	G4	G4	B2	G3	B2	1	B2	B2	B3	B4	D3	B2	H3	H3	H2	B3	B2	B3
40	I	T2	F5	Q2	E3	F3	F2	Q3	A5	A4	A4	B3	A4	A5	G5	G5	G4	B3	G5	G5	B3	D2	D3	B3	D5	D5	H4	H5	H3	H5	H5	H5

Note: I=group of quantitative factors; II=group of qualitative factors; 1=equal superiority; 2=slight superiority; 3=strong superiority; 4=very strong superiority; 5=absolute superiority; B=base system; A=telescopic beam and props system; G=shorebrace system; D=table form system; H=early striking; C=cost; T=construction time; E=expected familiarity; F=flexibility; Q=quality; S=safety.

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