A FUZZY NEURAL NETWORK APPROACH FOR CONTRACTOR PREQUALIFICATION

Lam, K. C.[1], Hu, Tiesong[2], Ng, S. Thomas[3], Skitmore, Martin[4] and Cheung, S. O.[1]

[1]*Department of Building and Construction, City University of Hong Kong, Hong Kong*
[2]*Department of Hydraulic Engineering, Wuhan University of Hydraulic and Electric Engineering, China*
[3]*Department of Civil Engineering, University of Hong Kong, Pokfulam, Hong Kong.*
[4]*School of Construction Management & property, Queensland University of Technology*

ABSTRACT

Nonlinearity, uncertainty and subjectivity are the three predominant characteristics of contractors prequalification which cause the process more of an art than a scientific evaluation. A fuzzy neural network (FNN) model, amalgamating both the fuzzy set and neural network theories, has been developed aiming to improve the objectiveness of contractor prequalification. Through the FNN theory, the fuzzy rules as used by the prequalifiers can be identified and the corresponding membership functions can be transformed. Eighty-five cases with detailed decision criteria and rules for prequalifying Hong Kong civil engineering contractors were collected. These cases were used for training (calibrating) and testing the FNN model. The performance of the FNN model was compared with the original results produced by the prequalifiers and those generated by the general feedforward neural network (GFNN, i.e. a crisp neural network) approach. Contractor's ranking orders, the model efficiency (R^2) and the mean absolute percentage error (MAPE) were examined during the testing phase. These results indicate the applicability of the neural network approach for contractor prequalification and the benefits of the FNN model over the GFNN model. The FNN is a practical approach for modelling contractor prequalification.

KEY WORDS: Fuzzy reasoning, neural network, contractor prequalification

INTRODUCTION

Contractor prequalification is a commonly used process to identify a pool of competitive, competent and capable contractors from which tenders may be sought. The aims of contractor prequalification are to minimise the possibility of contractor default and the time involved in bidding by restricting the number of eligible contractors involved. In practice, contractors' suitability to participate in a project bid is usually assessed by the project owners according to their previous experience, judgement and a set of criteria which might vary between projects and clients. It is one of the most challenging tasks performed by an owner or contract administrator due to the complexity involved in this process.

Contractor prequalification can be regarded as a complicated two-group nonlinear classification problem, in which decisions are made according to the prequalification criteria, contractor's attributes and prequalifier's judgement. The complexity stems from three main features: nonlinearity, uncertainty and subjectivity. *Nonlinearity* refers to the complicated nonlinear relationship between contractor's attributes and the corresponding prequalification decisions made by the prequalifier. As a result, the nonlinear models should be more effective than the linear models when modelling the process of contractor selection. This argument is supported when comparing the performance of the linear model incorporating multiple ratings (Russell, 1992), PERT approach (Hatush and Skitmore, 1997a) and multiattribute utility model (Diekmann, 1981). *Uncertainty* is mainly due to the fuzziness and randomness associated with contractor's performance, prequalifier's experience, prequalification criteria and the qualitative judgements. These led to the application of the fuzzy set theory (Nguyen, 1985) and some statistical techniques (Jaselskis and Ashley, 1991). *Subjectivity* is the most difficult obstacle encountered by the researchers and practitioners due to a diversity of prequalification criteria and the variability of input ratings to the same contractor, especially if they were assessed by different prequalifiers according to their own idiosyncratic perceptions. Multiattribute utility functions were used in an attempt to represent the decision-maker’s preference (Diekmann, 1981; Hatush and Skitmore, 1998). Despite that, contractor prequalification remains largely an art where subjective judgement, based on the individual’s experience, becomes an essential part of the process (Nguyen, 1985).

An artificial neural network (ANN) is a massively parallel distributed processor that has a natural propensity for storing the experimental knowledge and making it available for use. It has been successfully applied in a number of fields including pattern classification, prediction and optimisation. Owing to their excellent learning and generalising capabilities, neural networks have also been applied to a variety of construction domains, including the prediction of potentials to adopt new construction technology (Chao and Skibniewksi, 1993), the estimation of construction costs and mark-up (Moselhi *et al*, 1991; Hegazy and Moselhhi 1994; Li *et al*, 1999), the forecast of construction productivity (Chao and Skibniewksi, 1994) and the estimation of residential construction demand (Goh, 1998). Recently, Khosrowshahi (1999) has demonstrated the applicability of neural networks to contractor prequalification. Lam *et al* (2000) has explored the possibility of improving network performance by feeding network with both the actual real prequalification cases and the hypothetical cases. To date, most research efforts regarding the application of neural network to construction have been focusing on utilising the GFNN’s capability to handle highly nonlinear aspects. Fuzzy set theory, on the other hand, can tackle the uncertainties involved in the process of prequalification (Nguyen, 1985; Juang *et al*, 1987; Lam *et* *al*, 1998; Lam and Runeson, 1999). It is likely that substantial improvements on the contractor prequalification decisions can be made by merging the ANN and fuzzy set theories.

A fuzzy neural network is a layered, feedforward, network that processes fuzzy set signals and/or has fuzzy set weights (Buckley and Hayashi, 1994). It is a powerful approach to many engineering problems (Jang *et al*, 1997; Zhang and Morris, 1999; Brown and Harris, 1994; Horikawa *et al*, 1992). Several different types of fuzzy neural networks have been developed (Liu, 1999). Fuzzy neural networks combine the advantages of both fuzzy reasoning (i.e. ability in handling uncertainty associated with qualitative information) and neural networks (i.e. ability in learning and generalising from prequalification cases). However, little has been published on the application of fuzzy neural network to contractor prequalification.

The objective is to evaluate the practicality and effectiveness of the fuzzy neural network (FNN) model for contractor prequalification and selection. The versatility of this network is displayed through a series of tests using civil engineering projects in Hong Kong. A comparison of the results with those generated by the GFNN approach helps to establish the effectiveness of the FNN model.

FUZZY NEURAL NETWORK

Fuzzy Reasoning

In order to prequalify contractors on an impartial and objective basis, both qualitative and quantitative knowledge should be fully utilised and analysed (Ng, 1996). Fuzzy modelling is a method to describe the characteristics of a system using fuzzy inference rules (Takagi and Sugeno, 1985). The following is a sample base rule used in the prequalification decision-making:

Rule: **If** the candidate contractor's reputation is very good and financial stability is outstanding and technical expertise is excellent and past performance is …
Then the prequalification decision is qualified.

Generally, the following linguistic rules for contractor prequalification are based on the forms of above fuzzy rules:

$$R^j: \text{If } (x_1 \text{ is } A_1^{j_1}) \text{ and } (x_2 \text{ is } A_2^{j_2}) \text{ and} \cdots \text{and } (x_n \text{ is } A_n^{j_n}) \text{ then } Z \text{ is } B^j \tag{1}$$

where R^j denotes the j^{th} rule ($j = 1, 2, \cdots, M$), x_i $(i = 1, 2, \ldots, n)$ are the input variables to the fuzzy system, such as contractors' reputation, financial stability and technical expertise, etc. Z is the output variable of the fuzzy system; $A_i^{j_i}$ and B^j are linguistic terms characterised by fuzzy membership functions $\mu_{A_i^{j_i}(x_i)}$ and $\mu_{B^j(z)}$ respectively. Each R^j can be viewed as a fuzzy implication: $A_1^{j_1} \times A_2^{j_2} \times \cdots \times A_n^{j_n} \to B^j$, which is a fuzzy set in $U \times R$ with

$$\mu_{A_1^{j_1} \times A_2^{j_2} \cdots \times A_n^{j_n} \to B^j}(x_1', x_2', \cdots, x_n', z) = \mu_{A_1^{j_1}}(x_1') * \mu_{A_2^{j_2}}(x_2') * \cdots * \mu_{A_n^{j_n}}(x_n') * \mu_{B^j}(z) \tag{2}$$

where $X' = (x_1', x_2', \cdots, x_n')^{\mathrm{T}} \in U, Z \in R$.

Applying the sum-product composition, the fuzzy reasoning process can be expressed as follows:

$$Z^* = \frac{\sum_{j=1}^{M} Z_j (\mu_{A_1^{j_1}}(x_1) * \mu_{A_2^{j_2}}(x_2) * \cdots * \mu_{A_n^{j_n}}(x_n))}{\sum_{j=1}^{M} (\mu_{A_1^{j_1}}(x_1) * \mu_{A_2^{j_2}}(x_2) * \cdots * \mu_{A_n^{j_n}}(x_n))} \tag{3}$$

where the symbol "*" denotes an algebraic product.

The above fuzzy system enables the nonlinear prequalification decision making process to be expressed linguistically. Despite this, it is very difficult to identify rules and calibrate the membership functions of the fuzzy reasoning. However, the GFNN approach can learn and generalise from previous contractor prequalification cases, which is particularly useful for this assignment. Fuzzy reasoning is capable of handling uncertain and imprecise information while a neural network is capable of learning from prequalification cases. The fuzzy model in equation (3) can be represented by a FNN proposed hereinafter.

Fuzzy Neural Network Model

The FNN consists of five layers; i.e. an input layer, a fuzzification layer, a base rule layer, a normalisation layer and a defuzzification layer. Several different types of neurons may be employed in the network. They have different activation functions and carry out different information processing functions. Inputs to the fuzzification layer are the prequalification variables, which are in turn used to describe candidate contractors' attributes. Each of these variables is transformed into several fuzzy sets, such as "Good", "Fair" and "Poor". Each neuron corresponds to a particular fuzzy set with the membership function given by its output. Except for the neurons in the fuzzification layer, all the activation functions of the neurons in other layers can either be the identity functions or the linear functions, which distinguish the FNN from the GFNN. Detailed relationships between neurons are shown in Figure 1, and explained as follows.

The output of a neuron i in the input layer (O_i^{I}) is equal to its input (I_i^{I}). Three kinds of activation functions (S-type, Bell-type and Z-type fuzzy neurons) for the neurons in the fuzzification layer are employed, and shown in Figure 2. These are:

$$f(x) = 1/(1 + e^{-(x-\chi)/\sigma}) \tag{4}$$

$$f(x) = \exp(-(x-\chi)^2/\sigma^2) \tag{5}$$

$$f(x) = 1 - 1/(1 + e^{-(x-\chi)/\sigma}) \tag{6}$$

where χ *and* σ represent the centre and the half width of the Gaussian membership function respectively. χ is the parameter that controls the horizontal shift of nonlinear transformation of a neuron and σ is the parameter that controls the slope of nonlinear transformation of a neuron. All these parameters will be determined by training the FNN. The input and output of neurons can be expressed as follow:

$$I_i^{\mathrm{F}} = O_i^{\mathrm{I}} = x_i \tag{7}$$

$$O_i^{\mathrm{F}} = f(I_i^{\mathrm{F}}) = f(x_i) \tag{8}$$

In the base rule layer, neurons implement the fuzzy intersection and the inputs and the output of a neuron (I_j^{R}, $j = 1, 2, \ldots, M$) can be expressed as

$$O_j^{\mathrm{R}} = I_j^{\mathrm{R}} = \prod_{i=1}^{n} \mu_{A_i^j}(x_i) \tag{9}$$

Neurons in the fourth layer implement the normalisation function, which can be expressed as:

$$O_j^{\mathrm{N}} = I_j^{\mathrm{N}} = I_j^{\mathrm{R}} / \sum_{j=1}^{M} I_j^{\mathrm{R}} \qquad j = 1, 2, \cdots, M. \tag{10}$$

The final output, prequalification decisions, of the FNN can be computed via the centre of gravity (COG) algorithm. The defuzzification layer performed the COG defuzzification and gives the final network output, which can be expressed as:

$$O^D = I^{\mathrm{D}} = \sum_{j=1}^{M} Z_j O_j^{\mathrm{N}} \tag{11}$$

In contrast to the GFNN, it is shown in the above equations that the meaning of fuzzy network structure and the weightings are easier to interpret. Moreover, the structure of the FNN can be easily determined as compared to that of the GFNN if the number of neurons of the input layer is determined, which depends on the number of criteria/subcriteria used for prequalifying contractor.

Learning Algorithm of the FNN

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, the General Delta Rule algorithm is applied to train the FNN. The objective of training is to minimise the sum of squared errors (*E*) between the calculated output of the network (O_p^{D}, $p = 1, 2, \cdots, P$) and the actual prequalification decision in the real case, which can be written as:

$$E = \frac{1}{2} \sum_{p=1}^{P} (O_p^{\mathrm{D}} - PQD_p)^2 \tag{12}$$

where PQD_p, $p = 1, 2, \cdots, P$ denotes the prequalification decisions for a contractor *p*, whose performance attributes and prequalification decisions were collected for training the network. The parameters of the network can be adjusted as follows to minimise the sum of square errors:

$$\chi(k+1) = \chi(k) - \eta(t)\frac{\partial E}{\partial \chi} + \beta \Delta \chi(t) \tag{13}$$

$$\chi(t+1) = \chi(t) + \Delta \chi(t+1) \tag{14}$$

where $\chi(k)$ is the value of χ at the iteration of training step *k*. Other parameters can be adjusted similar to that of χ. $\eta(t)$ and β are the adaptive learning rate and momentum rate terms. 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 oscillations. Therefore, a momentum value is generally introduced into the Backpropagation-like algorithms in order to improve the convergence but inhibit continuous oscillations, as shown in equation (13). This determines the effect of previous parameter changes on the present change in the parameter space. $\frac{\partial E}{\partial \chi}$ can be calculated from the specific structure of the FNN.

CASE STUDY

To evaluation the applicability of the proposed FNN model, it was used for prequalifying contractors. 85 cases relating to 10 public sector projects between 1995-1999 were collected for this study, and the details of the cases can be found in Appendix 1. The following section outlines details in preparing the training pairs including the identification of decision criteria, selection of prequalification cases, partitioning fuzzy variables, etc.

Identifying Criteria

A wide variety of criteria have been proposed for contractor prequalification and selection (Hatush and Skitmore, 1997b; Holt *et al*, 1994b; Russell and Skibniewski, 1988; Ng *et al*, 1999). There are common characteristics in prequalification criteria notwithstanding some variations in owners' objectives and project requirements (Masterman, 1994). Research findings to date indicate that the most commonly used criteria are those pertaining to financial soundness, technical ability, management capability, and the health and safety performance of contractors (Hatush and Skitmore, 1997a). On the other hand, prequalification criteria should correspond to the client's organisational objectives and project requirements. They may differ from each other as the characteristics of the project and contractor are quite distinct and dynamic (Ng, 1996). In addition, since the training, background and experience of prequalifiers vary considerably, the prequalification criteria used by prequalifiers vary equally (Ng *et al*, 1999). Based on the above considerations, some criteria or subcriteria may be added or removed as the collected cases might have different prequalification criteria even though most of them could be the same while the number of neurons in the input layer of the FNN was fixed in this research.

Based on the current contractor prequalification practice of Hong Kong, 5 main criteria and 14 subcriteria were used in this research (see Appendix 1). The five criteria used for this research include: (1) Contractor's Experience, (2) Response to the Brief, (3) Approach to Cost-effectiveness, (4) Methodology & Work Programme and (5) Staffing. Four of the five criteria, except for the Contractor's Experience, were composed of second level sub-criteria. A summary of criteria is shown in Table 1.

Cases Selection

The training pairs are the "environment" which are supplied to the neural network, from which the neural network can learn and perform pattern recognition - qualification or disqualification. The generalisation performance of the neural network highly depends on the training set supplied, even though the neural network is capable of generalising from experiences. There are two parts in every training pair, each of which corresponds to the input and output of the FNN, i.e. contractor's performance attributes, and the prequalification decision. The input–output pair for a contractor can be shown as:

Training pair 1: [87, 92, 88, 96, 89, $\cdots$,] [Qualified]

Training pair 2: [62, 73, 58, 46, 89, $\cdots$,] [Disqualified]

The marks in the first part of the training pair are the contractor performance attributes, which are graded by prequalification practitioners. The second part is the prequalification decision for the contractor. The input-output pairs for all contractors collected were then used as training data in FNN.

In order to give the FNN a more powerful generalisation capability for the two-type pattern recognition problem, the following guidelines in collecting the prequalification cases are recommended. First, enough training pairs should be supplied to have the FNN model parameters calibrated; Secondly, it would be better to choose those prequalification cases in which the candidate contractor had successfully completed the contract or those cases in which the candidate contractor had failed in his contract after being prequalified instead of those cases in which a contractor was qualified and was eventually not selected for the contract in the later contractor selection phase. This means that those actual cases in which prequalification decisions have been practically verified are more preferable to those cases in which prequalifiers are unsure of the correctness of the prequalification decisions. As a result, the neural network can learn both from the successful and unsuccessful prequalification cases; Thirdly, it is also desirable to have a better distribution of training pairs to cover as many scenarios as possible rather than the one case scenario which dominates the others. This means a proper proportion of qualified and disqualified cases should be maintained in the training set. It is difficult to render the FNN with qualification recognition ability when all training samples were the disqualification cases, as this could deteriorate the generalisation performance of the neural network model.

Partitioning Fuzzy Variables

The fuzzy variables such as "very good", "good", "fair" and "poor" could be used to evaluate each attribute of candidate contractors' performance. A marking system was initially introduced such that, if the performance of candidate contractor on specific criterion was classified as “very good”, the marks would be above 80. A “good” performance means the score on that criterion to be between 60 and 80, a "fair" performance means the score is around 40 to 65, and a “poor” performance is below 50. The initial membership functions for the “very good” and “poor” were determined by the Z-type and S-type activation function (equations (4) and equation (6)), and the membership functions for the “good” and “fair” were determined the Bell-type function as specified in equation (5).

Pre-processing the inputs and outputs

Before training the neural network, the marks of each contractor (input data) graded by the panel member of prequalifiers were normalised and the prequalification decisions (output data) were quantified. The following normalisation formula of input data was used:

$$x' = \frac{x - \mu}{\gamma\sigma} \tag{18}$$

where x' is the normalised mark of the contractors' performance attribute, x is the original mark of the contractors' performance attribute, μ and σ are the mean and standard deviation of the input variables, γ is the parameter controlling the mapping range. About 95% of the input variables data falls within [–1,1] range when the input variable follows normal distribution and γ is 1.96. In this study, a value of $\gamma = 1.96$ is used.

The output values of training pairs were assigned as 0 or 1 for the prequalification decision belonging to the binary classification, where 0 represents "disqualified" and 1 represents "qualified". It can be seen that the derivatives of the logistic function are generally very small when values of the logistic function approach are 0 or 1, therefore resulting in very slow learning speed when adopting derivative based learning algorithms. In order to avoid this slow convergence, 0.05 and 0.95 were re-assigned for disqualification and qualification respectively (instead of 0 and 1).

Network performance indicator

The mean absolute percentage error (MAPE), the maximum of absolute percentage errors (MOAPE) and the R^2 efficiency were adopted as network performance indicators. These indicators are given by the following equations:

$$MAPE = \frac{\sum_{p=1}^{P} \left| pqd_p^D - pqd_p^N \right|}{P} \tag{19}$$

$$MOAPE = \operatorname*{MAX}_{p=1,2,\ldots,P} \left(\frac{\left| pqd_p^D - pqd_p^N \right|}{pqd_p^D} \right) \tag{20}$$

$$R^2 = 1 - \frac{\sum_{p=1}^{P} (pqd_p^D - \overline{pqd})^2}{\sum_{p=1}^{P} (pqd_p^D - pqd_p^N)^2} \tag{21}$$

where p is the serial number of training pairs and P is the total number of training or testing pairs. pqd_p^D *and* pqd_p^N are the desired prequalification decisions computed by the neural network for the training pair p. $\overline{pqd}$ is the mean value of prequalification decisions. It can be seen from the above equations that the lower the values for MAPE and MOAPE and the higher the value of R^2, the better is the model efficiency. The ideal value for MAPE and MOAPE is zero, in which case the value of R^2 model efficiency index is unity.

Results and Discussion

The optimum configuration of the GFNN is obtained through trial-and-error experiments with different learning rules, hidden nodes, learning rates and momentum coefficients. The learning rules applied included: back-propagation (BP), conjugated gradient method, hybrid gradient method (BP and conjugated gradient method) (Hu, 1997) and Quasi-Newton's method (BFGS) (Fletcher, 1970). The best network was found to consist of 18 hidden nodes in one hidden layer (14-18-1) and the hybrid gradient method is the best learning algorithm for this case study. The learning rate and momentum coefficient are 0.9 and 0.3 respectively. The stopping criterion was set such that the root mean square error (RMSE) is less than 0.001. As far as the FNN is concerned, the General Delta Rule is chosen as the learning algorithm for the simplicity of calculation of derivatives. The learning rate is not fixed but varied according to the performance of the objective function. If the objective function continues to decrease in consecutive steps, the learning rate would be increased by multiplying a value greater than 1 such as 1.07. Alternatively, it could be decreased by multiplying a value lesser than 1 such as 0.93. The structure of the FNN is 14-42-42-42-1, which means the number of neurons in input layer, fuzzification layer, base rule layer, normalisation layer and defuzzification layer are 14, 42, 42, 42 and 1 respectively. Owing to the difficulties in collecting prequalification cases, the number of neurons in the rule layer was not set as very large. Even though the structure of the FNN seems much more complicated than the GFNN, the parameters needing to be calibrated in the FNN model is less than that of the GFNN model.

The case as shown in Appendix 1 was used to validate the FNN and the GFNN. In this test, all 85 training pairs except the 4 pairs in Appendix 1 were used for training the FNN and GFNN, and the four cases were used as the testing pairs for evaluating the generalisation performance of the FNN and GFNN. The training procedure was stopped after the objective function of learning is less than the pre-designed value 0.001 both in the FNN and GFNN models. Table 2 summarises the results of contractor prequalification decisions made by the FNN, the GFNN and the original decisions made by the contractor owner. As shown in Table 2, both the FNN and GFNN models produce the same contractor ranking orders without much difference in model performance (if the models' performance are only measured by ranking orders). This is the same as the orders ranked by the contract owner. If two contractors were prequalified, as occurs in the case, the FNN and GFNN models would also qualify contractors A and C. The difference of the two models lies in that the output of the FNN for contractor B is lower than the output of the GFNN while Contractor D was assigned a higher value by the FNN than that by the GFNN. Furthermore, the training of the FNN is almost 3 times faster than that of the GFNN.

The cross-validation technique is a more accurate method to evaluate model performance (Leisch *et al*, 1998). This technique was also adapted for verifying the applicability and performance of the FNN model for contractor prequalification and comparing the performance of the FNN and GFNN models. The 85 cases were separated into two sets: 75 for training and 10 for testing. The ten testing cases were numbered as 4, 16, 27, 35, 39, 42, 56, 64, 74 and 82. Tables 3 and 4 present the results of comparisons between the two categories of prequalification cases (training and testing) on the networks' recognition errors in terms of above error criteria. Tables 3 and 4 show that the FNN model out performed the GFNN model both in training and testing phases. In the training phase, it should be noted that the difference in model performances between the FNN and the GFNN was very small, and both the FNN and the GFNN can learn from the prequalification cases with considerable accuracy due to their massive connections between the neurons. However, it is evidenced from Table 4 as the FNN presented the best overall performance considering the three numerical criteria. In terms of MAPE, the FNN model performed better than the GFNN model, with $\mathrm{MAPE}_{\mathrm{FNN}} = 4.51$, which is significantly lesser than $\mathrm{MAPE}_{\mathrm{GFNN}} = 8.87$ (almost two times lesser that of the FNN model). The better generalisation performance of the FNN model over the GFNN model can be further revealed by MOAPE and R^2. The maximum absolute percentage error decreased from 28.46% of the GFNN model to 17.69% of the FNN model and model efficiency R^2 increased from 0.9568 of the GFNN model to 0.9914 of the FNN model. Some tuned membership functions for the subcriteria such as "Relevant Experience & Knowledge", "Understanding of Objectives", etc, are shown in Figure 3. Moreover, the FNN model shows better training performance over the GFNN model as less training time was needed to reach a pre-specified RMSE. The details of the decrease in objective function of the training process with the iteration steps are shown in Figure 4. It is clear that the training of the FNN model is on average three times faster than that of the GFNN model.

CONCLUSIONS

The current practice of contractor prequalification is characterised by the strong nonlinearity between contractor's performance attributes and their corresponding prequalification decisions. The uncertainty associated with the assessment of contractor's data and the subjectivity aroused from the prequalifiers as their training, background and experience vary considerably. These characteristics require the modelling techniques for contractor prequalification to be capable of handling nonlinearity, uncertainty and subjectivity. In this research, a FNN model has been developed, based on the fuzzy set and ANN theories. It is possible for the FNN to identify the fuzzy rules used by the prequalifiers and tune the membership functions by utilising neural networks' learning capability. The FNN model applying to the case study of contractor selection in Hong Kong has produced encouraging results. A very close fit was obtained during the training phase and a mean absolute percentage error of 4.51% was achieved by the FNN model in the cross-validation. The case study also reveals the applicability of the GFNN to contractor prequalification. The ranking orders as produced by the FNN, GFNN and the actual prequalification cases were the same (see Appendix 1) indicating that the neural network approach is a feasible for contractor prequalification. The efficiency and effectiveness of both the FNN and GFNN models for the defined problem is due to the learning capability of the neural networks in highly nonlinear pattern recognition and the generalisation that matches the nonlinear nature of the problem.

Comparisons of model efficiency in terms of R^2, MAPE and MOAPE show that the FNN model can achieve significant improvements over the GFNN model, especially at the verification stage. Moreover, the training process of the FNN model is much faster than that of the GFNN model. Other advantages of the FNN model over the GFNN include a higher degree of comprehensibility and an easier way of determining the network structure. With the GFNN models, it is more difficult to interpret from the network parameters such as the weights and thresholds whilst it is easier to interpret from the FNN parameter such as χ *and* σ. These results suggest that the FNN model provides a superior alternative to the GFNN model for contractor prequalification, in which fuzzy inference rules and linguistic assessments are generally applied. By incorporating fuzzy inference, learning and generalisation from prequalifiers' experience, the FNN method has proven to be a practical way for resolving the contractor prequalification problem. The initial success of the application of the FNN model for prequalifying civil engineering contractors in Hong Kong indicates a bright future for its applications in other construction-related selection problems.

Finally, the implication of the results from this research is that the FNN model should be much more favourable to the practitioners and researchers in contractor prequalification when compared with the conventional feedforward neural network.

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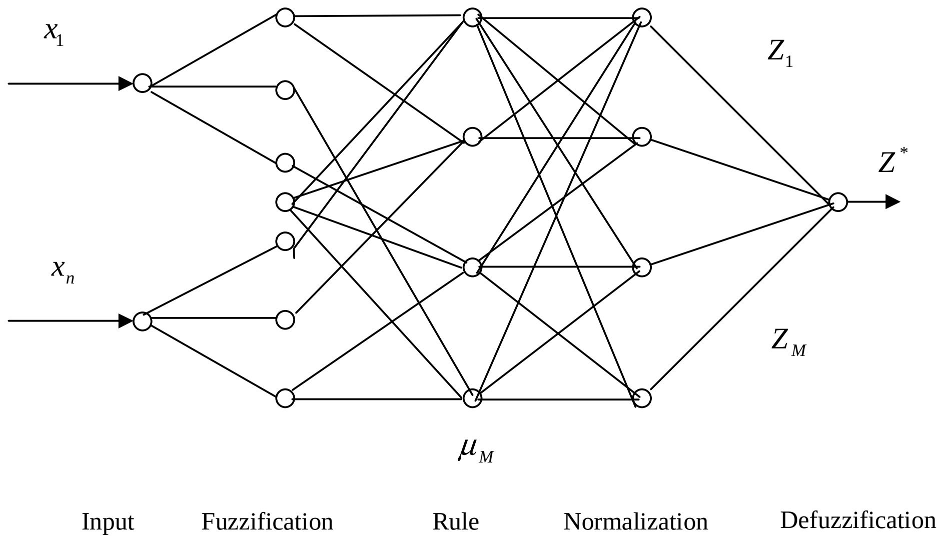

Figure 1. Configuration of the fuzzy neural network

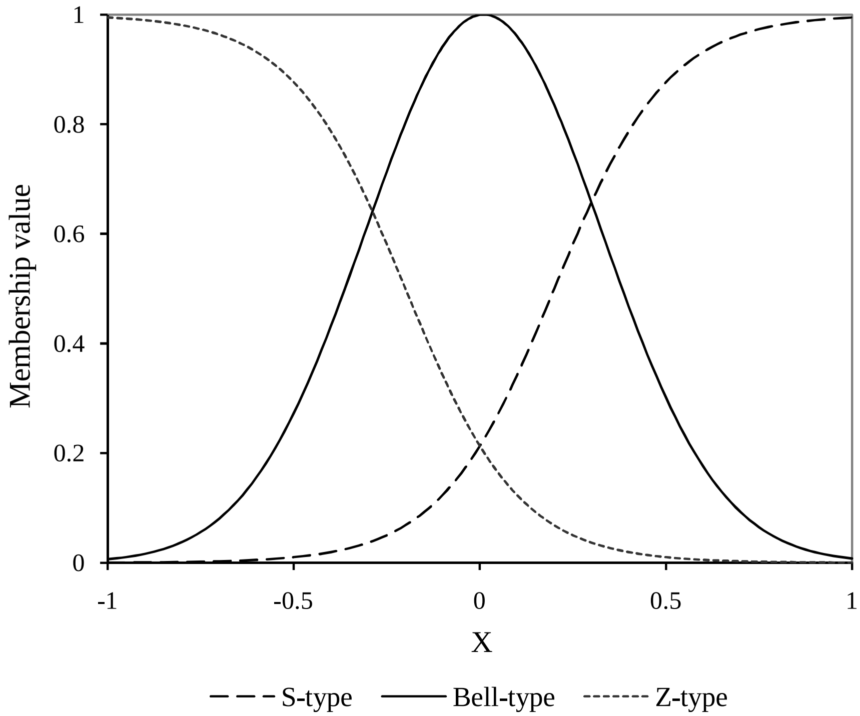

Figure 2 Three types of neuron

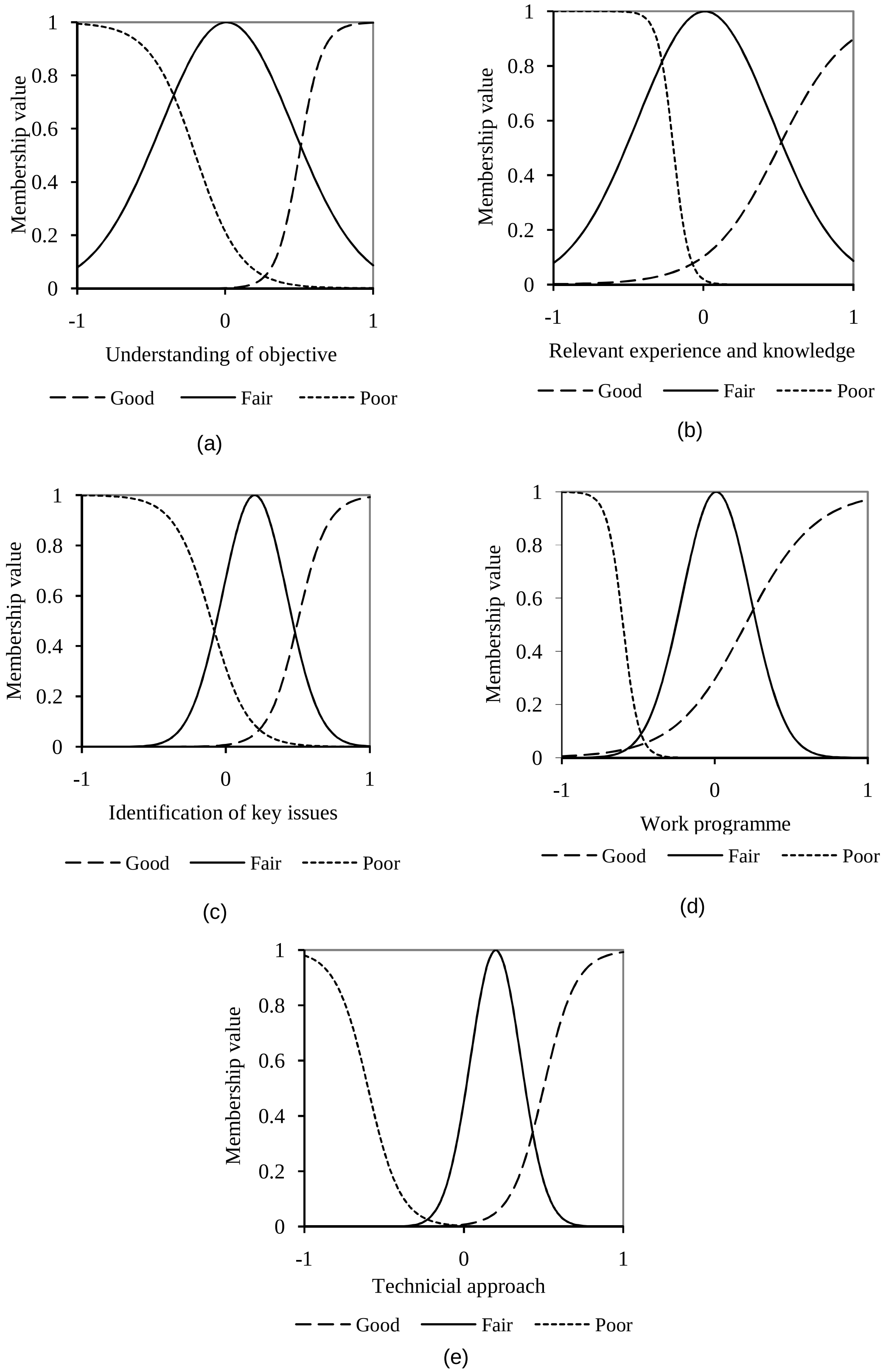

Figure 3 Membership functions

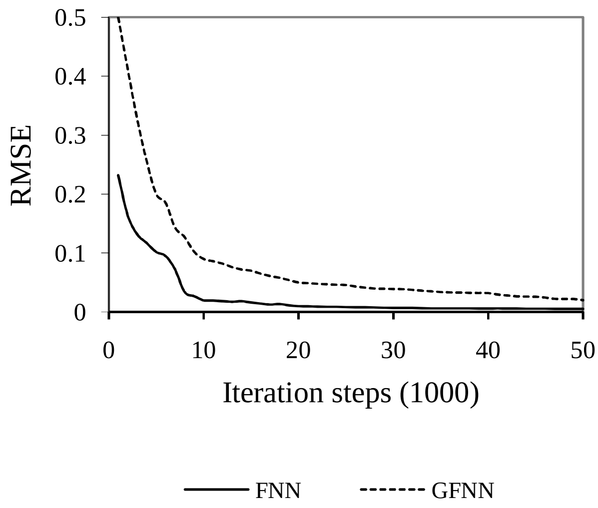

Figure 4 Comparisons of learning performance between the FNN model and GFNN model

Table 1 Case study of Contractor Selection in Hong Kong Project

Criteria and Subcriteria	A	B	C	D
1. Contractors’ Experience				
(a) Relevant Experience & Knowledge	98	95	85	63
2.Response to the Brief				
(a) Understanding of Objectives	97	95	96	96
(b) Identification of Key Issues	95	80	84	80
(c) Appreciation of Project Constraints & Special Requirement	96	60	82	80
(d) Presentation of Innovative Ideas	94	60	81	80
3. Approach to Cost-effectiveness				
(a) Examples & Discussion of Past Projects to demonstrate the Contractor's Will & Ability to produce Cost-effective Solution	86	80	81	80
(b) Approach to achieve Cost-effectiveness on this Project	83	80	62	60
4. Methodology & Work Programme				
(a) Technical Approach	82	80	81	80
(b) Work Programme	81	80	60	94
(c) Arrangement for Contract Management and Site Supervision	84	94	81	80
5. Staffing				
(a) project Team Organisation Structure	96	98	96	92
(b) Relevant Experience & Qualification of Key Staff	84	80	97	80
(c) Responsibility & Degree of Involvement of Key Staff	86	60	80	80
(d) Adequacy of Professional & Technical Manpower Input	82	60	97	96

Table 2 Neural Network Results on the Testing Prequalification Cases

Contractor	Output of FNN	Rank by FNN	Output of GFNN	Rank by FNN	Prequalification decisions made by contract owner	Rank by contract Owner
A	0.9476	1	0.9178	1	Qualified	1
B	0.2586	4	0.3476	4	Disqualified	4
C	0.9123	2	0.8489	2	Qualified	2
D	0.4835	3	0.4423	3	Disqualified	3

Table 3 Comparisons Results of Training by FNN and GFNN

Criteria	FNN	GFNN
MAPE	2.89	3.02
MOAPE	7.87	8.56
R^2	99.68	99.43

Table 4 Comparisons Results of Validating by FNN and GFNN

Criteria	FNN	GFNN
MAPE	4.51	8.87
MOAPE	17.69	28.46
R^2	99.14	95.68

APPENDIX 1 Evaluations of the candidate contractors' attributes

Sub-criteria	Contractor A	Contractor B	Contractor C	Contractor D
1. Consultants' Experience	Relevant projects: -Project A -Project B -Project C Relevant Geotechnical Works: -Project A -Project D -Project E -Project F **98**	Relevant projects: -Project G -Project H -Project I Relevant Geotechnical Works: -Project J **95**	Relevant projects: -Project J Relevant Geotechnical Works: -Project K -Project L -Project J **85**	Relevant projects: -Project N -Project E -Project O Relevant Geotechnical Works: -Not specified **63**
2. Response to the Brief				
(a) Understanding of Objectives	Especially spelt the objectives of the assignment. The location of access road at unstable geological and geotechnical features is highlighted. The description is quite comprehensive. **97**	Especially spelt the objectives of the assignment and understand the importance NAR and SAR. **95**	Especially spelt the objectives of the assignment. A specific section has been provided for geotechnical aspect. The description is quite comprehensive. **96**	Identified objectives of the assignment w.r.t. various phases. **95**
(b) Identification of Key Issues	Key issues on different aspects like traffic, highway, environmental, geotechnical and utilities have been identified. Interface issue was also especially discussed. Appreciation on the slope stability both during construction and operational stages. Natural terrain hazard is also noted. Preliminary assessment of slope stability is provided. **95**	Key issues on different aspects like traffic, highway, environmental, geotechnical and utilities have been identified. Natural terrain hazard assessment, construction assess and the planned western drainage tunnel were highlighted. **80**	Key issues in terms of design of highway structures, traffic, environment, E&M, landscape, geotechnics etc. were identified. Appreciation on the steep topography and natural terrain. **84**	Key issues in terms of design of highway structures, traffic, environment, E&M, landscape, geotechnics etc. were identified. Appreciation on the steep natural terrain. **80**

Sub-criteria	Contractor A	Contractor B	Contractor C	Contractor D
2. Response to the Brief. **(c) Appreciation of Project Constraints & Special Requirements.**	Understood the constrains of steep natural terrain and existing structure in the vicinity. Detailed description of soil mantle and boulders are given. Figures of extents of existing features and geology have also been presented. Accessibility of the site during construction is also appreciated. Discussion is quite comprehensive. **96**	Appreciation of project constraints in various aspect. However, the description is considered too brief. **60**	Understood the constraints of steep natural terrain and existing structure in the vicinity. Use of hand-dug caisson is suggested. **82**	Description of project constraints and requirements in various aspects including geotechnical issue were quite comprehensive. **80**
(d) Presentation of Innovative Ideas	Ideas on different aspects such as alignment (6 options), foundation, slope works etc have been presented with respect to various construction methods. Use of shallow foundation or mini-piles have been considered in lieu of large dia. Bored piles. **94**	Use of reinforced earth wall, panel and nail for steep cut slope have been discussed. **60**	Under the present constraints, Mott has proposed 2 alternatives, one of re-alignment of NAR and the other is to change the priority of junction so that major route will be along lower Sha Wan Drive. **81**	Under the present constraints, Scott has presented several ideas in various aspects including geotechnical, environmental, and highway engineering etc. to produce an optimal design. **80**
3. Approach to Cost-effectiveness **(a) Examples & Discussion of Past Projects to demonstrate the consultant' will & Ability to produce Cost-effective Solution**	**A** has quoted several past projects to demonstrate their ability and experience in achieving cost-effectiveness solution. Project A, D, C and D have been used as examples**.** **86**	**B** has quoted a nos. of past project to demonstrate their ability and experiences in achieving cost-effectiveness solution such as Project G, H. Projects on geotechnical works like RE wall at Shatin was also highlighted. **80**	C has quoted several past projects to demonstrate their ability and experience in achieving cost-effectiveness solution. Project J, K and L have been used as examples. **81**	D has quoted a nos. of past project to demonstrate their ability and experiences in achieving cost-effectiveness solution such as Project N, O. **80**

Sub-criteria	Contractor A	Contractor B	Contractor C	Contractor D
3. Approach to Cost-effectiveness **(b) Approach to achieve Cost-effectiveness on this project.**	A has elaborated approaches on different aspects to achieve cost-effectiveness, For example, use of alternative foundation and rock support method has been discussed. **83**	B claimed that by their project management and technical ability, a cost-effective solution could be derived. Various engineering aspects such as programming and form of contract have been specially described with respect to cost-effectiveness. **80**	C claimed that they would make use of their background knowledge of Hong Kong practice, SAR's requirement and regulation and highway experience to achieve cost-effectiveness solution. However, the description in geotechnical aspect is considered too general. **62**	D claimed that by their management ability and existing knowledge and past experience, a cost-effective solution could be derived. Various approach w.r.t. technical and management aspects were described. A specific section for geotechnical engineering was provided. **60**
4. Methodology & Work Program. **(a) Technical Approach.**	Technical Approach would involve the following aspects: -Traffic -Highway/Highways structure; -Geotechnical -drainage- -Waterworks **82**	Technical Approach would involve the following aspects: -Traffic -Highway/Highways structure; -Geotechnical -drainage- -Waterworks **80**	Technical Approach would involve the following aspects: -Traffic -Highway/Highways structure; -Geotechnical -drainage- -Waterworks **81**	Technical Approach would involve the following aspects: -Traffic -Highway/Highways structure; -Geotechnical -drainage- -Waterworks **80**
(b) Work Program.	Program for 4 phases (Review, Design, Tender and Construction) were provided. Brief discussion was provided. **81**	Programs for 4 phases (Review, Design, Tender and Construction) were provided. Brief discussion was provided. **80**	Program for 4 phases (Review, Design, Tender and Construction) were provided. Brief discussion was provided. **60**	Program for 4 phases were provided. Brief discussion was provided. Description of the program is quite comprehensive. **94**
(c) Arrangement for Contractor Management and Site Supervision.	General discussion on responsibility of construction management, site safety and supervision was provided. **84**	Discussion on contract management, site Supervision with respect to various aspects has been provided quite in detail. **94**	General discussion on responsibility of supervision in chief (contract admin.) and resident site staff (work supervision). **81**	General discussion of arrangement of contract management and site supervision was provided. **80**

Sub-criteria	Contractor A	Contractor B	Contractor C	Contractor D
5. Staffing **(a) Project Team Organisation Structure**	Staff organisation charts were provided. Organisation charts and description are considered adequate. **96**	Staff organisation charts were provided. Description of responsibility of key posts is considered adequate. **98**	Staff organisation charts were provided. It was mainly divided into two groups viz. Project management and project coordination. **96**	Staff organisation charts were provided. Description of the key posts is considered adequate. **92**
(b) Relevant Experience & qualifications of key staff.	Key Staff -staff A (PD) over 25 yrs. experience in civil engineering projects. -Staff B (PM) 15 yrs. experience -Staff C (PC) 15 yrs. experience Geotechnical: Team Leader: RPE (G), 24 yrs. exp. GE: 16 yrs. and 7 yrs. exp. Eng. Geologist: 10 yrs. exp. Hazard Assessor: 10 yrs.. exp. **84**	Key Staff -staff A (PD) over 27 yrs. experience in civil & highway engineering projects. -Staff B (PM) 18 yrs. experience Geotechnical: Team Leader: RPE (G), 22 yrs. exp. GE: MHKIE (Geo) 22 yrs. and RPE(G) 20 yrs. exp. Eng. Geologist: 11 yrs. exp. **80**	Key Staff -staff A (PD) over 20 yrs. exp. in civil engineering projects. -Staff B (QA manager) 10 yrs. exp. -Staff C (PM) 10 yrs. experience Geotechnical: Team Leader: RPE (G), 24 yrs. exp. GE: RPE(G), 19 yrs., RPE(G), 17 yrs. exp. and MHKIE,10 yrs. exp. Eng. Geologist: 10 yrs. exp. **97**	<u>Key Staff</u> -staff A (PD) over 27 yrs.. exp. in civil engineering projects. -Staff B (TD) 20 yrs.. experience -Staff C (PM) 15 yrs.. experience <u>Geotechnical:</u> Team Leader: MICE, MHKIE, 15 yrs. exp. GE: RPE(G),15 yrs. and 7 yrs. exp. Eng. Geologist: 20 and 21 yrs. exp. Hazard Assessor: 15 yrs.. exp. **80**
(c) Responsibility & Degree of Involvement of Key Staff	Input: PD (3 man weeks); PM (20 man weeks), Geotechnical Team Leaders (3 man weeks); others (14 man weeks) **86**	nput: PD (3.2 man weeks); PM (12 man weeks), Geotechnical Team Leaders (0.86 man weeks); others (10.55 man weeks) **60**	Input: PD (6.3 man weeks); PM (1.20 man weeks), Geotechnical Team Leaders (47 man weeks); others (23 man weeks) **80**	Input: PD (12%); PM (12%), Geotechnical Team Leaders (30%); others (30%+40%+25%+5%+20%) **80**
(d) Adequacy of Professional & Technical Manpower Input	CV of 31 nos. professional were submitted. -Professionals input: 172 man weeks -Technical input: 160 man weeks Based on TDD’s memo of 19 Aug. 1999. **82**	CV of 32 nos. professional were submitted. -Professionals input: 144.11 man weeks -Technical input: 49.1 man weeks **60**	CV of 40 nos. professional were submitted. -Professionals input: 252.1 man weeks -Technical input: 168 man weeks **97**	CV of 47 nos. professional were submitted. -Professionals input: 285.5 man weeks -Technical input: 156 man weeks **96**