Modeling a Contractor's Markup Estimation

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Abstract: The estimation of markup is a difficult process for contractors in a changeable and uncertain construction environment. In this study, a fuzzy logic-based artificial neural network (ANN) model, called the fuzzy neural network (FNN) model, is constructed to assist contractors in making markup decisions. With the fuzzy logic inference system integrated inside, the FNN model provides users with a clear explanation to justify the rationality of the estimated markup output. Meanwhile, with the self-learning ability of ANN, the accuracy of the estimation results is improved. From a survey and interview with local contractors, the factors that affect markup estimation and the rules applied in the markup decision are identified. Based on the finding, both ANN and FNN models were constructed and trained in different project scenarios. The comparison of the two models shows that FNN will assist contractors with markup estimation with more accurate results and convincing user-defined linguistic rules inside.

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Introduction

In the construction industry, bidding is generally the most popular form for contractors to secure the right to provide services in a new job (Ahmad and Minkarah 1987; De Neufville and Smith 1994). Identifying the optimum markup for a job is an essential part of the contractors' bid preparation. A slight difference in the markup percentage applied to the same job will affect the bidding outcomes, which would consequently influence the survival, growth, and profitability of the contract organization (Tah et al. 1994).

In the research domain related to bidding, there are many different definitions for markup. In this research, markup is defined as the sum of contingencies and profit. Markup is calculated as a percentage of the sum of overhead and direct costs for material, labor, and equipment. With this definition, the research effort is devoted to the aspect of competition analysis in markup estimation.

Determining the markup size for a construction project is not an easy task (Shash and Abdul-Hadi 1993). The complexity of this issue is magnified by many influencing factors (Shash and Abdul-Hadi 1992) and the uncertain potential outcomes of the decision (winning or losing the contract). Many uncertain and complex factors are involved in the early stage of bid preparation, such overall economy, competitiveness of other bidders, etc. Moreover, the relationship among the factors is dynamic and complex. Therefore, for a long time, markup estimation has been perceived as a kind of mysterious work, mainly based on the estimators' intuition and experience, with some specific rules and constraints applied (Li 1996).

The aim of this paper is to investigate whether a contractor's markup estimation can be accurately modeled. Under this aim, the specific objectives are: (1) To lay down the methodology for constructing and testing a markup estimation model using fuzzy neural network (FNN) technology and (2) to evaluate the practicality and effectiveness of FNN and artificial neural network (ANN) technologies for markup estimation.

It is important to be able to model markup estimation as the model can act as a decision aid to help contractors to overcome their shortcomings in judgment and limited short-term memory, which prevent them from processing large amounts of information. This study is also important because it contributes to knowledge in two ways. First, it expands the usage of FNN technology into markup estimation. Second, the study provides evidence that FNN is superior to ANN in being self-explanatory and having a higher accuracy in markup prediction for the examples given in this study.

The paper makes two new contributions. First, it provides contractors with a tool which uses the FNN technique to estimate the markup size. This FNN model is able to give contractors the reasons why a particular markup size was chosen. This is an improvement over previous works which were mainly based on the ANN technique [see, for example, Moselhi et al. (1991); Hegazy and Moselhi (1994)]. In ANN models, no explanations are provided as these models are "black boxes." With the explanations provided in the FNN model, it would be easier for contractors to understand the choice of a particular markup size and the bases of the rules. Hence, the results of the FNN would be more acceptable to the users. Unlike previous ANN models, the FNN model constructed in this paper is easier for users to make the necessary adjustments to meet their special requirements or accommodate changes in the market. Second, with the fuzzy inference rules embedded, the estimating accuracy of the FNN model is improved (see the section entitled, "Model Testing") compared to previous ANN models.

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This study may be of interest to contracting organizations and construction information technology (IT) consultants. Using the methodology proposed here, contracting organizations could model an expert's optimum markup. In the absence of the expert, the contracting organization could still estimate an optimal markup size. Contractors who have not been very successful in winning bids could learn from the markup estimation model constructed in this paper. Construction IT consultants may adopt the methodology proposed in this paper to construct markup estimation models for their individual contracting clients.

After the introduction, ANN and FNN systems are reviewed and important factors affecting markup estimation are identified. This is followed by a description of the research methodology and model development. After this, the test results are presented and discussed. The paper ends with conclusions and a discussion of the limitations of the study.

Fuzzy Neural Networks

Previous works on markup estimation have been based on ANN. In order to improve the estimating accuracy, and make the model more acceptable to users and more flexible, this study makes use of FNN which combines ANN and fuzzy logic. The three techniques: ANN, fuzzy logic, and FNN are now briefly reviewed.

The current practice of markup estimation is characterized by the strong nonlinearity between the factors influencing markup estimation and the markup size that should be applied accordingly. The uncertainty and complexity associated with the influencing factors vary considerably. These characteristics require modeling techniques for markup estimation to be capable of handling nonlinearity, uncertainty, and subjectivity.

ANN is a massive parallel-distributed processor that has a natural propensity for storing experiential knowledge and making it available for use (Lin and Lee 1996). Owing to their excellent learning and generalizing capabilities, ANN techniques have been applied to a variety of construction domains, including predicting potential to adopt new construction technology (Chao and Skibniewski 1995), forecasting of construction productivity (Chao and Skibniewski 1994), predicting earthmoving operations (Shi 1999), simulating activity duration (Lu 2002), and the forecast of residential construction demand (Goh 2000). In recent years, ANN techniques have also been used in predicting project cost. For example, Emsley et al. (2002) developed ANN cost models based on data collected from nearly 300 building projects to evaluate the total construction cost for clients. They used linear regression techniques as a benchmark to evaluate the ANN models and found out the ANN models have a higher ability to model the nonlinearity in the data. Williams (2002) used ANN and regression models to predict the completed cost of competitively bid highway projects constructed by the New Jersey Department of Transportation. It was found that the best performing regression model produced superior predictions to the best performing ANN model. Hybrid models that used a regression model prediction as an input to an ANN model produced reasonable predictions. Attalla and Hegazy (2003) used ANNs and statistical analysis to predate cost deviation in reconstruction projects. The results show that while both models had similar accuracy, the ANN model is more sensitive to a larger number of variables.

Research efforts have been made in developing ANN-based markup estimating systems (Moselhi et al. 1991). Hegazy and Moselhi (1994) proposed ANN systems for an analogy-based solution to markup estimation. Li (1996) compared the performance of ANN to a regression-based technique and identified the effect of different configurations of neural networks on estimating accuracy. Li and Love (1999) presented a computer-based markup decision support system that integrated a rule-based expert system and an ANN-based system.

To date, most research efforts regarding the application of ANN to construction have focused on utilizing the ANN's capability to handle highly nonlinear aspects. However, the ANN system has several disadvantages. As the calculation processes are in the black box, users do not know how the outputs are produced from the input variables. Moreover, the accuracy of the estimation results is not very high. These disadvantages can be partially overcome by adopting fuzzy logic.

The fuzzy set theory (Zadeh 1965), can tackle the uncertainties involved in the process markup estimation. However, fuzzy logic has its own disadvantages. As all the rules are extracted from experts' experience, the fuzzy systems are somewhat subjective and the rule-forming process is time consuming and expensive.

A FNN is a technology, which combines fuzzy logic with ANN (Haykin 1994). With fuzzy logic inference rules embodied in the structure, the FNN can learn knowledge and adjust the parameters of the system according to the training data. Therefore, by integrating the two systems, the strengths of both fuzzy reasoning (i.e., ability in handling uncertainty associated with qualitative information) and ANN (i.e., ability in learning and generalizing from historical markup estimation cases) are enhanced (Lam et al. 2001). It is likely that substantial improvements in ascertaining a contractor's markup can be made by merging ANN and fuzzy logic. However, little has been published on the application of FNN to a contractor's markup estimation. This study aims to fill this gap in knowledge.

Broadly speaking, there are three categories of the merging format of these two technologies: i.e., neural fuzzy systems (the use of ANN as a tool in fuzzy models), FNN (fuzzification of conventional ANN models), and fuzzy-neural hybrid systems (incorporating fuzzy technologies and ANN into hybrid systems) (Lin and Lee 1996). The second kind of combination, FNN, keeps the advantages from both sides while its structure is easily understood and applied. Therefore, it is adopted for the markup estimation model construction.

Research Methodology

The fieldwork was comprised of two parts. The first was to obtain feedback on the importance of factors from contractors. The second part was to enlist the help of a contractor with extensive experience in markup estimation to provide input to construct and validate the model.

The first part of the fieldwork was undertaken to determine the most important and significant variables that affect markup estimation. Data were collected via postal questionnaires. The primary section of the questionnaire was comprised of statements regarding the 52 attributes in 7 main categories that may affect markup estimation, identified in the literature. Respondents were asked to rank the main factors from 1 to 7. The most important five factors out of the seven were identified using the Hungarian method. Respondents were also asked to indicate the importance of these attributes on a five-point Likert scale, where 1 represented a response of "very unimportant," 3 represented "moderate," and 5 stood for "very important." Then, the most important attributes under some of those main factor categories were chosen to establish the model. Another part of the questionnaire invited

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respondents to add other factors, which would influence markup estimation, and to also rate their degree of importance.

The survey package consisted of a cover letter addressed to the managing director of the firm explaining the purpose of the survey, the questionnaire itself, and a self-addressed stamped envelope. Respondents' anonymity was guaranteed and they were given one month to return the completed questionnaire. They were also told that they could request a summary of the results.

A research decision was made to send the survey package to all 142 government registered General Building and Civil Engineering contractors with issued capital exceeding US$1 million each. This group was chosen because large contracting firms have more bidding experience, as compared with smaller firms.

The usable returned questionnaires were then edited and coded into the computer. Mean importance ratings and the statistical t-test of the mean were carried out to find out if the population would agree that the attribute was important. Using the t-test results, the most important attribute in the category was then identified. Five attributes that were found to be statistically most important were identified, and formed the basis for constructing the markup estimation model. More attributes were not used to construct the model because too many attributes or descriptions would require too many rules to be identified in the interview. The FNN model will then become very complex, with many parameters to be adjusted, and long training and calculation times to construct the model.

To construct the model, the data collection method used was based on a structured interview. The aims of the structured interview were to collect from an expert the following: (1) Fuzzy inference rules, (2) markups that are likely to be applied to different project scenarios, and (3) actual markups applied to past projects.

The rules were collected through a face-to-face interview with an expert. Several leading contracting organizations in Singapore were invited to participate in the study. One contractor then expressed interest in the study. He is a director of a large construction company and has more than 20 years of working experience in the construction industry. He has handled many projects from bid preparation to completion of construction. Thus, his opinions and views are very significant and valuable for this research.

Only one expert was interviewed because every construction company has a different managing style, and understanding about the project and economic conditions that it faces. As such, the rules for markup estimation differ. Therefore, the FNN model was constructed based on one particular construction company. By doing this, the estimation results can be useful and meaningful (at least to that particular company). If a FNN model was constructed based on the decision rules of many different contractors, the estimation accuracy may be low when a contractor tries to use the model. This method of constructing a FNN model based on one firm is consistent with previous studies. For example, Tavakoli and Utomo (1989) constructed an expert system based on the knowledge collected from an interview with one construction cost estimating and bidding expert. However, the findings of this paper are useful because the *method* and *shell* of the FNN model are laid down.

The collection of necessary samples for model training was also done in the structured interview. The Expert was also invited to give optimum markup sizes to a series of hypothetical project scenarios. The design of the hypothetical project scenarios is based on the five most important factors found in the survey. In the precondition part, each attribute was given an even value, which ranged randomly from 1 to 10. Generally, a bigger number represented a better condition. For example, on the attribute "availability of work," 10 means "there is an abundance of work in the current market," while 1 means "very few work chance available." A total of 32 different project scenarios were provided. The reason for using 32 hypothetical projects is that there are 32 fuzzy inference rules proposed in the first part. Theoretically, 32 randomly produced hypothetical projects are able to ensure a reasonable accuracy in the result (Li and Love 1999).

The Expert was also asked to provide the bidding information of three projects in which his company was successful in the bidding exercise. The three projects had to represent the three different bidding conditions of "bad," "normal," and "good." These cases were used to test the performance of the FNN and ANN models.

Table 1. Most Important Attributes Affecting Markup Estimation

Factor (in descending order of importance)	Attribute code	Most important attribute under each factor	Mean rating
Economic conditions	AW	Availability of work	4.03
Client characteristics	PRC	Payment record of client	4.31
Bidding situation	CB	Competitiveness of other bidders	4.17
Project characteristics	PC	Project complexity	4.00
Company characteristics	NW	Need for work	4.10
Consultant characteristics	—	Relationship with consultant[a]	4.10
Project documents	—	Presence to owner's special requirement[a]	4.00

[a]Not included in model construction because the factor is relatively unimportant.

Important Factors Influencing Markups

The likely factors that influence markup were obtained from past studies (Ahmad and Minkarah 1988; Shash and Abdul-Hadi 1992, 1993; Shash 1993; Akintola and Fitzgerald 2000). From these studies, 52 attributes were uncovered and grouped into seven categories. As described in the preceding section, a postal survey was conducted to identify the five most important factors affecting markup.

A total of 142 survey packages were sent out on September 1, 2000. Responses were received between September 5 2000 and October 6, 2000. Twenty-nine valid responds were received, giving a response rate of 20%. The respondents indicated that they had worked in the construction industry from 4 to 36 years, with an average of 15 years. The total sales volume was about 15% of the construction output, indicating that the survey had captured the interest of a significant portion of contractors. This indicates that the research is an important area and of great interest to contractors. The questionnaire listed seven main factors that may affect markup. Respondents were asked to rank them from 1 to 7, in decreasing order of importance. The 29 respondents provided different rankings and the Hungarian method was used to ascertain the overall rankings (Kuhn 1955; Yoon and Hwang 1995). The Hungarian method was used because it provides a scientific way to identify the rank of attributes by introducing a distance function as a measure of agreement or disagreement between rankings (Cook and Seiford 1978). After calculation, the relative importance of the seven main factors is ascertained (see results in Table 1).

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Under each of the seven major factors, several attributes were operationalized. Respondents were asked to rate on a five-point scale importance of these attributes when contractors decide on the markup. After the responses were processed, the mean importance ratings for all the attributes were calculated. The formula for calculating the mean importance rating is

$$T_h = (1(n_1) + 2(n_2) + 3(n_3) + 4(n_4) + 5(n_5))/(n_1 + n_2 + n_3 + n_4 + n_5) \quad (1)$$

where n_1, n_2, n_3, n_4, and n_5 = number of respondents who indicated on the five-point scale, the level of importance as 1, 2, 3, 4, and 5, respectively, for attribute h, where 1 represented "very unimportant," 2 for "unimportant," 3 for "moderate," 4 indicated "important," and 5 stood for "very important."

From the mean importance ratings calculated, the attributes are ranked in order of importance under each category (Table 2) and the most important attribute under each category is extracted and shown in Table 1. The most important attribute from each of the top five factors (ascertained through the Hungarian method described earlier) were chosen as input variables for the FNN model.

Model Development

The next stage of the study is to construct a markup estimation model. The model is then used to estimate markup in future projects. This predictive model also offers contractors insight into which factors are most likely to affect markup. The markup estimation model was constructed based on FNN and ANN technology. The performances of these two models were compared to ascertain which technology is superior.

Fuzzy Neural Network Modeling

There are many different variations of FNN model. For example, Lam (2001) used a five-layer model, which included a normalization layer. In this paper, the normalization function was included in the defuzzification layer, based on Lin and Lee (1996, 552–553). Therefore, the FNN model constructed for this study consists of four layers: An input layer of five nodes, a fuzzification layer with ten membership functions, a base rule layer with 32 fuzzy inference rules, and a defuzzification layer (see Fig. 1). The output layer has one node, which represents the markup percentage. Several different types of neurons were employed in the network. They had different activation functions and carried out different information processing functions.

In Fig. 1, AW represents availability of work, PRC represents payment record of client, CB represents competitiveness of other bidders, PC represents project complexity, and NW represents need for work. The first layer (input layer) reads the real number inputs for variables X_i $(i=1,2,\ldots,n)$. The evaluation of the five most important factors (AW, PRC, CB, PC, and NW) was entered. The second layer (fuzzification layer) fuzzifies X_i according to the membership functions. Every input value X_i has m membership degrees $\mu_{A_i^j}(X_i)$, $(j=1,2\ldots,m)$ of the linguistic characteristic terms. This is represented mathematically in Eq. (2) below.

$$\mu_{A_i^j}(X_i) = f(a_i^j, b_i^j) \quad (2)$$

where $f(a_i^j, b_i^j)$ = membership function employed; and a_i^j and b_i^j = parameters of the membership functions.

Table 2. Attributes Ranked by Mean Importance Ratings

Rank	Factors	Mean
1 Project characteristics		
1	Project complexity	4.00
2	Project cash flow	3.86
3	Degree of hazard (safety)	3.66
4	Type of equipment required	3.66
5	Project duration	3.62
6	Risk involved owing to the nature of the work	3.59
7	Job related contingency	3.48
8	Project size	3.41
9	Type of project (resident/office/hotel)	3.34
10	Past profit in similar jobs	3.27
11	Location of projects	2.97
2 Project documents		
1	Presence of owner's special requirement	4.00
2	Completeness of the documents	3.83
3	Quantum of liquidated damages	3.79
4	Design quality	3.76
5	Type of contract conditions used	3.72
6	Type of contract (Bills of quantities, lump sum, cost plus)	3.34
7	Insurance premium	3.06
8	Performance of bond requirement	3.00
3 Company characteristics		
1	Need for work	4.10
2	Reliability of company pricing	3.97
3	Portion of subcontracted to domestic subcontractors	3.90
4	Contractor involvement in the design phase	3.90
5	Portion of subcontracted to nominated subcontractors	3.86
6	Availability of qualified site management staff	3.76
7	Availability of reliable subcontractors	3.72
8	Availability of skilled workers	3.72
9	Current work load	3.69
10	Size of general (office) overhead	3.51
11	Availability of required cash to carry out the work	3.37
4 Bidding situation		
1	Competitiveness of other bidders	4.17
2	Identify of competitors	3.89
3	Number of bidders	3.62
4	Time allowed for submitting bids	3.48
5	Bidding method (e.g. open/selecting)	3.47
6	Prequalification requirements	3.34
7	Quantum of bid deposit	3.03
8	Time of bidding (e.g. close to Chinese New Year)	3.02
9	Bidding document price	2.7
5 Economic situation		
1	Overall economy (availability of work)	4.03
2	Availability of other project for bidding	3.93
3	Quality of available labor	3.86
4	Availability of labor	3.79
5	Risk of fluctuation in material prices	3.72
6	Risk of fluctuation in labor prices	3.10
7	Availability of equipment	3.00
6 Client characteristics		
1	Payment record of client	4.31
2	Size of client	4.21

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Table 2. (*Continued.*)

Rank	Factors	Mean
3	Type of client (public/private)	4.17
4	Relationship and past experience with project owner	4.07
7 Consultant characteristic		
1	Relationship with consultant	4.10
2	Character of consultant	4.07

There are many other types of functions available to be chosen as the membership function, for example, the generalized bell curve function, B-spline function, S-shape function, and Z-shape function. Under each main function category, there are many variations. According to Lin and Lee (1996), the membership functions commonly used are bell-shaped (Gaussian) functions, triangular functions, and trapezoidal functions. More complex parameterized functions, such as B-spline functions or even the functions implemented by neural networks, can also be used as input membership functions and tuned in much the same way. In this study, Gaussian functions are adopted because: (1) If we use the triangular or trapezoidal function as the membership function, in the training function, we will have 0 in the denominator when we need to adjust parameters in the membership function and (2) if we use the Gaussian function, we could avoid this problem.

In this FNN model, each of the input variables was transformed into two fuzzy sets using the Gaussian functions. For example, on the attribute "availability of work," "abundant" and "scarce" were used to describe it. Each neuron corresponds to a particular fuzzy set with the membership function given. Based on the general equation, Eq. (2), two membership functions were employed for each input variable, as shown in Eq. (3) below

$$\mu_{A_i^j} = \exp(-((X_i - a_i^j)/\sqrt{2}b_i^j)^2) \quad (3)$$

where X_i=input variable of the FNN model; and $\mu_{A_i^j}$ =membership degree of X_i. When the input variable is experiencing a negative trait, the parameter a_i^j determining the center value is set at 0. When the input variable is experiencing a positive trait, a_i^j is set at 10. In regard to the parameter determining the width of the membership function b_i^j, a trial-and-error process showed that $b_i^j=4$ is the most appropriate, because when $b_i^j=4$, the membership function can represent the membership degree logically (for a positive trait, when input $X_i=10$, the membership degree is 1; when $X_i=5$, the membership degree is close to 0.5; and when $X_i=0$, the membership degree is close to 0. For a negative trait, when input $X_i=0$, the membership degree is 1; when $X_i=5$, the membership degree is close to 0.5; and when $X_i=10$, the membership degree is close to 0).

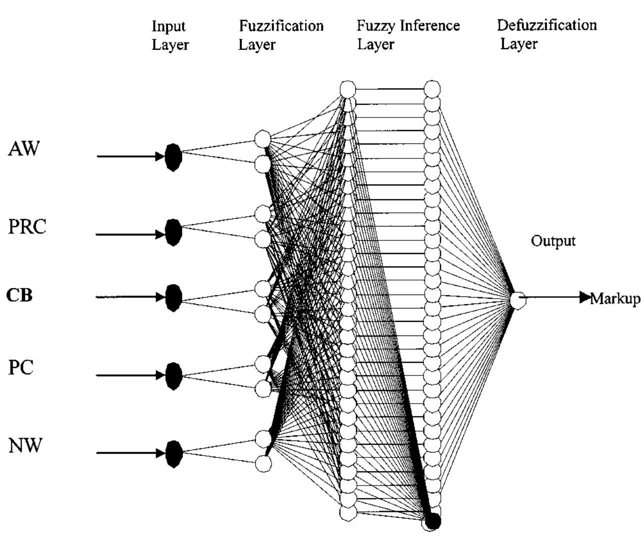

Fig. 1. Structure of the fuzzy neural network model

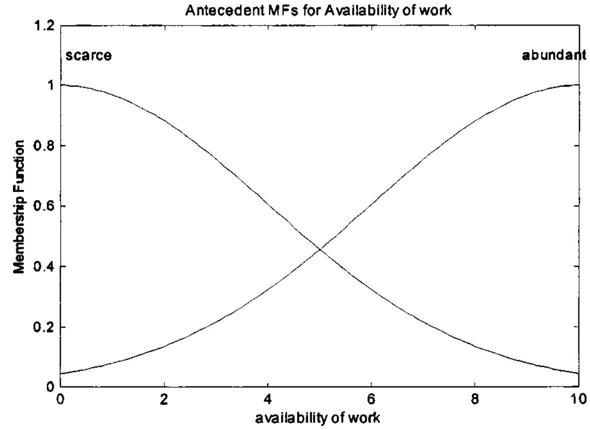

Fig. 2. Membership function of the input variable availability of work

As an example, the input variable availability of work is now used to illustrate how the membership functions are constructed. The membership function representing the scarcity of work for the input variable availability of work is as shown in Eq. (4)

$$\mu_{A_i^j} = \exp(-((X_i - 0)/(4\sqrt{2}))^2) \quad (4)$$

The membership function representing abundance of work for the input variable "availability of work" is as shown in Eq. (5)

$$\mu_{A_i^j} = \exp(-((X_i - 10)/(4\sqrt{2}))^2) \quad (5)$$

These membership functions are shown in Fig. 2.

The third layer is the fuzzy inference layer, where the rules generally employed for markup estimation are installed. This layer calculates μ_k as the active degree of the rule K, as shown in Eq. (6).

$$\mu_k = \mu_{A_1^j}(X_1)\mu_{A_2^j}(X_2)\cdots\mu_{A_n^j}(X_n) \quad (6)$$

In this study, fuzzy singleton rules were applied. The form of fuzzy singleton rules is: R^k :IF X_1 is A_1^j AND X_2 is A_2^j AND… AND X_n is A_n^j, THEN Y is W_k.

Examples of rules are given below.

1. IF "availability of work" is *Scarce*, "payment record of client" is *Good*, "competitiveness of other bidders" is *Strong*, "project complexity" is *Low*, and "need for work" is *High*, THEN "markup size" is *Very Low*.
2. IF "availability of work" is *Abundant*, "payment record of client" is *Not Good*, "competitiveness of other bidders" is *Weak*, "project complexity" is *High*, and "need for work" is *Low*, THEN "markup size" is *High*.

These rules were extracted from the Expert during the structured interview. These are a series of IF-THEN questions. The precondition part of each question is a combination of the five most important factors identified in the questionnaire survey. Every factor was given two terms to describe its status. With the five most important attributes and two descriptions for each attribute, the preconditions of 32 (being 2^5) rules were compiled. After

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Table 3. Thirty-Two Fuzzy Inference IF Rules

No.	IF	Availability of work	Payment record of client	Competitiveness of other bidders	Project complexity	Need for work	THEN	Markup provided by the expert
1	IF	Abundant	Good	Strong	High	High	THEN	Medium
2	IF	Abundant	Good	Strong	High	Low	THEN	Medium-high
3	IF	Abundant	Good	Strong	Low	High	THEN	Low
4	IF	Abundant	Good	Strong	Low	Low	THEN	Medium-high
5	IF	Abundant	Good	Weak	High	High	THEN	Medium-high
6	IF	Abundant	Good	Weak	High	Low	THEN	High
7	IF	Abundant	Good	Weak	Low	High	THEN	Medium
8	IF	Abundant	Good	Weak	Low	Low	THEN	Medium-high
9	IF	Abundant	Not Good	Strong	High	High	THEN	Medium
10	IF	Abundant	Not Good	Strong	High	Low	THEN	High
11	IF	Abundant	Not Good	Strong	Low	High	THEN	Medium
12	IF	Abundant	Not Good	Strong	Low	Low	THEN	Medium-high
13	IF	Abundant	Not Good	Weak	High	High	THEN	Medium
14	IF	Abundant	Not Good	Weak	High	Low	THEN	High
15	IF	Abundant	Not Good	Weak	Low	High	THEN	Medium
16	IF	Abundant	Not Good	Weak	Low	Low	THEN	Medium-high
17	IF	Scarce	Good	Strong	High	High	THEN	Very-low
18	IF	Scarce	Good	Strong	High	Low	THEN	Medium
19	IF	Scarce	Good	Strong	Low	High	THEN	Very-low
20	IF	Scarce	Good	Strong	Low	Low	THEN	Medium
21	IF	Scarce	Good	Weak	High	High	THEN	Very-low
22	IF	Scarce	Good	Weak	High	Low	THEN	Very-low
23	IF	Scarce	Good	Weak	Low	High	THEN	Very-low
24	IF	Scarce	Good	Weak	Low	Low	THEN	Low
25	IF	Scarce	Not Good	Strong	High	High	THEN	Low
26	IF	Scarce	Not Good	Strong	High	Low	THEN	Very-low
27	IF	Scarce	Not Good	Strong	Low	High	THEN	Very-low
28	IF	Scarce	Not Good	Strong	Low	Low	THEN	Low
29	IF	Scarce	Not Good	Weak	High	High	THEN	Very-low
30	IF	Scarce	Not Good	Weak	High	Low	THEN	Low
31	IF	Scarce	Not Good	Weak	Low	High	THEN	Very-low
32	IF	Scarce	Not Good	Weak	Low	Low	THEN	Very-low

interviewing the Expert who is the director of the company, 32 fuzzy inference rules are formed.

The expert was then asked to indicate the likely markup sizes that he would include in his bids, if he encountered each of the 32 bidding situations. In providing the likely markup size, he used five levels: "Very low" (2%), "low" (4%), "medium" (6%), "medium-high" (8%), and "high" (10%). The result of his estimation is shown in the last column of Table 3. After the Expert had indicated the level of markup, the relationships among the input attributes and output variable were transferred into a computer program. The 32 fuzzy inference rules collected from the interview were converted into mathematical equations according to Eq. (6), as shown in Eq. (7) below

$$\mu_k = \mu_{A_1^j}(X_1) \cdots \mu_{A_n^j}(X_5) \tag{7}$$

where μ_k=active degree of the kth rule; and $\mu_{A_i^j}(X_i)$ =membership degree of the ith input factor's jth characteristics.

Layer four defuzzifies the final output Y with centroid defuzzification equation [Eq. (8)] shown below

$$Y = \sum_{k=1}^{32} (\mu_k w_k) \Bigg/ \sum_{k=1}^{32} \mu_k \tag{8}$$

where w_k=markup percentage from the kth rule; and Y=final estimated markup percentage.

The computer program for the FNN model was written based on *MATLAB* software. The complete program that implemented the proposed system contained more than 2,000 lines of codes in the *MATLAB* programming language. Approximately 3,000 iterations were utilized to train the FNN model.

A number of algorithms are available for training the FNN, including the back propagation algorithm, back propagation on α-cuts method (Hayashi et al. 1993), conjugated gradient algorithm (Hu 1997), and genetic algorithm (Goldberg 1989). For simplicity, back propagation algorithm was used to train the FNN. The objective of training is to minimize the sum-of-square errors, E, between the calculated output of the network and the actual markup size applied in the real case. The formula for E is:

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$$E = 0.5 \cdot (Y - Y^d)^2 \quad (9)$$

where Y^d = desired output of the FNN system; and Y = output from the FNN model. The parameters of the network can be adjusted as follows to minimize the sum-of-square errors:

$$a_i^j(t+1) = a_i^j(t) - \eta_a \mu_k(X)(W_k - Y)(Y - Y^d) \Bigg/ \left(\left(\sum_{k=1}^{K} \mu_k(X) \right) \mu_{A_i^j}(X_i)(\partial \mu_{A_i^j}(X_i)/\partial a_i^j) \right) \quad (10)$$

$$b_i^j(t+1) = b_i^j(t) - \eta_b \mu_k(X)(W_k - Y)(Y - Y^d) \Bigg/ \left(\left(\sum_{k=1}^{K} \mu_k(X) \right) \mu_{A_i^j}(X_i)(\partial \mu_{A_i^j}(X_i)/\partial b_i^j) \right) \quad (11)$$

$$w_k(t+1) = w_k(t) - \eta_w (Y - Y^d) \mu_k(X) \Bigg/ \sum_{k=1}^{K} \mu_k(X) \quad (12)$$

where $a_i^j(t+1)$, $b_i^j(t+1)$ and $w_k(t+1)$ = value of a_i^j, b_i^j, and w_k at the iteration of training step i; and η_a, η_b, and η_w = learning rates of a_i^j, b_i^j, and w_k. The learning rate controls the rate at which the parameters are allowed to change at any given presentation. Higher learning rates speed up the convergence process, but can carry the potential risk of a network dipping into local minimum and lead to oscillation. In this study, a learning rate of 0.001 was adopted. Based on these update functions, the three sets of parameters of a_i^j, b_i^j, and w_k could be adjusted gradually. The results of the training are discussed in a later section.

Artificial Neural Network Modeling

In constructing the ANN model for this study, typical three-layered back propagation ANN models were first established. Each of the ANN models consisted of an input layer, a hidden layer, and an output layer. The input layer has five nodes which represent the five independent variables. The output layer has one node, which is the markup percentage. The number of nodes for the hidden layer was determined by trial and error. Using *MATLAB* software, different nodes in the hidden layer were experimented to investigate the estimating accuracy of the ANN models.

Starting from four hidden nodes structure, the ANN model was trained and analyzed. If the accuracy of the estimation result was good, one node was reduced from the hidden layer. Otherwise, one node was added. This process was repeated until the best ANN structure was established. For every model with the same nodes in the hidden layer, transfer function log-sigmoid and tangent-sigmoid were applied alternatively to find out the best learning rules of the network.

The experiment started with a network containing four hidden nodes and tangent-sigmoid active function (NT4) and a network of four hidden nodes and log-sigmoid active function (NL4). After 150,000 cycles of training, the error of the outputs during the training process converged to a certain amount. But the accuracy of the outputs measured by mean square error (MSE) from both models was not high. The experiment was continuously conducted until the MSE decreased to an acceptable range when seven nodes were embedded in the hidden layer. Eight ANN models were trained in this experiment. The training results are listed in Table 4. It shows that the ANN model with seven hidden nodes and log-sigmoid active functions (NL7) has the best estimation performance.

Table 4. Training Results of Artificial Neural Network Models

Network name	MSE	Times of training
(Group 1)		
Network T4 (NT4)	2.4011	150,000
Network T5 (NT5)	0.9077	150,000
Network T6 (NT6)	0.1240	150,000
Network T7 (NT7)	0.0649	150,000
(Group 2)		
Network L4 (NL4)	0.2133	150,000
Network L5 (NL5)	0.7644	150,000
Network L6 (NL6)	0.0731	150,000
Network L7 (NL7)	0.0499	69,304

Model Testing

The next step is to check whether the procedures for constructing the markup estimation model are correct, in that robust models were produced. Cross validation was used by comparing what the model proposed with the actual markup size used. In addition, another technique (ANN) was used to estimate the markup size under similar conditions, to enable comparison of FNN and ANN technologies. The Expert was asked to provide information about three real projects in which his firm successfully won the bids. More cases were not used to validate the model due to time limitations. However, this is not expected to nullify the work, following the triangulation concept (Hammersley and Atkinson 1983). The triangulation concept states that information about a single phenomenon should be collected from at least three different sources or using at least three different techniques.

An example of a test sample collected from the Expert is a project for the construction of an eight-story factory. The contract commenced in 1996 and finished in 1998. When the company prepared to bid for this project, the economy was good and the construction market was prospering. The Expert evaluated the five input factors on a ten-point scale as follows: Availability of work = 8; Payment record of client = 10; Competitiveness of other bidders = 10; Project complexity = 8; and Need for work = 6. This success markup size was 7%.

The ratings for the five input variables for each of the cases were entered into the ANN and FNN models. Based on the information, the forecasted markups were computed by the computer programs. These forecasted markups were compared to the actual markups used by the Expert. The accuracy of the models is determined by calculating the error, percentage error (PE), mean PE (MPE), and mean absolute PE (MAPE) (see Table 5). The formula are shown below.

$$\text{Error} = M - M_M \quad (13)$$

$$\text{PE} = ((M - M_M)/M) \times 100\% \quad (14)$$

$$\text{MPE} = \sum_{i=1}^{n} \text{PE}_i / n \quad (15)$$

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Table 5. Results of Forecast by the Fuzzy Neural Network (FNN) and Artificial Neural Network (ANN) Models

	FNN model				ANN model		
Case	Expert's actual markup (M) (%)	Model's markup (M_M) (%)	Error of FNN (%)	Percentage error (%)	Model's markup (M_M) (%)	Error of ANN (%)	Percentage error (%)
1	7	7.3	−0.3	−4.3	6.1	+0.9	+12.8
2	6	5.8	+0.2	+3.3	5.9	+0.1	+1.7
3	3	2.8	+0.2	+6.6	3.9	−0.9	−30
MPE	—	—	—	1.9	—	—	5.2
MAPE	—	—	—	4.8	—	—	14.8

Note: MPE=mean percentage error and MAPE=mean absolute percentage error.

$$\text{MAPE} = \sum_{i=1}^{n} |\text{PE}_i|/n \qquad (16)$$

The MPE gives an indication of whether a model has a greater tendency to over (negative sign) or under (positive sign) forecast. The MAPE is a good measure of the magnitude of the errors incurred by the forecasts.

In the FNN model, the PE is −4.3% for Case 1, 3.3% for Case 2, and 6.6% for Case 3. In the ANN model, the PE is 12.8% for Case 1. For Case 2, the PE is low at 1.7%. But for Case 3, PE is high at −30%. Although in the FNN model the PE for Case 2 is higher than that of the ANN model, the estimation results in the other two cases are better than those from the ANN model, especially for Case 3 where the PE is 6.6% in the FNN model, while the PE is −30% in ANN model. This indicates that the ANN model's performance is erratic. MPE calculations revealed that the FNN model performs better than the ANN model. In terms of MAPE, again the FNN model performed better than the ANN model, with $\text{MAPE}_{\text{FNN}}=4.8\%$, which is significantly less than $\text{MAPE}_{\text{ANN}}=14.8\%$.

Table 5 shows the markup sizes produced by the FNN model are more accurate. This suggests that the FNN has a higher ability to estimate markup size for different projects than ANN models.

Conclusion

This paper aimed to lay down the methodology for constructing and testing a markup estimation model using neural network technology. This aim was achieved because the constructed FNN model, when tested was found to have high predictive abilities. The practical application of this study is that the methodology laid down in modeling markup estimation can be followed by other contractors. This is important because the model becomes a decision aid to help contractors to overcome their limited cognitive capacity by providing consistent and structured frameworks for them to compare decision options. A FNN model to estimate markup helps contractors to reduce reliance on raw judgment and unreliable intuition by giving them a framework to operate. Another objective of this study was to compare the modeling capabilities of FNN and ANN technologies. From Table 5, it can be seen that for Cases 1 and 3, the FNN model predicted markup size with higher accuracy, while the for the Case 2, the ANN model predicted markup with higher accuracy. For the average of the three cases, in general, FNN has higher predictive ability, as its MAPE is 4.8%, compared to 14.8% for the ANN model.

The training cycles of the FNN model were fewer than that of the ANN model, indicating that FNN is more efficient. The theoretical reason behind this phenomenon may be that although the structure of the FNN model looks more complicated than the ANN model, actually, fewer parameters need to be adjusted in the FNN model than the ANN model.

Other advantages of the FNN model over the ANN model are a higher degree of comprehensibility and a relatively easier way of determining the network structure. Once the number of input factors and output nodes and the fuzzy inference rules are determined, the structure of the FNN model is decided. Whereas for the ANN model, even with the number of input variables and output nodes decided, the best structures (the number of layers and nodes of the hidden layer and the ways of connection among the nodes) still need to be determined through experiments.

To model users, it is more difficult to interpret the ANN network parameters, such as the weights and thresholds than those of the FNN parameters such as a_i^j and b_i^j. This is because the ANN's hidden layer is a black box (Li and Love 1999), while for FNN, fuzzy inference rules are set out. Thus, it is difficult for users to understand the inference process through ANN models. The FNN model, as tested on the real projects in Singapore, has produced encouraging results. The FNN model shows a significant ability to predict markup estimation over the ANN model. By incorporating fuzzy inference rules, which are generated from a contractor's experience, the FNN technology has proven to be a practical way for resolving the markup estimation problem.

The findings of this paper can be used by other construction firms to model and estimate its markup size because it has laid down the *method* and *shell* of the FNN model, which can be applied to all contractors. What each contractor needs to do is to adjust the rules inside the model, and the data which is used to train the model. The method of collecting and the types of fuzzy inference rules would remain the same (see Table 3). Other contributions include the way of inputting the inference rules, and training the model with the data collected, which will lead to a robust model.

Although the FNN model has many advantages, it also has some limitations in practical application. First, it is relatively time consuming and expensive to collect the fuzzy inference rules. Second, the structure of the FNN model is relatively more complicated than other models. Therefore, future research on writing a user-friendly software may be necessary to make users understand and accept it. There is also the potential to explore how the FNN model may differ using different types of functions in future. It is acknowledged that more than one expert within the firm

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should have been interviewed. This was not done because in this firm, the person being interviewed was the main decision maker on markup size.

Notation

The following symbols are used in this paper:

A_i^j = input variable X_i's jth character;
a_i^j = parameter of the ith input variable's jth membership function;
b_i^j = parameter of the ith input variable's jth membership function;
exp( ) = exp function;
$f(,)$ = membership function;
K = number of the fuzzy singleton rules;
M = expert's actual markup;
M_M = model's markup;
n = number of respondents who indicate the five scales;
R^k = kth fuzzy singleton rule;
T = mean importance rating;
W_k = output value of the kth rule;
X_i = ith input variable of fuzzy neural network model;
Y = output variable of the fuzzy neural network model;
Y^d = desired output of the fuzzy neural network model;
η = learning rate;
$\mu_{A_i^j}(X_i)$ = jth membership degree of input X_i; and
μ_k = active degree of the rule K.

Subscripts

a,b = parameters of the membership functions;
h = sequence of the attributes; and
i,j,k,t = positive integer indices.

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