FUZZY NEURAL NETWORK MODEL FOR MARK-UP ESTIMATION

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Abstract: Mark-up estimation involves many uncertain and complex factors making it difficult to model them using conventional mathematical methods. Artificial neural networks (ANNs), which can adapt themselves to training data, have recently been applied to mark-up estimation. However, there are two major drawbacks of this application; firstly, an ANN system is unable to explain why and how a particular recommendation is made, and secondly the prediction performance of ANNs may not be satisfying in some circumstances or near the boundaries of the training sets. This paper proposes a fuzzy neural network (FNN) model to rectify these drawbacks of ANN for mark-up estimation. The FNN model embodies the fuzzy logic in a neural network as a way of retaining the strengths of both methods. While experts' judgments in linguistic rules are captured by the network structure, neural network parameters are fine-tuned through training with objective quantitative data. Because the results are produced within the scope of clearly stated rules and interpretable parameters, the inference process is now transparent. At the same time, the accuracy also improves. An example is presented to illustrate the performance and applicability of the proposed FNN model in comparison with ANN models.

Keywords: mark-up, neural network, fuzzy logic, fuzzy neural network, construction management.

1. INTRODUCTION

Every construction company needs to prepare a bid price for a construction job. This price includes the cost for labor, materials and equipment. This price also includes the overhead and profit (mark-up) factor. While the cost of labor, machinery, and materials is based on a calculation with scope clearly defined, mark-up estimation represents the most variable category within the structure of the bid price.

Identifying the optimum mark-up for a job is critical, because even a slightly different mark-up percentage would possibly result in a totally different fate of the bid. Estimating the mark-up is also a challenging job because so many uncertain and complex factors are involved. It is impossible to provide detailed enough information to the decision-maker. Therefore, for a long time, mark-up percentage estimation is looked as a kind of art work mainly based on the estimators' intuition and experience with some specific rules and constraints applied [1].

A number of models have been developed to analyze and simulate the mark-up estimation mechanism based on uncertain and partial project information. Many of them tried to find the regularity by statistically analyzing past records and used it to estimate the similar projects. Unfortunately, many professionals tend to deny their usability as there seem to be too many uncertain and unique factors involved in the construction process and it is almost impossible to simulate the estimation mechanism of experienced experts with pure mathematical models.

There have also been research efforts attempting to form expert systems to capture the essence of the human estimating ability. But the creation of knowledge base is a long and expensive process [2, 3]. In addition, it is rarely clear how estimating expertise can be articulated, which makes it extremely difficult to acquire knowledge directly from estimators to form a knowledge base [1].

Artificial neural networks (ANNs) offer an alternative source of assistance to mark-up estimation with different features. They could self-adjust network parameters with training data and cope with complex relations with incomplete information. It seems that the properties of ANNs conform to the characters associated with mark-up estimation.

Research efforts have been made in developing ANN-based mark-up estimating systems. After Moselhi & Hegazy [4] identified the possibility of applying ANNs in mark-up optimization, many application examples emerged. Hegazy & Moselhi [5] proposed ANN systems for analogy-based solution to mark-up estimation. Heng Li [1] compared the performance of ANNs to a regression-based method and identified the effect of different configurations of neural networks on estimating accuracy. Li and Love [6] presented a computer based mark-up decision support system that integrated a rule-based expert system and an artificial neural network based system.

However, the wide use of ANNs for mark-up estimation has not been seen until now. One reason for this is perhaps that the accuracy of estimation results from ANNs is not high enough. Error rates of the output from some ANN systems are so large that the forecasting result becomes unreasonable or even meaningless. A more subtle and seldom quoted reason is that many estimators do not themselves fully appreciate how their results are arrived at in ANNs, and may tend to reject any further usage of this model, as the calculation and reference system of ANNs is in a 'black-box'. The above two main drawbacks significantly affect the users' acceptance of the ANNs and their results.

Recently, some research efforts have been devoted to solve these problems. Li and Love [6] embedded a rule base into an ANN model to form a mark-up estimation support system, which is called InMES. They also tried to apply the KT-1 method to extract rules from the trained ANN model. However, there are still some limitations of these researches. A fully informative explanation facility cannot be expected because the system does not have the built-in associative knowledge (i.e., professional knowledge, inference rules, etc.) needed to explain itself. Moreover, the accuracy of the estimate results of this system is not improved.

In this paper, a fuzzy neural network (FNN) model for estimating mark-up percentage is presented. FNN is a computer system, which combines fuzzy logic inference mechanism with a neural network system. With fuzzy logic inference rules embodied in the structure, FNNs could learn knowledge and adjust the parameters of the system according to the training data. By integrating the two systems together, the strengths of both sides are enhanced, thus the drawbacks of ANNs are overcome successfully. The inference processes of relating consequences to preconditions are shown clearly in the fuzzy rules of the system, while the accuracy of the estimate results is greatly improved as all the outputs are calculated within the reasonable range of the inference rules.

The principles and basic calculation processes of the FNN model are introduced first. Second, an FNN mark-up estimation example is presented to illustrate the usage of the FNN model and compare the performance of FNN with ANN models, which demonstrate both advantages and disadvantages of using FNN in modeling mark-up estimation.

2. BACKGROUND

2.1 Fuzzy logic

Fuzzy logic is one of the useful tools for decision analysis. One of the most significant merits of the approach lies in that it opens the way for direct storage of knowledge and inference mechanism with natural language. Natural language is not only the most convenient and effective means by which experts use to store and express their knowledge but also the best way for users and learners to grasp the knowledge from experts. Since 1980s fuzzy theory has been successfully applied to many areas to simulate the human decision process. Fuzzy sets introduce vagueness to classical crisp sets by eliminating the sharp boundary that divides members from nonmembers in the set.

One of the important uses of fuzzy sets is to describe linguistic variables. Using fuzzy set, the linguistic terms could be transferred into mathematics forms based on the defined membership functions. The membership functions commonly used are bell-shaped (Gaussian) functions, triangular functions, and trapezoidal functions. More complex parameterized functions or functions defined by users can also be used as membership functions.

In fuzzy logic systems, an expert's inference process could be transferred into mathematical forms, and the linguistic terms could also be changed into numbers. Thus it is possible to simulate an expert's decision process with mathematical models. In fuzzy logic, qualitative reasoning refers to a mode of reasoning in which the precondition-consequence relation of a system is expressed as a collection of fuzzy IF-THEN rules. Given certain inputs, such a system reaches a conclusion as a result of mathematical operations on the full rules. For details of applying fuzzy logic to a decision analysis problem in construction, refer to Chao and Skibniewski [7].

However, one of the main drawbacks of fuzzy logic systems is that as all of the rules and membership functions are decided by users' experience, a long and expensive process is needed to create it and the system is inevitably subjective.

2.2 Artificial Neural Networks

Artificial neural networks are a system that is deliberately constructed to make use of some organizational principles resembling those of the human brain. They represent the promising new generation of information processing systems. ANNs are good at tasks such as pattern matching and classification, function approximation, and data clustering.

It could be composed of many hidden layers and neurons. The output of the neuron is normally a nonlinear function of a simple aggregation of the weights and input values. Many different methods could be used to adjust the network parameters aiming at minimize the error E between the estimated output Y and the target result Y^d.

3. FUZZY NEURAL NETWORK

Fuzzy logic and neural networks are complementary technologies. A system integrating the above two will possess the advantages of both neural networks such as learning abilities, optimization abilities and connectionist structures, and fuzzy systems such as IF-THEN rules thinking and ease of incorporating expert knowledge. In this way, we can bring the low-level learning and computational power of neural networks into fuzzy systems and also high-level IF-THEN rules thinking and reasoning of fuzzy systems into neural networks. Thus, more transparency is obtained by a possible interpretation of the weight matrix following the learning stage. The structure of the network is determined based on the fuzzy inference system. The rules are used to calibrate it for better whole-system performance. Thus the structure is determined rationally at the beginning, while training allows automatic tuning of the network parameters that characterize the fuzzy system

In this paper, we use fuzzy singleton rules in the following form:

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. Where W_k is a real number k=1, 2… M. This fuzzy neural system has a network structure as shown in Fig. 1.

The FNN is composed of 4 layers.

1. Layer1 reads the real number inputs for variables X_i (i=1, 2, … n)

2. Layer2 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… m) of the linguistic characteristic terms.

$$\mu_{A_i^j}(X_i) = f(a_i^j, b_i^j) \tag{1}$$

3. Layer3 calculates μ_k the active degree of the rule k.

$$\mu_k = \mu_{A_1^j}(X_1)\ \mu_{A_2^j}(X_2) \ldots \mu_{A_n^j}(X_n) \tag{2}$$

4. Layer4 defuzzifies the final output Y* of such a fuzzy neural system with centroid defuzzification equation as follows.

$$Y^* = \frac{\sum_{k=1}^{M} \mu_k W_k}{\sum_{k=1}^{M} \mu_k} \tag{3}$$

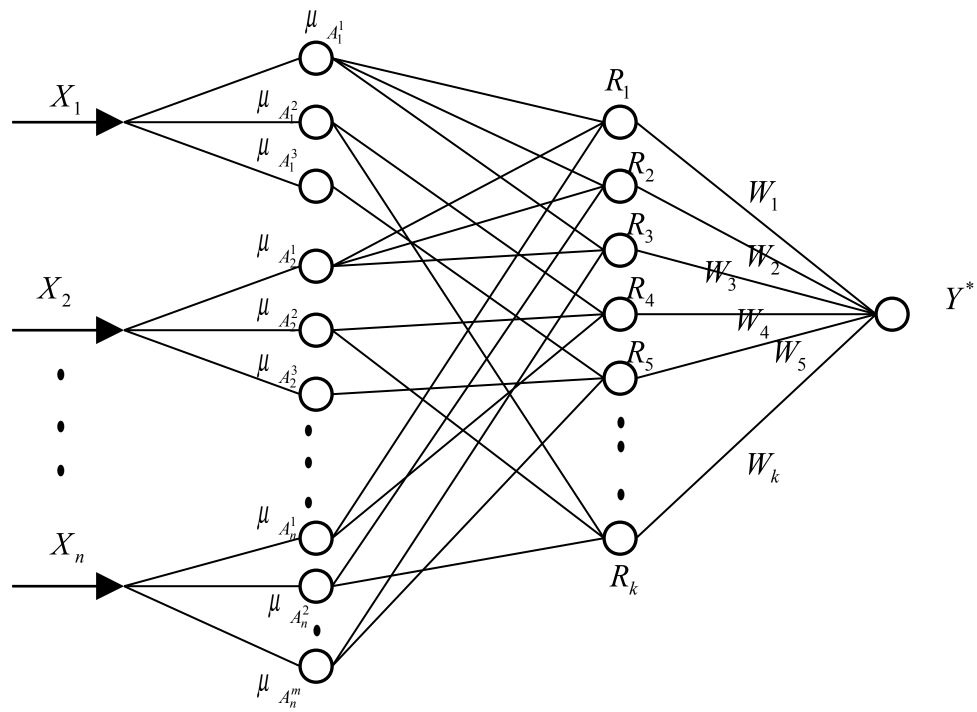


Figure 1. The Basic Structure of FNN model

Parameter learning of a singleton rule FNN system is the tuning of the parameters of the input membership functions $\mu_{A_i^j}(X_i)$ and the real numbers W_k. The learning rule is the same as the Back Propagation (BP) method. Assume that Y^d is the desired output of the FNN system. The parameter learning algorithm for the above fuzzy logic rules is derived as the following equations (4)-(7).

$$E=\frac{1}{2}(Y-Y^d)^2 \tag{4}$$

$$\frac{\partial E}{\partial a_i^j}=\frac{\mu_k(X)}{\sum_{k=1}^{M}\mu_k(X)}(Y-Y^d)\frac{(W_k-Y)}{\mu_{A_i^j}(X_i)}\frac{\partial \mu_{A_i^j}(X_i)}{\partial a_i^j} \tag{5}$$

$$\frac{\partial E}{\partial b_i^j}=\frac{\mu_k(X)}{\sum_{k=1}^{M}\mu_k(X)}(Y-Y^d)\frac{(W_k-Y)}{\mu_{A_i^j}(X_i)}\frac{\partial \mu_{A_i^j}(X_i)}{\partial b_i^j} \tag{6}$$

$$\frac{\partial E}{\partial W_k}=\frac{\mu_k(X)}{\sum_{k=1}^{M}\mu_k(X)}(Y-Y^d) \tag{7}$$

By following equations (4)-(7), the parameters a_i^j, b_i^j, and W_k can be tuned during network training to decrease the estimation error defined by Eq. (4). The system with tuned parameters after training has incorporated the effects of observation data in the knowledge base of inference rules [8].

4. EXAMPLE

This section presents a hypothetical example of applying the FNN system to mark-up estimation. Only market and project factors are considered in the model. Other factors could be added into the model if needed. The three considered factors are defined in Table 1.

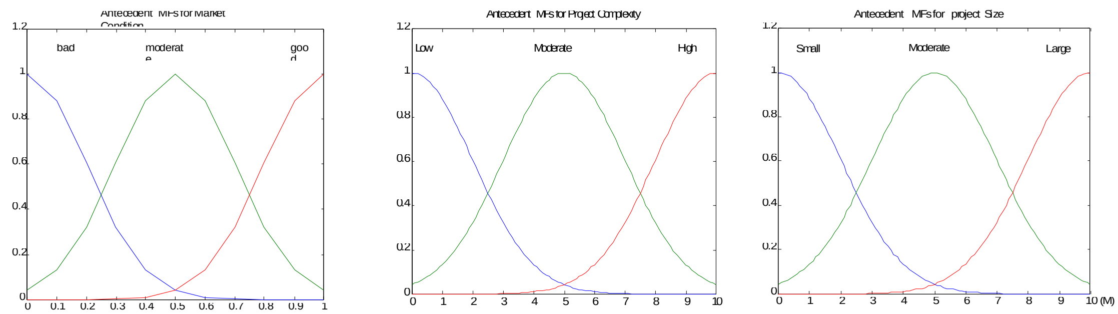
The membership functions for each factor are shown in Fig. 2.

The Gaussian Function is used to define all membership functions as:

$$\mu_{A_i^j}=\exp\left(-\left(\frac{x_i^j-a}{b}\right)^2\right) \tag{8}$$

TABLE 1. Three Influence Factors of FNN Model for Mark-up Estimation

Number	Influence Factors	Abbr.	Value Range	Evaluation Linguistic Terms
1	Market Condition	MC	0-1	Bad, Moderate, Good
2	Project Complexity	PC	0-10	Low, Moderate High
3	Project Size	PS	0-10 (M)	Small Moderate Large



(a) Market Condition (b) Project Complexity (c) Project Size

Figure 2. The Membership Functions of Input Variables before Training

Only two parameters are needed in this kind of membership functions. The three peak-points are spaced equally and there are overlaps between adjacent membership functions.

Six linguistic terms are used for the output factor mark-up. There are High, Medium-High, Medium, Medium-Low, Low and Very Low with the initial values of 10%, 8%, 6%, 4%, 2%, and 1%, respectively. As the FNN system uses singleton FNN rules, the output is a real number.

Since there are three input factors with three membership functions each, if all possible combinations are considered, there will be $3^3 = 27$ rules produced. Six of the 27 rules are quoted below.

1. If MC is *Bad*, PC is *Low*, PS is *Large*, THEN M is *Very Low.*
2. If MC is *Good*, PC is *High*, PS is *Moderate*, THEN M is *Medium High*.
3. If MC is *Bad*, PC is *Moderate*, PS is *Moderate*, THEN M is *Medium*.
4. If MC is *Moderate*, PC is *Low*, PS is *Large*, THEN M is Low.
5. If MC is *Good*, PC is *High*, PS is *Moderate*, THEN M is *High*.
6. If MC is *Moderate*, PC is *Moderate* and PS is *Moderate*, THEN M is *Medium*.

In practice, the subjective rules could be set by experts or experienced managers, while the objective data needed to train the model could be gained from the past records. In this example 276 bidding examples of building projects are produced. The 276 examples are separated into two sets: one for training and one for testing. The membership functions of the input after training are shown in Fig. 3.

There are some changes in the peak-points and shapes of the input factors' membership functions. The values of the output factor after training have also changed to some degree. The adjusted W_k for the six levels from High to Very Low level are 9.8%, 7.2%, 5.7%, 4.5%, 2.9%, and 1.2% respectively.

An ANN model is also developed for comparison. The same training and testing data are used in the ANN model. Comparisons of the average and maximum errors for testing data between the FNN and ANN models are shown in Table 2.

From the comparisons we can see the accuracy of FNN is improved and the estimation result of FNN is more acceptable because of the use of inference rules in the FNN system.

TABLE 2. Estimation Errors of FNN and ANN Models

Errors	FNN	ANN
Average	0.73%	1.93%

Maximum	1.8%	2.7%

(a) Market Condition (b) Project Complexity (c) Project Size

Figure 3. The Membership Functions of Input Variables after Training

5. CONCLUSION

We have described a fuzzy neural network based approach to estimating mark-up percentage. Our example shows that the fuzzy neural network is able to model the complex relationships between the influence factors and the mark-up and achieve an acceptable estimation accuracy. The strength of fuzzy neural networks is the transparent inference mechanism of the system, where the relation between preconditions and consequences are stated clearly in the rules. Moreover, the accuracy of estimation is better than the results of ANN, as all the outputs are drawn in the scope of fuzzy logic inference rules.

This research demonstrates the potential for applying fuzzy neural networks to construction management problems. To make this methodology more generic and applicable to other types of applications in construction, further experiment on implementation is recommend.

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