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Research Article

FNN model for IT Professionals Prequalification Decisions

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Abstract

A Fuzzy Neural Network (FNN) model, combining both the fuzzy set and neural network theories, has been developed aiming to improve the objectives of I.T professionals' analytical skills and prequalification. Through the FNN theory, the fuzzy rules as used by the prequalifiers can be identified and the corresponding membership functions can be transformed. Some cases with detailed decision criteria for prequalifying the I.T Professionals were collected. These cases were used for training and testing the FNN model in their Project-Management. The performance of the FNN model was compared with the original results produced by the prequalifiers and those generated by the general feed forward neural network (GFNN, (i.e.) a crisp neural network) approach. These results indicate the applicability of the neural network approach for I.T professionals prequalification and the benefits of the FNN model over the GFNN model.

Key Words: *Fuzzy reasoning, Neural network, I.T Professionals prequalification*

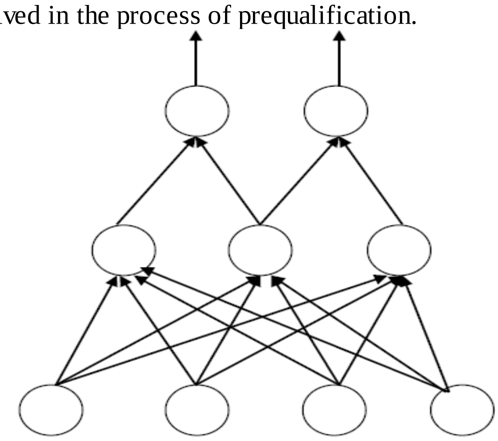
1. Introduction

A Fuzzy Neural Network or Neuro-fuzzy system is a learning machine that finds the parameters of a fuzzy system (i.e., fuzzy sets, fuzzy rules) by exploiting approximation techniques from neural networks. A Neuro-fuzzy system is represented as special three-layer feed forward neural network as it is shown in Figure.

- The first layer corresponds to the input variables.
- The second layer symbolizes the fuzzy rules.
- The third layer represents the output variables.
- The fuzzy sets are converted as (fuzzy) connection weights.

Some approaches also use five layers where the fuzzy sets are encoded in the units of the second and fourth layer, respectively. However, these models can be transformed into three-layer architecture.

IT Professionals prequalification can be regarded as a complicated two-group nonlinear classification problem, in which decisions are made according to the prequalification criteria, IT Professional's attributes and prequalifier's judgement. The complexity stems from three main features: nonlinearity, uncertainty and subjectivity.
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. 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.



A fuzzy neural network is a layered, feed forward, network that processes fuzzy set signals and/or has fuzzy set weights. Several different types of fuzzy neural networks have been developed (Liu, 1999). Fuzzy neural networks combine the advantages of both fuzzy reasoning

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(i.e. ability in handling uncertainty associated with qualitative information) and neural networks (i.e. ability in learning and generalizing from prequalification cases).

The objective is to evaluate the practicality and effectiveness of the fuzzy neural network (FNN) model for IT Professional prequalification and selection. A comparison of the results with those generated by the GFNN approach helps to establish the effectiveness of the FNN model.

In order to prequalify IT Professionals on an impartial and objective basis, both qualitative and quantitative knowledge should be fully utilized and analyzed. Fuzzy modeling 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 IT Professional's communication skill is very good and analytical skill is outstanding and technical knowledge is excellent and past performance is … **Then** the prequalification decision is qualified.

Generally, the following linguistic rules for IT Professional's prequalification are based on the forms of above fuzzy rule

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

where R^j denotes the j^{th} rule ($j = 1, 2, \ldots, M$) , x_i ($i = 1, 2, \ldots, n$) are the input variables to the fuzzy system, such as IT Professional's communication skill, analytical skill and technical knowledge, etc. Z is the output variable of the fuzzy system; $A_1^{j_1}$ and B^j are linguistic terms characterized by fuzzy membership functions $\mu_{A_1^{j_1}}(x1)$ and $\mu_{B^j}(z)$ respectively. Each R^j can be viewed as a fuzzy implication: $A_1^{j_1} \times A_2^{j_2} \times \ldots \times A_n^{j_n} \rightarrow B^j$, which is a fuzzy set in $U \times R$ with

$\mu(x_1', x_2', \ldots, x_n', z) = \mu(x_1')^* \mu(x_2')^* \ldots\ldots\mu(x_n')^* \mu_{B^j}(z)$

where $X' = (x_1', x_2', \ldots, x_n') \in U$, $Z \in R$.

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

$$Z^* = \sum_{j=1}^{M} \frac{Z_j(\mu(x_1')^*\mu(x_2')^* \ldots\ldots\mu(x_n'))}{\mu(x_1')^*\mu(x_2')^* \ldots\ldots\mu(x_n')}$$

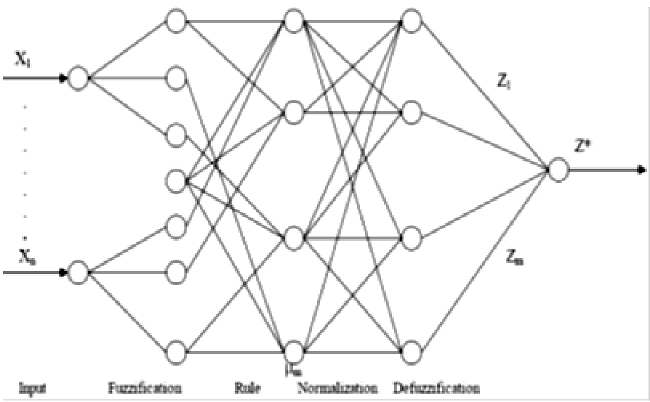
where the symbol * denotes an algebraic product.

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 IT Professionals 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 above equation 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 IT Professional's 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 below:



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. These are

$$f(x) = 1 / (1 + e^{-(x-\mu)/\lambda})$$
$$f(x) = \exp(-(x-\chi)^2 / \sigma^2)$$
$$f(x) = 1 - 1/(1 + e^{-(x-\mu)/\sigma})$$

where χ *and* σ represent the centre and the half width of the Gaussian membership function respectively. □□is the parameter that controls the horizontal shift of nonlinear transformation of a neuron and □□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:

$I_i^F = O_i^I = x$

$O_i^F = I_i^F = f(x_i)$

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

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

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

$$O_j^N = I_j^N = I_j^R / \sum_{j=1}^{M} I_j^R \qquad j=1, 2, 3\ldots M$$

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:

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

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/sub criteria used for prequalifying IT Professionals.

Case Study

To evaluation the applicability of the proposed FNN model, it was used for prequalifying IT Professionals. Many cases relating to several IT projects were collected for this study. The following section outlines details in preparing the training pairs including the identification of decision criteria, selection of prequalification cases, partitioning fuzzy variables, etc.

The training pairs are the environment that is supplied to the neural network, from which the neural network can learn and perform pattern recognition qualification or disqualification. The generalization performance of the neural network highly depends on the training set supplied, even though the neural network is capable of generalizing from experiences. There are two parts in every training pair, each of which corresponds to the input and output of the FNN, i.e. I.T Professionals' performance attributes, and the prequalification decision. The input–output pair for an I.T Professional can be shown as:

Training pair 1: [84, 89, 85, 93, 86…] [Qualified]

Training pair 2: [59, 70, 55, 43, 86…] [Disqualified]

The marks in the first part of the training pair are the I.T Professional's performance attributes, which are graded by prequalification practitioners. The second part is the prequalification decision for the I.T Professional. The input-output pairs for all I.T Professionals collected were then used as training data in FNN.

Pre-processing the inputs and outputs

Before training the neural network, the marks of each I.T Professional (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:

$$x' = \frac{(x-\mu)}{\gamma\sigma}$$

where *x'* is the normalised mark of the I.T Professional's performance attribute, *x* is the original mark of the I.T Professional's 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 γ is 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.

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:

$$MAPE = \frac{\sum_{p=1}^{P} \left| \mathrm{pqd}_p^D - \mathrm{pqd}_p^N \right|}{P}$$

$$MOAPE = \underset{p=1,2,\ldots.P}{MAX} \frac{\sqrt{\left| \mathrm{pqd}_p^D - \mathrm{pqd}_p^N \right|}}{\sqrt{\mathrm{pqd}_p^D}}$$

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

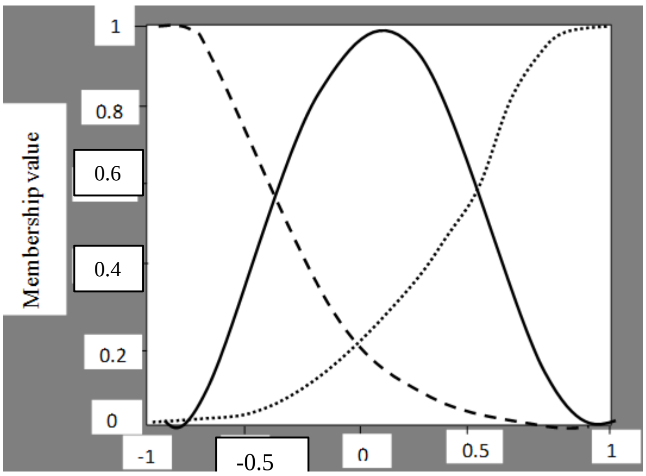
where p is the serial number of training pairs and P is the total number of training or testing pairs. pqd^D and pqd^N are the desired prequalification decisions computed by the neural network for the training pair p. $\overline{pqd}$ is the mean value of prequalification decisions. It can be seen from 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.

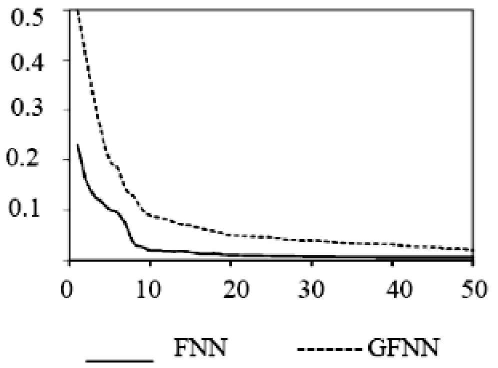
The optimum configuration of the GFNN is obtained through trial-and-error experiments with different learning rules, hidden nodes, learning rates and momentum coefficients.

Case Study

CRITERIA	A	B	C	D
1. I.T Professional's Experience				
(a) Relevant Experience and Knowledge	95	92	82	60
2.Response to the Brief				
(a) Understanding of objectives	94	92	93	93
(b) Identification of Key issues	92	77	81	77
(c) Appreciation of Project constraints	93	57	79	77
(d) Presentation of Innovative Ideas	91	57	78	77
3.Approach to Team work				
(a) Leadership qualities	83	77	78	77
(b) Team player	80	77	59	57
4.Methodology and Work programme				
(a) Technical Approach	79	77	78	77
(b) Work Programme	78	77	57	91
(c) Arrangement for Project Management	81	91	78	77
5.Skills				
(a) Communication skills	93	95	93	89
(b) Analytical skills	81	77	94	77
(c) Logical Thinking	83	57	77	77
(d) Design sense	79	57	94	93

Three types of Neuron





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

Conclusion

FNN model provides a superior alternative to the GFNN model for I.T.Professionals prequalification, in which fuzzy inference rules and linguistic assessments are generally applied. By incorporating fuzzy inference, learning and generalization from prequalifiers' experience, the FNN method has proven to be a practical way for resolving the I.T. Professionals prequalification problem. Finally, the implication of the results from this research is that the FNN model should be much more favorable to the practitioners and researchers in I.T. Professional prequalification when compared with the conventional feed forward neural network.

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