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Using fuzzy neural network approach to estimate contractors' markup

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Abstract

This paper presents a decision aid to assist contractors to estimate markup percentage to be included in their tenders, based on the Fuzzy neural network (FNN) approach. 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, as every output of the FNN model is produced through the fuzzy inference rules, the results from the FNN model are in a reasonable and acceptable scale. By using this model, the difficulties in markup estimation due to its heuristic nature can be overcome.
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Keywords: Markup; Artificial neural network; Fuzzy neural network; Construction management; Tender estimating

1. Introduction

Identifying the optimum markup for a job is an essential part of tendering, because a slight difference of markup percentage applied to the same job would result in different tendering results. Estimating markup is also a challenging job because many uncertain and complex factors are involved. Moreover, the relationship among the factors is dynamic and complex. Therefore, for a long time, markup percentage estimation is looked at as a kind of mysterious work mainly based on the estimators' intuition and experience with some specific rules and constraints applied [1].

A number of techniques have been used for modeling markup estimation. Hegazy and Moselhi [2] classified markup estimation into three main categories: (1) as a structured problem, leading to the development of probability-based models [3–5]; (2) as a semi-structured problem using decision analysis techniques such as the analytical hierarchy process [6,7]; (3) as an unstructured reasoning-intensive problem using expert systems [8,9]. The models developed based on these techniques have their limitations [10], which perhaps have contributed to the limited use of tendering models in practice and to their relatively modest addition to the state of the art since the mid 1950s [11].

The aim of this paper is to propose a modern approach to information and knowledge management in the area of markup estimation. The approach is based on the construction of a Fuzzy Neural Network (FNN) model to determine the optimal markup for a job. The objectives of this paper are: (1) to build a FNN model to help contractors decide on the size of markup; and (2) to explore the capability of FNN technology in construction problem solving.

The potential contribution of this paper to knowledge is that an ANN markup estimation model with fuzzy inference rules inside is constructed. This is useful because contractors can understand how the model works and this increase its chances to be accepted as a decision aid tool in tender preparation. It also expands the usage of FNN technology in construction problem solving.

2. Literature review

The FNN model makes use of two artificial intelligent (AI) techniques: fuzzy logic and artificial neural network (ANN). Fuzzy logic system is one of the good tools that closely represent how people make decisions as its mimics the thinking process of the brain.

One of the main drawbacks of fuzzy logic system is that a long and expensive process is needed to create it as all the rules and membership functions are decided mainly by users' experience. The system inevitably becomes too subjective.

ANN system mimics the framework of brain functions. A main drawback of ANN is the calculations and reference system are in a 'black-box' [12]. Research efforts have

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been made in developing ANN-based markup estimating systems. After Moselhi and Hegazy [13] identified the possibility of applying ANN in markup optimization, many application examples emerged. Li [1] compared the performance of ANN to a regression-based method and identified the effect of different configurations of neural networks on estimating accuracy. Further research involves improving its performance. One area is to improve its estimating accuracy. Another one is to dispel the 'black-box' [12] image of ANN. This is done by extracting the inference rules. Li and Love [14] proposed ANN systems for analogy-based solution to markup estimation. Li and Love [15] presented a computer based markup decision support system that integrated a rule-based expert system and an artificial neural network based system.

They embedded a rule base into an ANN model to form a markup estimation support system, which is called In-MES. 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, common sense, etc.) needed to explain itself. To remove the 'black-box' perception of the model, and improve its ability to explain what is inside the model, this paper proposes the use of FNN to predict markup. The FNN model, which contains a full explanation of its operations, could increase the user-acceptance of it.

3. Fuzzy neural network (FNN)

Fuzzy logic systems and ANNs share many similar characteristics [16]. The structures of both of them could be changed according to the different requirements of the problems. Eventually, both fuzzy logic model and ANN model are transferred into numerical format and results calculated by using computer programs. Compared to traditional statistical models, they share the ability to improve the intelligence of systems working in uncertain, imprecise, and noisy environments. They estimate a function without requiring a mathematical description of how the output functionally depends on the inputs, while they learn from numerical examples. Both fuzzy and neural approaches are numerical in nature, can be processed using mathematical tools, and can be partially described with theorems.

Fuzzy logic and ANN are complementary techniques. ANN system extracts information from systems to be learned or controlled, while fuzzy logic techniques use verbal and linguistic information from experts. A promising approach to obtain the benefits of both fuzzy system and ANN system and solve their respective problems is to combine them into an integrated system. For example, one can learn rules in a hybrid fashion and then calibrate them for better whole-system performance.

The integrated system, called FNN, will possess the advantages of both ANN system and fuzzy system. On the neural side, more and more transparency is pursued and obtained either by restructuring an ANN to improve its performance or by a possible interpretation of the weight matrix following the learning stage. On the fuzzy side, the development of methods allowing automatic tuning of the parameters with the data collected from real-life examples, decrease the subjectivity of the fuzzy system. Thus, ANN system can improve its transparency, making it closer to fuzzy logic system, while fuzzy logic system can self-adapt, making it closer to ANN system.

FNN technology has been applied in many areas to simulate the problem solving process of human brain and assist people to make decisions under complex situations, such as solving relational equations [17], objective recognition [18], linguistic processing [19], and sales forecasting [20].

4. Model construction

In this paper, a typical four-layer FNN structure is chosen for the markup estimation. It consists of an input layer with identified input factors, a fuzzification layer with membership functions, a rule layer with the collected rules for markup estimation and an output layer with one node which is the estimated markup percentage. Fig. 1 depicts the network topology of the FNN model. The function and calculation process of each layer is discussed below.

1. Layer 1 reads real number input variables X_i ($i = 1, 2, \ldots, n$), the evaluated value of each identified influencing factor for markup estimation,
2. Layer 2 fuzzifies X_i according to the membership functions. Every input value X_i has m membership degree $\mu_{A_i^j}(X_i)$ ($j = 1, 2, \ldots, m$), which represent the characteristic of the influencing factor.

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

   where $\mu_{A_i^j}$ is the membership degree of X_i, $f(a_i^j, b_i^j)$ is the membership function, a_i^j and b_i^j are the parameters of the membership function.
3. Layer 3 calculates μ_j, the active degree of the jth rule according to the relevant fuzzy inference rules collected for markup estimation.

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

4. Layer 4 defuzzifies the final output M of such a neural fuzzy system with centroid defuzzification equation as follows:

   $$M = \frac{\sum_{j=1}^{M} \mu_j w_j}{\sum_{j=1}^{M} \mu_j}, \tag{3}$$

   where w_j is the markup percentage from the jth rule, M is the final estimated markup percentage.

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